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Cost of Credit, Digital Finance and Bank Capital: Implications for MSME Lending and Performance in Kenya

Samuel Tiriongo, Hillary Mulindi, Hesborn Nyagaka and Davis Milimo

Abstract

The study examines how cost of credit, digital finance and bank capital shape MSME lending and performance in Kenya. Using FinAccess 2024 microdata and bank-level panel data (2011–2024), we estimate a control-function Probit, Mundlak Random Effects Logit and System-GMM model. Results show that perceived high borrowing costs are endogenous to loan access, but become insignificant once corrected. Firm age, size, formalization and female ownership significantly improve loan access. Digital finance usage for business transactions increases approval probabilities, while urban location widens access gaps. On the supply side, capital adequacy significantly anchors sustainable loan growth. Overall, MSME performance is driven more by structural firm characteristics and credit supply conditions than by cost perceptions alone.

1.0 Introduction

Access to credit has long been recognized as an anchor to the growth and sustainability of Micro, Small and Medium Enterprises (MSMEs). These enterprises play a critical role in Kenya's economic landscape, where they constitute about 98% of all businesses, create close to 30% of new jobs annually and contribute approximately 40% to national GDP (KNBS, 2020). Their importance extends beyond statistics. They are the engines of entrepreneurship, innovation and inclusive growth.

Moreover, they underpin sectors as diverse as manufacturing, agriculture and services, creating livelihoods for millions while enhancing domestic production and exports. Yet despite this pivotal role, MSMEs remain heavily constrained by limited and often unaffordable access to credit.

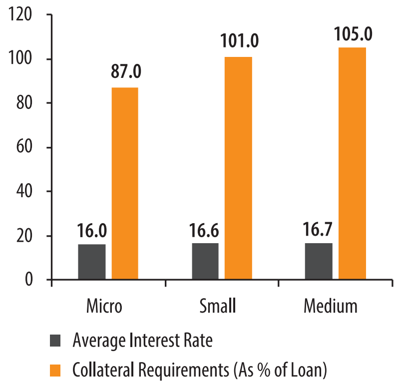
This contradiction is compelling. On one hand, the benefits of credit access are evident. Financing enables firms to expand operations, smooth cash flows, absorb shocks and invest in innovation, all of which are critical ingredients for raising productivity and long-term competitiveness. Studies consistently link financial access to higher welfare and stronger macroeconomic resilience (Sahay et al., 2015). On the other hand, credit markets in Kenya remain structurally dysfunctional, with MSMEs frequently excluded or underserved. Only 3.5% of businesses reported using loans to finance working capital needs in the latest FinAccess Survey (2024), and nearly a quarter (24.7%) cited limited access to credit as a key business challenge.

This disconnect reflects multiple reinforcing barriers. The most prominent among them is the cost of credit, a persistent impediment that significantly shapes MSMEs' borrowing decisions and performance outcomes. High interest rates, compounded by transaction fees, taxation and risk premiums, often push the effective cost of borrowing beyond the reach of small businesses. For instance, data from the CBK MSME Survey (2024) presented in **Figure 1a** shows that commercial banks charged micro, small and medium enterprises average interest rates of 16.0%, 16.6% and 16.7% respectively. Such elevated rates translate directly into higher debt servicing costs, constraining investment in expansion and innovation.

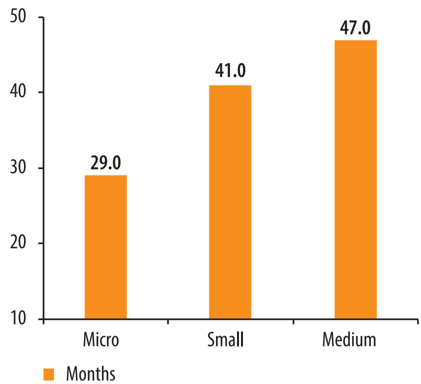
Moreover, affordability constraints are reinforced by collateral requirements, which remain onerous and misaligned with MSMEs' asset bases. Data from the CBK MSME Survey (2024) indicates that micro enterprises were required to pledge collateral averaging 87% of loan values, small enterprises 101.0% and medium enterprises 105.0% (**Figure 1a**). The particularly high collateral-to-loan ratio for medium enterprises reflects banks' conservative risk management and underscores structural rigidities that disproportionately discourage growing enterprises from taking excessive leverage.

Figure 1: MSME bank Financing trends in Kenya

1(a): Average interest rate and Average collateral required as a percentage of Loan (%)



1(b): Loan tenor in months (Proxy to perceived risk)



Source: CBK MSME survey 2024

Loan tenor disparities (**Figure 1b**) further illustrate how risk perceptions shape credit allocation. While micro enterprises accessed facilities averaging just 29 months, small enterprises benefited from 41 months and medium enterprises from 47 months. The shorter maturities for micro enterprises reflect lenders' heightened perception of risk, rooted in asymmetric information, incomplete credit histories and weak collateral frameworks.

These constraints echo scholarly findings. High lending rates elevate the perceived riskiness of formal credit, deterring entrepreneurs from seeking bank loans and limiting investment in growth - enhancing activities (Wajebo, 2022; Nair & Gopal, 2024). Moreover, structural features of credit markets, that is information asymmetry, weak collateral systems and potential discrimination, exacerbate exclusion (Cole, Dietrich & Frost, 2019; World Bank, 2019). As a result, many MSMEs remain confined to informal financing arrangements that, while accessible, are often inadequate, unstable and costly (Wellalage & Locke, 2016). Without reforms to ease borrowing costs, recalibrate collateral frameworks and lengthen loan maturities, the financing gap will persist, curtailing MSMEs' contribution to inclusive growth.

Yet cost alone does not define the pathway of MSMEs' credit access. The financial landscape in Kenya is being reshaped by the rapid rise of digital finance, which is increasingly regarded as a transformative lever for financial inclusion. The advent of mobile money and fintech platforms has created new avenues for extending financial services to previously excluded populations. Kenya stands out globally as a pioneer in this space, largely due to the success of M-Pesa, launched by Safaricom in 2007. Mobile money reduced the average distance to a financial service point from 9.2 kilometers to 1.4 kilometers between 2007 and 2015 (Suri & Jack, 2016), significantly lowering physical and logistical barriers to access.

