BANKING INDUSTRY RESPONSE TO COMPETITION FROM THE FINANCIAL INCLUSION PARADIGM IN AFRICA

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DECLARATION

This is my original PhD work, and it has not been presented to this or any other university for a degree.

Simon Kamau

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DEDICATION

To my parents: Benson Kamau and Margaret Wanjiku Kamau.

LIST OF ACRONYMS

AR	Arellano-Bond Test
ATMs	Automated Teller Machines
CGAP	Consultative Group to Assist the Poor
DEA	Data Envelopment Analysis Approach
ES	The Efficiency Structure Hypothesis
FE	Fixed Effects
FRM	Fractional Probit Regression Method
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
GNI	Gross National Income
HHI	Herfindahl-Hirschman Index
IFC	International Finance Corporation
IMF	The International Monetary Fund
MDGs	Millennium Development Goals
MENA	Middle East and North Africa
MFIs	Microfinance Institutions
MLE	Maximum Likelihood Estimation
NGOs	Non-Governmental Organizations
NPLs	Non-Performing Loans
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
QLH	The Quiet Life Hypothesis
RE	Random Effects
ROA	Return on Assets
RWAs	Risk Weighted Assets
SCP	Structure Conduct Performance Hypothesis
SFA	Stochastic Frontier Analysis
SMEs	Small and Medium Enterprises
TC	Total Cost
UFA	Universal Financial Access
VIF	Value Inflation Factors
VRS	Variable Returns to Scale

WDI	World Development Indicators

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ABSTRACT

This study examines the effects of increased competition from microfinance institutions (MFIs) – reflective of the financial inclusion paradigm – on commercial banks in Africa. More specifically, I analyze the banking industry's response to competition for financial inclusion and how the response affects the cost efficiency, asset portfolio risk, and social outreach (performance) of the banking industry. I employ panel data comprising 16 countries that possess the most advanced national banking markets in Africa, for the period 2010-2017. Fixed effects model (FE), Fractional Probit regression method (FRM), and Generalized methods of moments (GMM) are variously the main estimation techniques.

I find that banks are responding to the competition for financial inclusion by increasing the supply of credit to households and SMEs, in support of the market power hypothesis of competition. Furthermore, estimation results show strong evidence that increased supply of credits to households and SMEs, in response to competition for financial inclusion, contributes positively to the banking industry's cost-efficiency. Additionally, results suggest that increased bank lending to households and SMEs has a negative but statistically insignificant effect on banking stability. Interestingly, additional results indicate that banks' positive response to the financial inclusion paradigm is mainly limited to the relatively wealthier segment of the low-income population. Moreover, these findings are robust to using alternative measures of competition for financial inclusion, and banking industry response, among several other robustness checks.

From these results and more, I recommend policies such as enabling access to borrowers' information and supporting the development of financial market infrastructure, in order to promote competition in providing financial services to the low-income market and further drive financial inclusion. I also recommend the adoption of improved and proactive regulatory measures to ensure that competition for financial inclusion does not compromise the stability of the banking industry. Lastly, I propose policies that would ensure that competition for financial inclusion does not hurt outreach to the poorest segment of the population, as banks seek to enhance their efficiency while providing financial services to households and SMEs.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

In recent years, there has been a paradigm shift from microfinance to financial inclusion in terms of frontline finance-oriented development programs.[1] According to Allen et al. (2016), financial inclusion[2], which involves access to and use of financial services, represents a new phase in the effort to take financial services to the poor by building upon and going beyond microfinance.[3] The shift has created conditions that have facilitated mainstream commercial banks to expand their financial services to the poor.[4] Nonetheless, over the last two decades Microfinance Institutions (MFIs) have experienced unprecedented growth owing to the ongoing transformation of the microfinance industry and the increased support from governments and donor agencies (Arrassen, 2017; Chikalipah, 2018).

The remarkable growth of MFIs has increased competition in providing financial services to the low-income market segment (Assefa et al., 2013; Donou-Adonsou & Sylwester, 2017).[5] De la Torre et al. (2010) observe that despite the increasing competition for financial inclusion, commercial banks are expected to continue competing for clients in the low-income market. However, it is not clear how banks are responding to this particular paradigm shift based competition. Therefore, the current study investigates the banking industry's response to, and the effect of the increased competition for the financial inclusion paradigm in Africa.

[1] Frontline finance-oriented development programs aim at providing effective mechanisms to enable poor people to save, send, and borrow money in order to mitigate financial risks. Examples of these programs include basic savings account, deposit secured loans and financial literacy training (Bill and Melinda Gates Foundation, 2012).

[2] There are various definitions of financial inclusion; for instance, Chummun and Ojah (2016) view financial inclusion as a mechanism for enhancing welfare, whereby welfare involves access to relevant and affordable financial services when needed for smoothing consumption or enabling production. Dev (2006) define financial inclusion as delivery of banking services at affordable cost to the large sections of disadvantaged and low-income groups. In this study, we define financial inclusion as access to finance to households and SMEs (i.e., the often under-financed and/or un-financed by traditionally formal financial services institutions).

[3] Microfinance is a term used to refer to financial services for the poor (Helms, 2006), generally characterized by contracts of micro to small denominations.

[4] For the rest of this study, we use the terms "the poor", ''unbanked'', "under- or un-financed" and "low-income earners" interchangeably to refer to households and SMEs who have traditionally been financially constrained or excluded.

[5] According to Mersland (2013), the microfinance (MFI) industry is expected to become the world's largest banking market in relation to customer numbers. For example, between 2000 and 2014 the growth rate of MFI loan portfolio in Africa averaged 1312%. For more information see Fixler (2015).

Although the benefits of providing financial services access are clear, mainstream commercial banks had previously perceived the poor and small enterprises as 'unbankable.' The small amounts (denominations) of deposits and loans from low-income earners were seen as unprofitable by banks (Hamada, 2010). While MFIs have demonstrated that low-income earners represent a viable business proposition, they have not been able to reach most people in poor and remote areas of many countries (Helms, 2006; Hannig & Jansen, 2010). Indeed, a recent study by Demirgüç-Kunt et al. (2015b) shows that about 2 billion people around the world do not have access to financial services.

Against this background, there is an increasing consensus that banks are the best suited to take forward the financial inclusion agenda. A growing number of commercial banks, particularly in Africa, are gradually shifting their attention towards financial inclusion and serving markets that they had previously ignored (Isem & Porteous, 2005; Hermes & Lensink, 2007b). Johnson (2013) states that the banking industry has recognized the scale of unexploited market niche that exists by reaching low-income masses. With their traditional lines of business coming under stiff competition and the need to grow client numbers, commercial banks are compelled to diversify and reach the unserved and underserved segments of potential target markets (Manyika et al., 2016).

Further, there are ongoing regulatory and policy reforms in the financial sector to promote financial inclusion. For example, Demirgüç-Kunt et al. (2015a) note that most countries in Africa are adopting regulations that encourage competition and allow the establishment of information infrastructure to improve financial services access. These reforms are per the World Bank's goal for Universal Financial Access (UFA) by the year 2020. Through the UFA initiatives, both the International Finance Corporation (IFC) and the World Bank are said to be committed to enabling at least one billion people to access financial services. Additionally, other international organizations have emerged to advance financial inclusion to the poor.

The Consultative Group to Assist the Poor (CGAP)[6] endorsed the 'key principles of microfinance' framework. This framework recognizes that a significant number of excluded people can gain access if they are integrated into the mainstream financial sector (Helms, 2006). The policy and regulatory reforms coupled with the significant number of unbanked clients have increased competitive pressure on banks in the provisioning of financial services

[6] CGAP is a consortium of 31 public and private development agencies working together to expand access to financial services for the poor. For more about CGAP, visit www.cgap.org.

to the low-income market segment. The banking industry is facing intense competition from MFIs, particularly in emerging markets to attract and retain the currently many unbanked clients.

Small businesses and poor households are increasingly attracted to MFIs due to their ability to deliver better services than banks.[7] Although the entry of commercial entrants into this particular market segment is making more people to access financial services from the mainstream financial sector, there are concerns that competition may negatively affect poor clients (Helms, 2006). The competition for participation in financial inclusion programs means that the focus of financial services on the poor has and/or should inexorably shift from the traditional social mission movement towards commercial model and/or goals integration.

1.2 Overview of the Banking Industry in Africa

According to Beck and Cull (2014), the banking industry in Africa has experienced dramatic developments over the last two centuries. In the 1980s, the banking industry in most African countries was subject to restrictive regulations and dominated by government-owned banks. The International Monetary Fund (IMF) and World Bank's structural adjustment policies[8] in the mid-1980s saw many African countries implement financial sector reforms. These reforms were aimed at privatizing and restructuring government-controlled banks. Moreover, the reforms included guidelines that lessened entry and exit restrictions, capital, and interest controls, in conjunction with changes in the banking sector regulatory and supervisory frameworks.

Mutarindwa et al. (2020) observes that banks in most African countries are regulated by the Banking Act which contains the primary laws that relate to the authorization of persons to conduct banking business. The Banking Act also provides a framework used to regulate and supervise banking institutions. Generally, central banks (reserve banks) have the main responsibility of supervising and regulating banks in most countries in region except in the Economic and Monetary Community of central Africa and other francophone countries in which bank supervision is carried out by a separate entity. However, in South Africa, besides the Reserve bank, banks are also regulated by the Financial Sector Conduct Authority which

[7] By 'better services' we mean financial products that are designed to meet the needs of the unbanked segment of society at affordable cost (product prices).

[8] Structural adjustment policies are economic policies which IMF and the World Bank require countries to follow so as to qualify for loans and/or help them repay debts owed to governments, World Bank and commercial banks (Danaher, 1994).

has a responsibility of ensuring integrity and efficiency of the financial system (Coetzer & Naicker, 2021).

The banking market in Africa is also opening to implementation of international standards. Triki et al. (2017) observes that majority of the countries in the region have implemented Basel 1 and few countries (Morocco, South Africa and Mauritius) have either implemented Basel II or III. The banking market in the region is largely dominated by commercial banks that range from foreign owned banks, domestically owned banks, and government owned banks. For instance Allen et al. (2011) observes that two large state owned banks dominate the banking market in Egypt. Besides commercial banks, MFIs play an important role in the African banking market, particularly in providing credit to low income households and micro and small enterprises (Mecagni et al., 2015b; Stijns & Revoltella, 2016).

Stijns and Pelletier (2018) note that MFIs lead in providing financial services in East and North Africa and lag in Southern Africa. In recent years, financial technology (FinTech) firms have unleashed a disruptive movement across the African financial industry by providing avenues to extend financial access (Alexander et al., 2017). Didenko (2017) observes that the new financial technologies which are often deployed through mobile network operators have greatly improved the levels financial inclusion in the region. [9] Additionally, FinTech innovations have increased competition in the African financial industry by providing alternative ways of delivering financial services.[10] According to Sy et al. (2019), the FinTech inventions have made the region to become a global leader in mobile money innovation, adoption and usage, with East Africa leading in adoption rates.[11]

However, there is a wide variation in banking industry development within the African region. South Africa and Mauritius have the most developed banking industries while weak and smaller countries like South Sudan and Burundi have banking industries that are shallow (Beck et al., 2011). Furthermore, banks in Africa suffer from high costs due to their inability to benefit from economies of scale. A significant share of the African population has a limited demand for banking services and operate in the informal sector. Nonetheless, over the past three decades, the banking industry in Africa has shown remarkable growth with improvement in

[9] For example, M-Pesa uses mobile phone technology to deliver financial services in Africa (Bateman et al., 2019).

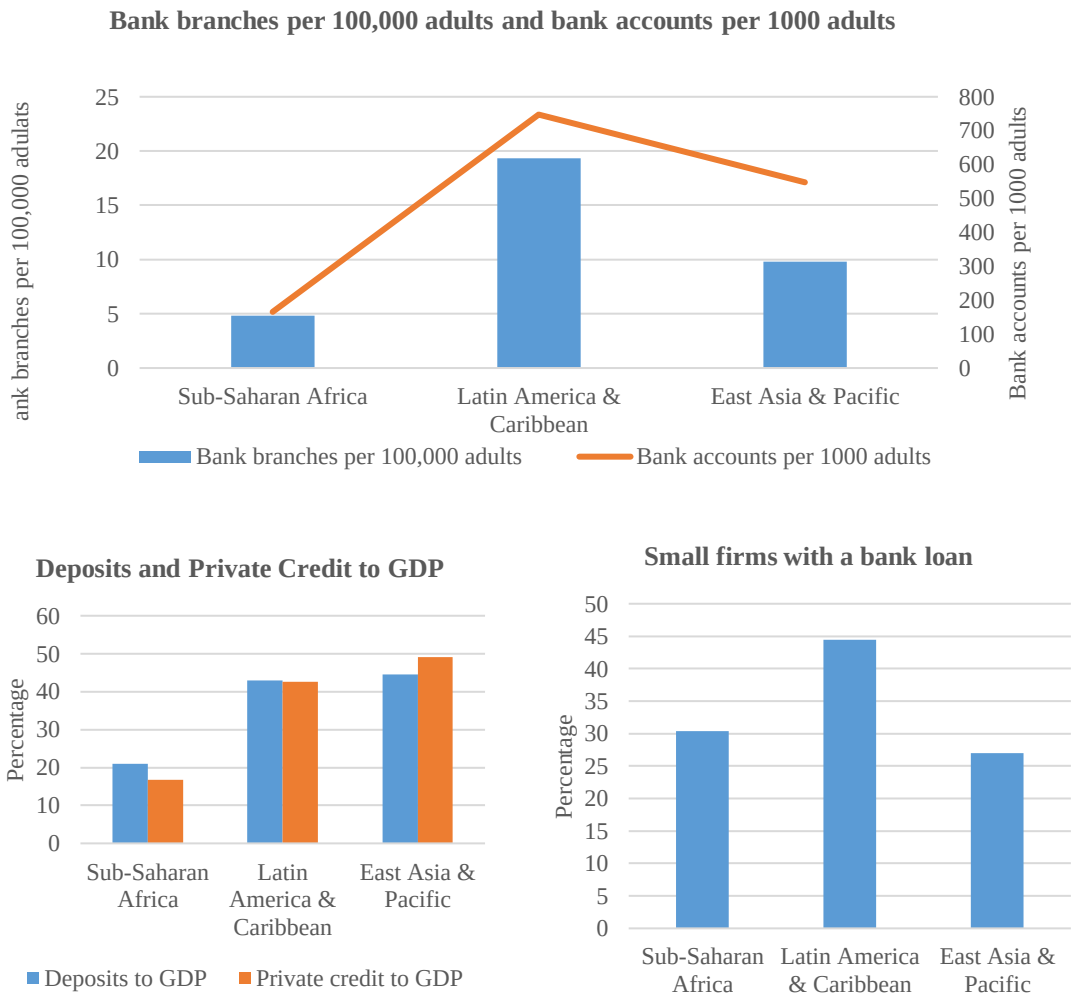
[10] While banks in South Africa are developing their own FinTech solutions, banks in the rest of Africa are in direct competition with FinTech solutions (Alexander et al., 2017).

[11] In sub-Saharan Africa, 12% of adults have a mobile money account as compared to 2% around the world (Demirgüç-Kunt et al., 2015b).

critical intermediation indicators like deposits to GDP, credit to GDP and Private credit to GDP (Beck & Cull, 2014).

Presently, most countries have deeper financial systems. For example, Makina (2017) note that 129 rural banks serve communities in Ghana. The outreach is due to the initiatives by the Bank of Ghana to broaden and deepen financial intermediation in the country sides. Nonetheless, most large banks invest in government securities in Africa, an investment practice that inhibits lending to the private sector, thus, leading to a dysfunctional banking intermediation process (Allen et al., 2011). Furthermore, Beck and Cull (2014) observe that the African banking industry has made considerable progress in the financial inclusion endeavour. Even so, it is less inclusive as compared to several other regions of the world.

Figure 1.1: International comparison of access to and use of banking services.



Source: Global Financial Development Database (2016)

Figure 1.1 above shows that both bank branches and the number of bank accounts in sub-Saharan Africa are lower compared to what they are in other developing regions around the world. Specifically, there are 4.8 branches per 100,000 adults, and for every 1000 adults, approximately 165.7 hold a bank account. Furthermore, the low deposits to GDP and Private credit to GDP indicate that African banks, on average have a lower depth. The number of small firms with a bank loan is higher in Africa (30.4%) than in East Asia and Pacific (27%) but is relatively lower in comparison with Latin America and the Caribbean (44.5%). The low number of small firms with a bank loan reflects the limited use of banks and limited extent of outreach by banks in Africa.

While the region has benefited from the increased presence of foreign banks in their industries, competition is still low with an approximate average Lerner index of 0.3. The low competition is related to the lack of scale in most African banking systems, which limits the number of banks that a country can support. Additionally, it is associated with the prevalent incidence of informality, which reduces the number of potential clients of the banking industry (Beck et al., 2009b). Within the sub-regions, South African banking environment is most competitive with a Lerner index of 0.2, followed by the West Africa with an estimated Lerner index of 0.29. North Africa has the lowest level of banking competition with a Lerner index of 0.37 (World Bank, 2020).

Amidu (2020) observes that pan-African banks are also playing an important role in promoting competition in the region. For example, Togo's Ecobank operates in 36 countries around Africa, while South Africa's Standard Bank has operations across 36 countries across Sub-Saharan Africa. Nigeria's United Bank for Africa has a presence in 20 African countries. Furthermore, Kenya's KCB and Equity banks have expanded their operations, with their branches spread across 7 East African countries. Other than promoting competition, the increased presence of foreign and pan-African banks in the continent is expected contribute to higher financial access and booster innovation in the banking industry (Nyantakyi & Sy, 2015).

