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Competition and Credit Allocation in Kenya

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Abstract

Literature has divergent views on the relationship between market structure and allocation of credit by banks. Using quarterly bank scope data from 23 banks operating in Kenya between 2006 and 2018, we find that, while an increase in competition may improve allocation of credit in the short run, in the long run, increased competition may be detrimental to the amount of credit supplied to the private sector by commercial banks. This finding provides policy makers with evidence of how the structure of the Kenyan banking industry affects banks' credit allocation decisions. The findings may help inform the ongoing banking sector consolidation narrative given that changes to the competition structure of the market may not materially alter banks' lending behavior in the short and long run.

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1.0 Introduction

Access to credit in Africa and the world over has remained a salient issue and continues to elicit significant debate in policy circles and in the academia. Indeed, the role of the financial sector in economic growth has been widely recognized. Early economists, such as Walter Bagehot (1873) and John Hicks (1969) argued that the financial system played an important role in the ease of capital mobility in England. In 1912, Joseph Schumpeter posited that identifying and funding entrepreneurs with the best chance of implementing innovative products was essential for economic development.

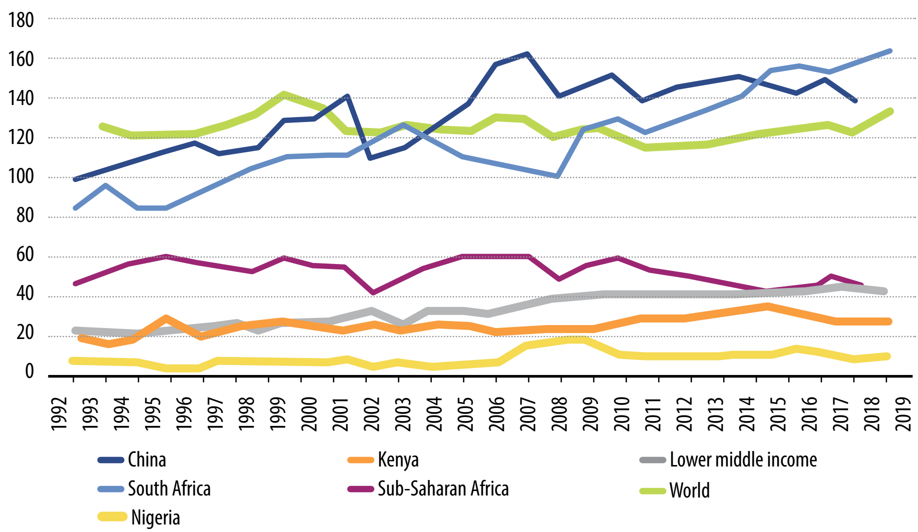
More recently, Samuelson & Nordhaus (2010) underlined the role of the financial sector in an economy as the circulatory system that links together goods, services, and finance in domestic and international markets. Ruto (2011) also found a strong and positive nexus between access to credit and sectoral gross domestic product measured as real value added. Elena & Alena (2015) posited that an increase in allocation of capital accelerates growth in credit leading to long run economic growth. The Financial Sector Deepening (FSD) Africa equally underlined the need for healthy credit markets and credit expansion in building a true middle class in Africa (FSD 2016).

However, the economic crisis of 2008/09 raised doubts as to the efficiency of the then credit-led economic model and the role that banks played in supporting economic growth (Raluca, Pop 2015). More recently, increased access to credit has also been credited for creating unsustainable asset booms with dire implications for overall economic stability. Consistent with conventional wisdom on macro-prudential regulation, Antonio & Kevin (2016) found that tighter monetary and credit policies can reduce or even eliminate such bubbles.

For developing markets, where liquidity support is crucial for the SME-led growth models, the role of financial intermediation cannot be gainsaid. While the momentum in credit expansion has been healthy, the pace has not been fast enough to enable the region catch up with its advanced and emerging peers. In Sub-Saharan Africa, confidence in the credit channels has somewhat waned in recent years on the back of increased economic imbalances and deeper structural challenges resulting from significant information asymmetry. This has weakened both the momentum and quality of economic expansion in the region. On a brighter note, deepening of financial systems can be observed in many African countries, with more financial services, especially credit, provided to more enterprises and households (Beck, Maimbo, Fay & Triki 2018). The broadening access has in part been underpinned by entry of new players and products, often enabled by new technologies, especially savings and payment products.

