KENYA BANKERS ASSOCIATION

One Industry. Transforming Kenya.

WPS/04/26

# Unlocking MSME Credit: Sector Specific Insights from Kenya

By Stephanie Kimani

March 2026

KBA Centre for Research on Financial Markets and Policy®
Working Paper Series

98

KENYA BANKERS
ASSOCIATION
One Industry. Transforming Kenya.

# Working Paper Series

## Centre for Research on Financial Markets and Policy

The Centre for Research on Financial Markets and Policy® was established by the Kenya Bankers Association in 2012 to offer an array of research, commentary, and dialogue regarding critical policy matters that impact on financial markets in Kenya. The Centre sponsors original research, provides thoughtful commentary, and hosts dialogues and conferences involving scholars and practitioners on key financial market issues. Through these activities, the Centre acts as a platform for intellectual engagement and dialogue between financial market experts, the banking sector and the policy makers in Kenya. It therefore contributes to an informed discussion that influences critical financial market debates and policies.

The Kenya Bankers Association (KBA) *Working Papers Series* disseminates research findings of studies conducted by the KBA Centre for Research on Financial Markets and Policy. *The Working Papers* constitute "work in progress" and are published to stimulate discussion and contribute to the advancement of the banking industry's knowledge of matters of markets, economic outcomes and policy. Constructive feedback on the *Working Papers* is welcome. *The Working Papers* are published in the names of the author(s). Therefore their views do not necessarily represent those of the KBA.

# Unlocking MSME Credit: Sector Specific Insights from Kenya

Stephanie Kimani*


## Abstract

*This study investigates the sector-specific determinants of MSME credit in Kenya across three dominant sectors—real estate, trade, and transport & communication—that collectively account for nearly 70% of bank MSME lending. Using quarterly data from 2012 to 2024, we apply sectoral Autoregressive Distributed Lag (ARDL) models to capture both short-run dynamics and long-run equilibrium relationships. The analysis integrates supply-side indicators (non-performing loan ratios, lending interest rates, and banking sector liquidity) with demand-side proxies (sectoral GDP), while also introducing a structural policy shock through the 2016–2019 interest rate cap as a dummy variable. Findings reveal significant sectoral heterogeneity: MSME credit in real estate is decoupled from GDP growth and more sensitive to liquidity; trade credit strongly follows sectoral GDP but is vulnerable to NPL shocks; and transport & communication lending exhibits the fastest adjustment to equilibrium, shaped by both demand conditions and borrowing costs. The results provide novel empirical evidence on the differentiated nature of MSME credit drivers in Kenya and highlight the importance of sector-sensitive credit policies, robust risk-sharing frameworks, and targeted liquidity support mechanisms.*

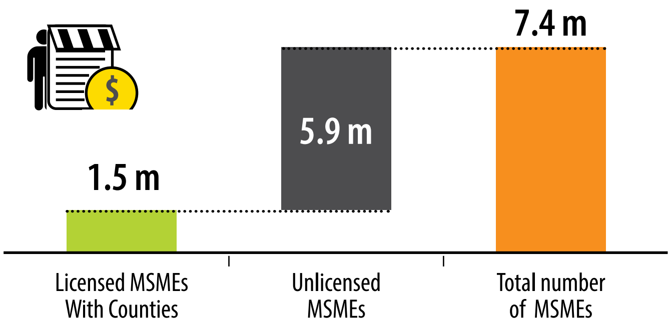

* The author is affiliated with I&M Bank Limited. The views expressed are her own and do not represent those of I&M Bank Limited.

# 1.0 Introduction

**Micro, Small and Medium Enterprises (MSMEs) form the backbone of Kenya's economy, accounting for approximately 33.8% of GDP and the government's ambition is to grow this contribution to 60%.**

This ambition remains relevant given that out of the 7.4 million MSMEs in Kenya only 1.5 million are formally licensed. This means that a about 80% of MSMEs operate in the informal sector and the significant size of this informality comes with negative repercussions such as limited access to credit, low productivity and weak regulatory oversight. This suggests that the formalization of these MSMEs would result in substantial gains for the Kenyan economy and thus align with the government's goal.

**Figure 1: Licensed and Unlicensed MSMEs in Kenya**




Additionally, the MSME sector is socially indispensable as it contributes to over 85% of non-farm jobs. That means that 9 out of every 10 livelihoods outside agriculture, especially for underserved segments such as youth and women, rely on this sector.

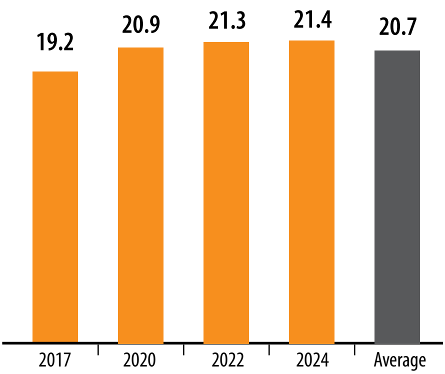
In terms of MSME characteristics, 98% of MSMEs are micro-enterprises who are often informal, have very low capital and are survivalist. As a result, they have limited ability to scale, formalize and withstand shocks. And this raises a red flag for policy, because the government's ambition to grow the MSMEs sector's contribution to 60% relies heavily on the most vulnerable players in the economy.

To note, agencies such as MSEA, the Credit Guarantee Scheme and County Governments have helped reduce structural barriers such as high borrowing costs, informality and limited market access. This has helped create a supportive policy and regulatory environment and continues to play a central role in enabling MSME growth and promoting sustainable MSME participation in the economy.

However, MSMEs still face chronic barriers to accessing formal credit. Estimates show that only 20–23% of MSMEs have access to bank financing with over 60% citing lack of collateral, high cost of credit and stringent documentation as key deterrents.

Meanwhile, Kenya's commercial banks continue to report robust liquidity positions and healthy balance sheets, yet MSME lending remains low and uneven across sectors.

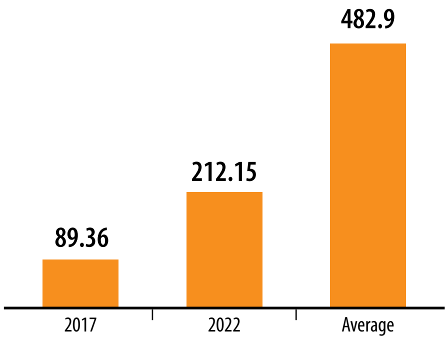
**Figure 2: Propotion of MSME loan portfolio to the total banking sector loan portfolio (%)**




**Source:** Survey Report on MSME Access to Bank Credit

It is also no surprise that micro-enterprises make up 80% of MSME loan accounts which aligns with the fact that they represent 98% of MSMEs in Kenya. However, when we shift from number of accounts to actual value, we see a staggering gap where only KES 89.4Bn goes to micro-enterprises as compared to KES 695.1Bn for small and medium enterprises. That is nearly 8times more the value going to a segment that constitutes only 2% of the MSME population.

**Figure 3: Distribution of the MSME lending portfolio by value**

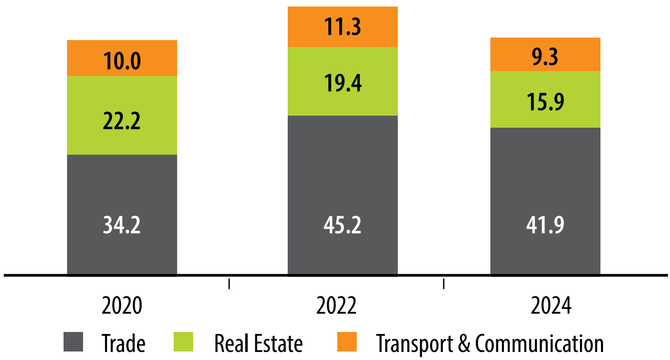



**Source:** Survey Report on MSME Access to Bank Credit

To note, the estimated MSME financing gap in Kenya is approximately KES 2.50 trillion.