Digital finance has since evolved far beyond payments. App-based lenders such as Tala, Branch and Saida have introduced digital microcredit, leveraging alternative data sources, including mobile transaction histories and social media activity, to assess creditworthiness (Ndung'u & Oguso, 2021a, 2021b; Gubbins & Totolo, 2018). By circumventing traditional collateral requirements, these models extend credit to borrowers who were previously invisible to banks. Although initially operating outside formal regulation, digital lenders were brought under the oversight of the Central Bank of Kenya through the 2021 Amendment of the CBK Act, strengthening consumer protection and transparency (Gwer et al., 2019).

At the same time, the relationship between digital finance and traditional banking is complex. Initially viewed as competitors, fintech platforms have increasingly entered symbiotic arrangements with banks, thus reshaping the financial landscape. Banks contribute regulatory compliance, capital depth and customer trust, while fintechs provide agility, innovation and digital solutions that enhance efficiency, reduce costs and broaden inclusion.

These collaborations have produced co-branded lending products, mobile banking integrations and shared payment infrastructure. Notable examples include mobile money platforms linked to core banking systems, enabling seamless transfers and wider access to credit and savings. Fintechs further enhance credit scoring with alternative data, while banks ensure sustainable scaling.

Even so, the ability of banks to extend loans is not limitless, but rather, it is directly conditioned by their capital positions. Adequate capital buffers are necessary to absorb shocks, sustain confidence and comply with regulatory requirements. But beyond these prudential functions, capital adequacy also shapes banks' risk appetite and lending behavior (Bernanke et al., 1991; Hancock & Wilcox, 1994; Peek & Rosengren, 1995; Kolcunová & Malovaná, 2019). In Kenya, where financial system is bank-dominated, the capital-lending nexus takes on heightened importance. Besides, the precise nature of this relationship remains underexplored in the regional context. International evidence suggests that capital levels significantly influence lending capacity (Steffen, 2014; Aiyar et al., 2014a, 2014b; Gambacorta & Shin, 2016).

On the account of the foregoing, the interplay between cost of credit, digital finance and bank capital is key to understanding the evolving dynamics of MSME financing and performance in Kenya. By considered the three perspectives, the study provides a holistic view of the constraints and opportunities defining MSME finance in Kenya. As such, the remainder of the paper is structured as follows. Section Two reviews relevant theoretical and empirical literature, while section three presents the study's data, variables and methodology. Section four discusses the study findings, while section five concludes with key policy implications and recommendations.

2.0 Literature Review

The dynamics of MSME credit access are best understood through three interrelated theoretical lenses: credit rationing theory, financial intermediation theory and transaction cost theory. These theories provide insights on both supply and demand-side imperfections in credit markets.

On one hand, the Credit Rationing Theory advanced by Stiglitz and Weiss (1981) is grounded in the imperfections of credit markets, particularly information asymmetry between lenders and borrowers. While MSME owners typically know more about their enterprises' risks and prospects than banks, lenders face difficulties in distinguishing between high and low-risk borrowers. In such circumstances, raising interest rates to cover higher perceived risks can generate perverse outcomes. Higher rates may discourage safer borrowers from applying, leaving a pool of riskier applicants (Adverse selection problem). At the same time, borrowers who accept loans at higher interest rates may take on riskier projects to meet repayment obligations, thus creating moral hazard.

As interest rates rise, the quality of borrowers declines, increasing default risk and reducing net returns for banks. To manage this trade-off, lenders often restrict the supply of credit at a rate below market-clearing levels, resulting in credit rationing. For MSMEs, this implies that even potentially viable businesses may be denied loans or discouraged from applying due to fear of rejection or burdensome application processes.

On the other hand, the financial Intermediation Theory sheds light on the role of digital finance in shaping access to credit. Traditional models of intermediation, from Bagehot (1873) to Diamond and Dybvig (1983), emphasized banks' role in reducing transaction costs, managing maturity mismatches and addressing information asymmetries between savers and borrowers. Intermediaries create value by mobilizing deposits, pooling risks and channelling funds to investment opportunities. Nonetheless, these classical models assumed high transaction costs and limited mechanisms for addressing information gaps, conditions that placed MSMEs at a disadvantage.

The rise of financial technology has altered this dynamic by enhancing intermediation efficiency. As Diamond (1984) argued, intermediaries reduce monitoring costs through economies of scale; fintech builds on this logic by using digital platforms, big data and alternative credit scoring to overcome traditional barriers. Digital lenders in Kenya, for example, draw on mobile transaction histories, airtime purchases and even social media footprints to assess creditworthiness, circumventing the collateral requirements that exclude many MSMEs (Bazarbash, 2019). In doing so, fintech directly addresses the asymmetry problem highlighted in credit rationing theory.

Moreover, digital platforms reduce search, negotiation and enforcement costs, consistent with Philippon's (2016) argument that fintech lowers intermediation costs relative to traditional banking. By leveraging mobile technologies, Kenya's digital finance ecosystem has expanded credit access to underserved populations.

In addition, banks' ability to sustain lending given capital adequacy constraints is well illustrated by transaction cost theory (Coase, 1937; Williamson, 1975, 1985) and its extensions into banking. Transaction costs in lending include both ex-ante costs (such as information collection, screening and contract design) and ex-post costs (such as monitoring, enforcement and recovery). High transaction costs increase the overall cost of lending, especially in markets characterized by information asymmetry and moral hazard. Banks manage these risks by holding adequate capital buffers to absorb shocks and ensure stability.

The link between capital and lending is further elucidated by the failure of the Modigliani-Miller irrelevance theorem (1958) in imperfect markets. In theory, capital structure should not affect lending decisions in frictionless environments. In practice, however, regulatory capital requirements, imperfect equity markets and loan losses create constraints. Heuvel's (2002) bank capital channel model demonstrates that when equity levels are low, banks may reduce lending to meet capital adequacy ratios, even if profitable lending opportunities exist. Monetary tightening can exacerbate this by raising short-term funding costs, reducing profits and eroding capital over time. For MSMEs, this dynamic translates into constrained credit supply when banks face capital pressures, especially in contexts of high non-performing loans.