Despite the increased presence of foreign and pan-African banks, African banking sectors are characterised by high concentration levels. For instance, the average bank concentration for the region over the 8-year period (2010-2017) was 75% with 5 bank concentration ratio of 85%. According to Fosu (2013), one reason for the high concentration is due to the recapitalisation programmes in several countries aimed at fostering financial stability that has led to increased consolidation. South Africa has the highest 5 bank concentration ratio of approximately 99%

while the banking industry in Ghana has the lowest level of concentration followed by Tanzania (39% and 45% respectively) (World Bank, 2020).

Besides the high concentration levels, banks in Africa have the highest ratio of non-performing loans (NPLs) with an average of 11.6 % in 2017. The high amount of NPLs can be attributed to lack of strong credit information systems that puts banks at a high risk on loans as they do not have sufficient information to assess the credit worthiness of potential borrowers (Beck et al., 2011; Dwumfour, 2017). Eyraud et al. (2021) observe that countries with highest NPLs in the region are largely clustered in central and western Africa with Ghana, Chad and Central Africa having the highest ratios. Southern African countries have the lowest amount of non-performing loans with South Africa and Namibia having NPLs ratio of 2.8% and 2.6%, respectively.

1.3 The Banking Industry and the Competition for the Financial Inclusion Project

Commercial banks have traditionally taken a limited role in serving low-income segments of society. Their position had been that providing financial services to the unbanked (i.e., the poor segment of the potential banking population) is risky and unprofitable. Indeed, policymakers and academics have for a long time claimed that provision of financial services to low-income earners and the poor requires subsidies (De la Torre et al., 2010). Consequently, donor agencies have characteristically provided grants to promote financial access to the poor through MFIs. Nonetheless, the challenges of high risk and unsustainability of profit in serving small businesses and poor households have reduced due to changes in regulation and advances in technology (Avery, 2016). These changes have led to the emergence of a competitive market in the provision of financial services to the poor.

Isem and Porteous (2005) and De la Torre et al. (2010) note that the market for low-income earners and poor households has emerged as a strategic market niche for most commercial banks, including foreign and large banks. The decline in margins due to competition from other capital market players has forced commercial banks to shift their focus towards low-income and unbanked segment – e.g., small business owners, poor households, people in remote areas and women.[12] Notably, banks' incentive to incur switching costs and serve low-income earners

[12] According to Bill and Melinda Gates Foundation (2012), women in particular, are to a large extent excluded from the mainstream financial system. Notably, only 37% of women in developing countries have an account in a formal financial institution as compared to 46% of men.

follows the increased competition in the retail sector and the evidence, by many MFIs, that SMEs and poor households represent profitable customer target groups.

Honohan and Beck (2007) affirm that commercial banks have grown beyond the notion that low-income earners and the poor are only corporate social responsibility and have realized that they present a potential attractive client base. These factors have forced commercial banks to become powerful actors in the provision of financial services to the unbanked. Banks see themselves at a comparative advantage in the contest to attract and reach the large number of people who are at present unable to access financial services. Most banks have extensive branch networks which can supplement current large distribution outlets such as agents and Automated Teller Machines (ATMs) (Harper & Arora, 2005; Helms, 2006).

Additionally, they have the financial capacity to make a substantial investment in technology like mobile and online banking platforms that can assist in reaching more people. These infrastructures can enable banks to increase personal contact, which is fundamental mainly for individuals with no previous experience of relating to formal financial institutions. Furthermore, banks can use sophisticated business models and risk management systems to gain from efficiency and manage both risks and costs (De la Torre et al., 2010). However, banks are not the only ones interested in providing financial services to the low-income market and pushing the financial inclusion agenda.

Over the last two decades the microfinance industry has experienced a remarkable growth in providing financial services to the poor (Assefa et al., 2013; Cull et al., 2014; Hermes & Hudon, 2018; Kar & Swain, 2018). For instance, the number of borrowers who borrow from MFIs in Africa increased from approximately 894 thousand in 2000 to more than 7 million in 2017. Over the same period, the total MFIs equity' increased from $111 million to $3 billion (MIX Market, 2018). According to Hudon and Traca (2011) and D'Espallier et al. (2013), the impressive growth of MFIs stems from the ongoing commercialization of the microfinance sector, increased support from governments and donor agencies and the diversification of MFIs funding sources.

The steady growth of MFIs has made them to be core in financial inclusion, particularly in Africa. This has in turn led to the emergence of a competitive low-income market, as banks and MFIs compete to provide financial services to households and SMEs (Assefa et al., 2013; Chikalipah, 2018). An important question that follows is how are commercial banks responding to this multi-prong increasing competition? Additionally, what are the effects of the responses

on the banks and the overall financial inclusion agenda? We argue that increased competition will enhance access to finance for households and SMEs, and most likely increase banking industry efficiency and risk taking.

1.4 Effect of Banking Industry Response to Competition for the Financial Inclusion Project

Theoretical debate exists in the literature on the effects of increased competition for small firms and households. Lloyd-Williams et al. (1994) argue that increased competition for low-income clients can force banks to reduce their costs and improve efficiency as well as increase the level of financial access. The efficiency hypothesis argues that firms that enjoy a high degree of effectiveness than their competitors can maximize profits by reducing prices and expanding their market share. However, increased focus on efficiency due to competition can push banks towards more riskier borrowers (Cetorelli, 2001). Northcott (2004) notes that as competition rise, the incentive to screen borrowers falls, leading to inefficient allocation of funds.

Furthermore, the need to increase cost efficiency may make banks to drop poor borrowers among a pool of borrowers or engage in more cautious and conservative lending (McIntosh et al., 2005; McIntosh & Wydick, 2005; Hermes et al., 2011). Still, empirical evidence suggests that bank portfolio risk can decline with an increase in competition (Chan et al., 1986; Agoraki et al., 2011; Soedarmono et al., 2013; Saif-Alyousfi et al., 2018). As stated earlier, increased competition for low-income earners can reduce the incentive of banks to screen borrowers. In turn, borrowers can be motivated to take up multiple loans in different financial institutions (McIntosh et al., 2005; McIntosh & Wydick, 2005).

Vogelgesang (2003) observes that multiple loans contracting both increases the levels of indebtedness among the portfolio of borrowers and decreases loan repayment rates. As a result of this likelihood of easy loan access, the performance and efficiency of banks may be affected, and borrowers may receive less favorable contract terms, which would further affect banks' balance sheet negatively, and thus, foster a vicious circle. A further theoretical issue is the question of the effect of competition in financial services industries on access to finance. Predominantly, empirical results (e.g., Beck et al., 2004; Cetorelli & Strahan, 2006; Cull et al., 2014; Leon, 2015; Love & Pería, 2015) show that banks can respond to competition by reducing financing obstacles.

However, Navajas et al. (2003), McIntosh et al. (2005) and Hossain et al. (2020) show that competition between MFIs may benefit wealthier borrowers and make poorer borrowers to

experience difficulties in accessing funds. Specifically, the information hypothesis, on explanation of financial intermediation, argues that banks may be unable to establish cost-effective lending relationships in the face of increasing competition, and as such may reduce finance access to low-income clients.

According to Rhyne and Christen (1999) and Assefa et al. (2013), a major theoretical issue of concern is whether increased competition for low-income clients may come at the expense of the banking industry abandoning social goals. On the one hand, reduction in market share associated with increased competition can force banks to innovate and expand their outreach to more unbanked clients in poor and remote areas (Schäfer et al., 2010; Cull & Spreng, 2011; Cull et al., 2014). Moreover, Isem and Porteous (2005) observe that banks may be forced to be more socially oriented in a competitive environment in order to enhance their reputation and attract formaly unbanked clients. In contrast to the foregoing, McIntosh and Wydick (2005) show that competition can reduce the ability of a profit-maximizing MFIs to earn rents and cross-subsidize loans to support poor borrowers.

Commercial banks are mainly motivated to compete and grow their profits, thus, serving poor customers may become less feasible. Indeed, Cull et al. (2009) argue that although commercial banks are necessary for promoting the financial inclusion agenda, they are not however best placed to reach and serve the poorest clients. Poor customers require additional socially oriented services (products), which non-MFI type financial institutions characterized by a strong profit motive may not provide. Nonetheless, we are not sure whether or not commercial banks consider in their decision a trade-off between social and financial goals.

1.5 Statement of the Problem

The financial inclusion paradigm has brought further to the fore the debate on the role of finance in poverty reduction. Within this context, a particular area of interest among researchers has been the effect of competition on access to finance. Theoretical literature provides contradictory predictions regarding the impact of competition on access to credit. The 'information hypothesis' argues that competition increases obstacles to financing. Banks that have market power are more willing to engage in relationship lending, which usually reduces information asymmetry and enhances the supply of funds to opaque firms, other factors assumed constant. However, competition encourages banks to reduce investment in relationship lending, and this increase obstacles to financing (Petersen & Rajan, 1995). The

market power hypothesis reject this view and instead suggest that competition increases firms' access to finance.

Bank competition and financial access have long been subjects of extensive research. In general, most studies (Beck et al., 2004; Love & Pería, 2015; Owen & Pereira, 2018; Hossain et al., 2020; Moyo & Sibindi, 2022) show that competition increases the level of financial access. For example, Love and Pería (2015) undertake a cross-country study to determine the effect of competition on firms' access to finance. They find evidence that low competition weakens firms' access to finance. Similarly, Beck and Demirguc-Kunt (2006) find that competitive banking structure alleviates SMEs' lack of access to finance. However, empirical literature has not paid much attention to the broader issue of competition between different financial intermediary industries and how it affects specific financial institutions as well as access to finance, especially for the poor.

A gap, therefore, exists in the literature on how the banking industry in particular is responding to the competition it is now facing due to intermediation activities attributable to financial inclusion projects for unbanked clients. Studies on financial institutions' response to competition are relatively scant. The existing papers predominantly focus on MFIs. For example, Vanroose and D'Espallier (2013) analyze the interaction between the level of development of the banking industry and performance of MFIs. They show that increased competition from the banking industry pushes MFIs down the lower segment of the consumers of financial products, making it less likely for them to abandon their mission of serving clients at the base of the pyramid.

Similarly, Cull et al. (2014) find evidence that MFIs react to increased competition from commercial banks by expanding their outreach to poorer areas. But, they do not find any significant changes in profitability in response to the increased competition. Baquero et al. (2012) observe that institutions respond differently to market conditions depending on whether they are profit oriented or not, and depending on the level of dispersion of borrower information. Banks mainly aim to maximize their profits; we are however unaware of how they are responding to this paradigm shift based competition, given that a natural response from activities associated with this paradigm-shift would require providing financial services to the unbanked poor, which had hitherto been considered by banks as an unattractive segment of banks' clientele.

Also, the study will consider the implications of the responses for both the banking industry and the financial inclusion agenda. Rhyne and Christen (1999) and Cull et al. (2011) note that the responses can benefit and, at the same time, create risks for both the banks and their clients. McIntosh et al. (2005) analyze the behavior of customers upon the increased entry of competing lenders in the microfinance industry in Uganda. Their results show that increased outreach does not lead to client drop-out but it induces borrowers to take up multiple loans and reduce loans repayments.

Navajas et al. (2003) use a model to investigate how changes in loan contracts due to increasing competition affect MFIs in Bolivia. Their results suggest that MFIs in Bolivia offered loan contracts that attracted lesser number of poor people as a result of increased competition. Nonetheless, it is not clear whether banks' response to competition affects loan repayment given that poor clients lack collateral or predictable cash flow. Also, we are unaware of whether banks are focusing on lowering their costs and increasing efficiency via higher productivity and scale economies or by reducing financial depth and breadth, which can affect their social objective.

This study pushes further and beyond MFIs by focusing on the ramifications of financial inclusion agenda on the banking industry in Africa. Africa provides a fertile ground for investigating how the banking sector is responding to the increasing competition prominence of financial inclusion development paradigm. First, the level of financial access in Africa is relatively low fundamentally, and banks are the primary source of external finance in Africa. Second, the financial industry in Africa is undergoing significant changes characterized by the entry of new financial service providers that focus mainly on the poor. Third, most countries in Africa lack or have weak information infrastructure to create and/or retrieve requisite credit information (Beck & Maimbo, 2012). McIntosh et al. (2005) tellingly observes that the degree of information sharing between lenders influence how banks respond to competition.

1.7 Research Questions

This study will specifically seek to answer the following questions:

i. How does banks' competition for financial inclusion affect MFIs activities/lending?
ii. To what extent does the response to competition for financial inclusion affect the efficiency of the banking industry in Africa?
iii. To what extent does the response to competition for financial inclusion change the asset portfolio risk of banks in Africa?

iv. What are the effects of banks' response on the degree of social performance (outreach) of the banking industry in Africa?

1.8 Significance and Findings of the Study

Policymakers and regulators around the world are focusing on building inclusive financial sectors by integrating the poor into the formal financial system. We expect that the results of this study will provide a better understanding of the effects of competition in the low-income market segment. Additionally, the results can assist in the design of competition policies which ensure that the poor benefits as much as possible. Furthermore, for regulators interested in the financial system stability, the current study provides evidence on the effect of competition for the unbanked on banks' portfolio of assets and risks.

The findings of this study are also valuable to the banking industry. Valenzuela (2002) observes that although commercial banks have the necessary infrastructure and plentiful resources, providing financial services to the unbanked poor in a competitive environment is difficult, if not unattractive. Additionally, Helms (2006) notes that for commercial banks to extensively support the financial inclusion agenda, they need to be fully persuaded that low-income earners and the poor represent a viable business opportunity. Thus, if competition for poor clients improves the performance of banks, then we expect that more banks will be convinced to increase their accessibility to the unbanked. This increase will see a rise in the number of commercial banks moving down the market ladder to reach more and more remotely located and poorer clients in Africa.

We also provide new evidence on the growing literature on the nexus between market structure matters and financial inclusion paradigm effects. As far as we know, this study is the first to focus on how banks are responding to the increasingly competitive market for unbanked clients. Although McIntosh et al. (2005), Cull et al. (2014) and Leon and Baraton (2021) conducted related studies on MFIs, this study undertakes a more comprehensive analyses focusing on the banking industry in Africa vis-à-vis MFIs related matters. Furthermore, the study is beneficial to scholars as it provides new literature and act as a basis for future research.

Our results indicate that banks in Africa are responding to the competition for financial inclusion by supplying more credit to households and SMEs, in support of the market power hypothesis. We also found that the increased lending by banks to households and SMEs, in response to the competition for financial inclusion, contributes positively and significantly to the banking industry's cost efficiency. However, our results confirm that greater lending to

households and SMEs due to competition leads to higher asset portfolio risk, although this effect is not statistically significant. Worryingly, we also found that competition for financial inclusion induces banks to target and offer larger loans to relatively wealthier clients in the low-income market. This may be a reflection of bank-oriented form of mission drift.

1.9 Organization of the Study

The rest of the study report unfolds as follows. In chapter two, we review the existing theoretical and empirical literature relating to banking industry response to competition and the potential effects of the responses on banks and the financial inclusion agenda. Next, we present the study's methodology, including the sources of data in Chapter three. Chapter four discusses the analyses of the data and documented results. Finally, Chapter five summarises the results, particularly in light of the objectives of the study and concludes with policy derivatives that would interest several stakeholders of the banking industry.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In this chapter, we discuss the theoretical and empirical foundation of this current work. We structure the chapter as follows: section 2.2 gives the conceptual definition of the major terms and concepts used in the study, while section 2.3 presents a discussion on microfinance and financial inclusion. Section 2.4 provides an overview of financial inclusion, and section 2.5 offers a discussion on competition for financial inclusion. Section 2.6 discusses the banking industry's known and potential responses to financial inclusion project, including the theories under competition, whereas section 2.7 explores how the banking industry response to competition affects their efficiency. Section 2.8 assesses the link between the banking industry response to financial inclusion paradigm and bank portfolio risk, while section 2.9 relates the banking industry response to competition and the social mission. Lastly, in section 2.10, we provide the concluding remarks (or take-away insights) on the thematic review of the literature.

2.2 Definition of Terms and Concepts

2.2.1 Financial Inclusion

There are various definitions of financial inclusion; for instance, Chummun and Ojah (2016) view financial inclusion as a mechanism for enhancing welfare, whereby welfare involves access to relevant and affordable financial services when needed for smoothing consumption or enabling production. Dev (2006) define financial inclusion as delivery of banking services at affordable cost to the large sections of disadvantaged and low-income groups. In this study, we define financial inclusion as access to finance to households and SMEs (i.e., the often under-financed and/or un-financed by traditionally formal financial services institutions).

2.2.2 Microfinance

According to Abdelkader and Mansouri (2018), the term microfinance refers to the provision of financial services to low-income households, the poor and microenterprises on a sustainable basis. The aim of microfinance is to provide financial access within the reach of the poor who have traditionally been viewed as unbankable by regular banks, often because of the high cost of reaching them, the perceived risks of loans and lack of adequate collateral. Microfinance activities are predominantly performed by MFIs although commercial banks have recently started providing microfinance services (Mia & Lee, 2017).

2.2.3 Competition

Competition refers to the attempt by two or more firms to secure the business of a client (Arora-Jonsson et al., 2021). In the banking market, competition encompasses efforts by banking institutions to attract and provide financial services (deposit and credit) to customers. In general, competition in the banking market is often cited as important in broadening outreach and access to finance, enhancing capital allocation and improving social welfare (Ayalew & Xianzhi, 2019; Rakshit & Bardhan, 2019).