To better understand the sectors that benefit from this funding across the three segments, over 60% of lending (by value) is spread across three key MSME sectors that is Trade, Real Estate, and Transport & Communication.

**Figure 4: Credit allocation to key sectors within the MSMEs loan book (%)**




**Source:** Survey Report on MSME Access to Bank Credit

While at first glance, there seems to be a 'micro' access problem this study appreciates that while the micro story is real there is need to understand it through a sectoral lens which is not only analytically richer but also more aligned to how banks allocate credit and how policymakers structure interventions.

Sectoral credit analysis therefore lets us capture the heterogeneity within the MSME sector, align with GDP contribution trends and identify policy levers as well as targeted credit tools that can uplift micro businesses within each sector.

While previous studies have analyzed MSME credit access challenges in aggregate, few have disaggregated lending behaviour across sectors to understand how risks and opportunities influence the allocation of credit. Moreover, recent shocks such as the 2016–2019 interest rate cap and the COVID-19 pandemic have significantly altered the lending landscape, introducing new policy and macroeconomic dynamics that require re-evaluation.

Theoretically, the study is grounded in the credit rationing model by Stiglitz and Weiss (1981), which explains how asymmetric information and risk perceptions lead banks to limit credit supply despite demand. The bank lending channel framework as discussed by Bernanke & Gertler (1995) also provides a lens to understand how monetary policy, liquidity conditions and regulatory actions influence banks' willingness and ability to lend. In the Kenyan context, both frameworks are relevant given the prevalence of informal MSME borrowers, information asymmetry and banks' reliance on collateral and macroeconomic signals to manage credit risk.

Empirically, this study addresses a gap in literature by modelling sectoral MSME lending behaviour using quarterly panel data spanning Q4-2011 to Q4-2024 across 3 key sectors. The selection of the 3 sectors (Real Estate, Trade and Transport and Communication) is informed by the significant proportion of commercial bank MSME lending to these sectors.

Using sector-specific lending trends, the study explores how variables such as non-performing loan (NPL) ratios, lending interest rates, bank liquidity, sectoral economic performance and policy interventions (interest rate cap) influence banks' credit decisions to MSMEs. This approach provides a granular understanding of how credit supply responds not just to risk but to sector-specific economic dynamics.

## 1.1 Research Questions

1. What are the main financial and policy-related drivers of MSME credit across sectors in Kenya?
2. What role does sectoral economic opportunity (proxied by GDP) play in credit allocation to MSMEs?
3. How did the 2016–2019 interest rate cap affect MSME credit across sectors?

## 1.2 Objectives of the Study

- To evaluate the impact of financial health indicators (NPLs, liquidity, lending rates) on MSME lending behaviour.
- To assess how sector-level economic performance correlates with MSME credit allocation.
- To analyze the policy impact of the interest rate cap on MSME credit across different sectors.

## 1.3 Significance of the Study

This study offers fresh empirical insights for regulators, commercial banks and policy makers seeking to enhance financial inclusion for MSMEs. By quantifying the role of sectoral risk, opportunity and policy disruptions in MSME lending, the findings provide a more differentiated understanding of credit dynamics in Kenya's banking system. The results can inform credit guarantee programs, sector-specific risk mitigation and future monetary and regulatory interventions targeting MSME access to finance. The study also contributes to academic literature by integrating both demand-side (GDP) and supply-side (bank health and policy) variables into a single panel model of MSME credit behaviour.

# 2.0 Literature Review

**Access to credit remains one of the most cited constraints facing MSMEs in developing economies despite the sector's well-documented contributions to GDP, employment and inclusive growth.**

In sub-Saharan Africa (SSA), there are over 44 million MSMEs primarily micro-enterprises in line with trends observed in Kenya. Additionally, MSMEs account for over 90% of new business ventures since 2016 and more than 60% of jobs (World Bank) yet credit to this segment is persistently low and uneven.

Kenya, as highlighted earlier, reflects this paradox and therefore understanding the sector-specific drivers of MSME lending is critical for designing effective credit expansion policies.

## 2.1 Theoretical Foundations

This study draws on two key theoretical frameworks: the credit rationing model by Stiglitz and Weiss (1981), and the bank lending channel of monetary transmission articulated by Bernanke and Gertler (1995).

The credit rationing theory posits that in the presence of information asymmetry and moral hazard, banks prefer to restrict lending rather than adjust interest rates upward, particularly for high-risk clients like MSMEs. Holmstrom and Tirole (1997) extended this to argue that external finance constraints are more binding for small borrowers with limited internal liquidity which is typical of MSMEs in emerging markets.

Complementing this, the bank lending channel framework asserts that banks adjust their credit supply in response to changes in their own liquidity and capital buffers particularly during monetary tightening or financial shocks. In SSA, Beck and Cull (2014) and Triki and Gajigo (2012) empirically show that weaker institutional environments, limited credit registries and bank conservatism exacerbate credit rationing for SMEs.

These frameworks are particularly relevant in Kenya where MSMEs are typically thin file borrowers, banks rely heavily on collateral and regulatory interventions such as interest rate caps have significantly distorted credit supply decisions.

## 2.2 Liquidity and MSME Lending

Bank liquidity has consistently emerged as a key determinant of credit availability especially to riskier segments. Gambacorta and Marques-Ibanez (2011) find that higher liquidity ratios enable banks to maintain or increase lending during downturns. In Nigeria, Okafor et al. (2016) confirm that liquidity-constrained banks significantly cut SME lending following monetary tightening.

In the Kenyan context, Ngugi et al. (2020) find that banks with stronger liquidity buffers were more likely to extend loans to MSMEs following the partial lifting of the interest rate cap in 2019. CBK Credit Officer Surveys (2022–2023) also report that credit rationing to SMEs intensifies during periods of liquidity stress.

Across SSA, the African Development Bank (2022) notes that excess liquidity does not always translate into MSME lending unless supported by risk-sharing mechanisms, such as credit guarantees. This suggests that liquidity is a necessary but insufficient condition for credit expansion, particularly where credit risk remains high.

## 2.3 Lending Rates, Interest Rate Controls and Credit Supply

While classical economic theory suggests that lower lending rates encourage credit uptake, several studies show that MSMEs are often non-price constrained. This means that they are excluded from formal credit not because of interest rate levels but due to eligibility issues, lack of collateral and/or banks' risk aversion (IFC, 2020; Beck & Cull, 2014).

In Kenya, the 2016–2019 interest rate cap had a profound impact on SME credit markets. Were et al. (2019) show that capped lending rates distorted risk pricing, leading banks to cut off SMEs altogether. The IMF (2021) notes that commercial banks reallocated their portfolios toward government securities and personal loans during the cap thereby shrinking SME lending by over 10%.

Ghana's post-cap era exhibited similar dynamics where the Bank of Ghana (2020) reported a 19% reduction in SME credit when interest ceilings were imposed on microfinance institutions. In India, Ghosh (2005) found that mandatory lending quotas to small businesses when implemented alongside rate controls led to suboptimal credit allocation and higher default rates. These studies underscore the limitations of interest rate caps as tools for expanding credit access.

## 2.4 Non-Performing Loans (NPLs) and Risk Aversion

Credit risk is one of the most significant constraints to MSME lending. Gonzalez (2013) and Beck et al. (2015) argue that high NPL ratios increase provisioning costs and reduce banks' willingness to lend to high-risk segments. This is particularly acute in MSME lending where lack of credit history and weak financial documentation make borrower screening more difficult.

In SSA, Fowowe (2017) uses cross-country panel data to demonstrate that rising NPLs are strongly associated with reduced SME credit growth. In Kenya, the Central Bank's supervision reports show that rising NPLs in sectors like trade, agriculture and real estate often precede sharp pullbacks in credit to those sectors (CBK, 2022).