From an empirical standpoint, the high cost of credit remain one of the most significant barriers to MSME financing. Cole, Dietrich and Frost (2019), drawing on World Bank Enterprise Surveys covering 133 countries, demonstrated how governance and firm characteristics influence SMEs' engagement with credit markets. They showed that smaller and younger firms, particularly those operating informally or under inexperienced management, were more discouraged from seeking bank loans due to high interest rates and perceived rejection risks. These dynamics reinforce the adverse selection problems that arise when borrowing costs increase, leading to a credit market where riskier firms are overrepresented. Complementing this, Nguyen *et al.* (2022) found that SMEs priced out of formal loans often substitute with informal credit, such as borrowing from family, friends or trade credit, underscoring how interest rate pressures reshape financing channels rather than resolve liquidity needs.

Other studies confirm that structural factors amplify the impact of credit costs. Wellalage and Locke (2016), using World Bank Informal and Formal Enterprise Surveys, established that informality significantly heightens credit constraints, with formal MSEs facing on average 18% fewer obstacles. Gourène *et al.* (2025) further showed that family-owned SMEs, despite higher credit needs, were less likely to apply for loans and more constrained than non-family enterprises, indicating that credit costs interact with governance and ownership structures to deepen exclusion.

However, the rise of digital financial services has reshaped credit markets by reducing transaction costs and addressing information asymmetries. Jack and Suri (2016) provided seminal evidence that adoption of M-Pesa in Kenya enhanced access to credit and improved households' ability to manage financial risks, particularly for low-income groups excluded from traditional banking. Subsequent studies have reinforced these findings. Koomson *et al.* (2021) found that mobile money usage in sub-Saharan Africa significantly boosted formal credit uptake, with disproportionately positive effects for women and rural populations. By enabling digital footprints, FinTech platforms have also revolutionized credit scoring. Chen and Faz (2015) demonstrated that alternative data sources, including mobile phone usage and transactional histories, expanded access to first-time borrowers while reducing default rates, offering a pathway to mitigate the information barriers that discourage banks from lending to small firms. Even so, digital finance is not without challenges. Gwer *et al.* (2023) analyzed digital lending in East Africa and found that while mobile credit increased inclusion, it also fostered borrower over-indebtedness due to high effective interest rates and short repayment cycles.

On the supply side, bank capital adequacy is central in determining the ability of financial institutions to support sustainable credit growth. A wide body of empirical research shows that well-capitalized banks are more willing to lend, especially during periods of economic stress. Francis and Osborne (2010), Michelangeli and Sette (2016) and the European Banking Authority (2015) documented that higher capital buffers increase loan supply, particularly in times of crisis when risk perceptions are elevated. Conversely, Gambacorta *et al.* (2016) demonstrated that weakly capitalized banks often cut back on lending to improve solvency, a response that can exacerbate downturns when many institutions face simultaneous capital pressures.

The interaction between regulation, capital requirements and credit supply also reveals important trade-offs. Calomiris and Wieladek (2014) showed that higher capital requirements reduce lending when raising new equity is costly, while Darracq et al. (2010) found that capital shocks increase loan-deposit margins, raising lending rates and suppressing loan demand. Agur (2010) further established that wholesale-dependent banks transmit capital requirements more strongly to the real economy because higher loan rates raise funding costs, creating a feedback loop between credit supply and financial stability. At a systemic level, studies such as Gobbi and Sette (2015) and Bolton *et al.* (2016) highlight that adequately capitalized banks can shield banks from shocks.

3.0 Data, Variables and Methodology

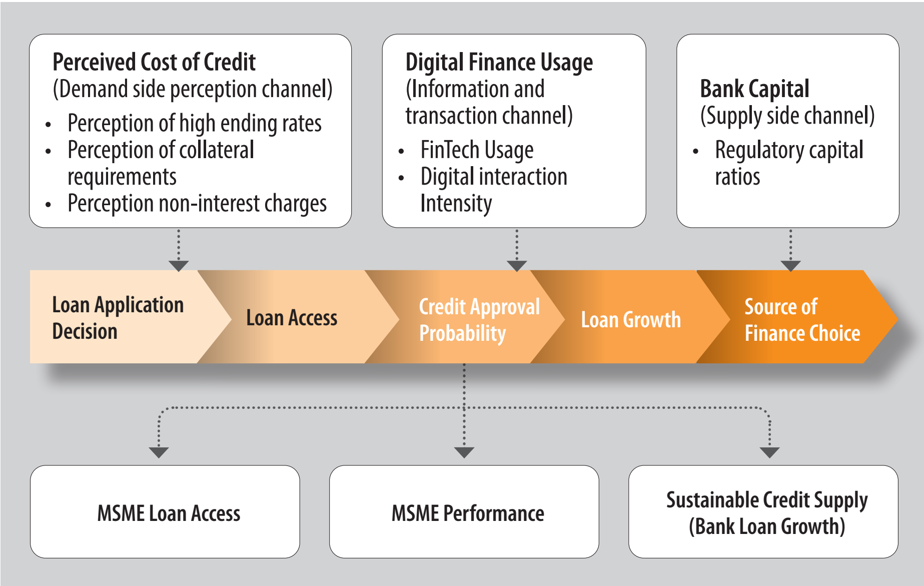
3.1 Data

The study draws on two complementary data sources. First, is the Micro-level data, where the FinAccess 2024 survey provides nationally representative cross-sectional information on Kenyan households and MSMEs. The latter captures MSME characteristics, credit application outcomes, perceptions of credit costs, financial record keeping, business formality and use of digital finance. Second is the annual Macro and bank-level data. This comprises of the annual audited financial statements of commercial banks in Kenya (2011–2024) and macroeconomic indicators, that is Gross Domestic Product (GDP), inflation and Central Bank Rate (CBR) over the same period.