Despite an impressive annual credit growth of between 10-18% in Sub-Saharan Africa, the pace has not been sufficient to support the necessary growth in infrastructure and create sufficient jobs for the fast-growing population (FSD 2016). The need to preserve capital by the lending agents continues to impose on borrowers a heavy security requirement, locking most of them out of formal credit channels. Meanwhile, the past decade has seen numerous policy missteps (especially around anti-trust regulations) in relation to credit markets, well-intended initiatives that have not been grounded on good evidence (FSD, 2018). For example, interest rate controls in Kenya between 2017-2019 led to an average decline in aggregate private sector credit growth of about 3.5% (Rodger &

Figure 1: Credit Growth-to-GDP Evolution



Tiriongo, 2018). Given the evident economic impact resulting from underperforming credit markets, the need for bigger and better functioning credit markets remains central to financial sector reforms. To minimize the risk of more policy missteps, there is need to understand the unique factors that drive allocation of credit in Kenya. In Kenya, private sector credit as a percentage of GDP has remained relatively low at 27.5% relative to the global average of 133.8% and even the lower middle-income countries and Sub-Saharan Africa's averages of 55% and 45.5% respectively (The World Bank, 2019).

While still significantly below the emerging and even lower income peers, private sector lending in Kenya as a percentage of GDP has dropped from the 2015 peak. Evidence from credit markets reveals a general lethargy that may be explained by reasons beyond the public investment led economic growth, regulations, economic environment, fiscal policy, and monetary policy in play. The disconnect in the credit market presents a significant economic problem considering that over 75% of GDP is linked to private expenditure and investments, naturally powered by credit. To this end, researchers and policy makers continue to explore causes of this misalignment and the appropriate policy responses. So far findings from other markets on causes of this policy failure and specifically the role of the market structure to allocation of credit have been contentious.

On one hand, it is often argued that a departure from competition is detrimental to growth because banks with market power, restrain the supply of loanable funds by setting higher interest rates. On the other hand, competition policies in banking may involve difficult trade-offs. While increased competition may enhance the efficiency of banks with positive implications for economic growth, greater competition may also destabilize banks with costly repercussions for the economy. While the recent literature provides empirical evidence on the positive role of the banking sector in enhancing economic growth through more efficient resource allocation, less emphasis has been placed on the effect of the structure on credit allocation decisions of banks in Kenya. We therefore explore how competition is altering the structure of the banking sector and how the competition landscape affects allocation of credit by banks in Kenya.

2.0 Stylised Facts: Bank Competition in Kenya

In Kenya, competition in the banking sector has increased over the years from both traditional and non-traditional sources including non-bank financial intermediaries, market based financial institutions and most recently from fin-tech companies (Faith, Raphael, and Stephanie, 2019). As technology promise better and cheaper ways to compete for core banking business, banks' dominant position will continue to be challenged (Yves Mersch ECB, 2019). Changes in regulation have also defined the competitive landscape in the Kenyan finance sector. Using Panzar-Rosse H-statistic, Faith et. al (2019) found that the competition regime for the Kenyan banking sector is consistent with a monopolistic market structure. Odour et. al, (2017) argued that raising capital requirements increased concentration in banking reducing competition.

Like the impact of market structure on pricing, the relationship between the structure and allocation of credit has remained a subject of debate, with conflicting findings. On one hand, the market power hypothesis, holds that greater competition leads to higher and cheaper allocation of credit to firms (Pagano 1993). On the other hand, the information hypothesis argues that banks are more likely to form long term relationships with borrowers when operating in a non-competitive market, strong competition would therefore discourage relationship lending, impairing firms' access to credit (Dell Aricca & Marques, 2006). Yet, the subject remains salient, given the global interest in banking sector consolidation as a means to enhanced stability and efficiency. This stability driven push for consolidation could increase as the CoVid-19 pandemic tests the resilience of the global financial system by undermining the quality of assets, with potential severe implications for the liquidity, profitability, and capital.