Tiriongo (2023) shows that NPL dynamics vary significantly across sectors. While agriculture NPLs often reflect weather shocks, trade-sector defaults tend to track macroeconomic volatility.

This suggests that sectoral NPLs are not just outcomes but drivers of future credit allocation decisions, justifying their inclusion in credit behaviour models.

## 2.5 Sectoral GDP as a Proxy for Credit Demand

While most MSME credit studies focus on supply-side constraints, few incorporate sectoral GDP or gross value added (GVA) as a proxy for economic opportunity or credit demand. Rajan and Zingales (1998) pioneered this approach in studying how financial development supports sectoral growth. More recently, Beck et al. (2013) use sectoral GVA in cross-country models to estimate how credit flows respond to real economic conditions.

In Kenya, Kairu (2020) applies sectoral GDP in modelling credit allocation, finding that banks tend to align credit supply with sectors exhibiting faster GVA growth especially in manufacturing and services. This approach allows researchers to distinguish between credit rationing due to risk and low credit volumes due to limited economic activity.

Incorporating GVA therefore enhances model robustness by accounting for sector-specific credit demand drivers.

## 2.6 Empirical Approaches to MSME Lending

Recent empirical studies increasingly apply panel data techniques to explore the determinants of MSME credit. For example, Triki and Gajigo (2012) use fixed effects models across 28 African countries and find that non-performing loans (NPLs) and regulatory quality are key predictors of SME credit volumes. Nampewo et al. (2018), focusing on East African economies, employ panel regressions and demonstrate that liquidity, inflation, and GDP growth significantly influence private sector credit allocation. Similarly, Aboagye and Agyemang (2021) adopt a random effects framework to analyze regional SME lending trends in Ghana, underscoring the importance of NPLs and the cost of funds in shaping credit supply.

While these studies validate the utility of panel data approaches in capturing intertemporal and cross-sectional variation in MSME credit, they often treat MSME lending as a homogenous phenomenon. Specifically, they do not differentiate across economic sectors, despite growing evidence that MSMEs in different industries face distinct credit risks, capital needs, and macro sensitivities.

This study advances the literature by employing sector-specific Autoregressive Distributed Lag (ARDL) models, using quarterly data from 2012 to 2024 for the real estate, trade, and transport & communication sectors. This approach captures sector-level heterogeneity in both the short- and long-run dynamics of MSME lending and enables the inclusion of structural features such as the interest rate cap period, banking sector liquidity, and sector-specific NPL and GDP indicators.

## 2.7 Gaps in Literature

Despite progress in MSME finance research, most empirical work on Kenya continues to rely on either aggregate national data or qualitative surveys. There remains a notable gap in quantitative, sector-disaggregated analysis of MSME lending. Few studies incorporate sectoral GDP or value-added metrics as proxies for credit opportunity and fewer still examine how lending behaviour varies in response to sector-specific risks such as NPLs, capital needs, and growth patterns.

Moreover, empirical evidence on how banks adjust MSME credit supply in response to simultaneous shifts in macroeconomic and regulatory conditions, including changes in liquidity, interest rate ceilings, and credit risk, remains limited. This paper addresses these gaps by applying sector-specific ARDL models that allow for dynamic and cointegrated relationships between credit supply and its determinants across MSME-dominant sectors.

By integrating both supply-side constraints (e.g. bank liquidity, NPLs) and demand-side indicators (e.g. sectoral GDP) over a 12-year panel, the analysis provides more granular insights into the functioning of MSME credit markets in Kenya.

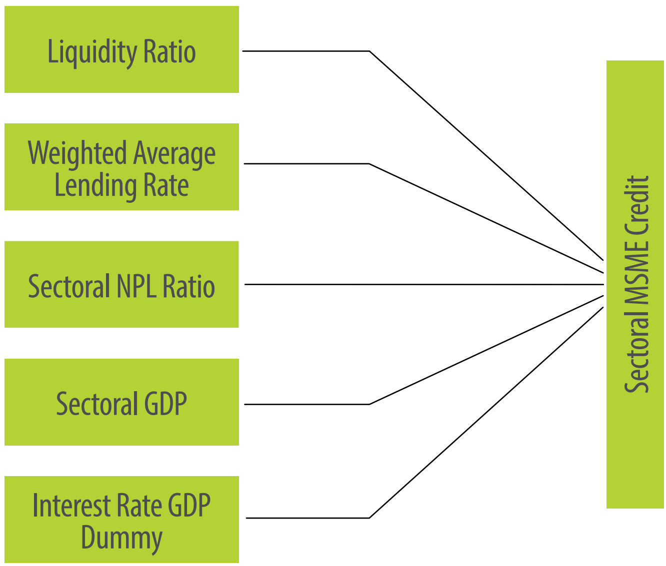
# 3.0 Conceptual Framework and Hypotheses

**This study is framed by two interrelated theoretical lenses: the credit rationing hypothesis and the bank lending channel of monetary policy transmission.**

Together, these theories posit that banks' decisions to lend to MSMEs depend not only on interest rate signals but also on the availability of liquidity and risk perceptions shaped by defaults (NPLs) and regulatory constraints (such as interest rate caps).

The diagram below illustrates the conceptual relationships:

**Figure 5: Conceptual Relationships and Sectoral MSME Credit**



Variables:

- **Sectoral MSME Credit (Dependent variable**) – total credit extended to MSMEs per sector, in natural log.
- **Liquidity Ratio:** Supply-side bank health indicator; higher ratios expected to increase MSME lending.
- **Weighted Average Lending Rate:** Price of credit; the higher the rate the expected negative influence on MSME lending.
- **Sectoral NPL Ratio:** Credit risk proxy; expected to negatively influence lending decisions.
- **Interest Rate Cap Dummy:** during 2016–2019 cap period; expected to reduce MSME credit due to risk pricing constraints.
- **Sectoral GDP:** Proxy for demand-side credit opportunity in natural log; higher GDP implies more creditworthy economic activity.

Hypotheses:

- **H1:** Higher bank liquidity ratios are positively associated with increased MSME lending across sectors.
- **H2:** Higher NPL ratios are negatively associated with MSME lending due to heightened credit risk aversion.
- **H3:** Higher lending rates are negatively associated with MSME lending due to affordability constraints.
- **H4:** The interest rate cap (2016–2019) significantly constrained MSME credit growth in most sectors.

# 4.0 Research Methodology

## 4.1. Data and Scope

**This study utilizes a balanced panel dataset comprising quarterly data from Q4-2011 to Q4-2024 across 3 economic sectors in Kenya. The sectors are evaluated from a credit risk perspective (proxied by Gross NPLs), a lending perspective (proxied by Banking Sector Gross Loans) and from an economic contribution perspective (proxied by Sectoral GDP).**

The sectors are as below:

**Table 1: Sectoral Evaluations**

| Gross NPLs (KES, Mn) | Gross Loans (KES, Mn) | GDP (KES, Mn) | Notes |
|---|---|---|---|
| **Trade** | Trade | Wholesale and Retail Trade | |
| **Real Estate** | Real Estate | Real Estate | |
| **Transport & Communication** | Transport & Communication | Transport & Communication | GDP sector data is a summation of transport and storage with ICT |

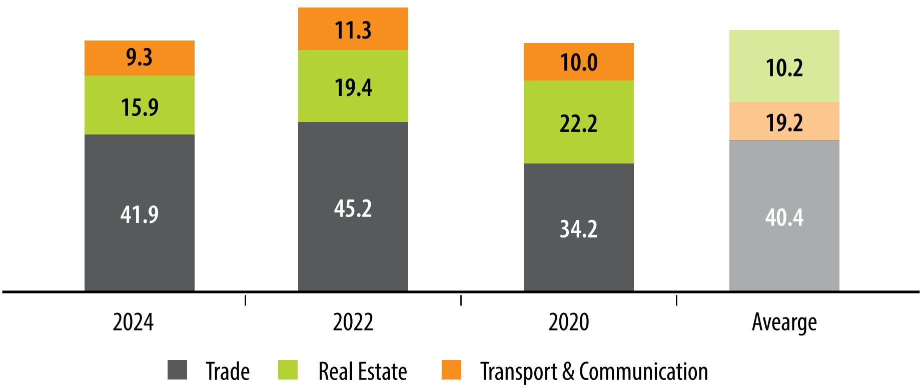
**Source:** Author's Compilation

These sectors reflect the structure of MSME participation in Kenya's economy, as classified in Central Bank of Kenya (CBK) and Kenya National Bureau of Statistics (KNBS) reporting frameworks.