3.2 Conceptual Framework

Cost of credit, digital finance and bank capital shape MSME lending through interacting demand and supply channels (**Figure 3.1**). High lending rates intensify adverse selection and moral hazard, as demonstrated by Joseph Stiglitz and Andrew Weiss, discouraging safer borrowers while encouraging riskier applicants, thereby prompting banks to ration credit rather than clear the market through higher prices. Elevated borrowing costs therefore suppress effective demand and distort borrower composition. Digital finance, however, mitigates these frictions by reducing information asymmetries and transaction costs through alternative data, automated screening and digital footprints. By improving credit scoring and lowering monitoring costs, digital platforms enhance intermediation efficiency and expand outreach to underserved MSMEs. On the supply side, bank capital plays a central role through the capital channel. When banks are weakly capitalized, regulatory constraints and funding pressures induce them to contract lending, even where profitable opportunities exist. Conversely, well-capitalized banks can sustain credit growth during monetary tightening or macroeconomic stress. Together, borrowing costs shape loan demand, digital finance improves screening and access, and capital adequacy determines banks' capacity to sustain MSME lending over the business cycle. These channels interact through mediated pathways, ultimately determining MSME loan access, firm performance outcomes, and the stability of credit expansion.

Figure 3.1: Conceptual Framework



Source: Authors' illustration

3.3 Model Specification

To examine the interlinkages between perceived cost of credit, digital finance and bank capital on MSMEs lending and performance, the study specified three empirical models aligned with the conceptualized framework presented in **Figure 3.1**.

(i) Perceived Cost of Credit and Loan Access

To assess the effect of perceived cost of credit on MSME loan access while correcting for endogeneity, a two-step Probit model with a control function is specified.

First stage (Perception equation)

The probability that an MSME perceives the cost of credit as high is modeled as:

$$\text{Perception of the cost of credit}_i(D_i)=f(\text{age}_i, \text{ownership}_i, \text{gender}_i, \text{total employees}_i, \text{location}_i, \text{education level}_i) \quad \text{...... .... equation 1}$$

Where D_i is the dependent variable perception of cost of credit and Z_i are explanatory variables age of the MSMEs, ownership, gender of the owner, location, business formality, keeping business records

$$D_i = Z_i \beta + V_i \qquad \text{equation 2}$$

And the generalized residual (V_i) is the expected value of the latent error term given the observed binary outcome and is given by:

$$\widehat{V_i} = \frac{\phi(Z_i\hat{\gamma})}{\Phi(Z_i\hat{\gamma})}, if\ D_i = 1\ and\ \widehat{V_i} = -\frac{\phi(Z_i\hat{\gamma})}{\Phi(Z_i\hat{\gamma})}, if\ D_i = 0 \qquad \text{equation 3}$$

Where $\phi(.)$ is standard normal density, $\Phi(.)$ is standard normal CDF, $Z_i\,\hat{\gamma}$ is fitted index from the first stage probit

Second stage regression (Loan access equation):

$$\text{Bank loan to } MSME_i = f\,(age_i,\ ownership_i,\ gender\ of\ the\ owner_i,\ total\ employees_i,\ location_i, education\ level_i, keeping\ business\ records_i,\ business\ formality_i,\ perception\ of\ cost\ of\ credit,\ generalized\ residual \qquad \text{equation 4}$$

Where Y_i^* is bank loan to MSME, X_i include: age of the MSME, ownership, gender of the owner, business formality, books of accounts D_i is the perception of cost of credit and $\hat{V}_i$ captures the generalized residual and is the control function. The coefficient of $\hat{V}_i\,(\rho)$ indicates whether endogeneity is present. The coefficient of $D_i(\delta)$ gives the treatment effect corrected for endogeneity

$$Y_i^* = X_i\,\beta + \delta D_i + \rho \hat{V}_i + \varepsilon_i \qquad \text{equation 5}$$

In equation 6, we test for endogeneity,

$$\rho = 0 \qquad \text{equation 6}$$

However, in analyzing the performance of MSMEs that have obtained loan products from either banks or other sources, a key econometric concern is *selection bias*, often accompanied by *endogeneity*. Loan source is typically not assigned randomly; rather, MSMEs self-select based on characteristics such as collateral availability, credit history, financial literacy, risk preferences, and managerial capability. Many of these same characteristics also directly influence performance indicators such as profitability, sales growth, or productivity. Consequently, the sample of MSMEs choosing bank loans is likely systematically different from those opting for alternative finance, causing the estimated impact of loan source on performance to be biased if these differences are not properly accounted for. In addition, loan type may be endogenous if it is correlated with unobserved determinants of performance, for instance, more capable entrepreneurs may both secure bank financing and achieve higher returns. Thus, to address the unobserved heterogeneity, we use the Mundlak Random Effects Logit Model[1] presented in equation 7, where $\bar{x}_i = 1/T_i \sum_t X_{it}$ is the vector of time average of covariates for firm i; θ is the parameter capturing the correlation between $\bar{x}_{it}$ and unobserved heterogeneity. $x_{it}\,\beta$ measures the within-unit effect (variation over time inside each firm affect performance); $\bar{x}_i\theta$ measures between-unit effect (how firms that on average differ in a charactestic compare to each other); μ_i is residual heterogeneity, assumed independent of X_{it} .

$$\Pr(y_{it} = 1 | \, x_{it}, \bar{x}_i, \mu_i) = \frac{\exp\,(x_{it}\beta + \bar{x}_i\theta + \mu_i)}{1 + exp(x_{it}\beta + \bar{x}_i\theta + \mu_i)} \quad \text{equation 7}$$

$$\theta = 0 \quad \text{equation 8}$$

To test the null hypothesis that X_{it} is uncorrelated with y_{it} , in equation 8 we fail to reject, plain Random Effect Logit Model is valid. However, when $\theta \neq 0$ we reject the null hypothesis. Plain Random Effect Logit Model will result to biased estimates. Mundlak Random Effect logit model will be used where we reject the null hypothesis to allow estimating both within and between effects and test whether the Random Effect independence assumption holds.

Linking equation 7 and equation 9, y_{it} is MSMEs performance, X_{it} include: age of the MSME, ownership, gender of the owner, total employees, location, education level, business formality, keeping business records, the perception of cost of credit and bank loan to MSME

$$\begin{gathered} \textit{MSMEs performance}_{it} = \textit{age}_{it}, \textit{ownership}_{it}, \textit{gender of the owner}_{it}, \\ \textit{total employees}_i, \textit{location}_i, \textit{education level}_i, \textit{business formality}_i, \\ \textit{keeping business records}_i, \textit{perception of cost of credit}_i, \textit{bank loan to} \\ \textit{MSME}_i \quad \text{equation 9} \end{gathered}$$

1 Mundlak Random Effect logit allows for controlling the MSMEs heterogeneity. Mundlak (1978) proposed relaxing independence assumption since firm characteristics are usually correlated with unobserved heterogeneity (economic activity).