In this paper, we assess the effect of competition on credit allocation within the context of Kenya. Competition in the banking industry is measured by the Panzar-Rosse H-statistic, a non-structural measure of competition. Like Leon (2016), the effect of bank competition on credit availability is obtained by running an Autoregressive Distributive Lag (ARDL) to test for the presence of long-term relationship between the structure of banks as defined by competition and credit allocation, controlling for firm and country-level macroeconomic conditions

3.0 Literature Review

There is a ton of literature that attempts to explain the rationale behind banks' credit allocation decisions, including regulation, the policy regime, the macroeconomic landscape and the risk appetite of the holders of capital. Locally, while studies have continuously assessed the relationship between the market structure and pricing of credit, literature on the structure of the banking sector as an explanatory variable to credit allocation remains thin. No doubt, the increasingly blurry distinction between banking and nonbanking financial institutions has transformed the financial services sector into one of the most dynamic and challenging industries (Boot 2000). This has cast doubt on the effectiveness of regulation and whether it imposes a heavy compliance burden on quality banks. When regulation by adjusting capital, requirements changes the cost of funding loans, higher quality banks suffer a greater loss in profit than lower quality banks. Additionally, a change in funding costs caused by regulation induces a greater loss in profit when regulated banks face competition from non-regulated competitors (Boot et al 2000).

Historically, the relationship between market structure and the competitiveness of market outcomes has played a major role in anti-trust enforcement, regulatory proceedings, and industrial organization research (Dunne et. Al, 2009). While the effect of market structure, industry concentration, pricing, markups, and profits is generally the focus of interest, it has long been recognized that market structure cannot be viewed as exogenous to the competitive process. Market structure is determined by entry and exit decisions of individual producers and these are affected by expectations of future profits which, in turn, depend on the nature of competition within the market (Dunne et.al, 2009). Recent work suggests that the number of banks and the degree of concentration are not, in themselves, sufficient indicators of contestability. Other factors play a strong role, including regulatory policies that promote competition, a well-developed financial system, the effects of branch networks, and the effect and uptake of technological advancements (Carol 2004).

Greater financial developments including access to credit have been linked to the structure of the banking industry. However, empirical studies have often focused on the impact of the structure on pricing of financial products with little focus on the quantum of credit availed by commercial banks. At the same time, consolidation of banks in the aftermath of the Global Financial Crisis of 2008/09 and the attendant increase in the scrutiny of banking regulations have intensified the policy debate on the influence of concentration and competition on the banking and real sector outcomes including access to finance (Beck et al.,2014). So far, evidence remains inconclusive.

The traditional market power view argues that competition in the banking sector reduces the cost of finance and increases the availability of financial services (Berger and Hannah 1998). Fierce competition leads to lower costs and improved access to finance (Besanko and Thakor 1992, Guzman, 2000). Moreover, bank competition alleviates credit constraints and not only leads to less severe loan approval decisions but also reduces borrowers' discouragement (Leon, 2016). Leon also concluded that banking competition enhances credit availability by reducing prices and increasing relationship lending. Chong, Lu and Ongena (2013) found that financing constraints in China were alleviated in regions where banking markets were less concentrated, irrespective of whether concentration is measured by the Herfindahl–Hirsch-man Index (HHI) or the three-bank concentration ratio (CR3) based on bank branch presence, supporting the market power hypothesis.

The alternative view argues that competition could have a negative impact on credit, explained by the role of information asymmetry. The information hypothesis argues that competitive banking systems can weaken relationship-building by lowering banks' incentive to invest in soft information. In the presence of information asymmetries and agency costs, competition can reduce access by depriving banks of the incentive to build lending relationships (Peterson and Rajan, 1995). Others posit that banks' incentive to invest in information technologies are higher in less competitive markets (Hauswald and Marquez, 2006). Banerjee et al (2017) analyzed the real effects of relationship banking in Italy. They found that following Lehman's default, banks offered lending terms that were more favorable to firms with which they had stronger relationships.