2.2.4 Competition for Financial Inclusion

We define competition for financial inclusion as attempts by commercial banks and MFIs to compete and provide financial access to households and SMEs (i.e., the often under-financed and/or un-financed by traditionally formal financial services institutions).

2.3 Microfinance and Financial inclusion

Over the last three decades, the provision of financial services to low-income earners and poor households has been dominated by the microfinance policy. The microfinance agenda can be viewed as a response to credit market failure and vulnerability of formal lending contracts to information asymmetries (Cull & Morduch, 2017). Consequently, the microfinance policy was characterized by the introduction of innovative lending contracts, notably group lending and group liability programmes. According to Robinson (2001), the microfinance policy has largely been guided by two opposing lending approaches: the poverty lending approach and the financial systems approach.

The poverty lending approach focuses on reducing poverty by providing credit to the poor via MFIs, which are largely funded through donations and government subsidies. The goal of this approach is to reach the poorest of the poor with credit to help overcome poverty and achieve empowerment. However, Sangwan and Nayak (2019) observe that the major limitation with the poverty lending approach is that the institutions are usually unsustainable because the interest rates on loans are too low to cover the operating costs. This makes the approach to be unaffordable due to the continued need for subsidies. Additionally, the approach does not meet the demand for saving services by the poor (Hermes & Lensink, 2007a).

On the other hand, the financial systems approach promotes provision of commercial microfinance services (credit and savings) for the economically creditworthy active poor and use of charitable and subsidized non-financial methods of alleviating poverty for the extremely

poor (Robinson, 2001). The emphasis of the financial systems approach is on institutional self-sufficiency of MFIs. Consequently, it advocates for commercialization of MFIs to enable them cover the risks and costs involved in delivering financial services and maximize efficiency and productivity. Mehta and Bhattacharya (2017) note that large scale outreach may not be feasible if MFIs are not financially sustainable, particularly given the worldwide scale of the demand for microfinance.

However, Hermes and Lensink (2007a) observes that the financial system lending approach has been criticized because it goes against the aim of serving large groups of poor borrowers who may not afford higher interest rates. Studies (e.g., Donou-Adonsou & Sylwester, 2016; Agbola et al., 2017; Khan et al., 2017) show evidence that commercialized MFIs do not have a significant impact on poverty alleviation because they are associated with high-interest rates that are unaffordable by the poor. Furthermore, the focus on financial sustainability may go at a cost of lending to the poor (Mersland & Strøm, 2010; Hermes et al., 2011). Because lending money to the very poor is expensive, outreach and financial sustainability goal maybe conflicting.

Given the criticisms against the two models, there has been a shift over the last decade from the microfinance policy to the financial inclusion paradigm. The shift reflects an adjustment from the focus on building sustainable MFIs to serve poor people to the development and/or expansion of the formal financial sector (Johnson, 2013). According to Mader (2018), the expansion involves inviting formal financial institutions into the financial dealings with the poor while still counting on MFIs. Additionally, the financial inclusion paradigm entails a move from the poverty alleviation approach to the wider development policy on 'making markets work for the poor' approach.

Under this approach, the focus is on financial intermediation. Accordingly, the role of financial services is to enable low-income earners to reallocate expenditure across time[13] and to connect lenders and borrowers in order to drive economic growth, which would ultimately reach and benefit the poor (Mader, 2018; Keuschnigg & Kogler, 2020). Demirgüç-Kunt et al. (2008) note that the financial inclusion paradigm and its embodiment of 'making markets work for the poor' also advocate for reforms in the financial sector like encouraging competition so as to

[13] The main financial problem for low-income people is irregular income. Thus, financial intermediaries should be able to create a link between when the poor have money and when they need money (Rutherford, 2000).

promote broader access to financial services. The idea is that competition can expand financial intermediation and spur banks to seek profitable ways to serve low-income clients.

The widened financial inclusion agenda is supported by findings (e.g., Beck et al., 2007a; Sarma & Pais, 2011; Bruhn & Love, 2014) that for financial development to have a maximum impact on the growth of the poor, the focus should be widened from improving finance for the poor to improving financial access for all (Demirgüç-Kunt et al., 2008). According to Beck et al. (2009a), imperfections in the financial markets such as transaction costs and information asymmetries most often affect small businesses and poor households. Without an inclusive financial system, these parties are restricted by lack of collateral, connections, and credit histories, and they have to rely on their earnings or savings.

Financial inclusion has thus emerged as an important priority for regulators and policymakers interested in the financial sector development and in long-term and sustainable economic growth. It represents a multidimensional incentive aimed at ensuring that low-income households and SMEs, who have traditionally been excluded from the formal financial services sector, access appropriate financing services (Triki & Faye, 2013). Within the broader inclusive development context, financial inclusion is regarded as an important way to tackle inequality and poverty and to address the millennium development goals (MDGs). As a result, financial inclusion has been recognized as one of the pillars of the global development agenda, and it has become a fundamental part of many development institutions.

2.4 Financial Inclusion in Africa

In Africa, financial inclusion is a major policy concern for policymakers. A high population of people in most African countries are financially excluded, which reflects a lack of access to and use of formal financial services (Oji, 2015). The bulk of those who are financially excluded are in the households and SMEs sectors. Indeed, many small firms in the region cite access to finance as the major obstacle to their growth (Stein et al., 2013; Brixiová et al., 2020). The exclusion is mainly related to income issues and barriers associated with accessing formal financial institutions.[14] Nonetheless, Demirgüç-Kunt and Klapper (2013) and Inoue and Hamori (2016) observe that in recent years there has been a dramatic improvement in access to financial services in Africa.

[14] For example, opening a bank account in South Africa requires presentation of proof of residence, employment and address, and proof of income.

Financial services, particularly credit, is now being provided to small businesses and households. For instance, in 2014, only 33.1% of firms in Nigeria cited access to finance as a major constraint compared to 53.1% in 2007. Likewise, the percentage of firms financing their investments using bank credit in Malawi increased from 20.6% in 2007 to 30.3% in 2014 (World Bank, 2017a). Furthermore, the percentage of adults who borrowed from a formal financial institution in Kenya increased from 23% in 2011 to 27% in 2017 (Table 2.1). According to Beck and Cull (2014) and Chikalipah (2017), the increased access to credit in Africa can be attributed to financial sector deepening as a result of the increased emphasis on financial inclusion.

Table 2.1: Financial inclusion in selected African countries

Country	Indicator	2011	2014	2017
Egypt.	Saved at a financial institution	0.01	0.04	0.06
	Borrowed from a financial institution	0.04	0.06	0.06
Ghana	Saved at a financial institution	0.16	0.19	0.16
	Borrowed from a financial institution	0.06	0.08	0.10
Kenya	Saved at a financial institution	0.23	0.30	0.27
	Borrowed from a financial institution	0.10	0.15	0.17
Mauritius	Saved at a financial institution	0.31	0.36	0.24
	Borrowed from a financial institution	0.14	0.17	0.10
Nigeria	Saved at a financial institution	0.24	0.27	0.21
	Borrowed from a financial institution	0.02	0.05	0.04
Uganda	Saved at a financial institution	0.16	0.17	0.13
	Borrowed from a financial institution	0.09	0.16	0.14
South Africa	Saved at a financial institution	0.22	0.33	0.22
	Borrowed from a financial institution	0.09	0.12	0.09

Source: World Bank (2017b)

Additionally, new technologies like mobile money, relaxation of entry barriers and the creation of new delivery channels such as agency banking are also playing an important role in broadening access to financial services in the region (Demirgüç-Kunt et al., 2015a; Asuming et al., 2019).[15] According to Table 2.1, the level of financial inclusion in the African continent

[15] According to Demirguc-Kunt et al. (2018), Africa leads in mobile banking with more than 10% of the population owning a mobile money account.

varies substantially between countries. For example, while 22% of adults in South Africa saved money at a financial institution in 2017, only 6% of adults in Egypt did (Table 2.1). Zins and Weill (2016) note that the variation is mainly due to disparities in education and income levels between different countries in the region.

Furthermore, access to formal financial services remains a major constraint in Africa with the share of the adult population borrowing from a financial institution remaining low. For instance, only 4% and 10% of adults borrowed from a formal financial institution in Nigeria and Ghana, respectively (Table 2.1). Formal financial institutions are associated with costly lending procedures which contributes to low credit uptake in the continent (Deli et al., 2019). Additionally, Alhassan et al. (2019) and Moyo and Sibindi (2020) observe that the use of informal finance by many adults in the region contribute significantly to the low percentage of borrowers from formal financial institutions.[16].

2.5 Financial Inclusion and Competition

The broader financial inclusion paradigm is offering exciting opportunities for financial service providers in the market for low-income earners, which has not been fully explored. On one hand, Li et al. (2019) observe that the shift towards financial inclusion has triggered commercial banks to enter the low-income market. This follows the success of the microfinance concept and the increasing emphasis on policy changes so as to build more inclusive financial systems.[17] Beck and Demirgüç-Kunt (2008) observe that these policies have mainly concentrated on the deregulation of the financial system with the aim of broadening banking outreach (Beck et al., 2010).

On the other hand, Assefa et al. (2013) and Chikalipah (2019) observe that MFIs in Africa have recorded significant growth over the last two decades. The growth rates of MFIs in Africa are estimated to be between 15%-20%, which is only second to Asia (Mlachila et al., 2016). According to Kar and Swain (2018), the rapid growth of MFIs can be attributed to at least three new developments in the microfinance sector. First, the entry of more funding agencies in the microfinance sector has enabled MFIs to diversify their funding sources and expand their loan portfolios. According to Mader and Sabrow (2019), the financial inclusion paradigm

[16] Informal sector accounts for over 40 % of loans in Sub-Saharan Africa with only 5% of adults borrowing from formal financial institutions (Demirgüç-Kunt & Klapper, 2013; Ky et al., 2021).

[17] For instance, countries in East Africa are shifting to more coordinated policies in the provision of financial services. This has made it easy for providers of financial services to enter the markets and compete for clients (Bull, 2017).

necessitates MFIs to broaden their activities in order to meet the demand for credit by the poor. This has forced them to seek alternative sources of financing ranging from private equity investments, bank loans and capital markets.

Secondly, there has been an ongoing process to commercialize and transform the microfinance industry in an attempt to achieve financial sustainability and establish permanent sources of funding for MFIs (Ledgerwood & White, 2006). According to Taylor (2012), financial inclusion has also become the hallmark of the initiative to commercialize MFIs. Commercialization which involves a change in legal status from NGOs to shareholder-owned entities, has enabled MFIs to be sustainable and to intensify the scale of their operations. Weiss and Montgomery (2005) show evidence that commercialization can be linked to the strong financial performance and growth of MFIs.

Lastly, in recent years MFIs have received a substantial amount of support from governments and development organizations (Hudon & Traca, 2011; Al-Azzam, 2019). Under the financial inclusion paradigm, governments and development agencies are expected to actively promote the growth of MFIs by providing subsidies as well as financial and policy support (Mader, 2018). This has assisted MFIs in expanding their operations and serving more poor people. With the rapid growth of MFIs, the market for low-income earners has become increasingly competitive (Li et al., 2019). Accordingly, commercial banks are being forced to respond so as to attract and retain households and SMEs.

Figure 2.1: Trend in MFIs' gross loan portfolio, total assets and profits in Africa.

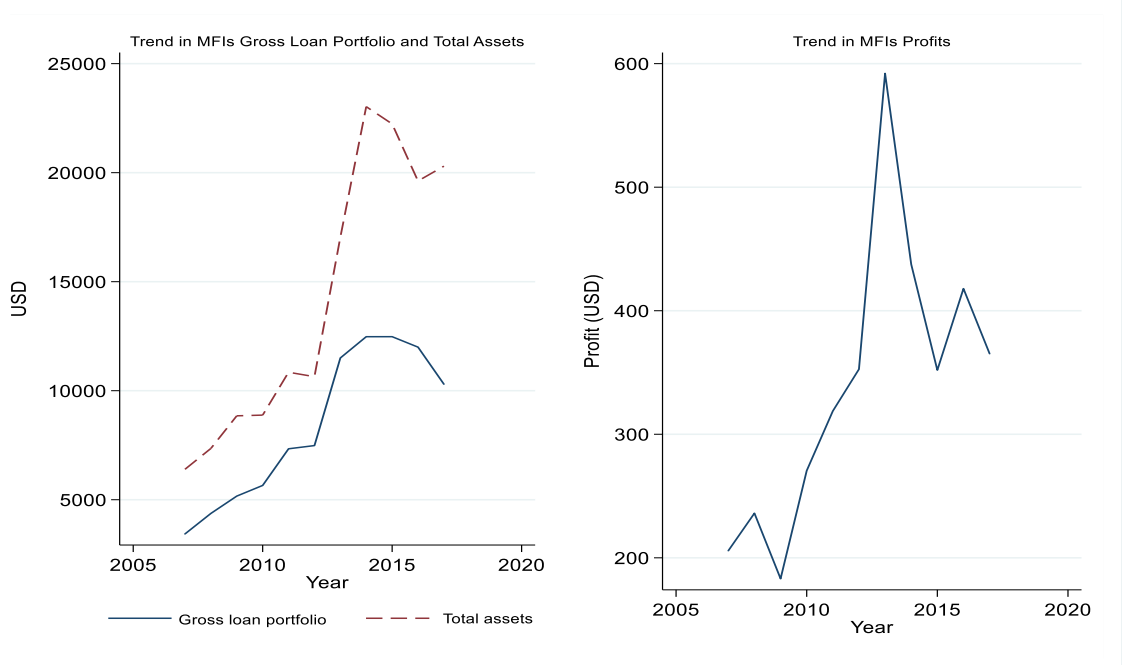


Figure 2.1 shows the growth in gross loans, total assets and profits of MFIs in Africa between 2007 and 2017. According to Figure 2.1, MFIs in Africa recorded significant growth between 2007 and 2014. As noted earlier, this growth may be attributed to the shift towards financial inclusion that enabled MFIs to access more funding and expand their outreach (Mlachila et al., 2016; Chikalipah, 2019). However, from 2014 there was a decline in MFIs growth, particularly the gross loans portfolio and profits. The decline in loans may be due to the uncertainty and volatility in the global economy in 2014 that could have affected MFIs financing and the ability of borrowers to borrow and repay their loans (PWC, 2016b).

The issue of competition for low-income clients is an important subject for policymakers. Soledad and Peria (2012) note that competition may make banks to engage in risky lending practices as they search for higher profits. Moreover, competition may erode the profit margins of banks and leave them with amounts that are insufficient to cushion them against various typical bank risks. Nonetheless, Beck and Demirgüç-Kunt (2008) argue that competition can improve financial access, specifically for small firms, as financial intermediaries seek to expand their client base. Moreover, competition is seen as the most effective way of reducing cost among providers of financial services, which can be essential in improving efficiency and expanding banking outreach.[18]

2.6 Banking Industry Response to Competition for Financial Inclusion

2.6.1 The Market Power Hypothesis

The market power hypothesis/the Structural-Conduct-Performance (SCP) attempts to analyse and explain the competitive conditions of an industry by investigating how the fundamental market structure of a sector is related to and affects the behaviour (conduct) and economic performance of firms (Bain, 1956; George, 2006). The market power theory assumes that there is a casual and stable relationship between the industry structure, conduct of firms and market performance. According to Church and Ware (2000), under the market power hypothesis, the industry structure is determined by the degree of competition between firms.

Furthermore, the market power theory argues that in the absence of entry barriers, higher growth may provide an indication of greater market power by incumbent firms in the industry. Such market power may arise due to the advantages that incumbent firms have over new entrants in the market (Shaik et al., 2012). In the low-income market, MFIs may have greater market power due to advantages in the form of borrowers' preference, particularly because

[18] For example, Helms (2006) finds that competition has dramatically reduced interest rates in Bolivia.

they may have historically transacted with the low-income earners. This may inhibit banks from making significant inroad into the low-income market.

Under the market power paradigm, an important aspect is the market conduct or behaviour of firms in response to changes in the industry structure. According to Bain (1968), market conduct represents the total actions of firms regarding prices and outputs, aimed at eliminating, weakening or discouraging competitors. Firms respond to competition by adopting behaviours that are aimed at changing the industry structure and, at the same time, enhancing their performance. Accordingly, we would expect banks to respond to the increase in MFIs market power by increasing their output in the form of credit.

Finally, market performance involves the strategic end results of the industry conduct of both buyers and sellers (Bain, 1968). An important aspect of market performance under the market power theory is the efficiency advantages that arise as firms respond to competition. Therefore, the performance of the banking industry due to competition for financial inclusion could be determined by the resultant efficiency improvement that may arise as a result of increasing credit to households and SMEs.

2.6.2 Asymmetric Information Hypothesis

The asymmetry of information hypothesis (Akerlof, 1970; Myers & Majluf, 1984; Diamond, 1991) tries to explain why economic outcomes may be inefficient where agents in a transaction possess differences in information. Mostly, in competitive markets that have no externalities, prices adjust so that there is an optimal allocation of resources. A fundamental assumption is that all parties in the market have equal information. However, if the assumption fails, asymmetry of information arises, and prices are distorted, and optimal resource allocation does not occur. Particularly, information asymmetries are pronounced in financial markets where financial institutions that offer credit face uncertainty about the creditworthiness of borrowers (Dell'Ariccia, 2001).