(ii) Digital Finance and Credit Access

The effect of digital finance usage on credit access is estimated using a logistic regression model, Equation 10:

$$P(Credit\ access_i\ ) = 1/(1+exp^{(-y)}) \quad \text{equation 10}$$

where is the probability of a customer being able to access credit.

$$y_{i,z} = \beta_0 + \beta_1\ Fintech\ Usage_i + \beta_2\ Income\ level_i + \beta_3\ Education_i + \beta_4\ Region_i + \beta_5\ Age\ group_i + e_i \quad \text{equation 11}$$

$\beta_1,\beta_2,\ldots,\beta_5$ are the coefficients corresponding to the independent and control variables. β_0 is the constant and e_i a disturbance term. The dependent variable, that is, access to credit (y_i), takes three possible outcomes, namely: The customer applies for credit and gets approved, applying for credit and being denied, or the customer fails to apply at all. For this study, we focus on customers that apply for credit.

(iii) Bank Capital and Credit Supply

To estimate the optimal capital threshold anchoring sustainable lending, a dynamic panel System-GMM model (Arellano-Bover/Blundell-Bond) was estimated using equation 12

$$\Delta lnL_{it} = \alpha + \beta_j\ \Delta lnL_{it-1} + \delta_j\ X_{it-1} + \delta_j\ X^2_{it-1} + \varrho_j\ (X_{it-1}\Delta MP_{t-1}) + \Gamma_j\ (\ X^2_{it-1}\Delta MP_{t-1}) + \tau_j\ \Delta MP_{t-1} + \omega_j\ \pi_{t-1} + \gamma_j\ y_{t-1} + \varphi_j\ \vartheta_{it-1} + \Pi_j\ (\vartheta_{it-1}\ \Delta MP_{t-1}) + \varepsilon\_{it} \quad \text{equation 12}$$

Where L_{it} is the amount of loans at bank i, at time, t, and ΔlnL_{it} is the private sector loan growth rate. ΔlnL_{it-1} is the lagged loan growth rate, and is included to capture the dynamic adjustment of bank loan growth to some target path, X_{it} is the measure of capital, X^2_{it} is the squared term of bank total capital, which included to test for the existence of a threshold-effect beyond which excess bank capital is either beneficial or harmful to loan growth. ΔMP_t is an indicator of monetary policy. π_t and y_t is the inflation rate and real GDP, respectively. Inflation and real GDP are included to control for the loan demand effects and facilitate the analyses to incorporate the cyclicality of loan demand along the business cycles. ϑ_{it} is the bank-specific characteristics which are included as control variables, and they include loan-to-deposit rate and log of total assets which are liquidity and size indicators, respectively. These variables enter the dynamic regression in their lagged t erms to mitigate against any possible endogeneity in the estimation.

3.4 Operationalization of Variables

Variable Name	Measurement / Construction
Dependent Variables	
Bank Loan to MSME	Binary variable: 1 = MSME obtained bank loan; 0 = otherwise
MSME Performance	Binary indicator: 1 = improved performance (profit/sales/productivity); 0 = otherwise
Credit Access	Binary outcome among applicants: 1 = approved; 0 = rejected
Loan Growth	Annual growth rate of bank private sector loans (log difference)
Independent Variables	
Perception of Cost of Credit	Binary: 1 = MSME perceives credit cost as high; 0 = otherwise
FinTech Usage	Categorical dummies: Insurance transactions (reference category), Utility payments, Business/financial transactions
Bank Capital Ratio	Regulatory capital-to-asset ratio
Capital Squared	Square of capital ratio to test threshold effects
Monetary Policy Indicator	Central Bank of Kenya monetary policy rate
Firm-Level (MSMEs) Controls	
MSME Age	Natural log of years in operation
MSME Age Squared	Square of logged age (non-linearity)
Firm Size	Log of total number of employees
Ownership Structure	Dummy: 1 = jointly owned; 0 = sole proprietorship
Gender of Owner	Dummy: 1 = female-owned; 0 = male-owned
Location	Dummy: 1 = urban; 0 = rural
Education Level	Categorical: No education (reference Category), Primary, Secondary, Post-secondary
Business Formality	Dummy: 1 = holds valid permit; 0 = otherwise
Record Keeping	Dummy: 1 = keeps hardcopy & electronic records; 0 = otherwise

Variable Name	Measurement / Construction
Household-Level Controls	
Income Source	Categorical: Farming (reference category), Self-employed, Informal, Formal sector, Financial support
Age Group	Categorical: <20 (reference category), 20 - 24, 25 - 29, 30 - 38, 39 - 44, 45 - 49, >50
Region	Dummy: 1 = urban; 0 = rural
Bank-Level Controls	
Loan-to-Deposit Ratio	Ratio of total loans to total deposits
Bank Size	Log of total bank assets
Inflation	Annual inflation rate
GDP Growth	Annual real GDP growth rate
Interaction Terms	
Capital × Monetary Policy	Interaction term capturing policy-capital channel
Capital^2 × Monetary Policy	Tests non-linear policy effects
Bank Controls × Monetary Policy	Liquidity/size policy interaction

3.5 Estimation Strategy

Different econometric strategies are adopted to address endogeneity, selection bias and dynamic panel concerns. First, the control function approach corrects for endogeneity in perceived cost of credit by including the generalized residual from the first-stage Probit. Second, to address unobserved heterogeneity and potential correlation between regressors and individual effects in the performance model, the Mundlak Random Effects Logit is estimated alongside the standard Random Effects Logit. Third, the digital finance model is estimated using logistic regression with categorical controls to capture heterogeneous credit outcomes across demographic and socio-economic groups. Finally, the capital - lending nexus is estimated using the two-step System-GMM estimator (Arellano–Bover/Blundell–Bond) with Windmeijer-corrected standard errors. Lagged dependent variables, capital, capital squared, interactions and bank-specific controls are treated as endogenous and instrumented using internal instruments. The instrument matrix is collapsed and lag depth restricted to avoid proliferation.