The sectoral credit data is obtained from CBK reports (Quarterly Economic Review) which provide the gross banking loans disbursed by sector.

Given that MSME-specific breakdowns are limited, the paper uses total sectoral credit from banks as a proxy, adjusted with average proportions of MSME lending. This average proportion is informed by CBK's Survey Reports on MSME Access to Bank Credit over the 2020 and 2024 periods. The reports indicate that

**Figure 6: Credit allocation to key sectors within the MSMEs loan book (%)**




**Source:** Author's Compilation

the proportion of MSME loans by value to the total banking sector loan portfolio rose from 19.2% to 21.4%.

The paper assumes that the proportion of MSME lending over the study horizon of Q4-2011 to Q4-2024 is on average 20% of the total banking sector loan portfolio.

Of this MSME proportion, majority of the lending is to Trade, Real Estate and Transport and Communication sectors accounting for over 70% over the MSME loan book.

The paper further assumes that the distribution by sector is at an average of 40.4%, 19.2% and 10.2% for Trade, Real Estate and Transport and Communication sectors respectively over the sample period.

The dependent variable in our model will therefore be a measure of credit allocation to each sector:

- The share of total MSME credit that goes to sector i in year t.

Independent variables including sectoral non-performing loan (NPL) ratios, lending interest rates and liquidity ratios were sourced from CBK's quarterly statistical bulletins and banking supervision reports.

- Sectoral NPL Ratio: For each sector the study includes the non-performing loan (NPL) ratio, defined as the value of non-performing loans in that sector divided by total loans in that sector (for the banking industry). Given that direct MSME NPL by sector is directly unavailable, we proxy with overall sector NPL. This variable serves as a proxy for credit risk in the respective sectors.
- The weighted average lending interest rate is used to capture the general cost of credit which can affect overall credit supply and/or demand.
- Banks' liquidity will be proxied by the banking sector liquidity ratio.

A dummy variable was constructed to capture the interest rate cap period (2016–2019), which was implemented through the Banking (Amendment) Act 2016. The interest rate cap dummy takes value 1 for Q3 2016 to Q3 2019, corresponding to the period of capped lending rates and 0 otherwise.

Sectoral GDP, used to control for credit demand potential, was obtained from the KNBS Quarterly GDP Reports.

The panel dataset contains N = 3 sectors over T = 53 quarters. The dataset is cleaned, lagged where necessary and maintained at quarterly frequency to preserve seasonality and macro-policy signals.

## 4.2. Model Specification

To estimate the determinants of MSME lending behavior across sectors, the study employs a panel regression model that accounts for both sector-specific heterogeneity and temporal variation.

The dependent variable is the natural logarithm of MSME credit extended to each sector per quarter. This transformation allows interpretation of coefficients as elasticities and helps stabilize variance.

**Baseline Model (without sectoral GDP):**

$$ln(MSME\_Credit_{it}) = \beta_0 + \beta_1 NPL_{i,t-1} + \beta_2 LendingRate_{i,t-1} + \beta_3 Liquidity_{i,t-1} + \beta_4 CapDummy_t + \mu_i + \varepsilon_{it}$$

Where:

- $ln(MSME\_Credit_{it})$ = Natural log of total MSME credit in sector i at time t
- $NPL_{i,t-1}$ = Lagged sectoral non-performing loan ratio
- $LendingRate_{i,t-1}$ = Lagged average lending rate in the banking sector
- $Liquidity_{i,t-1}$ = Lagged sector liquidity ratio (liquid assets to total deposits)
- $CapDummy_t$ = Dummy variable = 1 for Q3 2016 – Q3 2019 (interest rate cap period), 0 otherwise
- $\mu_i$ = Time-invariant unobserved sector effects
- $\varepsilon_{it}$ = Idiosyncratic error term

This model captures the effect of credit risk, pricing and regulatory conditions on MSME credit flows while controlling for sector-specific structural differences.

Given the log-level nature of the model, coefficient estimates for level variables (e.g., liquidity ratio) reflect semi-elasticities. For example, a one-unit change in X leads to a %Δ in MSME credit.

### Extended Model with Sectoral GDP:

Following preliminary estimation, a new specification is introduced to account for sector-specific credit demand by including sectoral GDP as an explanatory variable. This enables the model to distinguish between MSME credit driven by bank-side factors versus real economic activity in the respective sectors. That is, GDP was excluded in the baseline model to isolate the impact of supply-side factors before introducing demand-side dynamics.

### Extended Model:

$$ln(MSME\_Credit_{it}) = \beta_0 + \beta_1 NPL_{i,t-1} + \beta_2 LendingRate_{i,t-1} + \beta_3 Liquidity_{i,t-1} + \beta_4 CapDummy_t + \beta_5 \ln(GDP_t) + \mu_i + \varepsilon_{it}$$

**Table 2: Variable Summary and Expected Signs:**

| Variable/Notation | Definition | Expected Sign | Rationale |
|---|---|---|---|
| *ln(MSME_Creditit)* | Log of MSME credit by sector | | — |
| *NPLi,t−1* | Lagged NPL ratio | Negative (−) | High defaults reduce willingness to lend |
| *LendingRatei,t−* | Lagged lending rate | Negative (−) | High lending rates reduce affordability for MSMEs |
| *Liquidityi,t−1* | Lagged liquidity ratio | Positive (+) | High liquidity enhances risk appetite |
| *InterestRateCapt* | Interest rate cap dummy (2016–2019) | Negative (−) | Interest rate cap distorts risk pricing and deters SME lending |
| *ln(GDPit)* | Log of sectoral Gross Value Added (real) | Positive (+) | High GDP signals strong credit demand and repayment capacity |

**Source:** Author's Compilation

## 4.3. Model Justification

In analyzing the determinants of MSME lending in Kenya across the real estate, trade, and transport & communication sectors, the study adopts sector-specific Autoregressive Distributed Lag (ARDL) models. This modelling framework is methodologically appropriate due to both theoretical and empirical considerations.

First, the sectors under consideration differ significantly in capital intensity, credit absorption behaviour, economic cycles and default risk profiles. A pooled analysis would likely mask such heterogeneity, leading to biased estimates or misleading policy recommendations. Therefore, sectoral disaggregation is essential to ensure valid inference and effective policy targeting.

Second, the ARDL framework is particularly suited for time-series analyses involving a mixture of I(0) and I(1) variables. This flexibility is particularly important in macro-financial research where variables such as sectoral GDP, interest rates, and non-performing loans may exhibit diverse integration properties (Ochepa et al., 2025; Kahveci & Gurgur, 2025).

Third, the ARDL bounds testing approach to cointegration allows for robust detection of long-run relationships even in small samples, which is particularly useful for sector-specific analyses constrained by data availability (Papadavid, 2017). Moreover, the model's capacity to estimate both short and long run elasticities within a single equation provides insights into both transitory shocks and structural lending dynamics.

Furthermore, the model integrates a structural policy dummy for the interest rate cap period (2016–2019) in Kenya, enabling the empirical isolation of its sector-specific impacts on credit flow.

Finally, bank liquidity ratios, included as a dynamic control, tend to influence lending decisions with a lag. ARDL's structure captures such delayed responses effectively, unlike static models which may underestimate their significance (Das, 2015).