Typically, borrowers know their own moral rectitude, collateral, and industriousness better than lenders. The differences in information can thus invalidate the standard results of competitive industries. Nonetheless, the information asymmetry problem decreases with market share (Dell'Ariccia et al., 1999; Dell'Ariccia, 2001). Financial institutions with higher market power are able to erode the problem of information asymmetry by investing in lending relationships. Given that MFIs may have higher market power in the low-income market, they can be able to resolve the information asymmetry problem by building lending relationships.

Cull et al. (2014) observe that MFIs are able to develop deep relationships that enable small borrowers to convey information about their creditworthiness.

Such a relationship may allow MFIs to have information advantage and reduce the ability of commercial banks to attract low-income earners (Dell'Ariccia, 2001). According to Kano et al. (2011), the information hypothesis argues that in the presence of competition, firms may find it difficult to acquire information about borrowers. Additionally, due to the high cost of establishing lending relationships, firms may be discouraged from poaching clients from incumbent firms that have higher market power (Mudd, 2013). Thus, banks may respond to the increased competition from MFIs by reducing their investment in lending relationships, leading to a decrease in credit extended to households and SMEs.

2.6.3 Commercial Banking Competition for the Financial Inclusion and MFIs Lending

Literature provides contradicting predictions on banks response to competition for financial inclusion. Aysan et al. (2013) and Owen and Pereira (2018) argue that competition reduces financing constraints and ensures that credit is supplied to a greater proportion of the population. Banks may thus respond to the competition for financial inclusion by increasing the amount of loans to low-income earners in accordance with the market power hypothesis. This can occur via three channels. First, the increase in loans may be due to the need for banks to expand their outreach and capture a larger share of the low-income market (Love & Pería, 2015).

Secondly, Pham et al. (2019) observe that competition may push banks to lend to riskier borrowers. Since low-income earners are considered to be riskier, banks may respond to the competition for financial inclusion by granting them more credit. Álvarez and Bertin (2016) note that although granting more loans to opaque borrowers may reduce the portfolio quality of banks, it can increase the returns and the market share of banks in the low-income market. Lastly, Corvoisier and Gropp (2002) and Soedarmono and Tarazi (2016) show that banks operating in a competitive environment tend to upsurge their loans by setting lower loan prices to attract new clients. Therefore, banks can respond to the competition for financial inclusion by increasing the demand for their loans in the low-income market via price reduction.

However, Ayalew and Xianzhi (2019) observe that competition may have a negative impact on credit, particularly to low-income earners, in line with the information asymmetry hypothesis and the quiet life hypothesis. Because of information asymmetry, competition may weaken the market power of banks and reduce their incentive to build lending relationships

(Petersen & Rajan, 1995; McIntosh & Wydick, 2005; Gropp et al., 2014). This is because the marginal rents that banks derive from relationship lending decline with higher competition. Additionally, Marquez (2002) and Hauswald and Marquez (2006) show that in competitive markets, banks may relax their screening standards and reduce their investments in information acquisition technologies.

The reason for this is that information about borrower's creditworthiness becomes more dispersed in competitive markets, and this reduces banks screening ability. Banks may thus reduce the supply of credit to low-income earners in response to the increased competition from MFIs due to the reduction in their ability to screen households and SMEs. Furthermore, Horvath et al. (2016) note that competition increases the fragility of banks by reducing profits that act as a buffer against negative shocks. Accordingly, banks may react to the competition for financial inclusion by reducing the amount of loans granted to households and SMEs in order to reduce the risk of bank runs. Studies on competition and financial inclusion have mainly focused on two areas: The first wave of studies analyses the effect of competition for microfinance clients on MFIs.

For example, Leon and Baraton (2021) investigate whether the loan conditions provided by MFIs change with the entry of commercial banks. They use a dataset comprising a total of 32,374 loans granted by one of the largest MFIs in Madagascar between 2008 and 2014. Their findings show that borrowers located closer to a bank received larger loan sizes with fewer collateral requirements. Likewise, Vanroose and D'Espallier (2013) use a fixed-effects model to analyse the consequence of banking sector development on MFIs performance. They employ the MIX database to collect data comprising 1073 MFIs for the period 1997-2006. According to their findings, MFIs react to banking sector development by supplying smaller loans indicating increased outreach to poorer borrowers.

Lastly, Cull et al. (2014) examine the effect of bank presence on the performance of MFIs. They use the number of bank branches and the average loan size to measure bank presence and MFIs performance, respectively. They find that MFIs react to higher competition as indicated by greater bank penetration by issuing lower loan sizes as they expand their outreach to poorer markets. The second strand of studies focus on how competition between banks and competition between MFIs affect financial inclusion. For instance, Pham et al. (2019), uses cross-country data from 93 countries to investigate how competition in the banking industry

affects financial inclusion. They find evidence that higher competition encourages banks to relieve financing constraints for low-income earners.

Similarly, Marín and Schwabe (2019) analyse the relationship between bank competition and financial inclusion in Mexico. They use bank accounts penetration to measure financial inclusion. According to their findings, there is a positive relationship between banking competition and accounts penetration. Furthermore, Ayalew and Xianzhi (2019) investigate the effect of competition and access to finance. The population of their study comprise 9632 firms across 27 countries in Africa. Their findings show that competition increases financing constraints, particularly for SMEs. Kar and Swain (2018) assess the effects of competition on the performance of MFIs across 10 microfinance markets. They use the Boone indicator to measure competition and the average loan size to measure MFIs performance. They find evidence that competition between MFIs leads to a reduction in the amount of loans to the poor.

2.7 Commercial Banking Competition for Financial Inclusion and Bank Efficiency

2.7.1 The Concept of Efficiency

Efficiency is one of the many aspects of measuring the performance of a firm. It shows the ability of a firm to produce the most possible outputs using the least amount of resources. According to Kablan (2010), efficiency shows how production units get to their possibility frontier, which comprises a set of points that combine inputs optimally to produce a unit of output. Specifically, efficiency indicates the ratio between the quantity of output and input and the amount of output and input that defines the best possible frontier in an industry.

Coelli et al. (2005) state that in pursuing efficiency, a firm may either aim to maximize its output, minimize its cost or maximize its profits. Producers may, therefore, aim to produce given outputs at the most minimum cost, utilize given inputs to maximize revenue or to allocate inputs at the maximum amount of outputs so as to maximize the amount of economic profit. Mokhtar et al. (2008) note that the technique of combining production inputs so as to maximize profits is known as economic efficiency, and the main objective of producers is to achieve a high degree of economic efficiency

In the banking industry, the efficiency of a bank can be assessed on the basis of two criteria: allocative and technical efficiency (Farrell, 1957; Leibenstein, 1966; Berger & Mester, 1997). Allocative efficiency measures the success of a bank in choosing an optimal set of inputs given their respective prices. Mokhtar et al. (2008) point out that allocative efficiency relates to the

optimal combination of outputs and inputs at a given price. A bank is, therefore, regarded as allocative efficient if it assigns financial resources to projects with the highest expected value.

On the other hand, technical efficiency measures the ability of a bank to produce the maximum amount of output using a given input level or to produce a given amount of output using a minimum amount of inputs (Sharma et al., 2013). The ratio compares the relationship between outputs and inputs or the observed minimum potential input that is required to produce a given amount of output. According to Isik and Hassan (2002), technical efficiency has two elements: 'pure' technical efficiency and scale efficiency. 'Pure' technical efficiency relates to the ability of managers to utilize given firm resources. Drake and Hall (2003) note that pure technical inefficiency results due to the failure of a firm to extract the maximum output from its given input levels. Scale efficiency occurs because a firm can exploit economies of scale by operating at a point where the production frontier curve shows constant returns to scale (CRS) (Pasiouras, 2008).[19] Both allocative and technical inefficiencies represent a measure of a bank cost inefficiency (efficiency) because they arise on the inputs side.[20]

Berger et al. (2009) note that profit efficiency measure how close bank earnings are to the best practice bank that operates under the same conditions and produces similar outputs. The decomposition of efficiency into different components is necessary because it provides a better means of identifying the sources of inefficiency in the intermediation process (Berger et al., 1993; Isik & Hassan, 2002). For example, a bank can be inefficient if it produces non-optimal or too few outputs for a given amount of inputs and input prices. The output means that the bank may not only be cost-inefficient (input) but also profit (output) inefficient.

2.7.2 Measuring Bank Efficiency

Banks emerge to reduce market imperfections. Consequently, they must be efficient in order to allocate financial resources effectively. According to Casu and Molyneux (2003) and Hughes and Mester (2015), the ability of banks to reduce or eliminate information asymmetry between lenders and borrowers and the capability to manage risk is the essence of bank production. In contrast with other types of production, the uniqueness of bank production is

[19] CRS assumes that decision making units in an organization perform on an optimal scale of operations (Charnes et al., 1978). However, this is impractical; hence, firms ideally produce in variable returns to scale see (Banker et al., 1984).

[20] Farrell (1957) uses the term economic efficiency to refer to the combination of allocative and technical efficiencies. It relates to both cost and profit efficiency because it involves a production technique where producers aim to either allocate inputs and outputs to maximize profits or produce a given amount of output using minimum cost or utilize certain inputs to maximize revenues (revenue, cost or profit efficiency).

derived from the distinctive features of banks' capital structure where demand deposits and borrowed funds are used to fund opaque assets. Although the ability of banks to perform efficiently depends on the regulatory and the contracting environment, efficiency in the intermediation process is an integral part of bank output.

Hughes and Mester (2015) observe that there are two expansive approaches that are used to explain and measure performance in the banking industry: structural and non-structural. The non-structural approach relies on a multiplicity of financial ratios to capture the various aspects of efficiency. Chen (2009) observes that the non-structural approaches focus on explaining efficiency by using a number of financial measures, for instance, interest rate spreads and bank cost to income ratio. The ratios permit comparison among banks of different sizes and control for segment features, thereby allowing comparison between individual banks with some sector benchmark.

Table 2.1 below shows the ratio of bank cost to income and leading spread in selected countries in Africa. In general, banks in Mozambique and Sierra Leone are least efficient, with an average cost to income ratio of 66.2 % and 68.51%, respectively. However, the bank leading-deposit spread is highest in Uganda and Sierra Leone, with an average of 10.66 and 13.33, respectively. Mauritius and Egypt have the most efficient banking industries, with an average cost to income ratio of 48.43% and 45.79%, correspondingly. Furthermore, South Africa and Mauritius have the lowest leading-deposit spread, with spreads of 3.33 and 2.16, respectively.

Table 2.1: Bank cost to income ratio and bank lending-deposit spread in selected African countries

Country Name	Indicator Name	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
	Bank cost to income ratio (%)	39.37	47.83	38.62	52.91	44.84	43.56	38.54	35.21	29.27	30.39	40.05
Egypt	Bank lending-deposit spread	5.74	5.48	4.78	4.29	4.36	4.61	4.79	4.72	5.74	6.08	5.06
	Bank cost to income ratio (%)	57.69	81.37	71.92	69.66	61.81	64.20	62.41	59.20	49.18	50.95	62.84
Nigeria	Bank lending-deposit spread	3.27	6.03	11.06	10.33	8.39	8.78	7.21	7.70	9.37	8.00	8.01
	Bank cost to income ratio (%)	63.75	63.76	57.49	61.7	52.94	47.07	47.62	51.67	52.34	52.88	55.12
Ghana	Bank lending-deposit spread	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
	Bank cost to income ratio (%)	53.83	59.14	51.28	53.3	51.34	49.8	49.73	49.37	45.79	50.21	51.38
Kenya	Bank credit to bank deposits (%)	8.71	8.84	9.81	9.42	8.15	8.67	8.14	6.9	7.87	5.99	8.25
	Bank cost to income ratio (%)	67.72	42.18	38.5	39.13	37.85	54.41	53.72	45.59	42.65	42.55	46.43
Mauritius	Bank lending-deposit spread	1.43	0.8	0.53	1.81	2.43	1.69	1.72	2.41	3.35	5.45	2.16
	Bank cost to income ratio (%)	54.04	48.72	48.04	54.58	48.9	47.92	49.4	45.12	43.29	52.07	49.21
Morocco	Bank lending-deposit spread	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
	Bank cost to income ratio (%)	65.83	64.57	69.73	69.73	63.87	63.37	60.57	90.44	56.98	56.88	66.2
Mozambique	Bank lending-deposit spread	7.33	6.15	6.58	6.12	5.38	6.53	6.22	6.33	10.42	10.77	7.18
	Bank cost to income ratio (%)	58.03	59.22	60.53	58.47	55.21	54.45	54.61	49.55	50.53	53.07	55.37
Namibia	Bank lending-deposit spread	5.35	4.88	4.72	4.45	4.44	4.31	4.45	4.61	4.2	4.14	4.56
	Bank cost to income ratio (%)	80.16	77.59	68.15	69.11	68.13	68.36	63.94	60.01	75.82	53.87	68.51
Sierra Leone	Bank lending-deposit spread	13.91	12.44	11.78	10.69	10.61	11.65	12.81	14.24	17.6	17.58	13.33
	Bank cost to income ratio (%)	50.41	52.24	57.94	57.6	55.05	55.87	56.77	58.6	58.75	60.02	56.32
South Africa	Bank lending-deposit spread	3.51	3.17	3.37	3.33	3.31	3.35	3.32	3.26	3.29	3.13	3.3
	Bank cost to income ratio (%)	48.26	49.88	48.92	53.07	52.62	49.02	50.26	50.86	49.24	50.11	50.22
Tunisia	Bank lending-deposit spread	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
	Bank cost to income ratio (%)	59.35	57.48	61.72	53.37	49.75	56.13	57.27	62.1	57.87	56.35	57.14
Uganda	Bank lending-deposit spread	9.78	11.2	12.49	8.81	10.08	11.41	10.72	9.83	10.65	11.58	10.66

Source: World Bank (2017b)

However, the use of the non-structural based measure of bank efficiency has been criticized. Halkos and Salamouris (2004) note that the use of accounting data in computing ratios disregards the bank current market value and does not reflect properly economic value-maximizing behaviour. Besides, the ratios do not consider the output mix and input prices, given that the selection of financial ratios weights is subjective (Berger & Humphrey, 1992). In contrast, the structural approach relies on the concept of optimization and a theoretical banking model (Hughes & Mester, 2015). This approach views banks as financial intermediaries that produce financial services that are informationally intensive and diversify risk. The structural approach combines bank microeconomics of production with the theory of financial intermediation.

According to De Guevara and Maudos (2017), the structural approach relies on the economics of profit maximization and cost minimization. A bank is assumed to select a production strategy that minimizes costs given its prices of inputs and mix of output that maximizes profits given the prices of outputs and inputs. Outputs may include total loans, total securities, and off-balance sheet items, while inputs may include labor, capital, and deposits (Drake & Hall, 2003; Ahmad & Burki, 2016).Under the structural approach, the efficiency of a bank (cost and profit) can be assessed by parametric and non-parametric methods (Farrell, 1957; Leibenstein, 1966; Berger & Mester, 1997). Both approaches use a set of banks in an industry to estimate the cost or profit frontiers of fully efficient banks.

A bank located on the derived efficient frontier is referred to as the best-practice bank, and the efficiency of specific banks is assessed relative to the frontier. The parametric methods involve the specification of a functional form for the cost or profit frontier from which the efficiency scores are derived from either the dummy variables or the residuals (Silva et al., 2018). There are three main parametric frontier techniques: the stochastic frontier approach (SFA), the distribution-free approach (DFA) and the thick frontier approach (TFA). Delis et al. (2009) observe that SFA approach specifies a functional form, usually a translog form, for the cost or profit relationship among inputs, outputs and environmental factors and allows for random error.

The error term is assumed to consist of inefficiencies, which follow an asymmetric distribution (usually a half normal or truncated distribution), and random errors that follow asymmetric distribution (usually the standard normal distribution). DFA approach also specifies a functional form for the frontier. However, this approach does not make any assumptions

regarding the specific distributions of the random errors or inefficiencies. Instead, DFA assumes that the inefficiency of each firm is constant over time while random error tends to vanish over time (Semih & Philippatos, 2007).

Valverde et al. (2007) note that under the DFA approach, the inefficiency of a firm is determined as the difference between average residual and the average residual of a firm on the frontier, with the failure of the random error to average out to zero accounted for by performing some truncation. Lastly, TFA approach specifies a functional form that is used to estimate the highest and lowest cost quantiles. According Berger and Humphrey (1997), the assumption under this approach is that the error terms within the lowest and highest cost quantiles represent random error, while the differences between the lowest and highest cost quartiles represent inefficiency. An important drawback of the parametric approaches is that they require specification of a functional form which predetermines the shape of the frontier.

The estimated efficiency scores may be confounded with significant bias if the functional form is mis specified (Delis et al., 2009). The non-parametric approaches are based on mathematical estimation of a linear programming function that connects inputs and outputs, and they do not require specification of the functional form (Fall et al., 2018). Additionally, the non-parametric approaches do not require prior assumption in relation to the distribution of inefficiencies. Berger and Humphrey (1997), observe that there are two main non-parametric approaches: the Data Envelopment Analysis model (DEA) and the Free Disposal Hull (FDH) model. The DEA approach is a linear programming technique that uses multiple inputs and outputs to determine the efficiency of firms in the same sector.

It compares each firm with other firms which have the same inputs and outputs by enveloping the observed data points yielding a convex production possibilities set (Semih & Philippatos, 2007). Under the DEA approach, the efficiency frontier is defined as a linear set of the most efficient firms. The efficiency of a firm is then evaluated based on the distance from the efficient frontier with firms farther away from the efficient frontier regarded as less efficient (Nguyen & Pham, 2020a). According to the Delis et al. (2009), the FDA approach is a special case of the DEA approach and assumes free disposability of inputs and output, instead of the convexity. This approach generates larger efficiency estimates as compared to DEA because the FDH frontier is either interior or congruent to the DEA frontier. Berger and Humphrey (1997) observe that the main drawback of the non-parametric approaches is that they do not permit for random error and as such, noise may misposition the efficient frontier.