4.0 Results and Discussion

Table 1 presents the Probit model with control function correcting for endogeneity in perceived cost of credit. The first-stage results show that MSME characteristics such as age, ownership structure, gender, location and education do not significantly explain the perception that credit is costly. This is an indication that cost perception may be shaped more by market-wide lending conditions than firm-specific traits.

In the second stage, firm characteristics significantly influence loan access. MSME age exhibits a non-linear (U-shaped) relationship with bank loan access: the linear term is negative (–4.439, $p<0.05$) while the squared term is positive (2.348, $p<0.01$). Marginal effects confirm that younger firms are initially disadvantaged, but credit access improves as firms mature, consistent with lifecycle and reputation-building arguments.

Female-owned firms are significantly more likely to obtain bank loans (6.745, $p<0.01$), with a 2.1% higher probability. Firm size (which is proxied by log of employees) positively affects loan access ($p<0.05$), reflecting scale and collateral advantages. Moreover, the results show that formalization matters. Holding a business permit increases the probability of loan access by 1.9% ($p<0.01$). Interestingly, keeping hardcopy and electronic records is negatively associated with loan access at 10%, possibly reflecting reverse causality where firms denied formal credit resort to better record-keeping to strengthen future applications.

Perceived cost of credit is negative but statistically insignificant once endogeneity is corrected. However, the generalized residual is weakly significant ($p<0.10$), rejecting the null $\rho=0$ and confirming endogeneity. This validates the control function approach and indicates that naïve Probit estimates would have been biased.

Table 1: Cost of Credit and Loan access

	Probit model with control function		
	First stage	Second stage	
	Perception of cost of credit	Bank loan to MSME	Marginal effects
In (MSME age)	0.18 (0.144)	-4.439** (0.024)	-0.014*** (0.001)
In (MSME Age)^2		2.348*** (0.001)	0.007*** (0.000)
Joint Ownership	0.071 (0.748)	-0.711 (0.277)	-0.002 (0.199)
Female	0.215 (0.307)	6.745*** (0.005)	0.021*** (0.003)
In (Total employees)	0.018 (0.789)	0.58** (0.017)	0.002** (0.042)
Urban	0.041 (0.848)	-0.308 (0.674)	0.001 (0.694)
Education level	0.051 (0.611)	-1.05** (0.011)	-0.003*** (0.000)
Business permit		6.286*** (0.003)	0.019*** (0.000)
Hardcopy and electronic business records		-1.66** (0.034)	-0.005* (0.092)
Perception of cost of credit		-25.8 (0.160)	-0.785 (0.17)
Generalized residual		15.687*	0.477 (0.104)
Constant	-2.263*** (0.000)	-19.077*** (0.003)	
Observations	817	817	817

Note: The standard errors are in parentheses, ***Significance level at 1%, **Significance level at 5%, *Significance level at 10%.

Moreover, **Table 2** reports results from the Random Effects Logit and the Mundlak Random Effects Logit models. In the baseline model, perception of high credit cost increases the probability of reporting strong performance (marginal effect 13.6%, $p<0.05$). This counterintuitive result likely reflects survivorship bias, where more resilient firms both perceive credit as costly and remain profitable. Even so, once unobserved heterogeneity is controlled using the Mundlak specification, the perception variable becomes insignificant. The test for the Random Effects independence assumption ($\chi^2=1.11$, $p=0.573$) fails to reject the null, implying that the standard Random Effects Logit is appropriate. The disappearance of significance in the Mundlak model suggests that the earlier positive association was driven by between-firm heterogeneity rather than true within-firm effects.

Firm size remains weakly positive, while female ownership reduces the probability of higher performance in the baseline specification, though this effect also disappears under the Mundlak correction. Overall, performance appears more strongly driven by structural firm characteristics than by perceived borrowing costs per se.

Table 2: Cost of Credit and MSME Performance

	Baseline		Robustness test	
	Random Effect Logit model		Mundlak Random Effect Logit model	
	MSMEs performance	Marginal effects	MSMEs performance	Marginal effects
Bank loan to MSMEs	-	-	-	-
Perception of cost of credit	0.738 (0.260)	0.136** (0.012)	0.725 (0.719)	0.135 (0.957)
ln (Total employees)	0.161 (0.422)	0.03* (0.087)	0.157 (0.74)	0.029 (0.961)
ln (MSMEs Age)	-0.267 (0.314)	-0.049** (0.039)	-0.979 (0.327)	-0.182 (0.962)
ln (MSME Age)^2	0.003 (0.927)	0.001 (0.927)	0.358 (0.892)	0.066 (0.971)
Joint ownership	0.256 (0.270)	0.047** (0.036)	0.257 (0.697)	0.048 (0.960)
Female	-0.346 (0.218)	-0.064** (0.017)	-0.345 (0.669)	-0.064 (0.959)
Urban	0.029 (0.754)	0.005 (0.769)	0.027 (0.774)	0.005 (0.983)
Education_level	-0.005 (0.948)	-0.001 (0.947)	-0.004 (0.949)	-0.001 (0.998)
Business permit	0.069 (0.663)	0.013 (0.557)	0.071 (0.769)	0.013 (0.968)
Keeping business records	0.274 (0.383)	0.05 (0.116)	0.28 (0.696)	0.052 (0.960)
Mean [ln (MSMEs Age)]			0.683 (0.292)	0.127 (0.962)
Mean [ln (MSMEs Age)^2]			-0.355 (0.883)	-0.066 (0.971)
Constant	-0.88 (0.349)		-0.833 (0.751)	
Observations	813	813	813	813
Sigma u	0.216		0.036	
rho	0.139		0.0003	
Test for Random effect independence assumption				1.11 (0.573)

Note: The standard errors are in parentheses, ***Significance level at 1%, **Significance level at 5%, *Significance level at 10%.

In terms of digital finance and credit access, Table 3 shows that usage of FinTech for business and financial transactions significantly increases the probability of loan approval ($p<0.10$), supporting the hypothesis that digital footprints reduce information asymmetry. Urban residence also increases approval probability ($p<0.05$), highlighting spatial disparities in financial access.