## 4.4. Model Specification

$$\Delta LENDING_t = \alpha + \sum_{i=1}^{p} \beta_i \, \Delta LENDING_{t-i} + \sum_{j=0}^{q} \gamma_j \, \Delta NPL_{t-j} + \sum_{k=0}^{r} \delta_k \, \Delta GDP_{t-k} + \sum_{l=0}^{s} \theta_l \, \Delta RATE_{t-l} + \sum_{m=0}^{v} \varphi_m \, \Delta LIQUIDITY_{t-m} + \eta IRCAP + \lambda \, ECM_{t-1} + \varepsilon_t$$

$$\beta_4 CapDummy_t + \mu_i + \varepsilon_{it}$$

**Table 3: Variable Structure and Integration**

| Variable | Stationarity (Level) |
|---|---|
| *Levin-Lin-Chu (LLC)* | |
| *ln_msme_credit - dependent* | I(1) |
| *npl_rate* | I(1) |
| *Weighted_Average_Lending_Rate* | I(1) |
| *Liquidity_Ratio* | I(1) |
| *CapDummy (binary variable)* | Assumed I(0) |
| *ln_GDP* | I(1) |

This setup supports ARDL estimation, as recommended by Eberhardt and Teal (2010) and Samargandi et al. (2015) who apply similar techniques in financial development and sectoral finance studies.

## 4.5 Estimation Procedure

1. Stationarity Testing: First and second-generation unit root tests to confirm the integration order.
2. Lag Selection: Optimal lag lengths are selected using information criteria.
3. Cointegration Testing: Pedroni test to confirm the presence of a long-run relationship.

# 5.0 Research Findings and Discussion

**This chapter presents the results of the econometric analysis. Logarithm is only used for the MSME lending and Sectoral GDP consistent with Cruz and Teixeira (1999), who argued that the data's logarithm increases the stability for variance and the optimization of empirical estimates.** Diagnostic tests were conducted. These tests included descriptive tests for serial correlation, heterogeneity and normality of the data. Descriptive statistics, unit root tests and serial correlation tests are in the appendix.

## Sector Specific Insights

**Table 4: Summary of ARDL results**

| Category | Variable | Sector 1 Coef. Real Estate | Sector 2 Coef. Trade | Sector 3 Coef. Transport & Communication |
|---|---|---|---|---|
| **Adjustment Term (ECM)** | L.lnMSME_credit | **−0.093** (p=0.073) | **−0.112** (p=0.032) | **−0.144** (p=0.000) |
| **Long–Run Effects (LR)** | lngdp | **−0.329** (ns) | +2.366* | +1.326* |
| | lendingrate | −14.575 (p=0.084) | −4.657 (p=0.087) | −7.655* |
| | liquidity | −5.647 (p=0.041) | −2.544 (p=0.023) | −2.621 (p=0.005) |
| | npl | 6.054 (ns) | −1.332 (ns) | 0.166 (ns) |
| | capdummy | −0.486 (p=0.080) | −0.184 (p=0.085) | −0.369* |
| **Short–Run Effects (SR)** | LD.lnMSME_credit | −0.616* | −0.147 (ns) | −0.552* |
| | D1.lendingrate | +1.047 (p=0.020) | — | +1.037 (p=0.020) |
| | D1.lngdp | — | −0.183 (p=0.012) | — |
| | LD.lngdp | — | −0.148 (p=0.025) | — |
| | D1.npl | −0.386 (ns) | −0.912* | — |
| | _cons | 1.240 (ns) | −2.332 (p=0.044) | −1.421 (p=0.028) |

### Sector 1: Real Estate

The ARDL(2,0,1,0,1,0) results show that the error correction term is negative (-0.093) but only weakly significant (p=0.073), suggesting that MSME credit in the real estate sector converges slowly to its long-run equilibrium.

In the long run, nominal sector GDP has a negative but insignificant effect (-0.329, p=0.847), implying that growth in the sector does not strongly translate into credit expansion. By contrast, the weighted average lending rate for the banking industry reduces real estate credit by -14.58, although this effect is only weakly significant at the 10% level (p=0.084). Liquidity ratio, a bank-wide variable, exerts a significant negative effect (-5.65, p=0.041), underscoring how tighter liquidity in the industry directly constrains credit supply to real estate MSMEs. The sector-specific NPL ratio is positive (6.05) but insignificant (p=0.275), suggesting that defaults do not strongly influence long-run credit. The interest rate cap dummy has a negative effect (-0.486, p=0.080), showing that policy intervention in credit markets constrained real estate MSME lending.

In the short run, past credit flows are highly influential. The first lag of credit reduces current lending (-0.616, p=0.000) indicating persistence and adjustment dynamics. The first lag of lending rates is positive and significant (1.047, p=0.020), implying that higher lending rates may temporarily increase observed credit flows, possibly due to repricing effects or a shift of borrowers rushing to lock in credit before rates rise further. Sector-specific NPLs reduce lending in the short run (-0.386) but remain insignificant (p=0.153).

### Sector 2: Trade

The ARDL(2,2,0,0,1,0) model finds a statistically significant error correction term (-0.112, p=0.032), implying that about 11% of disequilibrium is corrected each quarter, ensuring convergence of trade-sector MSME credit to long-run equilibrium.

Long-run estimates highlight nominal sector GDP as a strong positive driver (2.37, p=0.000), confirming that expansion in trade activity stimulates demand for credit. The banking industry's liquidity ratio reduces credit (-2.54, p=0.023), consistent with supply-side constraints. The weighted average lending rate is negative (-4.66) but only weakly significant (p=0.087), showing that trade-sector MSMEs are sensitive to higher borrowing costs. The interest rate cap dummy is negative (-0.184, p=0.085), reflecting restrictive impacts of credit policy. In contrast, the trade-sector NPL ratio is negative (-1.33) but not significant (p=0.596), suggesting defaults have weaker long-run effects.

In the short run, GDP changes significantly reduce credit (-0.183, p=0.012; -0.148, p=0.025), showing cyclical corrections in trade financing. Importantly, the sector-specific NPL ratio strongly reduces lending (-0.912, p=0.001), highlighting that defaults have immediate short-run consequences on new credit supply.

### Sector 3: Transport & Communication

The ARDL(2,0,1,0,0,0) results confirm a significant error correction term (-0.144, p=0.000), indicating robust adjustment of MSME credit in this sector, with about 14% of disequilibrium corrected each quarter.

In the long run, nominal sector GDP is the strongest driver of credit (1.33, p=0.000), reflecting demand-pull effects of sector growth. The banking industry's weighted average lending rate significantly reduces credit (-7.65, p=0.001), underscoring high sensitivity of transport and communication MSMEs to borrowing costs. Similarly, liquidity ratio exerts a negative effect (-2.62, p=0.005), confirming supply-side constraints. The interest rate cap dummy strongly reduces credit (-0.369, p=0.000), implying policy restrictions weighed heavily on this sector. Sector-specific NPLs remain insignificant (0.166, p=0.861), showing limited long-run effect.

Short-run dynamics reveal correction effects: lagged credit is negative (-0.552, p=0.000), while lending rates surprisingly show a positive short-run effect (1.037, p=0.020), possibly reflecting repricing or short-term credit rationing adjustments.

## Cross-Sectional Insights on MSME Credit Dynamics

The cross-sector analysis reveals both commonalities and distinct patterns in how MSME credit in real estate, trade, and transport responds to macroeconomic, financial, and policy variables.

All three sectors display negative error correction terms, confirming the presence of long-run convergence in MSME credit. However, the speed of adjustment differs. Credit in the real estate sector adjusts most sluggishly, with an error correction coefficient of -0.093 that is only weakly significant, while trade converges more quickly at -0.112 and transport at -0.144, the latter being highly significant. This suggests that MSME credit markets in transport are more responsive to shocks, whereas real estate lending is slower to revert to equilibrium.