2.7.3 Competition for the Financial Inclusion and Efficiency in Banking

2.7.3.1 The Quiet Life Hypothesis

The quiet life hypothesis (QLH) (Hicks, 1935) postulates that firms with high market power exert less effort in pursuing efficiency but take advantage of their position in the industry to set prices above marginal cost and maximize their profits. Accordingly, the QLH focuses on the implications of market power on the efficiency of firms in an industry. Under this hypothesis, managers have fewer incentives to maximize efficiency if their firms have high market power.

According to Berger and Hannan (1998), inefficiency in banks with a high market power arises for several reasons. First, Managers lack the incentive to work hard if the banks can charge prices that are higher than competitive level price if there is no competition consequence. Accordingly, managers would enjoy a 'quiet life' because they do not need to work hard in order to maintain control over costs. Second, market power may provide an opportunity for managers to pursue other objectives other than maximizing the profit of a firm. Finally, in markets that are not competitive, managers allocate resources mainly towards obtaining and maintaining their market share.

Hicks (1935) argues that the risk preference of firms is influenced by their market power. Firms with market power tend to undertake little risk so as to enjoy the quiet life. Rhoades and Rutz (1982) state that firms with substantial market power can obtain a higher rate of return for the same amount of risk, or they can earn the same return at a lower degree of risk. Banks may therefore respond to the competition for financial inclusion by avoiding low-income borrowers and focusing on well-off clients due to their market power in the formal financial industry and as such, avoid escalating their business risk.

2.7.3.2 The Efficiency Structure Hypothesis

The efficiency structure (ES) theory suggests that market structure and performance is determined by the cost-efficiency effects of individual firms in an industry (Demsetz, 1973; Peltzman, 1977). In this paradigm, firm performance and market structure reflect differences in efficiency across firms. Berger and Mester (1997) note that under the ES theory, the assumption is that firms' gain high market share because of being efficient as compared to their competitors. Thus, the ES theory proposes that banks can increase their market share in the low-income market by gaining differential efficiency advantages in expanding their output (loans) while responding to competition from MFIs.

According to Al-Muharrami and Matthews (2009), the ES hypothesis is proposed to exist in two forms, depending on the type of efficiency under consideration. The scale efficiency form assumes that banks have equal technology and management capability. However, some banks operate under lower unit costs and higher profitability because they produce at more efficient scales, that is, closer to the minimum average cost as compared to other firms. In contrast, the cost efficiency form postulates that firms which possess superior management capability are able to control costs and move closer to the best practice frontier (Berger, 1995). Generally, the efficient frontier is assumed to be that of the least cost or best practice firm in the industry that produces similar outputs and operates in the same environment.

2.7.3.3 Empirical Literature

The existing theoretical literature provides conflicting predictions on the effect of bank response to competition on efficiency. As discussed earlier, the efficient structure hypothesis suggests that competition leads to an increase in the efficiency of firms. The efficiency improvement can be explained based on how banks respond to competition. Zarutskie (2013) argues that increased competition can prompt banks to focus on specific market niches or on enhancing their loan growth. For instance, banks may respond to competition by focusing on well-off borrowers based on the ownership of soft information. This can enable banks to lower their credit risk and improve their efficiency (Hauswald & Marquez, 2006).

However, bank ownership of soft information can allow them to enjoy monopoly rents, generating inefficiency in accordance with the Quiet life hypothesis (Andrieş & Căpraru, 2014). The efficiency of banks may decline under competitive conditions due to the short-term and unstable relationship between banks and clients (Tan & Anchor, 2017). Competition increases the tendency of clients to switch to other financial services providers. Accordingly, this phenomenon increases the asymmetries of information, and banks incur additional expenses in monitoring and screening borrowers. In a competitive banking environment, the decline in the ability of banks to build customer relationships limits the value and reusability of information, leading to an increase in bank costs and a decrease in efficiency (Chan et al., 1986).

The financial inclusion paradigm has created a competitive environment that can provide banks with incentives to reduce their costs and maintain their profitability. Assefa et al. (2013) note that typically banks may respond to competition for financial inclusion by focusing on growing their loans in the low-income market. This can enable them to attract a large mass of the low-

income clients leading to more efficient intermediation process and lower costs due to potential economies of scale. However, Banyen and Biekpe (2020) observe that the need for banks to seek for clients from previously unserved market increases credit risk and both the cost of gathering information and monitoring borrowers. Consequently, competition for financial inclusion may hamper the cost efficiency of banks due to the additional monitoring costs and increased probability of having low-quality borrowers.

Competition for financial inclusion may also encourage bank managers to concentrate on improving their cost efficiency by way of reducing the supply of loans to opaque borrowers (low-income earners) (Dick & Lehnert, 2010). The cost-efficiency improvement results due to the rise in banks credit quality, leading to lower monitoring costs and default rates. Nonetheless, by focusing on less opaque clients, banks may fail to benefit from the possible scale economies associated with providing credit to the large market of low-income earners in Africa.

Studies on competition and bank efficiency have mainly centred on the relationship between the levels of banking competition and efficiency. Using data over the period 2003-2013 from the Chinese banking industry, Tan and Anchor (2017) examine the impact of competition and risk on efficiency. They use the Lerner index to measure competition and the Data Envelopment Analyses approach (DEA) to measure efficiency. They show evidence of a negative relationship between competition and the efficiency of banks. Apergis and Polemis (2016) use granger causality methodology to assess the relationship between banking sector competition and efficiency in the Middle East and North Africa (MENA) from 1997-2011. They use H-statistic, a non-structural measure of the level of competition and DEA with Bootstrap to generate efficiency scores. They find evidence that an increase in competition reduces the level of banking efficiency in MENA countries.

Hermes et al. (2011) use Stochastic Frontier Analyses (SFA) to assess whether MFIs trade-off between outreach to the poor and efficiency. They use a sample of 435 MFIs around the world to determine the relationship between MFIs outreach and efficiency. They find evidence that MFIs with more extensive outreach, measured by both low average loans and a higher number of women borrowers, are less efficient. Sarmiento and Galán (2017) use a Stochastic Frontier Model (SFM) to examine the influence of risk-taking on the efficiency of banks in Colombia. Particularly, they assess the effect of credit risk, market risk exposures, and capitalization as

well as liquidity risk on bank efficiency. Their results indicate that exposure to higher levels of credit and market risk increases the efficiency of large foreign banks.

Banyen and Biekpe (2020) examine the nexus between competition and efficiency of banks in five regional economic communities in Africa. They use data comprising 405 banks from 47 countries in Africa over the 2007 to 2014 period. They use the SFA approach to measure efficiency and the Lerner index to measure banks market power. Their findings show that competition improves the efficiency of banks in Africa. Finally, Sarpong-Kumankoma et al. (2017) study the effect of banking freedom and competition on efficiency using data from 11 sub-Saharan countries in Africa. They estimate efficiency using SFA approach and competition using the Lerner index. According to their results, lower bank competition leads to higher cost-efficiency.

2.8 Commercial Banking Competition for Financial Inclusion and Bank Asset Quality

2.8.1 Banking Asset Portfolio Risk

An important issue for regulatory authorities interested in the stability of the financial system is the management of bank asset portfolio. According to Ghosh (2015), the recent global financial crisis that was characterized by a surge in non-performing loans (NPLs) in different regions around the world can be attributed to poor asset portfolio risk management. Accordingly, a central component of asset portfolio risk is credit risk. Connor et al. (2010) state that credit risk arises because of uncertainty regarding whether a counterparty in a financial transaction will honour its obligation. Consequently, the ex-post credit risk takes the form of NPLs (Louzis et al., 2012). An increase in the share of NPLs in the asset portfolio of banks shows greater risk that can affect both bank profitability and liquidity and symbolises a weakening bank balance sheet. The deterioration of the bank asset quality due to a rise in NPLs can destabilize the banking industry and impair its economic and social activities.

Table 2.2: Banking industry NPLs and Z-Scores in selected African countries

Country	Indicator Name	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
	NPLs to gross loans (%)	14.8	13.4	13.6	10.9	9.8	9.3	8.5	7.2	n/a	n/a	10.94
Egypt	Bank Z-score	13.57	14.75	14.74	14.39	16.44	17.46	18.94	18.67	19.08	20.84	16.89
	NPLs to gross loans (%)	6.30	37.30	20.14	5.77	3.71	3.39	2.96	4.86	12.82	n/a	10.81
Nigeria	Bank Z-score	16.49	19.84	20.07	12.78	15.83	14.84	14.96	15.29	15.53	16.24	16.19
	NPLs to gross loans (%)	7.7	16.2	17.6	14.15	13.2	12	11.27	14.67	17.29	21.59	14.57
Ghana	Bank Z-score	5.26	6.03	6.7	6.55	7.43	8.05	7.54	7.13	7.72	8.98	7.14
	NPLs to gross loans (%)	8.8	8	6.29	4.43	4.59	5.05	5.46	5.99	8.69	10.08	6.74
Kenya	Bank Z-score	12.99	13.88	16.3	14.33	15.54	16.12	15.18	19.23	21.54	18.36	16.35
	NPLs to gross loans (%)	2	3.3	2.76	2.81	3.64	4.15	4.92	7.2	7.76	7.03	4.56
Mauritius	Bank Z-score	16.3	13.73	16.89	17.06	16.83	16.56	11.39	12.17	15.27	15.92	15.21
	NPLs to gross loans (%)	6	5.5	4.8	4.8	5	5.9	6.9	n/a	n/a	n/a	5.56
Morocco	Bank Z-score	38.52	41.21	44.54	41.57	44.95	45.4	47.73	46.78	44.36	44	43.91
	NPLs to gross loans (%)	1.9	1.8	1.93	2.62	3.2	2.3	3.2	4.3	n/a	n/a	2.66
Mozambique	Bank Z-score	3.09	2.97	3.09	3.56	4.07	3.79	3.96	3.89	4.42	6.08	3.89
	NPLs to gross loans (%)	3.1	2.7	1.96	1.49	1.34	1.29	1.45	1.55	1.54	2.59	1.9
Namibia	Bank Z-score	9.39	8.88	8.88	9.4	8.86	7.58	8.1	8.64	8.69	8.79	8.72
	NPLs to gross loans (%)	17.9	10.6	15.61	15.08	14.74	22.42	33.44	31.73	n/a	n/a	20.19
Sierra Leone	Bank Z-score	5.06	4.36	4.63	4.39	4.79	4.59	4.74	4.83	4.16	4.95	4.65
	NPLs to gross loans (%)	3.9	5.9	5.79	4.68	4.04	3.64	3.24	3.12	2.86	2.84	4
South Africa	Bank Z-score	11.36	12.27	13.02	13.63	14.74	13.99	13.81	13.93	14.91	16.68	13.83
	NPLs to gross loans (%)	n/a	13.2	13	11.3	12.8	14.5	13.8	14.5	n/a	n/a	13.3
Tunisia	Bank Z-score	18.47	18.91	18.44	17.27	15.47	15.72	24.02	32.25	33.2	38.47	23.22
	NPLs to gross loans (%)	2.2	4.2	1.86	2.03	4.06	5.76	4.01	5.13	10.4	5.51	4.52
Uganda	Bank Z-score	9.85	10.85	9.27	10.77	11.68	10.74	10.91	12.61	14.15	14.95	11.58

Source: World Bank (2017b).

Table 2.2 above shows the percentage of banks NPLs and Z-scores in selected countries in Africa. Generally, most countries have low levels of NPLs except Sierra Leone, which had 31.73% of NPLs in 2015. Countries in the south of Africa have the lowest average percentage of NPLs, with Namibia, South Africa and Mozambique reporting 1.9%, 4% and 2.66% of NPLs, respectively. Furthermore, Countries in the north of Africa have the most stable banking industries, with Morocco, Tunisia and Egypt having the highest average Z-scores of 43.91, 23.22 and 16.89, correspondingly. This indicates that North African banks have the lowest probability of default. Nonetheless, Mozambique, Sierra Leone, and Ghana have the lowest Z-scores (3.89, 4.65 & 7.14, respectively), reflecting a higher likelihood of default.

2.8.2 Competition and Bank Asset Portfolio Risk

The literature on competition and banking industry stability provides contrasting predictions on the effect of competition for financial inclusion on banks asset portfolio risk. On one side, the competition-stability hypothesis suggests that competition can lead to greater stability in the banking industry (Azmi et al., 2019; Phan et al., 2019). One reason for this is that increased lending to SMEs and households in response to competition for financial inclusion leads to more diversification of assets which can reduce banks overall asset portfolio risk. Additionally, competition for financial inclusion may force banks to lower their loan rates in order to increase their competitiveness and expand the pool of borrowers in the low-income market.

The lower loan rates may make borrowers to invest in less risky assets resulting in lower default rates (Saif-Alyousfi et al., 2018). Nonetheless, because of information asymmetry, competition for financial inclusion may make banks to act prudently and reduce the supply of loans to SMEs and households. Although this may hinder financial access to low-income earners, it can lead to improved stability in the banking industry. On the other side, the competition-fragility hypothesis proposes that competition in the banking industry leads to higher risk-taking that is harmful to the stability of the financial system (Tabak et al., 2012; Dwumfour, 2017). The idea is that competition can force banks to seek risky lending practices so as to remain profitable and/or maintain their market share.

Bashir et al. (2017) observe that when banks compete intensely for borrowers, they reduce their screening standards, loan restrictions, and collateral requirements. Although the reduction in collateral requirements can be desirable for financial inclusion, Dell'Ariccia et al. (1999) find evidence that the resulting lending activity attracts risky borrowers exposing banks to increased risk of non-performing loans. According to Assefa et al. (2013), the resultant increase in loan

supply as banks compete for low-income earners may encourage impatient borrowers to engage in double-dipping, which may lead to the risk of over-indebtedness and low rates of repayment.

McIntosh and Wydick (2005) show evidence that the effect of competition on bank asset portfolio risk originates from the probability of increasing information asymmetry between lenders. Information sharing between competing lenders can become difficult, with many lenders in the loan market. Consequently, impatient borrowers can be motivated to take multiple loans, increasing their average levels of debt and reducing the expected rate of repayment. Studies on competition and portfolio risk have majorly focused on the relationship between banking market competition and risk-taking.

For instance, Agostino et al. (2010) employ a large data panel consisting of SMEs in Italy to assess the link between the degree of competition and the amount of bank debt that a firm receives and the probability that it may default. They find evidence that in competitive credit market structures, bank financing is lower for SMEs that are perceived to be riskier, and the amount of bank debt reduces with increase in competition. They conclude that competitive pressures may force banks to undertake more accurate screening of borrowers leading to increased efficiency by banks in credit allocation and reduction in non-performing loans.

Bashir et al. (2017) employ a two-step system GMM dynamic panel model to explore the effect of banking competition on nonperforming loans (NPLs) in the Chinese banking sector. According to their results, a high degree of competition as measured using the Lerner index increases the amount of NPLs. González et al. (2017) assess the effect of competition and concentration on risk-taking behaviour of banks in the Middle East and North African (MENA) countries from 2005-2012. Using the Z-score to measure risk-taking behaviour and Panzar-Rosse H-statistic to determine the degree of competition, they show that in countries where the level of competition is high, the probability of default increases.

Brei et al. (2020) investigate the impact of bank competition on credit risk in sub-Saharan Africa. They use the Lerner index and NPLs ratio to measure competition and credit risk, respectively. They provide evidence of a U-shaped relationship between banking competition and credit risk. Lastly, Akande et al. (2018) study the relationship between competition and risk-taking altitude of 440 banks in 37 sub-Saharan countries in Africa. They employ the GMM estimation method and both the Lerner index and the ratio of loan loss provisions to gross loans to measure competition and banks risk taking altitude, correspondingly. They find evidence of a positive relationship between competition and banks risk-taking.

Few studies have examined the effect of competition between MFIs and portfolio quality. For example, Kar and Swain (2018) investigate how competition affects the performance and portfolio quality of MFIs using data comprising 568 MFIs for the period 2003-2014. They measure portfolio quality using portfolio-at-risk past 30 days and HHI to measure competition. Their results show that competition worsens MFIs outreach to the poor but leads to better portfolio quality. Similarly, Hossain et al. (2020) analyse the effects of competition on social performance and stability of MFIs operating in 59 countries. They provide evidence that competition reduces MFIs stability and outreach.

A small number of studies have also investigated the effect of financial inclusion on banking industry stability. Dwumfour (2017) analyse the determinants of banking stability in sub-Saharan Africa using data from 32 countries in sub-Saharan Africa for the period 2000-2014. Using the system GMM and the Z-score to measure banking stability, the author finds evidence of a positive but weak relationship between financial access and banking stability. Furthermore, Saha and Dutta (2020) assess the relationship between financial inclusion, competition and financial stability. They use the Boone indicator and the Z-score to measure competition and banking stability using data comprising 92 countries. Their results show that higher levels of financial inclusion and competition contribute to banking industry instability.