Education strongly predicts credit outcomes. Higher education levels significantly increase the probability of rejection relative to no education, possibly reflecting greater credit demand among educated applicants. Age cohorts **between 30 - 44** years show significantly higher approval probabilities, consistent with peak entrepreneurial productivity years. The model is jointly significant (LR χ^2=33863.63, $p<0.000$) with strong explanatory power (Pseudo R^2=0.684).

Table 3: Access to digital credit

	Y=1 (Applied for credit and got Approved)		Y=2 (Applied for credit and got rejected)	
		Marginal Effects		Marginal Effects
Usage of Fintech (reference category are insurance related transactions)				
None	1.429 (0.899)	0.044	0.658 (0.892)	-0.030
Utility Payments	0.630 (0.915)	0.045	0.337 (0.901)	-0.011
Business and Financial Transactions	2.634* (1.437)	0.054	0.520 (1.048)	-0.022
Income generating activity (reference category are farming activities)				
Self employed	-0.667 (2706.96)	0.028	-0.343 (2706.96)	0.416
Money from other people	-45.581 (2621.69)	-0.005	-24.063 (1742.05)	0.891
Informal sector	-45.537 (2640.98)	0.037	-23.662 (1742.05)	0.849
Formal sector	-21.159 (1742.06)	0.012	-21.04 (1742.05)	0.080
Education (reference category is no education)				
Primary	-0.166 (3201.19)	0.067	0.906*** (0.133)	-0.031
Secondary	0.251 (3170.11)	0.099	1.198*** (0.135)	-0.048
Post secondary	23.178 (2768.16)	0.120	1.538*** (0.143)	-0.072

	Y=1 (Applied for credit and got Approved)		Y=2 (Applied for credit and got rejected)	
		Marginal Effects		Marginal Effects
Region (reference category is rural area)				
Urban	0.185** (0.134)	0.008	0.127** (0.060)	-0.007
Age group (reference category is below 20)				
20-24	0.909 (0.812)	0.100	1.629*** (0.143)	-0.068
25-29	1.317 (0.803)	0.120	1.789*** (0.147)	-0.080
30-38	1.771** (0.801)	0.100	1.783*** (0.144)	-0.080
39-44	2.261*** (0.829)	0.093	1.794*** (0.160)	-0.082
45-49	1.604 (0.833)	0.077	1.560*** (0.178)	-0.065
Over 50 years	-0.096 (0.808)	0.018	0.046 (0.168)	0.002
Constant	-1.598 (3270.64)		18.839 (1742.055)	
Observations	20,871			
LR chi2(52)	33863.63			
Prob > chi2	0.0000			
Pseudo R2	0.6839			

Note: The standard errors are in parentheses, ***Significance level at 1%, **Significance level at 5%, *Significance level at 10%.

Lastly, **Table 4** reports System-GMM results. The lagged loan growth term is negative and significant (–0.290, $p<0.10$), indicating mean reversion in lending growth. Capital positively affects loan growth (0.065, $p<0.05$), but the squared term is negative (–0.008, $p<0.10$), confirming a concave (threshold) relationship. Beyond an optimal level, excess capital dampens credit expansion.

The interaction between monetary policy and capital is negative ($p<0.10$), suggesting that tighter policy weakens the capital - lending transmission channel.

Table 4: Capital-credit supply regression model

	Regression Results	
Lagged Loan Growth$_{t-1}$	-0.290*	(0.090)
Capital$_{t-1}$	0.065**	(0.021)
Capital$^2_{t-1}$	-0.008*	(0.003)
Monetary Policy Rate(t)	-0.012	(0.008)
Inflation (t)	0.007	(0.015)
GDP Growth (t)	-0.009	(0.012)
Loan-to-Deposit Ratio$_{t-1}$	-0.240	(0.110)
Log assets$_{t-1}$	-0.330	(0.090)
Monitory policy X Capital interaction	-0.015*	(0.007)
Capital X GDP interraction	-0.018*	(-0.008)
Constant	6.827**	(1.724)
AR(1) p-value	0.00	
AR(2) p-value	0.39	
Hansen J p-value	0.26	

Notes: ***, **, and * denote significance at 1%, 5% and 10%. Standard Errors in parenthesis.

5.0 Summary, Conclusion and Policy implication

This study sheds light on MSME financing dynamics in Kenya by examining perceived cost of credit, digital finance usage and bank capital adequacy. Using nationally representative FinAccess 2024 data combined with commercial bank panel data (2011–2024), the analysis applies a control-function Probit model, Mundlak Random Effects Logit and dynamic System-GMM estimation.

The findings reveal that perceived high cost of credit is endogenous to borrowing decisions. Once corrected, it does not independently reduce loan access. This is a clear indication that structural firm characteristics matter more than perception alone. Additionally, MSME age exhibits a non-linear (U-shaped) relationship with credit access, while firm size, formalization and female ownership significantly improve approval probabilities. Digital finance usage, more particularly for business and financial transactions, raises the likelihood of credit approval, confirming that digital footprints mitigate information asymmetries. However, with the urban bias persistence, the results affirm spatial inequalities in financial access.

On the supply side, bank capital adequacy plays a pivotal role in sustaining private sector loan growth. Well-capitalized banks are better positioned to maintain credit expansion across monetary cycles, while weak capital buffers constrain lending capacity.

Overall, MSME performance appears more strongly influenced by structural characteristics and stable credit supply than by perceived borrowing costs alone.

Policy implications arising from this study are threefold. First, reforms should focus on reducing structural lending rigidities, more so around collateral intensity, rather than solely targeting nominal interest rates. Second, scaling responsible digital finance can deepen inclusion, provided consumer protection safeguards remain strong. Third, prudential regulation must balance capital adequacy with credit growth objectives to prevent procyclical lending contractions. A coordinated approach across demand, intermediation and supply channels is therefore essential to unlock MSME productivity and inclusive growth.