Nominal sector GDP exerts heterogeneous effects across sectors. In real estate, GDP is negative but insignificant (-0.329, p=0.847), implying that credit flows are decoupled from sectoral growth. By contrast, trade shows a strong and highly significant positive effect (2.37, p=0.000), reflecting pro-cyclical credit allocation in line with rising sectoral output. Transport also exhibits a positive and significant long-run relationship (1.33, p=0.000), confirming that sector expansion attracts greater credit. Together, these results highlight that while credit in trade and transport is demand-driven, real estate credit is less sensitive to output dynamics, possibly due to collateral concerns and the longer-term nature of loans.

The weighted average lending rate, representing the industry-wide cost of credit, consistently constrains MSME credit across sectors. The effect is strongest in transport (-7.65, p=0.001), indicating acute interest rate sensitivity. In real estate, the coefficient is even larger in magnitude (-14.58) but only weakly significant (p=0.084), while trade registers a smaller though still negative effect (-4.66, p=0.087). These findings suggest that interest rates weigh most heavily on transport MSMEs, moderately on real estate, and least on trade.

Bank-wide liquidity ratios also exert a uniform negative impact, reducing MSME credit in all sectors. The effect is most pronounced in real estate (-5.65, p=0.041), followed by transport (-2.62, p=0.005) and trade (-2.54, p=0.023). This underscores that tighter liquidity conditions systematically constrain

MSME credit, though real estate appears especially vulnerable given the large-ticket, long-term nature of its loans.

The role of non-performing loans is more nuanced. In the long run, NPL ratios are statistically insignificant across all sectors, with real estate showing a positive but insignificant effect, and trade and transport recording negative but insignificant coefficients. In the short run, however, NPLs strongly and significantly reduce credit in trade (-0.912, p=0.001), pointing to banks' heightened risk aversion when defaults rise. By contrast, NPLs in real estate and transport do not appear to have immediate effects on credit flows.

Policy shocks in the form of the interest rate cap dummy are uniformly negative, reflecting the restrictive impact of credit market interventions. The effect is strongest and highly significant in transport (-0.369, p=0.000), followed by real estate (-0.486, weakly significant) and trade (-0.184, weakly significant). This suggests that the cap period disproportionately affected MSMEs in the transport sector.

Short-run dynamics further reinforce these sectoral differences. Lagged credit is negative and significant in both real estate (-0.616, p=0.000) and transport (-0.552, p=0.000), reflecting strong correction mechanisms, but is weaker in trade. Lending rates, interestingly, show positive and significant short-run effects in real estate and transport (both around +1.04, p=0.020), possibly due to repricing dynamics or credit front-loading before higher rates take effect, while no such relationship is observed in trade. Finally, NPL ratios exert significant short-run effects only in trade, underscoring the immediate impact of rising defaults on credit supply in this sector.

Overall, the evidence demonstrates that MSME credit dynamics are highly sector-specific. Trade and transport are demand-driven and responsive to GDP, with transport particularly sensitive to interest rates and policy shocks. Real estate, in contrast, is more constrained by liquidity and adjusts sluggishly to shocks, with sectoral output growth playing little role in credit allocation.

Across all three sectors, the diagnostic tests suggest that the ARDL models are dynamically well specified.

The Portmanteau Q-statistics indicate no evidence of serial correlation in the residuals, meaning that the models adequately capture the underlying dynamics of sectoral MSME credit.

Similarly, the Breusch–Pagan/Cook–Weisberg tests fail to reject the null of homoskedasticity across all sectors, suggesting that the variance of the residuals is stable and that the models do not suffer from heteroskedasticity.

However, the skewness–kurtosis normality tests consistently reject the null of normally distributed residuals in each sector. This result is not unusual in applied economic and financial datasets, where residuals often display fat tails or asymmetry. While this does not invalidate the ARDL models, it highlights the importance of using robust inference procedures.

# 6.0 Conclusion, Recommendations and Policy Inferences

**This study examined the sectoral determinants of MSME credit in Kenya's real estate, trade, and transport and communication sectors using ARDL models with quarterly data from 2011–2024.** The results reveal heterogeneity in how credit responds to sector-specific demand (GDP), bank-wide supply conditions (liquidity, lending rates), credit risk (NPL ratios), and policy shocks (interest rate cap).

**Table 5: Post-Estimation Diagnostic Tests by Sector**

| Sector | Serial Correlation (Portmanteau Q) | Heteroskedasticity (BP/CW) | Normality (Skewness–Kurtosis) | Interpretation |
|---|---|---|---|---|
| **Real Estate** | $Q(4) = 2.7987$ $(p = 0.5921)$ Fail to reject $H_0$ | $\chi^2(1) = 1.52$ $(p = 0.2171)$ Fail to reject $H_0$ | $\chi^2(2) = 9.04$ $(p = 0.0109)$ Reject $H_0$ | No autocorrelation or heteroskedasticity; residuals deviate from normality |
| **Trade** | $Q(4) = 5.5518$ $(p = 0.2352)$ Fail to reject $H_0$ | $\chi^2(1) = 1.28$ $(p = 0.2582)$ Fail to reject $H_0$ | $\chi^2(2) = 86.27$ $(p = 0.0000)$ Reject $H_0$ | No autocorrelation or heteroskedasticity; strong non-normality |
| **Trade & Communication** | $Q(4) = 2.3204$ $(p = 0.6771)$ Fail to reject $H_0$ | $\chi^2(1) = 2.70$ $(p = 0.1006)$ Fail to reject $H_0$ | $\chi^2(2) = 16.50$ $(p = 0.0003)$ Reject $H_0$ | No autocorrelation or heteroskedasticity; residuals not normally distributed |

The findings indicate that MSME credit in real estate is largely decoupled from sectoral output growth, constrained instead by liquidity conditions, with sluggish adjustment to long-run equilibrium. Trade credit is strongly demand-driven, closely linked to sectoral GDP, but vulnerable to short-run spikes in defaults. Transport and communication credit is both demand-driven and highly sensitive to borrowing costs, liquidity conditions, and policy interventions, with the fastest adjustment speed among the three.

Beyond these sectoral dynamics, the recent introduction of Risk-based pricing/KESONIA, Kenya's national credit risk information system, represents a potential structural shift in the MSME credit landscape. By strengthening information sharing, reducing asymmetric risk perceptions, and enabling risk-based pricing, KESONIA can help correct distortions identified in this study. Specifically, it can realign the weak GDP–credit link in real estate by improving confidence in borrower repayment capacity, and it may mitigate the strong short-run NPL effects in trade by enabling more accurate credit risk modelling.

Emerging digital platforms offer new risk assessment tools, such as mobile transaction histories, which could expand access. Additionally, Islamic banking models, such as murabaha and mudaraba, offer asset-backed and profit-sharing alternatives, suitable for MSMEs wary of conventional debt.

## Recommendations

Tailored Credit Policies by Sector: Credit expansion strategies should reflect sectoral heterogeneity. For real estate, interventions should target liquidity channels (e.g., long-term funding lines, infrastructure bonds) rather than demand stimuli. In trade, policies should focus on credit guarantee schemes to cushion banks against short-run NPL shocks. For transport, lowering borrowing costs and improving risk-sharing arrangements will have the highest payoff given the sector's strong interest rate sensitivity.

Strengthening Credit Risk Mitigation: The strong short-run effects of NPLs in trade highlight the need for robust credit guarantee schemes and better collateral frameworks. Sanjaya and Widjaja (2025) demonstrate how land title certification expands collateral value for SMEs; Kenya could enhance the utility of property and movable collateral registries to ease lending risks. KESONIA should be integrated into these mechanisms to provide banks with real-time borrower credit data, thereby reducing reliance on collateral-heavy lending.

Balancing Interest Rate Policy with Inclusion Goals: The adverse impact of the 2016–2019 interest rate cap on all three sectors confirms the trade-off between consumer protection and SME financial exclusion. Inayah (2025) stresses that interest rate policy should be carefully calibrated in the digital financial inclusion era to avoid undermining SME credit growth. With KESONIA providing borrower-specific risk scores, banks can adopt risk-based lending frameworks, thereby reducing the need for blunt instruments such as rate caps.