2.9 Commercial Banking Competition for Financial Inclusion and Bank Social Performance

2.9.1 Banks Social Performance

The financial inclusion paradigm is mainly anchored in the view that providing access to financial services can assist in improving the lives of particularly low-income clients. Accordingly, social performance is a critical element of banks mission. According to Simanowitz (2003) and Hermes and Hudon (2018), social performance encompasses the impacts of a financial institution on the social and economic welfare of low-income earners, including poverty elevation. Banks can thus have a positive impact on the overall incidence of poverty if they can reach out and lend to SMEs and households. Besides, social performance can assist banks in improving their bottom line capability by providing them with an opportunity to understand how to improve client retention in the low-income market and increase returns (Hashemi, 2007).

The importance of social performance analyses follows the argument on the need for banks to balance financial performance with ‘other bottom lines’ relevant for their clients. Nonetheless,

there is a concern in literature that financial institutions may respond to increased competition for low-income clients by focusing on affluent clients (Mersland & Strøm, 2014). Indeed, Assefa et al. (2013) note that competitive pressure may come at the expense of social goals as banks abandon social objectives in order to remain financially sustainable and profitable. However, with the increasing competition for low-income clients, a path that is equally likely is for the banking industry to drift to clients with lower levels of income where they can be able to gain a greater competitive advantage.

2.9.2 The Aspect of Social Performance

An important aspect of social performance relates to whether financial institutions reach the groups that they actually intend to reach (Schreiner, 2002; Helms, 2006). As a result, outreach is a fundamental concept that is used to gauge the social objectives of a bank. Bibi et al. (2018) note that outreach is a multi-dimensional concept with a six-fold orientation. These dimensions include: worth of users outreach, depth, cost to users, breadth, scope, and length. According to Navajas et al. (2000), worth to users outreach shows the degree by which users are willing to pay for a loan. Generally, the worth is contingent on the borrower opportunities, constraints and tastes, and the loan contract.

As a result, the worth of a loan contract increases as the contract terms march the demands of a borrower. The depth of outreach reflects the profile or type of clients served by a bank (Hermes & Hudon, 2018). Usually, deeper outreach increases both social cost and social value. According to Copestake (2007), providing financial services to poorer areas does not always translate to lower profits since there may be less competition in such areas. Besides, a bank may achieve a higher depth of outreach by moving to areas with poorer clients. However, this can weaken the competitiveness of a bank by reducing prospects of growth and cross-subsidization (McIntosh & Wydick, 2005).

Furthermore, it costs more to judge the riskiness of a borrower with a decrease in wealth and income. Conning (1999) notes that the increase in cost associated with judging the riskiness of a borrower occurs because the poor, as compared to the rich, are more dissimilar and less able to hint their willingness and ability to repay loans. Nonetheless, when lenders identify better ways to assess borrower's risk, only social value can increase with deeper outreach. Such improvement can increase access to finance and social performance since the acquisition of loans would largely depend on the borrower creditworthiness rather than the ability of the lender to judge borrower's risk (Navajas et al., 2000).

Cost of outreach relates to a borrower's loan cost (Navajas et al., 2000; Schreiner, 2002). The cost to users encompasses a sum of both transaction costs and loan price. Progress in financial access and social performance arises from the reduction in the cost of supplying credit which can increase the willingness and ability of borrowers to acquire loans (De Blas & Russ, 2013). Accordingly, the demand for financial services would rely more on demand and less on the supply limitations. According to Bibi et al. (2018), the scale or breadth of outreach reflects the number of clients that a bank is serving. Mostly, it includes people who were not previously served by the bank because they could not meet the necessary requirements.

Breadth is important because the financial needs of the poor exceed their ability to acquire loans. Schreiner (2002) observes that the profit motive of commercial banks can encourage them to increase their breadth and reach many poor people as compared to non-profit institutions that are poverty-oriented. The scope of outreach shows the types and the number of loans and financial contracts that a bank supplies (Navajas et al., 2000). Banks with a good scope should offer small loans and accept small deposits. Finally, length of outreach relates to the time period for which a bank provides loans.

Schreiner (2002) states that length is critical because society is concerned about the present and future welfare of the poor. MFIs with financial support can achieve a meaningful length of outreach without being concerned with sustainability (Morduch, 2000). However, banks' incentives to achieve sustainability can force them to strengthen their structures so as to maximize their social value and achieve longer outreach. Nonetheless, Hermes and Hudon (2018) observe that literature on social performance mainly focuses on depth and breadth of outreach dimension.

According to Sharma (2016) and Hermes and Hudon (2018), there are two widely used indicators of the depth of outreach; the average loan size per borrower and geographic outreach of banks. The average loan size is a proxy of the average income level of clients borrowing from a bank. The idea is that households and SMEs are expected to take out smaller loans due to their low incomes. Besides, banks may be unwilling to grant larger loan sizes to low-income earners due to the possible risk of non-payment and lack of collateral. Consequently, lower average loan size could indicate that banks are serving more households and SMEs (D'Espallier et al., 2017).

Geographic outreach characterizes the penetration of the banking sector. Accordingly, higher geographic penetration of ATMs and bank branches would indicate higher probabilities of

accessing banking services by households and SMEs (Beck et al., 2007b). On the other hand, Churchill (2019) notes that the commonly used proxy for the breadth of outreach is the average number of borrowers served. Banks' lending to a larger number of households and SMEs are expected to promote more financial inclusion. However, D'Espallier et al. (2017) observe that the proxies for both depth and breadth of outreach have been criticized as they present indirect and rough indicators of social performance.

For instance, larger loan sizes may indicate that banks are focusing on well-off clients. Yet, the larger loan sizes may be due to accumulation of loan arrears and the need by banks to cross-subsidize lower loan rates charged to poor borrowers with higher rates charged to wealthier borrowers (Copestake, 2007; Armendáriz & Szafarz, 2011). Additionally, the average loan size may be skewed due to a small number of relatively large loans. Nonetheless, Hermes and Hudon (2018) observe that due to data limitations and lack of extensive data on households and SMEs, the average loan size and the number of borrowers are the commonly used measures of social performance in the microfinance literature. However, they are not the ideal proxies of outreach.

Table 2.3 below shows the number of ATMs and Bank branches per 100,000 adults in selected African countries. South Africa, Namibia, and Mauritius have the highest number of ATMs per 100,000 adults, with an average of 60, 52 and 43, respectively, reflecting higher outreach and social performance. In contrast, Sierra Leone and Uganda have the lowest number of ATMs, with an average of 0.40 and 3.97 ATMs per 100,000 adults, respectively. Furthermore, Mauritius has the largest number of bank branches, with an average of 22 bank branches per 100,000 adults. Uganda and Sierra Leone have the lowest bank outreach, with an average of 2.64 and 2.76 bank branches per 100,000 adults, correspondingly.

Table 2.3: ATMs and bank branches per 100,000 adults in selected African countries

Country Name	Outreach Indicators	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
	ATMs per 100,000 adults	6.46	7.68	8.63	9.22	10.34	10.99	12.14	13.78	15.69	17.71	11.26
Egypt	Bank branches per 100,000 adults	4.45	4.57	4.6	4.62	4.58	4.58	4.59	4.65	4.74	4.88	4.63
	ATMs per 100,000 adults	6.27	6.48	6.56	6.41	5.82	5.90	5.61	4.98	4.74	4.44	5.72
Nigeria	Bank branches per 100,000 adults	8.64	11.46	11.22	11.94	11.49	13.31	16.18	16.21	16.73	16.32	13.35
	ATMs per 100,000 adults	3.84	3.88	3.93	4.06	5.46	8.11	8.18	10.26	10.92	11.29	6.99
Ghana	Bank branches per 100,000 adults	4.77	5.09	5.36	5.38	5.68	5.85	5.94	6.98	6.98	8.42	6.04
	ATMs per 100,000 adults	6.05	7.62	8.55	9.26	9.72	9.86	9.64	9.69	9.16	9.43	8.9
Kenya	Bank branches per 100,000 adults	4.25	4.63	4.78	5.06	5.37	5.5	5.73	5.85	5.37	5.21	5.17
	ATMs per 100,000 adults	38.06	39.51	40.88	43.43	44.33	44.87	45.02	45.55	44.5	43.49	42.96
Mauritius	Bank branches per 100,000 adults	19.55	21.1	21.31	21.62	21.91	22.24	24.34	23.95	20.4	18.6	21.5
	ATMs per 100,000 adults	16.27	18.26	19.68	21.4	22.94	24.28	25.29	26.1	26.84	27.21	22.83
Morocco	Bank branches per 100,000 adults	14.15	19.58	20.81	21.86	22.9	23.61	24.07	24.61	24.8	24.85	22.12
	ATMs per 100,000 adults	4.13	4.59	5.57	6.3	6.81	7.5	8.89	10.3	11.01	11.07	7.62
Mozambique	Bank branches per 100,000 adults	2.5	2.86	3.28	3.51	3.73	3.74	3.98	4.14	4.36	4.3	3.64
	ATMs per 100,000 adults	29.24	41.02	48.46	49.67	47.68	51.13	56.7	58.33	67.72	70.43	52.04
Namibia	Bank branches per 100,000 adults	12.5	12.52	12.52	12.54	12.34	12.34	13.53	13.62	15.45	10.48	12.78
	ATMs per 100,000 adults	0.32	0.44	0.43	0.42	0.41	n/a	n/a	n/a	n/a	n/a	0.4
Sierra Leone	Bank branches per 100,000 adults	2.26	2.74	2.88	2.96	2.97	n/a	n/a	n/a	n/a	n/a	2.76
	ATMs per 100,000 adults	44.18	52.49	56.83	58.71	58.31	58.99	66.25	68.79	68.96	67.75	60.13
South Africa	Bank branches per 100,000 adults	7.93	9.34	10.03	10.46	10.13	10.24	10.95	10.5	10.13	10.4	10.01
	ATMs per 100,000 adults	15.51	17.89	20.64	21.69	22.43	23.36	24.71	26.64	27.76	29.99	23.06
Tunisia	Bank branches per 100,000 adults	14.44	15	16.52	16.96	17.53	18.16	19.27	19.9	20.66	21.7	18.01
	ATMs per 100,000 adults	2.57	3.28	3.54	3.78	4.12	4.74	4.36	4.55	4.54	4.2	3.97
Uganda	Bank branches per 100,000 adults	2.04	2.36	2.46	2.39	2.7	2.9	2.99	2.98	2.88	2.67	2.64

Source: World Bank (2017b).

2.9.3 Competition for Financial Inclusion and Banking Industry Social Performance

Banks mainly aim to enhance their financial performance. Consequently, they may abandon their social goals if they pay too much attention on reducing costs and improving their profitability, particularly when faced with competition. The challenge, therefore, for banks in the current competitive conditions for financial inclusion is that the simultaneous objectives of social and financial performance may conflict. According to Dorfleitner et al. (2017), the conflict may occur because financial institutions trade-off outreach and financial performance. Outreach to people who are poor is expensive as compared to focusing on wealthier clients, which can harm the financial performance of banks.

Moreover, lending to low-income earners is perceived as a risky undertaking which entails costly administrative effort (Beisland et al., 2017). The focus on wealthier clients can hypothetically impact the services of a bank, and it is an ethical issue that banks may fail to provide financial services to less wealthy (vulnerable and poor) clients. However, the concentration on wealthier clients, especially under increasingly competitive conditions, can be justified by the need for banks to achieve financial sustainability by way of ensuring that the costs involved in providing financial services are less than the income generated.

Although financial performance is essential, particularly for expanding outreach, it may go against the goal of serving the large groups of poor people because they may not afford the necessary or commensurate higher prices (Hashemi, 2007; Hermes & Lensink, 2011). The task for banks in the current competitive environment for financial inclusion is to find the appropriate balance between achieving social goals while remaining profitable. Nonetheless, innovations that result in a reduction of the cost involved in providing financial services can lead to simultaneous progress in both social and financial performance.

Even so, Copestake (2007) notes that many decisions encompass a trade-off between achieving both social and financial goals. For instance, increasing loan interest rates can enhance the financial performance of a bank, but this may come at the expense of reducing social performance. Schreiner (2002) affirms that for banks to realise more profits, they must charge higher prices, thus, increasing costs incurred by clients, which reduces their net social gains from the financial service. However, banks can still achieve both social and financial performance at the same time. For example, banks may realize economies of scale by improving outreach and innovating products that attract more clients which can in turn enhance their financial performance.

The social performance of the banking industry can thus increase with greater breadth and depth. Mersland and Strøm (2014) state that banks can improve their social performance by moving to clients with lower levels of income and by increasing their geographical penetration via ATMs and bank branches. Even though the cost of setting up new branches and ATMs can have adverse effects on the banks, the cost can be offset by the realization of economies of scale/or scope (Copestake, 2007).

The empirical literature on the effect of competition in the low-income market and social performance provides an inconclusive prediction on the effect of competition on the outreach of profit-oriented financial institutions. Kai (2009) argues that competition for financial inclusion may have a negative impact on outreach performance as it may make banks to drop poorer borrowers. As indicated earlier, competition may reduce the incentive of borrowers to repay their loans due to the increased opportunities to borrow from multiple sources, raising the default rates (McIntosh & Wydick, 2005). The increase in default rates can reduce the profitability of banks and reduce their ability to reach more clients.

Furthermore, the profit orientation of banks may motivate them to target wealthier borrowers and offer-larger loans in the presence of MFIs who supply smaller loans. Jia et al. (2016) and Hossain et al. (2020) show evidence that in competitive low-income markets, profit-oriented MFIs are motivated to serve safer and wealthier clients with larger loan sizes, which reduces the default rates and outreach. Indeed, Assefa et al. (2013) note that in the face of competition, banks need to put more efforts into monitoring existing borrowers and evaluating new applicants due to rise in information dispersion, which increases the loan costs. Consequently, the need to reduce costs in the face of competition may lead to a reduced focus on outreach since providing small loans is more expensive as compared to providing larger loans.

Lastly, competition may lead to a decline in income by diminishing net interest-margins which could lessen the ability of banks to cross-subsidize loans to low-income earners (Kai, 2009). Consequently, banks may not generate enough rents to afford lending to the least profitable poor. Accordingly, banks may respond to the increased competition for financial inclusion by shifting their focus to serving better-off clients with larger loan sizes, and this can adversely affect both the depth and breadth of outreach.

Nonetheless, Hossain et al. (2020) argue that competitive pressure in the low-income market may provoke banks to search for new clients. To do this, banks may reduce their credit constraints in an aim to attract new clients (Cull et al., 2014). Furthermore, competitive

pressure may force banks to focus on new unexplored markets. In such a case, competition may serve to increase both the depth and breadth of outreach. Moreover, the need to reduce cost under competition may make banks to be more efficient, resulting in better financial performance and better outreach to poorer clients (Hermes & Hudon, 2018).

There are a number of studies that have tried to assess the social performance of banks and whether there is a trade-off between social performance and financial performance. However, most of these studies focus on MFIs. Beisland et al. (2017) explore whether the reduced emphasis on poorer clients by MFIs can be explained by 'personal mission drift' at the credit officer level. Using a data set covering credit officers in Ecuador, they find evidence of a negative relationship between the experience of credit officers and loan provision to disabled and young clients. Specifically, they find that loan officers who have more experience serve less poor clients.

Dorfleitner et al. (2017) use global data of 215 MFIs to investigate the reasons why MFIs fail to meet their social objectives. They find a positive relationship between MFIs social failure and the amount of written-off loans as measured by the write-off ratio. Furthermore, they show evidence that MFIs with good outreach, measured by high personnel expenses, a high percentage of female loan officers and low outstanding loan balances, have a low probability of failing in their social mission. Moreover, they find a positive relationship between the growth of MFIs, measured by the number of active borrowers and failure in meeting their social objectives.

Using a random sample of 622 microfinance borrowers, Navajas et al. (2000) investigate the depth of outreach of MFI in La Paz, Bolivia. Precisely, they assess whether MFIs reach the poorest of the poor, whether group loans reach the poorest better than the individual loans and whether rural MFIs reach the poorest better than urban MFIs. They construct a theoretical framework on the social worth of MFIs output in order to determine whether MFIs trade-off service to the poor versus service to others. They find that most MFIs in Bolivia do not reach the poorest of the poor, but group lenders reach more poor people than individual lenders. Finally, they find evidence that urban MFIs have more lenders as compared to MFIs in rural areas. Also, they find that outreach reduces with individual lending as compared to group lending.

Mersland and Strøm (2009) use random effects panel data to study the relationship between the performance of MFIs and corporate governance. They examine the impact of CEO and

board characteristics, type of firm ownership, and competition on the financial and outreach objective of MFIs. In general, they find that corporate governance mechanisms have little effect on financial and outreach performances.

Cull et al. (2014) analyse the effects of bank presence on the outreach and profitability of MFIs. They combine two data sets on bank penetration and microfinance institutions from developing and developed countries. They find that MFIs respond to increased competition, as measured by the number of bank branches, by moving downwards towards markets that are poorer, as evidenced by lower average loan size and increased share of women borrowers. However, their results indicate that commercialized MFIs in countries with lower competition tend to focus on clients that are better-off, but this effect reduces with greater competition.

Lastly, using microfinance data in 73 countries from 362 MFIs, Assefa et al. (2013) show evidence of a negative relationship between competition among MFIs and outreach as well as repayment performance. Their study focused on examining the relationship between competition and MFIs performance for the period between 1995 and 2008. Specifically, they analysed whether competition, measured by Lerner index, affects both MFIs outreach and portfolio quality.

2.10 Chapter Summary

In summary, the review of the literature has provided the following insights:

- The shift from microfinance fairly specific intervention towards a broader financial inclusion paradigm has increased competition in offering financial services to low-income earners. Consequently, commercial banks are finding themselves under increased competition from MFIs to attract and retain household and SME clientele.