While general economic theory points to inefficiencies of market power, resulting in less loans supplied at a higher interest rate, information asymmetries and agency problems might result in a positive or nonlinear relation between the market power of intermediaries and the amount of loans supplied to opaque borrowers, in a dynamic setting. Similarly, empirical studies have derived conflicting results, showing a positive or a negative relation between competition in banking and the access to credit, its costs and economic growth (Thorsten Beck, Asli Demirgüç-Kunt, and Vojislav Maksimovic). Owen & Pereira 2018 found that countries in which regulations allow banks to engage in a broader scope of activities are characterized by greater inclusion. Greater banking industry concentration is associated with more access to deposit accounts and loans, provided that the market power of banks is limited. Therefore, less competitive markets may be associated with more credit availability (Petersen and Rajan 1995; Dell'Ariccia and Marquez, 2004).

Within the partial equilibrium framework, literature finds that under monopoly, the severity of the particular bank-borrower problem is reduced. On the other hand, general equilibrium models tend to find that less competitive banking systems may be detrimental to the economy. In particular, Smith (1998) finds a negative impact of a monopolist banking system on income and the business cycle. Guzman (2000) also finds that under monopoly, banks ration credit more heavily than competitive banks increasing monitoring costs, which results in negative consequences for capital accumulation and growth.

4.0 Data, Variables and Methodology

To ascertain the relationship between the explanatory variables as indicated in the conceptual framework, the study adopted a panel Autoregressive Distributed Lag model (ARDL) that was developed by Peseran et al. (2001). The model seeks to examine the long run relationship between each explanatory variable with the measure of credit allocation, loans and advances. We use the ARDL methodology for several reasons. Our variables have different levels of stationarity – Some at level and others at first difference. The ARDL methodology would be applicable in this case as it can be applied regardless of the level of stationarity of the variables in the sample so long as the variables are not stationary at second difference. Secondly, it allows for inferences on long run estimates which are not possible under alternative co-integration procedures. Finally, the ARDL Model can accommodate greater number of variables in comparison to other Vector Autoregressive (VAR) models. The model as well is best suited when N<T. The general ARDL model is formulated as follows:

$$y_{it} = \Sigma_{j=1}^{p} \delta_i \, y_{i,t-j} + \Sigma_{j=0} \, \beta_{i,j} \, X_{i,t-j} + \phi_i + e_{it}$$

where:

y_{it} = dependent variable

$X_{i,t}$ = is a kx1 vector of either I(0) or I (1)

δ_{ij} = coefficient of lagged dependent varibales

$\beta_{i,j}$ = kx1 coefficent vectors

ϕ_i = unit specific fixed effects

i = 1, . . ., N

t = 1, 2, . . . T

p, q = optimal lag lengths

e_{it} = error term

From the above generalized form, our ARDL model is :

$$\Delta y_{it} = \Theta i\ (y_{i,t-1} - \lambda X_{it}) + \Sigma^{p-1}_{j=1} \xi_{i,j}\ \Delta y_{i,t-j} + \Sigma_{j=0}\ \beta_{i,j} \Delta X_{i,t-j} + \phi_i + e_{it}$$

The model specification is therefore as follows:

$$\Delta la_{it} = \Theta_i\ (la_{i,t-1} - \lambda X_{it}) + \Sigma^{p-1}_{j=1} \xi_{i,j}\ \ \Delta LA_{i,t-j} + \Sigma_{j=0}\ \beta_{i,j}\ \Delta X_{i,t-j} + \phi_i + e_{it}$$

where:

$\Theta i = -(1 - \delta_I)$, group specific speed of adjustment coffecient where $\Theta_i < 0$

λ_I = vector of long run coeeficients

ξ_{ij}, β_{ij} = short run dynamic coefficients

$LA_{i,t-1} - \lambda X_{it}$ = error correction term (ECT)

The study was guided by a multiple regression model as specified below:

$$LA_{i,t-1} = f(LA_{it}, NPL_{it}, LDR_{it}, ROA_{it}, CIR_{it}, GVT_{it}, R_{it}, GDP_t, e_t)$$

Where:

LA_{it} = year on year growth in loans and advances (Measure of credit allocation)

NPL_i = non-performing loans ratio (Measure of credit risk). There is comprehensive literature to support the fact that bank's allocation of credit is positively correlated to its risk appetite. In our model, this will be proxied by the non-performing loans ratio. The bank specific approach may reveal the propensity of different banks to supply credit to borrowers, considering the ex-post performance of loans (Santiago et.al, 2006).