Leveraging Digital and Alternative Financing: The weak linkage between GDP and credit in real estate underscores the structural inefficiencies in bank lending. Digital finance and fintech partnerships, highlighted by Nurhaedha (2025), can improve efficiency in financial management and open alternative channels for SMEs. KESONIA's integration with fintech platforms can further streamline credit scoring. Likewise, Rahmani and Siregar (2025) recommend partnership-based financing models, including Islamic banking products, which can diversify sources of credit and reduce dependency on traditional banks.

## Policy Inferences

The evidence underscores the need for a multi-pronged MSME financing strategy.

First, policymakers should design sector-sensitive interventions: trade requires stronger NPL resolution mechanisms, transport benefits from interest rate stabilization and infrastructure-backed credit, while real estate requires liquidity-enhancing solutions.

Second, Kenya should strengthen credit risk-sharing frameworks, including credit guarantees, performance-based loans (Mulyati et al., 2025), and innovative Islamic finance instruments such as cash waqf models (Rantaprasaja et al., 2025), to reduce banks' risk aversion.

Third, improving financial literacy among MSMEs, as emphasized by Ichim and Neagu-lorga (2025), can enhance creditworthiness and facilitate more efficient intermediation.

Finally, the rollout of KESONIA offers a structural lever to expand credit supply. By reducing information asymmetry, supporting differentiated sectoral risk models, and enabling risk-based pricing, KESONIA can address the core drivers of credit rationing identified in this study. Its integration with digital financial inclusion reforms (Nurhaedha, 2025) and regional experiences (Adam et al., 2025) will be critical to ensuring that MSME financing evolves into a sustainable, data-driven model that balances profitability with inclusion.

# 7.0 Appendix

## Sector 1: Real Estate

### Table A1: Unit Root Test

| SECTOR_ID2 | I(0) | I(1) |
|---|---|---|
| lncredit | | *, **, *** |
| lngdp | | *, **, *** |
| walr | | *, **, *** |
| liq | | *, **, *** |
| npl | | *, **, *** |
| Cap (dummy) | Assumed to be I(0) | |

### Descriptive Statistics

### Table A2: Summary Statistics for Sector 1

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| lncredit | 53 | 4.583772 | 0.3550176 | 3.854561 | 5.114221 |
| lngdp | 53 | 12.18886 | 0.2285393 | 11.84906 | 12.55345 |
| walr | 53 | 0.1484774 | 0.0254805 | 0.12 | 0.20 |
| liq | 53 | 0.4651321 | 0.0652604 | 0.37 | 0.568 |
| npl | 53 | 0.1110068 | 0.0610872 | 0.0378549 | 0.2342 |
| cap | 53 | 0.2641509 | 0.4450991 | 0 | 1 |

## Correlation Matrix

| | ln_msm~t | ln_gdp | Weight~e | Liquid~o | npl_ra~o | Intere~p |
|---|---|---|---|---|---|---|
| ln_msme_cr~t | 1.0000 | | | | | |
| ln_gdp | 0.9679 | 1.0000 | | | | |
| | 0.0000 | | | | | |
| Weighted_A~e | -0.6532 | -0.6367 | 1.0000 | | | |
| | 0.0000 | 0.0000 | | | | |
| Liquidity_~o | 0.8244 | 0.9019 | -0.7121 | 1.0000 | | |
| | 0.0000 | 0.0000 | 0.0000 | | | |
| npl_ratio | 0.9086 | 0.9700 | -0.5165 | 0.8887 | 1.0000 | |
| | 0.0000 | 0.0000 | 0.0001 | 0.0000 | | |
| InterestRa~p | 0.0147 | 0.0146 | -0.3878 | 0.0186 | -0.0485 | 1.0000 |
| | 0.9165 | 0.9174 | 0.0041 | 0.8946 | 0.7302 | |

Although multicollinearity exists, especially between sectoral GDP and credit, the ARDL framework partially mitigates this through lag structures. However, this remains a limitation.

## ARDL Model

ARDL(2,0,1,0,1,0) regression

| | | | |
|---|---|---|---|
| Sample: 2012q2 - 2024q4 | Number of obs | = | 51 |
| | R-squared | = | 0.5834 |
| | Adj R-squared | = | 0.4920 |
| Log likelihood = 134.75173 | Root MSE | = | 0.0192 |

| D.lncredit | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| **ADJ** | | | | | | |
| lncredit L1. | -.0934784 | .0507116 | -1.84 | 0.073 | -.1958925 | .0089357 |
| **LR** | | | | | | |
| lngdp | -.3289158 | 1.698018 | -0.19 | 0.847 | -3.758132 | 3.100301 |
| walr | -14.57574 | 8.231082 | -1.77 | 0.084 | -31.19874 | 2.04727 |
| liq | -5.646593 | 2.674609 | -2.11 | 0.041 | -11.04808 | -.2451115 |
| npl | 6.054 | 5.471334 | 1.11 | 0.275 | -4.995583 | 17.10358 |
| cap | -.4857821 | .2702739 | -1.80 | 0.080 | -1.031611 | .060047 |
| **SR** | | | | | | |
| lncredit LD. | -.6157902 | .1334094 | -4.62 | 0.000 | -.885216 | -.3463644 |
| walr D1. | 1.047414 | .4330113 | 2.42 | 0.020 | .1729303 | 1.921898 |
| npl D1. | -.3860388 | .2650176 | -1.46 | 0.153 | -.9212528 | .1491751 |
| _cons | 1.239599 | 1.523587 | 0.81 | 0.421 | -1.837347 | 4.316546 |

## Sector 2: Trade

Unit Root Test

| SECTOR_ID2 | I(0) | I(1) |
|---|---|---|
| lncredit | | *,**,*** |
| lngdp | | *,**,*** |
| walr | | *,**,*** |
| liq | | *,**,*** |
| npl | | **,*** |
| Cap (dummy) | Assumed to be I(0) | |

### Descriptive Statistics

```
. summarize lncredit lngdp walr liq npl cap if sector_id==2

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
    lncredit |         53    5.330712    .3550176     4.6015   5.861161
       lngdp |         53    12.04273    .1734469   11.69758   12.37554
        walr |         53    .1484774    .0254805        .12         .2
         liq |         53    .4651321    .0652604        .37       .568
         npl |         53    .1351233    .0547893   .0416846   .1986559
-------------+---------------------------------------------------------
         cap |         53    .2641509    .4450991          0          1

.
```

## Correlation Matrix

```
. pwcorr lncredit lngdp walr liq npl cap, sig

             | lncredit    lngdp     walr      liq      npl      cap
-------------+------------------------------------------------------
    lncredit |   1.0000
             |
             |
       lngdp |   0.9489   1.0000
             |   0.0000
             |
        walr |  -0.6532  -0.6527   1.0000
             |   0.0000   0.0000
             |
         liq |   0.8244   0.8493  -0.7121   1.0000
             |   0.0000   0.0000   0.0000
             |
         npl |   0.8633   0.8523  -0.7798   0.8857   1.0000
             |   0.0000   0.0000   0.0000   0.0000
             |
         cap |   0.0147   0.0334  -0.3878   0.0186   0.3453   1.0000
             |   0.9165   0.8121   0.0041   0.8946   0.0113
             |
```

Although multicollinearity exists, especially between sectoral GDP and credit, the ARDL framework partially mitigates this through lag structures. However, this remains a limitation.
ARDL Model

### Sector 3: Transport and Communication

Unit Root Test

| SECTOR_ID2 | I(0) | I(1) |
|---|---|---|
| lncredit | | *, **, *** |
| lngdp | | *, **, *** |
| walr | | *, **, *** |
| liq | | *, **, *** |
| npl | | *, **, *** |
| Cap (dummy) | Assumed to be I(0) | |