- The market power hypothesis suggests that banks may respond to the increasing competition for financial inclusion by increasing the supply of credit to low-income earners. Similarly, the efficiency structure theory suggests that banks can respond to the competition for financial inclusion by expanding their loan output and gain differential efficiency benefits.

- In contrast, the asymmetry of information hypothesis and the quiet life hypothesis (QLH) predict that banks may respond to the increased competition from MFIs by reducing the amount of credit extended to households and SMEs in order to reduce their risk exposures.

- Generally, theoretical literature provides conflicting predictions on the banking industry response to competition for financial inclusion and the effect of such response to both banking industry efficiency and asset portfolio risk.
- One view holds that competition for financial inclusion may prompt banks to relax lending procedures and increase the supply of credit to households and SMEs. Although this may enhance banks' efficiency via economies of scale advantages, it can attract low-quality borrowers, and thus increase the probability of loan defaults and its associated deteriorating bank asset portfolio quality.
- A compromise view argues that competition for unbanked clients can reduce the ability of banks to build customer relationships. This can prompt banks to reduce the supply of credit to low-income earners due to higher monitoring costs and a decrease in efficiency. Reduced lending to low-income earners can lower the incidence of NPLs; thus, leading to an improvement in bank portfolio quality and efficiency.
- A major concern in the literature is that banks may respond to increased competition for low-income clients by focusing on affluent clients in order to remain financially sustainable and profitable. Alternatively, competition for low-income clients may force banks to respond by focusing on expanding their lending to households and SMEs so as to increase their clientele base and enhance their social performance.
- The empirical literature has mainly focused on the effect of competition on access to finance, how competition between MFIs affect their outreach to the poor, and the effect of competition on banking industry efficiency and risk-taking. And most of these studies focus on developed countries. Furthermore, studies on competition and social performance have mainly concentrated on within-MFIs analyses.
- From the foregoing, it is evident that empirical literature has not paid adequate attention to how the banking industry, particularly in Africa, is responding to the heightened competition for low-income earners and the effects of such responses. Consequently, this study attempts to fill this gap.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Research Design

This study examines how the banking industry is responding to competition for the 'financial inclusion' drive and how such responses affect banking efficiency, asset portfolio risk, and the social performance of banks. To achieve this, the study employs both descriptive and correlational research designs. According to Emory and Cooper (1991), descriptive research design provides a systematic and accurate description of the characteristics of a given population of study. Although descriptive research is vital, Saunders (2011) observes that it is not an end in itself but rather a means to an end.

Thus, description research is mainly used as a precursor to correlational research design. Gravetter and Forzano (2018) note that correlational research shows how one variable affects or influences change in another variable and the degree, along with the direction of the relationship. It is suitable for establishing causal relationships between variables in a quantitative study. The study adopts a quantitative research approach in accordance with our research designs. According to Saunders (2011), the emphasis of quantitative research is on quantifiable observations and measurements that lend themselves to statistical analyses, so as to establish causal relationships between variables.

3.2 Population, Sampling, and Data Collection

The population for this study consists of all commercial banks in Africa from 2010 to 2017 based on availability of data. To adequately capture banking industry response to competition for financial inclusion, and the effects of such response, we picked a sample of 16 countries namely, South Africa, Swaziland, Botswana, Zambia, Namibia, Tanzania, Kenya, Uganda, Ethiopia, Egypt, Morocco, Tunisia, Nigeria, Ghana, The Gambia, and Rwanda. These countries have the highest level of financial access in Africa according to global financial access survey ranking by the World Bank (2017a) and Lewis et al. (2017). In addition, the countries have data covering the study period.

We collected our data from all the 235 banks (see Table A1 in the Appendix) and 333 MFIs operating in the selected countries with commercial banks forming our unit of analysis. We obtained MFIs-specific data (competition for financial inclusion paradigm) from the MIX database. The MIX market database provides data that allows assessment of individual

financial service provider's performance, market conditions and financial inclusion landscape (MIX Market, 2018).[21] On the other hand, data on banking industry response to competition for financial inclusion paradigm and banking industry social performance was derived from the International Monetary Fund (IMF) financial access survey database, central banks of the respective countries, and the World Bank's World Development Indicators (WDI) database. Finally, data relating to banking industry efficiency and banks' asset portfolio risk were obtained from the Bankfocus database and supplemented by individual banks' annual financial reports.

3.3 Banking Industry Response to Competition for Financial Inclusion Project

3.3.1 Model Specification

To evaluate the banking industry response to competition from the financial inclusion paradigm in Africa, we model our estimation equation as follows:

$$\text{Response}_{jt} = \propto_0 + \beta_1 \text{MFIsMS}_{jt} + \sum_{k=2}^{k} \beta_{k-1} X_{jt} + \acute{\varepsilon}_{jt} \qquad (3.1)$$

Where MFIsMS_{jt} is our measure of competition for financial inclusion paradigm and represents the market share (influence) of MFI j in year t. $\propto$ denotes the y-intercept while Response is our measure of banking industry response to financial inclusion paradigm. X are our set of control variables. $B_1, \ldots, \beta_k$ represent coefficients of the explanatory variables, while $\acute{\varepsilon}$ is the error term. We use the "ratio of MFIs' loans, to credit to the private sector" (MFIs loans to CPS) as our target independent variable (competition for financial inclusion) to measure MFIs market share (MFIsMS_{jt}). On the other hand, we employ the "ratio of banks' households and SMEs loans, to credit to the private sector" (HHSMES loans to CPS) as our dependent variable to measure banking industry response to competition for financial inclusion project. The credit to private sector variable is commonly used to construct measures of national financial development and financial depth of financial institutions in the finance and growth literature (Ahlin et al., 2011).

3.3.2 Control Variables

We control for both bank-specific variables, and institutional and macroeconomic variables. In terms of bank-specific variables, we include banks' return on assets (Banks ROA) and banks' efficiency (Banks efficiency). Im and Sun (2015) argue that financial gains in terms of profits

[21] For more information see https://www.themix.org/mix-market.

can encourage MFIs and other credit providing financial institutions to increase their loan output. Thus, we expect profits as measured by return on assets (ROA) to have a positive impact on banks' competitive activity (production outreach to usually excluded segment of potential customers of banks). According to Sanfilippo-Azofra et al. (2019), banks may trade off efficiency for more outreach. Accordingly, we expect the coefficient of banks' efficiency to have a negative sign. We measure banks' efficiency as the ratio of operating costs to gross loans.

For institutional and macroeconomic factors, we control for income inequality, financial development, institutional quality, population and GDP growth. Chmelíková et al. (2019) observe that income inequality, as measured by the Gini coefficient, reduces opportunities for the creation of social networks around which financial inclusion type lending revolves. This can reduce the ability of banks to lend. On the other hand, inequality may lead to high unbanked incidences; therefore, needing MFIs' intervention or provide a highly ready market for credit expanding banks. Thus, a positive sign for income inequality, seems more likely. According to Vanroose and D'Espallier (2013), MFIs reach more clients in countries with financial sectors that are less developed. Conversely, banks are at the center of most countries' financial development (Ojah & Kodongo, 2015; Donou-Adonsou & Sylvester, 2016/2017); thus, we anticipate a positive relationship between financial development and our measures of banks' response to the financial inclusion paradigm. We calculate a composite index for financial development by using principal component analysis (PCA), and it comprises stock market capitalization to GDP, stock value traded to GDP, and credit to the private sector to GDP.

According to Ahlin et al. (2011), high-quality institutions may push micro-lenders from the traditional financial institutions/markets to the microfinance markets. However, well-functioning institutions can benefit banks by enabling them to evolve contracts of competitive smaller denomination loans (Cull et al., 2014). This can potentially reduce the market share of MFIs in the micro-loans market. Therefore, the direction of the relationship between institutional quality and banks' play in the financial inclusion space seems positive-leaning. We use PCA to compute an index of institutional quality, which comprises six institutions/governance indicators – i.e., control of corruption, the rule of law, government effectiveness, voice and accountability, political stability and legal quality (as assembled by (Kaufmann et al., 2011).

In terms of population, Hermes and Hudon (2018) argue that formal financial institutions are more developed in regions with a high populations, which may then make the development of the microfinance sector less of an imperative. However, Hulme and Moore (2006) and Vanroose (2008) observe that MFIs tend to develop much faster in urban areas that are densely populated. Consequently, the direction of the relationship between population and banks' foray into the financial inclusion project seems ambiguous. Finally, a growing economy can stimulate demand for micro-loans and outreach of MFIs (Vanroose & D'Espallier, 2013; Sanfilippo-Azofra et al., 2019). Similarly, banks' lending pattern have been documented to be largely pro-cyclical (Siriopoulos & Tziogkidis, 2010; Sanfilippo-Azofra et al., 2018; and Chen et al., 2018). Thus, we expect the coefficient of GDP growth to have a positive sign. And we measure GDP growth as the change in real GDP.

3.3.3 Robustness Tests

To test the robustness of our model results, we re-estimate our baseline model using two alternative measures of MFIs' market share (competitive influence) and banking industry response. We first employ the "ratio of MFIs' assets, to the population living below the poverty line" (MFIs assets to poverty)[22] as our dependent variable and the "ratio of banks' loans to households, SMEs and agriculture, to the population living below the poverty line" (HHSMEs Agric loans to poverty)[23] as our predictor variable. The rationale behind the use of MFIs' assets is because MFIs are involved in the provision of financial services to the poor. Therefore, the expansion of their assets (most which are naturally interest-earning assets) can be considered as a proxy of their competitiveness in the low-income market (Liñares-Zegarra & Wilson, 2018).

Finally, we also re-estimate our baseline model by using the "ratio of MFIs' loans, to banks' loans to households and SMEs" (MFIs loans to HHSMEs) as our dependent variable. We use the proportion of MFIs' loans to bank loans since MFIs can be able to exert more competitive influence and prevent banks from crowding them out if they offer more loans to low-income earners compared to commercial banks (Vanroose & D'Espallier, 2013). Correspondingly, we employ the ratio of bank loans to household and SMEs to gross loans (HHSMES to gross loans) as our target-independent variable.

[22] Based on people living with below $1.90 per day.

[23] We include agriculture loans since provision of credit to agriculture is considered as an important aspect of financial inclusion, particularly in Africa (Kodongo, 2018).

3.3.4 Estimation Technique

We employ a fixed-effects model (FE) with time fixed effects for both our baseline regression model and our first robustness test and a random effects (RE) model for our second robustness test, following previous related studies by Assefa et al. (2013), Vanroose and D'Espallier (2013), and guidance from the results of the Hausman test. The time-FE estimation model allows the intercept in the regression model to vary over time but it is assumed to be constant cross-sectionally (Brooks, 2014). The model permits correlation between the individual unobserved effects with other variables in the model. The time-fixed effects model can be stated as follows:

$$Y_{jt} = \propto_0 + \beta_{jt} + \lambda_t + \acute{\varepsilon}_{jt} \quad (3.2)$$

Where, λ_t denotes the time-varying explanatory variables that affect Y_{jt} (MFIs market share) which are constant cross-sectionally but vary over time. In contrast, the RE model assumes that the unobserved effects are uncorrelated with independent variables (Verbeek, 2008). The RE model proposes different intercept terms for each entity that is constant over time, with the relationship between the dependent and the explanatory variables assumed to be the same both temporally and cross-sectionally.

Specifically, in the RE model, the intercepts for each cross-sectional units are assumed to arise from a common intercept which is the same over time and for all cross-sectional units, plus a random variable that is constant over time but has a cross-sectional variation (Brooks, 2014). The random RE model can be stated as follows:

$$Y_{jt} = \propto_0 + \beta x_{jt} + \acute{\varepsilon}_{jt} \quad (3.3)$$

Where x_{jt} is a vector of explanatory variables that affect Y_{jt} (MFIs market share). We use robust standard errors in the presence of heteroscedasticity. Furthermore, we include time dummies in our regression models to control for the effects of time. To capture the effects of our time dummies on the R-squared in models where we employ fixed effects, we include the estimation results using Areg.[24] On the other hand, we enhance our random effects estimations by including the results of ordinary least squares (OLS). We also conduct unit root tests for each variable and use differencing for variables with unit root problems.

[24] Areg allows inclusion of unit level effects in a model which are not factored in the fixed effects one-level within transformation(McCaffrey et al., 2012).

3.4 Banking Industry Response to Competition for the Financial Inclusion Project and Efficiency

3.4.1 Measurement of Banking Industry Efficiency

We use a two-stage approach to determine the efficiency effects of the banking industry response to competition for financial inclusion. In the first stage, we generate the cost efficiency scores for the banking industry in Africa. In the second stage, we regress the efficiency scores obtained in the first stage against our explanatory variables. We use four alternative approaches to estimate the cost efficiency scores of the banks sampled. First, we employ the DEA technique under the variable returns to scale (VRS) assumption as introduced by Banker et al. (1984). Our preference for DEA approach is because it does not require specification of the production functional form, which is more complex in the services sector like the banking industry (Coelli et al., 2005; Havrylchyk, 2006). Moreover, the DEA approach can be applied to multi-input and multi-output variables.

Thilakaweera et al. (2016) observe that most of the time, institutions in the financial sector, particularly banks; do not operate at optimum scale due to regulations, imperfect competition, and other restrictions. Thus, DEA under VRS is appropriate as it ensures that a bank is only compared with another bank operating at the best practice frontier. Furthermore and following other studies (e.g., Aly et al., 1990; Miller & Noulas, 1996; Casu & Molyneux, 2003; Sharma et al., 2013), we use the input based orientation approach since banks may have higher control of their expenses (inputs) particularly in responding to competition for financial inclusion more than their incomes (outputs).[25]

We follow Farrell (1957), Banker et al. (1984) and Coelli et al.'s (2005) DEA mathematical formulation to construct the overall cost efficiency index which is calculated by solving a linear programming problem. We assume that a bank will aim to select input quantities that will minimize costs holding the prices of inputs and the quantities of output constant. We express this problem as follows:

$$\min\ \lambda, x^{*}i\, Pi' Xi^{*}\ ,$$

$$subject\ to - yi + Y\lambda \geq\ 0,$$

$$xi^{*} - X\lambda \geq 0,$$

[25] Studies (e.g., Beccalli et al., 2006; Siriopoulos & Tziogkidis, 2010) report similar findings for both input-orientation and output-orientation under CRS and different results under VRS.

$$N1'\lambda = 1,$$

$$\lambda \geq 0 \qquad (3.4)$$

Where *Pi* is a vector of prices of inputs for the i^{th} bank and xi^* is the cost-minimizing vector of quantities of input for the i^{th} bank, given the input price *(Pi*) and the output quantities (*yi*). CE for bank *i* is calculated as the ratio of *Pi'xi*/Pi'xi,* where *Pi* represents the transpose of input price vector of bank *i*.

Prediction of efficiency requires definitions and measurements of input, output, and variable input prices. To determine what constitutes banking inputs and outputs, there is a need to determine the nature of banking technology. In this respect, there are two main approaches used in the selection of input-output combinations: the intermediation approach and the production approach. Berger and Humphrey (1997) and Kwan (2006) observe that the intermediation approach is the most widely used technique for evaluating bank efficiency. This approach views banks as financial services intermediaries that use labour and accumulated deposits to generate loans and other financial services. On the other hand, the production approach is more suited for evaluating bank branch efficiency and frontier techniques.