LDR_{it} = loans to deposits ratio (Measure of bank liquidity). This study deploys the loans to deposit ratio as a proxy for liquidity. According to Kim & Sohn, 2017, bank capital exerts a significantly positive effect on lending only after large banks retain sufficient liquid assets.

ROA_{it} = return on assets (Measure of bank profitability). Like any business, profitability is very crucial in the growth and allocation of capital. The return from the core intermediation role is therefore very important to the banks' asset allocation decisions. This variable captures the link between profitability and the supply of credit (Carter et. al, 2004) and is measured by the Return on Assets (RoA).

CIR_{it} = cost to income ratio (Measure of bank efficiency). More efficient firms have been associated with higher supply of credit. Considering that the bulk of efficiency benefits result from effective cost management, we proxy efficiency measure using the cost to income ratio.

GVT_{it} = year on year growth in government securities (Measure of crowding out effect). Fiscal deficits of a country has significant implications for credit supplied to the private sector by diverting bank liquidity to the government. Theoretically, an increase in public debt as a percentage of GDP, particularly from the domestic market, is associated with higher interest rates that attract liquidity that may have otherwise been channeled to the productive sector. This in turn leads to a reduction in the bank's level of loans and advances. To control for its impact on private sector lending, we proxy the crowding out effect with the growth in government securities.

LnTA_{it} = log of total assets (Control for bank size). This is proxed by total banks assets. Literature on the size of the bank is conflicting. Santiago et.al (2006) argue that the large banks are at a disadvantage in lending to informally opaque firms due to their organizational diseconomies in providing relationship lending and because soft information may be difficult to transmit within large organization (Stein 2020), creating agency problems (Berger and Udell 2020). However later studies challenged this finding suggesting that large banks tend to adjust to competition conditions in local markets and were better placed to transfer liquidity from one region to another.

R_{it} = yields on loans (Measure of interest rate effect). The study uses the yield on loans as a proxy for the interest rate effect. Demetriades and Luintel (2001) argue that under imperfect competition, mild repression in or a 'fixing of' the lending rate has a positive effect on bank loans. That is, under government intervention with an interest rate fixed below the monopoly equilibrium level, it is optimal for bankers to increase the amount of loans. However, repressing interest rate levels below those that would prevail under perfect competition will likely reduce the amount of loans and consequently have a negative effect in the economy.

$\mathrm{LnHSTAT}_{t}$ = H-statistic (Measure of competition). Given the conflict in outcomes from different measures of competition on the assessment of credit allocation, the choice of the competition proxy is particularly crucial. Like in our previous paper (Faith et.al, 2019) we use the structural Panzar-Rosse H-statistic to determine the level of competition within the banking sector. This is a non-structural approach to competition that derives a profit maximizing equilibrium conditions i.e assesses variations in a firm's revenue relative to input prices. Its use of bank-level data makes it robust to the geographic extent of the market. Where $H=1$, shows a market in equilibrium/ perfect competition, 0=1 in a monopolistic market, $H<1$ reflects monopolistic competition.

GDP_{t} = growth in economic activity (Measure of business activity). The business environment defines among other things the credit risk that banks may be exposed to in the course of doing business. This measure represent factors beyond the firms that influence credit allocation decisions in commercial banks. We capture this with the real GDP growth rate.

e_{t} = error term

Table 1: Apriori Expectations

Variable Name	Notation	Expected Sign (Study)
Growth in Loans and Advances	LA	
Economic Growth	GDP	(+)
Yield on Loans	R	(+) or (-)
Non-performing Loans Ratio	NPL	(-)
Loan to Deposit Ratio	LDR	(+) or (-)
Return on Assets Ratio	ROA	(+)
Cost to Income Ratio	CIR	(-)
Growth in Stock of Government Securitites	GVT	(-)
Log of Total Assets	LnTA	(+)
Log of H-statistic	LnHSTAT	(+) or (-)

Source: Authors Compilation

The main target population is the Kenyan banking sector as the main providers of credit to the private sector, the government given the need to control for effects of public borrowing (crowding out effect) mechanism as well as policy makers given the need to understand the relationship between lending rates and credit allocation.