References

1. Agur, I. (2010). "Capital Requirements and credit rationing", *DNB Working Paper no 257*
2. Aiyar, S., Calomiris, C. & Wieledek, T. (2014a). Does Macroprudential regulation leak? Evidence from UK policy experiment. *Journal of money, credit and banking, 46 (51),* 181 - 124
3. Aiyar, S., Calomiris, C. & Wieledek, T. (2014b). Identifying channels of credit substitution when bank capital requirements are varied. *Economic policy, 29 (77)*, 45 - 77
4. Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics, 68(1)*, 29-51.
5. Bagehot, W. (1873). *Lombard Street: A description of the money market.* John Wiley and Sons.
6. Bazarbash, M. (2019). *FinTech in Financial Inclusion: Machine Learning Applications in Assessing Credit Risk.* International Monetary Fund.
7. Bernanke, B. S., Lown, C. S. & Friedman, B. M. (1991). "The credit crunch." *Brookings Papers on Economic Activity, 1991(2)*:205–247.
8. Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87(1)*, 115-143.
9. Chen, G. C., & Faz De Los Santos, P. X. (2015). *The potential of digital data: far can it advance financial inclusion?* (No. 95202, pp. 1-4). The World Bank.
10. Cole, R. A., Dietrich, A., & Frost, T. (2019, December). SME credit availability around the world: Evidence from the World Bank's Enterprise Surveys. *In Midwest finance association 2013 annual meeting paper*.
11. Darracq Paries, M. C., Kok, S. and D Rodriguez, P. (2010). "Macroeconomic propagation under different regulatory regimes: evidence from an estimated DSGE model for the Euro area", *European Central Bank Working Paper Series,* no 1251.
12. Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *Review of Economic Studies, 51(3)*, 393–414.
13. Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of political economy, 91(3)*, 401-419.
14. Francis, W. and Osborne, M. (2010). "Bank regulation, capital and credit supply: measuring the impact of prudential standards", *Financial Services Authority Occasional Paper Series.*

15. Gambacorta, L. & Shin, H. (2016). Why bank capital matters for policy. *Journal of financial intermediation*, 1 – 13

16. Gourène, G., Schwidrowski, Z. B., Balcar, J., & Filipova, L. J. (2025). How credit constrained are family-owned SMEs in Arab countries?. E*merging Markets Review, 65*, 101249.

17. Gubbins, P., and E. Totolo (2018). '*Digital Credit in Kenya: Evidence from Demand-Side Surveys*.' Nairobi: Financial Sector Deepening Trust Kenya.

18. Gwer, F., Odero, J., and Totolo, E. (2019). *Digital Credit Audit Report: Evaluating the Conduct and Practice of Digital Lending in Kenya*. FSD Kenya, September.

19. Hancock, D. & Wilcox, J. A. (1994). "Bank capital and the credit crunch: The roles of risk-weighted and unweighted capital regulations." *Real Estate Economics, 22(1)*:59–94.

20. Hsiao, C. (2014). *Analysis of panel data*. Cambridge University Press.

21. Jack, W., Kremer, M., De Laat, J., & Suri, T. (2016). *Borrowing requirements, credit access, and adverse selection: Evidence from Kenya (No. w22686)*. National Bureau of Economic Research.

22. Modigliani, F. and Miller, M. (1958). "The cost of capital, corporate finance and Theory of investment", *The American Economic Review, Vol 48*, No.2 pages 261 - 297.

23. Ndung'u, N., and A. Oguso (2021a). 'Fintech Revolutionizing Financial Services: The Case of Virtual Savings and Credit Supply Technological Platforms in Africa'. In R. Rau, R. Wardrop, and L. Zingales (eds), *The Palgrave Handbook of Technological Finance, pp. 189–215.* Basingstoke: Palgrave Macmillan. https://doi.org/10.1007/978-3-030-65117-6_8.

24. Ndung'u, N., and A. Oguso (2021b). 'Financial Sector Development and Financial Inclusion in Africa: Gaps, Challenges and Policy Options'. In A. H. Ahmad, D. T. Llewellyn, and V. Murinde (eds), *Inclusive Financial Development, pp. 28–51*. Cheltenham: Edward Elgar. https://doi.org/10.4337/9781800376380.00008.

25. Nguyen, H. T., Nguyen, T. T., Dang, X. L. P., & Nguyen, H. M. (2022). Informal financing choice in SMEs: do the types of formal credit constraints matter?. *Journal of Small Business & Entrepreneurship, 34(3)*, 313-332.

26. Nickell, S. (1981). Biases in dynamic models with fixed effects. Econometrica: *Journal of the Econometric Society, 1417-1426.*

27. Peek, J. & Rosengren, E. (1995). "The capital crunch: neither a borrower nor a lender be." *Journal of Money, Credit and Banking, 27(3):625–638.*

28. Philippon, T. (2016). The FinTech Opportunity. National Bureau of Economic Research (NBER) *Working Paper No. 22476.*

29. Roodman. (2009b). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71(1), 135-158.

30. Sahay et al. (2015). Rethinking Financial

Deepening: Stability and Growth in Emerging Markets. *IMF Staff Discussion Note 15/08*, International Monetary Fund, Washington.

31. Steffen, S. (2014). Robustness, validity and significance of the ECB's asset quality review and stress testing exercise. Economic and monetary affairs committee study.

32. Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review, 71(3)*, 393–410.

33. Suri, T., and W. Jack (2016). 'The Long-Run Poverty and Gender Impacts of Mobile Money'. *Science, 354(6317):* 1288–92. https://doi.org/10.1126/science.aah5309

34. Van den Heuvel, S. (2002). "Does bank capital matter for monetary transmission?" *Economic Policy Review,* Federal Reserve Bank of New York, pages 259 -265.

35. Wajebo, T. W. (2022). Micro, small and medium enterprises access to finance constraints in Ethiopia: Demand side analysis. *International Journal of Small and Medium Enterprises, 5(1)*, 32-39.

36. Wellalage, N. H., & Locke, S. (2016). Informality and credit constraints: evidence from Sub-Saharan African MSEs. *Applied Economics, 48(29)*, 2756-2770.

37. World Bank (2019). *Small and medium enterprises (smes) finance.*

Kenya Bankers Association
13th Floor, International House, Mama Ngina Street
P.O. Box 73100– 00200 NAIROBI
Telephone: 254 20 2221704/2217757/2224014/5
Cell: 0733 812770/0711 562910
Fax: 254 20 2221792
Email: research@kba.co.ke
Website: www.kba.co.ke

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