### Descriptive Statistics

```
. summarize lncredit lngdp walr liq npl cap if sector_id==3
```

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| lncredit | 53 | 3.953857 | .3550176 | 3.224646 | 4.484306 |
| lngdp | 53 | 12.46331 | .2090065 | 12.05928 | 12.81816 |
| walr | 53 | .1484774 | .0254805 | .12 | .2 |
| liq | 53 | .4651321 | .0652604 | .37 | .568 |
| npl | 53 | .1035408 | .0438445 | .0321285 | .1890295 |
| cap | 53 | .2641509 | .4450991 | 0 | 1 |

### Correlation Matrix

```
. pwcorr lncredit lngdp walr liq npl cap, sig
```

| | lncredit | lngdp | walr | liq | npl | cap |
|---|---|---|---|---|---|---|
| lncredit | 1.0000 | | | | | |
| | | | | | | |
| lngdp | 0.9677 | 1.0000 | | | | |
| | 0.0000 | | | | | |
| walr | -0.6532 | -0.6494 | 1.0000 | | | |
| | 0.0000 | 0.0000 | | | | |
| liq | 0.8244 | 0.8442 | -0.7121 | 1.0000 | | |
| | 0.0000 | 0.0000 | 0.0000 | | | |
| npl | 0.8018 | 0.8003 | -0.7230 | 0.8715 | 1.0000 | |
| | 0.0000 | 0.0000 | 0.0000 | 0.0000 | | |
| cap | 0.0147 | 0.1275 | -0.3878 | 0.0186 | 0.0725 | 1.0000 |
| | 0.9165 | 0.3631 | 0.0041 | 0.8946 | 0.6060 | |

Although multicollinearity exists, especially between sectoral GDP and credit, the ARDL framework partially mitigates this through lag structures. However, this remains a limitation.

ARDL Model

```
ARDL(2,0,1,0,0,0) regression

Sample: 2012q2 - 2024q4                         Number of obs     =         51
                                                R-squared         =     0.5887
                                                Adj R-squared     =     0.5104
Log likelihood =   135.0801                     Root MSE          =     0.0189
```

| D.lncredit | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| **ADJ** | | | | | | |
| lncredit | | | | | | |
| L1. | -.1435837 | .0345153 | -4.16 | 0.000 | -.2132384 | -.073929 |
| **LR** | | | | | | |
| lngdp | 1.326368 | .1945165 | 6.82 | 0.000 | .9338178 | 1.718918 |
| walr | -7.65459 | 2.051665 | -3.73 | 0.001 | -11.79502 | -3.514162 |
| liq | -2.620626 | .8868346 | -2.96 | 0.005 | -4.410331 | -.8309212 |
| npl | .1656632 | .9410793 | 0.18 | 0.861 | -1.733512 | 2.064838 |
| cap | -.3688855 | .0859446 | -4.29 | 0.000 | -.5423287 | -.1954424 |
| **SR** | | | | | | |
| lncredit | | | | | | |
| LD. | -.5522859 | .1332976 | -4.14 | 0.000 | -.8212915 | -.2832804 |
| walr | | | | | | |
| D1. | 1.036608 | .4301614 | 2.41 | 0.020 | .1685073 | 1.904709 |
| _cons | -1.421179 | .6225321 | -2.28 | 0.028 | -2.6775 | -.1648584 |

# REFERENCES


1. Aboagye, A. Q. Q., & Agyemang, E. (2021). Regional determinants of SME credit in Ghana: Evidence from random effects models. *African Journal of Economic Policy,* 28(1), 55–74.
2. Adam, J., Kamau, R., & Mensah, T. (2025). Regional integration and SME credit expansion in Africa. *Journal of African Financial Studies,* 17(2), 89–112.
3. African Development Bank. (2022). *African Economic Outlook 2022: Supporting SME Finance through Risk-Sharing.* AfDB.
4. Bank of Ghana. (2020). *Monetary policy report: SME credit under interest rate ceilings.* Accra: Bank of Ghana.
5. Beck, T., & Cull, R. (2014). SME finance in Africa. *Journal of African Economies,* 23(5), 583–613.
6. Beck, T., & Cull, R. (2015). Banking in Africa. In A. Demirgüç-Kunt, T. Beck, & P. Honohan (Eds.), *Finance for All? Policies and Pitfalls in Expanding Access* (pp. 145–176). World Bank.
7. Beck, T., Degryse, H., & Kneer, C. (2013). Is more finance better? Disentangling intermediation and size effects of financial systems. Journal of Financial Stability, 9(4), 605–622. https://doi.org/10.1016/j.jfs.2012.11.001
8. Central Bank of Kenya. (2022). *Bank supervision annual report* 2022. Nairobi: CBK.
9. Fowowe, B. (2017). Access to finance and firm performance: Evidence from African countries. *Review of Development Finance,* 7(1), 6–17. https://doi.org/10.1016/j.rdf.2017.01.006
10. Gambacorta, L., & Marques-Ibanez, D. (2011). The bank lending channel: Lessons from the crisis. *Economic Policy, 26(66),* 135–182. https://doi.org/10.1111/j.1468-0327.2011.00261.x
11. Ghosh, S. (2005). Does bank efficiency matter for growth? Evidence from the Indian banking sector. *Applied Economics Letters*, 12(9), 557–560.
12. Gonzalez, A. (2013). The effects of non-performing loans on credit growth. *International Journal of Finance & Economics,* 18(2), 132–147.
13. Holmstrom, B., & Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *Quarterly Journal of Economics,* 112(3), 663–691.
14. International Finance Corporation (IFC). (2020). *MSME finance gap: Assessment of shortfalls and opportunities in financing micro, small, and medium enterprises in emerging markets.* Washington, DC: World Bank Group.
15. International Monetary Fund (IMF). (2021). *Kenya: Selected Issues Paper.* Washington, DC: IMF.

16. Kairu, P. (2020). Sectoral credit allocation and GDP linkages in Kenya. *Journal of African Business, 21(3), 312–330*.

17. Nampewo, D., Opolot, J., & Turyareeba, C. (2018). Determinants of private sector credit in East Africa. *African Development Review, 30(1), 33–45.*

18. Ngugi, R., Karingi, S., & Mwangi, I. (2020). Bank liquidity, monetary policy and SME credit supply in Kenya. *Kenya Institute for Public Policy Research and Analysis (KIPPRA) Discussion Paper.*

19. Nurhaedha, A. (2025). Digital finance for SMEs in emerging economies. *Journal of Financial Inclusion Studies, 12(1), 45–63.*

20. Okafor, L. E., Ike, P. C., & Nwankwo, O. (2016). Liquidity constraints and SME lending in Nigeria. *Journal of Economics and Sustainable Development, 7(12), 120–131.*

21. Rajan, R. G., & Zingales, L. (1998). Financial dependence and growth. *American Economic Review, 88(3), 559–586.*

22. Rantaprasaja, S., Idris, R., & Ahmad, F. (2025). Cash waqf and SME financing models: Evidence from Indonesia. *Journal of Islamic Economics and Finance, 18(2), 144–162.*

23. Sanjaya, P., & Widjaja, Y. (2025). Land titling and SME collateral value: Evidence from Indonesia. World Development, 162, 106114. *https://doi.org/10.1016/j.worlddev.2022.106114*

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

25. Tiriongo, S. (2023). Sectoral drivers of NPLs in Kenya: Evidence from disaggregated data. Kenya Bankers Association Centre for Research on Financial Markets and *Policy Working Paper.*

26. Triki, T., & Gajigo, O. (2012). Credit bureaus and registries and access to finance: New evidence from 42 African countries. *African Development Review, 24(3), 245–263.*

27. Were, M., Ngugi, R., & Wambua, J. (2019). Interest rate caps and credit rationing: Evidence from Kenya. *African Development Bank Policy Paper.*

**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

KENYA BANKERS
ASSOCIATION

One Industry. Transforming Kenya.