The sample for the study includes bank scope quarterly data for 23 banks operating in Kenya in the period between 2006 and 2018. The number of banks was determined by the availability of the data over the period. Collectively the sample constitutes 53% of the banking population, which accounts for 78% of banking sector's loans and advances. Bank specific data was obtained from respective bank statements while macroeconomic data was sourced from the Kenya National Bureau of Statistics. The collected data was analyzed using trend analysis through the use of tabular representations that explicitly revealed trends among the different data sets. Diagnostic tests were performed so as to ensure no violation of assumptions of normality, homogeneity, stationarity, heteroscedasticity and serial correlation using the Stata software package version 16.

The model estimates a reduced form equation relating total revenues to a vector of input prices using the equation below;

$$log\ (TR/TA) = \alpha + \Sigma_{i=1}^{n} \beta_i log\omega_i + \Sigma_{i=1}^{n} \lambda_i logCF + log(TA) + e_i$$

Where TR denotes total revenues, TA is total assets, ωi ith input factor and CF entails other bank specific control factors. Where interest income/total assets is used as a proxy for price Input cost variables include; interest expense to customer deposit ratio (W_1), capital to total assets ratio (W_2), and total other operating expense to total assets ratio (W_3). We control for bank size by incorporating the logarithm of total assets (Log (TA)).

4.1 Pre and Post Estimation Tests

This section presents the results of the econometric analysis. Logarithm is used for the variables total assets and the H-statistic consistent with Cruz and Teixeira (1999), who argued that the data's logarithm increases the stability for variance and the optimization of empirical estimates. The majority of the variables, LA_{it}, NPL_{it}, LDR_{it}, ROA_{it}, CIR_{it}, GVT_{it}, R_{it}, and GDP_t are not transformed into logs as they are either ratios or percentages. Diagnostic tests were conducted. These tests included descriptive tests for normality of the data, unit root test for stationarity, the granger causality test to test the causal relationship between the variables, the test for heteroscedasticity and the test for serial correlation.

The computed Panza-Rosse H-statistic over the sample period is 0.78 which is consistent with a monopolistic competiton market structure. Such a competitive environment can drive collusive behavior among banks especially when demand is low (Green and Porter, 1981) and supervisory framework weak.

Table 2: Descriptive Statistics

Variable Name	Obs	Mean	Std. Dev.	Min	Max	Kurtosis	Skewness
La	1,099	18.828	31.694	-531.093	200.000	88.004	-3.921
Gdp	1,193	0.050	0.017	0.030	0.083	3.813	-0.889
R	1,113	0.127	0.052	0.021	0.416	10.520	2.052
Npl	1,193	0.129	0.165	0.004	1.360	19.407	3.502
Ldr	1,193	0.833	2.702	0.192	93.335	1,153.453	33.702
Roa	1,193	0.053	0.035	- 0.060	0.200	3.930	0.639
Cir	1,193	0.777	1.490	-4.367	39.106	398.868	17.004
Gvt	1,056	32.984	97.104	-100.000	1,872.283	146.400	9.544
Lnta	1,192	10.702	1.282	7.863	13.337	2.091	-0.152
Lnhstat	1,057	-1.359	0.627	-3.779	-0.335	5.954	-1.256

Source: Authors' Compilation

The descriptive statistics table shows that the sample size is unbalanced with the number of observations ranging between 1,056 and 1,193. The unbalanced data set is as a result of mergers and acquisitions in the period. This is in line with the recommended range of at least 50 observations as larger samples often provide more precise estimates of process parameters such as mean and standard deviation.

The study uses the mean as the standard measure of the center of distribution for all the data variables. The standard deviations of the data variables, NPL_{it}, LDR_{it}, ROA_{it}, CIR_{it}, $Yields_{it}$ and GDP_t, are close to 0 indicating that the variables are not volatile. The non-normality of the variables is established by their skewness and kurtosis coefficients. The skewness of the data measures the degree and direction of asymmetry. A symmetric distribution, such as a normal distribution, has a skewness of 0. The sample exhibits a close to balanced proportion of positively and negatively skewed data sets. A positive skewness suggests that the distribution is skewed to the right while a negative skewness suggests the distribution is skewed to the left. Meanwhile, the kurtosis for all data variables are positive. The kurtosis number is evaluated in relation to the normal distribution on which the kurtosis is equal to 3. All of the data variables, except lnta, have a kurtosis greater than 3 suggesting that their respective distributions have heavier tails than a normal distribution (more in the tails).

4.1.1 Correlation Matrix

The table shows that there is no multicollinearity among the variables given the above correlation matrix (Table 3). Serial correlation occurs when the correlation is more than 0.70 (70%).

Table 3: Pearson Correlation Matrix

	LA	R	GDP	NPL	LDR	ROA	CIR	GVT	LnTA	LnHSTAT
LA	1									
R	0.0528	1								
GDP	-0.1069	-0.0255	1							
NPL	-0.2443	0.0404	0.0881	1						
LDR	0.0359	-0.0315	-0.0442	-0.0073	1					
ROA	0.0483	0.2318	-0.1218	0.0149	-0.0076	1				
CIR	-0.12222	-0.0311	-0.0127	0.0901	-0.0088	-0.074	1			
GVT	0.0586	0.119	-0.1352	0.0987	-0.0023	0.0087	-0.0166	1		
LnTA	-0.032	0.1019	0.0499	-0.297	-0.0211	0.1009	-0.1185	0.02893	1	
LnHSTAT	0.1859	0.0023	0.0595	0.1028	-0.0322	-0.0666	-0.0707	0	0.9414	1

4.1.2 Unit Root Test

This test established whether the data variables have a unit root or not. That is, whether the data variables are stationary and at what level of integration. The Stata Software Package implements a variety of tests for unit roots or stationarity in panel datasets, that is the Levin–Lin–Chu (2002), Harris–Tzavalis (1999), Breitung (2000; Breitung and Das 2005), Im–Pesaran–Shin (2003), and Fisher-type (Choi 2001) unit root tests. The null hypothesis of all the aforementioned tests is that all the panels contain a unit root. That said, our data set is unbalanced and as well contains gaps limiting the study to employ the Fisher-type tests. The results from the table indicate that the variables at stationary at different levels but none of the variables is integrated of order I (2). Therefore, the ARDL model with an optimal lag order of order 1.

Table 4: Unit Root Testing

Variable Name	Trend	I(0)	I(1)
LA	No	***	
GDP	No	***	
R	No	***	
NPL	No	***	
LDR	No	***	
ROA	No	***	
CIR	No	***	
GVT	No	***	
LnTA	Yes	***	***
LnHSTAT	No	***	

*** variable is stationary at the 1%, 5% and 10% significance level

4.1.3 Hausman Test

For this study we compare the suitability between the pool mean group (PMG) and the dynamic fixed effect (DFE) estimators. The PMG estimator is consistent under the assumption of long-run slope homogeneity the DFE is consistent under the assumption of homogeneous slope, wherein the slopes are fixed and the intercepts are allowed to vary across banks (Pesaran et al. (1999)). The study will compare the PMG, and DFE estimation results. It is also possible to test for the suitability of the PMG estimator relative to the DFE estimator based on the consistency and efficiency properties of the two estimators, using a Hausman test. From the test result, the value of the chi^2 statistic (0.09) and a corresponding probability value of 1.00 clearly indicates that we fail to reject the null hypothesis against the alternative (Table 5). This signifies the preference of the PMG estimator ahead of the DFE estimator, as a result, the focus of the study is on estimates obtained from the PMG estimator.

Table 5: Hausman Test

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	DFE	pmg	Difference	S.E.
GDP L1.	-64.86949	-32.68095	-32.18853	1318.384
R	35.30394	-10.33915	45.64308	755.4747
NPL	-78.94395	-50.52697	-28.41698	213.3059
LDR	0.3091163	-0.19724	0.5063562	8.65223
ROA	-2.47178	-77.03977	74.56799	969.5477
CIR	2.874939	1.734997	1.139942	30.32075
GVT	0.0113641	-0.011567	0.0229309	0.23687
LnTA	-13.01419	-16.46741	3.453221	44.92679
LnHSTAT	7.060453	-3.429236	10.48969	47.4251
b =	consistent under H0 and Ha	**$chi^2(9)$ =**	b-B)'[(V_b-V_B)^(-1)](b-B)	
B =	inconsistent under Ha, efficient under H0		0.09	
Test: H0:	difference in coefficients not systematic	**Prob>chi^2 =**	1.000	

4.2 Empirical Results and Discussions

The pool mean group (PMG) method proposed by Pesaran et al. (1999) considers a lower degree of heterogeneity, as it imposes homogeneity in the long-run coefficients while still allowing for heterogeneity in the short-run coefficients and error variances. The basic assumptions of the PMG estimator are as follows: first, the error terms are serially uncorrelated and are distributed independently of the regressors, that is, the explanatory variables can be treated as exogenous; second, there is a long-run relationship between the dependent and explanatory variables; and third, the long-run parameters are the same across countries. This estimator is also flexible enough to allow for long-run coefficient homogeneity over a single subset of regressors and/or banks.

The ARDL table presents the result of the panel ARDL estimated model. In the long run, the PMG estimate of NPL was found to have a significant negative effect on growth in loans and advances, showing that an increase in the NPL ratio results in a reduction in the pace of credit allocation. In the same vein, the PMG estimate of LnTA was found to have a significant negative effect on growth in loans and advances in the short run. In particular, LDR and LnTA were found to exert a significant positive effect on growth in loans and advances. The error correction term (ECT) represents the speed of adjustment of credit allocation to the private sector to a deviation in the relationship between credit allocation and the explanatory variables. The coefficient of -0.3892 indicates that credit allocation adjusts by 38.92% per period, that is 4 quarters, towards long run equilibrium after a shock.

Table 6: Panel ARDL Estimation Results

	Long Run (PMG)	Short Run (PMG)
GDP	-32.68095	10.933
	(61.88898)	(35.15877)
R	-10.33915	-125.8139
	(43.97248)	(85.29007)
NPL	-50.52697***	10.11057
	(12.82423)	(54.28011)
LDR	-0.1972399	92.86677***
	(0.6900429)	(11.42045)
ROA	-77.03977	0.6691059
	(48.41967)	(22.53055)
CIR	1.734997	0.8877057
	(2.177491)	(1.374245)
GVT	-0.0115668	0.0137079
	(0.0149737)	(0.0168243)
LnTA	-16.46741***	74.04499***
	(2.132769)	(10.41662)
LnHSTAT	-3.429236	3.956956
	(2.191631)	(3.437289)
ECT		-0.3891908
Constant		72.90257

*** significant at the 1%, 5% and 10% level. Standard errors in parentheses.

5.0 Conclusion

This paper assessed the impact of market structure, in the context of the Kenyan-banking sector, on credit allocation, while controlling for other firm level and economic variables that influence bank-lending decisions. The study finds that, in the short run, an increase in competition leads to an increase in credit allocation, consistent with the market power hypothesis. This however changes in the long run with increased competition having a negative impact on credit allocation, in line with the information hypothesis school of thought. The divergent short- and long-term relationships between competition and credit allocation, suggest that competition is healthy but only to a certain point. However, the study does not establish at what point competition becomes destructive. The findings also reveal a strong relationship between credit allocation and banks' credit risk appetite, profitability as well as the economic environment that banks operate in.

These findings may support the ongoing banking sector consolidation narrative, which propagates for fewer efficient and more stable banks, that still ensures enhanced access to credit. However, the structure as measured by competition explains a very small proportion of the growth in lending. This suggests that the structure of the market should perhaps not warrant as much attention from policy makers especially concerning anti-trust regulations. Meanwhile, the joint relationship between the explanatory variables only explains about 27.10% of the changes in lending to the private sector. This is a limitation to the model and provides scope for further analysis using either bank specific or macroeconomic variables to better explain the changes in lending to the private sector. The research also makes one more contribution to literature. From the model, the coefficient of the Error correction term, which measures the speed of adjustment towards the long run equilibrium, implies that 38.90% of the impact of any shock could dissipate in 4 quarters. Therefore about 61.10% of the shock remains, ceteris paribus.

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