Accordingly, this study employs the intermediation approach since we are interested in assessing bank's efficiency as a whole. Using the aforementioned approach, and following other similar studies (Isik & Hassan, 2002; Sharma et al., 2013; Batir et al., 2017; Tan & Anchor, 2017), we model banks as multi-product units that employ 3 inputs: labour, capital and purchased funds, to produce 4 outputs: total loans, off-balance sheet items, deposits and other earning assets. In this study, we consider deposits as having a twofold role of both input (source of loans) and output (depositors withdrawals) as suggested by Berger and Humphrey (1997). However, the treatment of deposits as a source of both bank input and output is controversial since revenues on deposits are relatively small. The measurements of the inputs and the outputs are tabulated below:

Table 3: Measurement of inputs and outputs variables

Variable	Measurement	Study that applied the measure
Inputs		
Labour	Personnel expenses	Alhassan and Ohene-Asare (2016).
Physical capital	Book value of fixed assets	Batir et al. (2017).
Purchased Funds	Sum of deposits and borrowed funds	Chen et al. (2018).
Outputs		
Total loans	Sum of long-term and short-term loans	Sufian et al. (2016).
Off-balance sheet items	Sum of financial derivatives, commitments, and guarantees	Batir et al. (2017).
Deposits	Sum of transaction deposits, non-transaction deposits, demand deposits, fixed deposits, and savings deposits.	Stewart et al. (2016).
Other earning assets	loans to special sectors, inter-bank funds and investment in securities	Alhassan and Ohene-Asare (2016).
Input prices		
Price of labour	Personnel expenses divided by total assets	Chen et al. (2018).
Price of physical capital	Expenditure on equipment and plant (Non-interest expenses) divided by book value of fixed assets.	Sufian et al. (2016).
Price of purchased funds	Interest expense divided by total deposits	Batir et al. (2017)

Second, since the role of deposits as outputs in the banks production process is controversial, we compute DEA robust efficiency scores where the 'input-output' relation does not consider deposits as outputs. Third, we use a multi-product translog Stochastic Frontier Analyses (SFA) approach to generate the cost efficiency scores. Under the SFA approach, a bank is assumed to be inefficient if it produces outputs at costs higher than its peers that are producing the same outputs and operating under similar conditions (Alhassan, 2015). The deviations from the efficient frontier are theoretically classified into random noise and managerial inefficiency. We

employ Coelli et al.'s (2005) SFA model and later expanded it by Lozano-Vivas and Pasiouras (2010) to include non-traditional banking activities:

$$\begin{aligned}\ln\left(\frac{TC}{W_3}\right) = {} & \beta_0 + \beta_1 \ln(Q_1) + \beta_2 \ln(Q_2) + \beta_3 \ln(Q_3) + \beta_4 \ln\left(\frac{W_1}{W_3}\right) + \beta_5 \ln\left(\frac{W_2}{W_3}\right) \\ & + \beta_6 \frac{1}{2}(\ln(Q_1))^2 \\ & + \beta_7 \ln(Q_1)\ln(Q_2) + \beta_8 \ln(Q_1)\ln(Q_3) + \beta_9 \frac{1}{2}(\ln(Q_2))^2 \\ & + \beta_{10} \ln(Q_2)\ln(Q_3) + \beta_{11} \frac{1}{2}(\ln(Q_3))^2 + \beta_{12} \frac{1}{2}\left(\ln\left(\frac{W_1}{W_3}\right)\right)^2 \\ & + \beta_{13} \ln\left(\frac{W_1}{W_3}\right)\ln\left(\frac{W_2}{W_3}\right) + \beta_{14} \frac{1}{2}\left(\ln\left(\frac{W_2}{W_3}\right)\right)^2 \\ & + \beta_{15} \ln(Q_1)\ln\left(\frac{W_1}{W_3}\right) + \beta_{16} \ln(Q_1)\ln\left(\frac{W_2}{W_3}\right) \\ & + \beta_{17} \ln(Q_2)\ln\left(\frac{W_1}{W_3}\right) + \beta_{18} \ln(Q_3)\ln\left(\frac{W_2}{W_3}\right) + \beta_{20} \ln(Q_3)\ln\left(\frac{W_2}{W_3}\right) + \beta_{21} T \\ & + \beta_{22} \frac{1}{2} T^2 + \beta_{23} \ln(Q_1) T + \beta_{24} \ln(Q_3) T + \beta_{35} \ln(Q_3) T + \beta_{26} \ln\left(\frac{W_1}{W_3}\right) T \\ & + \beta_{27} \ln\left(\frac{W_2}{W_3}\right) T + \beta_{38} \ln(Equity) + \mu_{jt} + v_{jt} \end{aligned} \quad (3.5)$$

Where $Q_1, Q_2,$ and Q_3 are banks outputs (off-balance sheet activities, loans and other earning assets), W_1, W_2 and W_3 are the costs of inputs (cost of fixed assets, cost of borrowed funds and cost of labour). We define TC (total cost) as the sum of interest and non-interest expenses. v_{jt} is the random noise variable that captures measurement errors, and it is assumed to follow normal distribution. μ_{jt} measures inefficiency, which results from managerial slack, which is assumed to follow a truncated distribution. 'Equity' controls for the extent of bank risk.

Lastly, we use Simar and Wilson (2007) bootstrap technique to generate more robust DEA cost efficiency scores. A major limitation of the DEA approach is that it measures efficiency relative to a non-parametric estimate of an unobserved true frontier (Simar & Wilson, 2007). This makes the DEA efficiency scores estimates to be biased and serially correlated. According to Apergis and Polemis (2016), the Simar and Wilson bootstrapping approach generates bias-corrected cost efficiency scores by correcting the serial correlation bias that arises when estimating DEA efficiency estimates.

Additionally, the method guarantees consistent inferences and resolves the issue of inter-dependence of the efficiency scores given that they represent a relative measure by construction (Triki et al., 2017). Accordingly, using the Simar and Wilson approach, we bootstrap the DEA

efficiency scores generated in our first estimation approach. We follow previous studies by Kao and Liu (2009) and Badunenko and Tauchmann (2019), and bootstrap the DEA efficiency scores over 1000 replications.

3.4.2 Model Specification and Estimation Technique

We conduct the second stage analyses using the efficiency scores generated in the first stage. Since we expect the efficiency of banks to depend on how they respond to competition for financial inclusion as well as other control variables, we express the basic regression equation as follows:

$$CE_{\mathrm{jt}} = \propto_0 + \beta_1 \mathrm{Response}_{\mathrm{jt}} + \sum_{k=2}^{k} \beta_{\mathrm{k}-1} \mathrm{X}_{\mathrm{jt}} + \acute{\varepsilon}_{\mathrm{jt}} \qquad (3.6)$$

CE_{jt} is the DEA cost efficiency, DEA robust cost efficiency, SFA cost efficiency, and Simar and Wilson bootstrap cost efficiency score of bank j at year t. $\propto$ is the y-intercept while β_1 *to* β_k are the coefficients of the explanatory variables. X is a set of control variables, and $\acute{\varepsilon}$ is the error term. We estimate our four baseline equations using the "ratio of banks' households and SMEs loans, to banks' gross loans" (HHSMEs to gross loans) as our measure of banking industry response to competition for the financial inclusion paradigm.

Given that the DEA cost efficiency scores range from 0 to 1 ($0< \theta \leq 1$), studies by Casu and Molyneux (2003), Wanke et al. (2016) and Peng et al. (2017), among others, have traditionally preferred the Tobit model because it allows the use of censored data as the response variable. However, Simar and Wilson (2007) argue that the DEA scores generation process is truncated rather than censored. As a result, the second stage Tobit estimation should account for the serial correlations among the efficiency scores. Indeed, Saxonhouse (1976) and Arabmazar and Schmidt (1982) show evidence that the second stage Tobit estimation analyses is unreliable because the Tobit estimator cannot account for heteroskedastic disturbance terms associated with the second stage efficiency scores.

Moreover, McDonald (2009) argues that the second stage Tobit estimation analyses is biased since the efficiency scores generation process is fractional rather than censored.[26] This makes the estimation process using Tobit to be inconsistent. Accordingly, we employ the fractional probit regression model proposed by Papke and Wooldridge (1996). The fractional probit regression model yields marginal effects predictions that are restricted between 0 and 1. In the

[26] The DEA cost efficiency scores are generated by normalizing the efficiency scores by the maximum efficiency score of one, thereby generating proportional (fractional) efficiency scores data (McDonald, 2009).

fractional regression model, the dependent variable y is assumed to be a proportion generated by the logistic function. The conditional expected value of the dependent variable y is modelled as a logistic function as follows:

$$E\left(\frac{y}{x}\right) = \frac{\exp(x\beta)}{[1 + \exp(x\beta)]} \tag{3.7}$$

The β's are estimated by specifying a generalized linear model with a probit link function and a binomial distribution. The model is based on maximum quasi-likelihood estimation (Papke & Wooldridge, 1996).[27] Furthermore, for the model with SFA cost efficiency scores, we use maximum likelihood estimation (MLE) technique as proposed by Battese and Coelli (1995) and following previous studies by Andries (2011) and Fernández et al. (2020), among others.[28]

Similarly, for the Simar and Wilson bootstrapped DEA efficiency scores, we use MLE technique to estimate the truncated regression model consistent with earlier related studies (e.g., Huang et al., 2018; Jiménez-Hernandez et al., 2019; Cabrera-Suárez & Pérez-Rodríguez, 2020).[29] Simar and Wilson (2007) argue that MLE yields valid estimates for the parameters with bias-corrected efficiency scores.

3.4.3 Control Variables Identification and Measurement

The factors that influence banking efficiency can be grouped into bank-specific variables, and institutional and macroeconomic variables (Pasiouras, 2008; Sharma et al., 2013). The typical bank-specific factors include non-performing loans, bank size, profitability, liquidity, revenue diversification, and competition. According to Assaf et al. (2013), high levels of non-performing loans (NPLs) increase banks spending on monitoring borrowers, and this may reduce the cost efficiency of banks. We thus anticipate NPLs to have a negative effect on the efficiency of the banking industry. We measure NPLs as a ratio of non-performing loans to gross loans.

[27] Since the MLE is based on the distribution of y given x, the heteroscedasticity in Var(y|x) is automatically accounted for (Wooldridge, 2010).

[28] SFA assumes that the error term is composed of managerial inefficiency and the normal error (half-normal distribution). Consequently, the method of MLE is proposed so as to maximize the SFA log-likelihood function (Battese & Coelli, 1995; Humphrey, 2019).

[29] The Simar and Wilson bootstrap procedure generates cost efficiency estimates that are not true variables, particularly because they are based on DEA efficiency scores measured by comparing the efficiency of firms to an unobserved true frontier. The MLE is thus used to construct more precise bootstrap confidence intervals for the cost efficiency estimate parameters by maximizing the corresponding likelihood function (Simar & Wilson, 2007; Barros & Dieke, 2008).

Debate exists on the relationship between bank size and efficiency. Studies by Xiaogang et al. (2005), Hauner and Peiris (2008) and Triki et al. (2017), among others, find a positive relationship between bank size and efficiency. Farhana et al. (2013) argue that large banks can benefit from economies of scale that enable them to minimize their costs. However, Tan and Anchor (2017) find banking efficiency to be negatively related to size. Large banks may be associated with dysfunction and coordination problems, leading to lower efficiency scores. As a result, we are unclear on the direction of the relationship between bank size and efficiency. We measure bank size as a log of total assets.

Most studies (e.g., Farhana et al., 2013; Batir et al., 2017; Tan & Anchor, 2017) report a consistent negative relationship between profitability and efficiency of banks. Berger and Humphrey (1997) argue that increased concentration in the banking industry may lead to a relaxed environment where banks have no incentives to reduce costs. Given that a few large banks dominate the African banking industry, we expect an inverse relationship between the efficiency of banks and profitability. We use return on assets (ROA) ratio (net income divided by total assets) to measure profitability.

According to Sarmiento and Galán (2017), holding liquid assets can be costless for banks since they have shorter maturity periods. Accordingly, we expect liquidity to have a positive sign. We measure liquidity as the ratio of cash and marketable securities divided by total assets. Furthermore, literature provides contradicting findings on the effect of diversification on banks' efficiency. On one hand, Laeven and Levine (2007) and Nguyen (2018) show that diversification helps banks gain economies of scale by spreading costs over different products. However, diversification may increase costs by diluting banks competitive advantage and making managers operate outside their areas of expertise (Louzis et al., 2012; Doan et al., 2018).

Therefore, we are uncertain on the direction of the relationship between revenue diversification and banking industry efficiency. Similar to other studies (e.g., Shim, 2013; Baselga-Pascual et al., 2015; Abuzayed et al., 2018), we measure revenue diversification as 1-Herfindahl-Hirschman index (HHI) of banks income, which we classify into three types: interest income, investment income and other income. Similarly, the effect of competition on the efficiency of banks is ambiguous. According to Andrieș and Căpraru (2014), competition may force banks to be more efficient so as to be able to lower prices and increase market shares. Nonetheless, competition may increase inefficiency by making banks to incur more costs as they seek for

new clients (Banyen & Biekpe, 2020). We are thus unclear on the sign of the coefficient for competition. Consistent with other studies (e.g., Boone, 2008; Leon, 2015; Căpraru et al., 2020), we use the Boone index to measure the level of competition among banks.

In relation to institutional and macroeconomic variables, we control for financial development, GDP growth, and inflation. Well-developed financial markets are associated with lower frictions, which may lead to lower financing costs for banks hence improved efficiency (Ngo & Le, 2019). Additionally, developed financial markets are characterized by better procedures for assessing credit, and this can lead to a reduction in non-performing loans and the cost of monitoring borrowers. Accordingly, we expect the coefficient of financial development to have a positive sign. As indicated earlier, we use stock market capitalization to GDP, stock value traded to GDP and credit to the private sector to GDP to calculate a composite index for quality of financial development using principal component analyses (PCA).

Triki et al. (2017) and Batir et al. (2017) find evidence that the efficiency of banks is likely to improve in countries with a low level of inflation due to lower costs. Thus, we expect an inverse relationship between inflation and bank efficiency. Studies by Tan and Anchor (2017) and Triki et al. (2017) show that GDP growth is positively related to banking efficiency. The demand for banking services can increase during periods of economic boom, and, at the same time, the quality of borrowers can improve, leading to a reduction in monitoring costs and improvement in efficiency. Accordingly, we anticipate a positive relationship between real GDP growth and bank efficiency. We measure real GDP growth as the percentage change in real GDP.

3.4.4 Robustness Tests

From the above baseline tests, we check the robustness of our model's results by re-estimating our baseline equations using our two alternative measures of banking industry response to competition for the financial inclusion paradigm: the "ratio of banks' households and SMEs loans, to credit to the private sector" (HHSMEs loans to CPS), and the "ratio of banks' households, SMEs and agriculture loans, to people living below the poverty line" (HHSMEs Agric loans to poverty).

3.5 Banking Industry Response to Competition for the Financial Inclusion Project and Asset Portfolio Risk

3.5.1 Model Specification

To evaluate the effect of banking industry response to competition for financial inclusion on banks asset portfolio risk in Africa, we specify our model following Abuzayed et al. (2018) and Teixeira et al. (2020), as follows:

$$\text{Risk}_{jt} = \propto + \text{Risk}_{jt-1} + \beta_1 \text{Response}_{jt} + \sum_{k=2}^{k} \beta_{k-1} X_{jt} + \acute{\varepsilon}_{jt} \quad (3.8)$$

Where Risk_{jt} is the asset portfolio risk of bank j at year t, while $\propto$ is the y-intercept. Response denotes our measure of banking industry response to competition for the financial inclusion paradigm. X represent our set of control variables while β_1 to β_K are the independent variables coefficients. $\acute{\varepsilon}$ is the error term. We use one period lagged dependent variable as a predictor variable to account for the persistence of banks risk as shown by Bermpei et al. (2018) and Ibrahim and Rizvi (2018). We proxy our dependent variable (Risk) by using the "ratio of non-performing loans, to banks' gross loans" (NPLstoGLs). The non-performing loans ratio provides a good measure of how the portfolio loan risk of a bank evolves over time.

Accordingly, it is considered as a good predictor of bank asset quality since bank failures mainly occur after a period of rapid deterioration in loan portfolios (non-performing loans) (González-Hermosillo, 1999; Delis et al., 2014). We measure banking industry response to competition for financial inclusion paradigm using three proxies: the "ratio of banks' households and SMEs loans, to banks' gross loans" (HHSMEs to gross loans), the "ratio of banks' households and SMEs loans, to credit to the private sector" (HHSMEs loans to CPS), and the "ratio of banks' households, SMEs and agriculture loans, to people living below the poverty line" (HHSMEs Agric loans to poverty).

3.5.2 Control Variables Identification and Measurement

Consistent with previous studies (e.g., Baselga-Pascual et al., 2015; Bermpei et al., 2018; Teixeira et al., 2020), we include a number of control variables for bank-specific, and both institutional and macroeconomic factors that influence banks' asset portfolio risk. For bank-specific variables, we control for loan loss reserves, bank size, capital, loan ratio, profitability, and revenue diversification. Loan loss reserves reflect the amount of losses that banks expect in their loan portfolios and the overall attitude of the banking industry towards controlling risk

(Shim, 2013; Ghosh, 2015). We expect the coefficient for loan loss reserves to have a positive sign. We measure loan loss reserves as the ratio of a bank loan loss reserves to gross loans.

According to Berger et al. (2014) and Ghosh (2015), large banks are considered to be too big to fail. This may increase their appetite to take more risk since they expect government bailout in case of distress. However, large banks may be prone to less risk due to their managerial capacity. Moreover, large banks have the ability to diversify their loan portfolios more efficiently (Baselga-Pascual et al., 2015). Accordingly, we are ambiguous on the direction of the relationship between bank size and asset portfolio risk. As indicated earlier, we measure bank size as the log of total assets.

Similarly, the effect of capital on bank risk-taking is ambiguous. On one hand, capital promotes monitoring incentives and decreases banks' managers' moral hazard to assume more risk (Louzis et al., 2012). Additionally, highly capitalized banks are less likely to take excessive risk in their loan portfolios in order to preserve their charter value (Aparicio et al., 2018). On the other hand, banks with higher capital ratios have a lower probability of default, and this may encourage them to take more risk (Baselga-Pascual et al., 2015). We measure capital as the ratio of total equity to total assets.

Sobarsyah et al. (2020) find evidence that a higher proportion of loans in banks' asset portfolio is associated with increased liquidity risk. Besides, banks may reduce their credit standards when they increase their loan supply, thus, increasing the chances of default by borrowers (Ghosh, 2015). We anticipate a positive relationship between the loan ratio and banks' asset portfolio risk. Consistent with previous studies (Sanya & Wolfe, 2011; Baselga-Pascual et al., 2015; Abuzayed et al., 2018), we measure loans ratio as the proportion of a bank gross loans to total assets.

According to Shim (2019), highly profitable banks may have lower incentives to engage in risky activities. Additionally, since profitability reflects managerial efficiency, we may expect banks with good management to take a lower risk (Dimitrios et al., 2016). We thus expect the coefficient for profitability to have a negative sign. We measure profitability as the ratio of earnings before tax to total assets. Debate exists on the effects of diversification on banks' portfolio risk. According to Markowitz (1952) and Lee et al. (2014), diversification can reduce the overall risk profile of a bank by reducing variations in profits, particularly if the returns across banking activities are not perfectly correlated.

However, diversification to non-traditional banking activities is associated with higher instability in the banking industry (Sanya & Wolfe, 2011; Teixeira et al., 2020). This is because banks may diversify into more volatile activities or in areas where they lack the necessary management capabilities and competitive advantage. We are thus unclear on the sign of the coefficient between revenue diversification and banks' asset portfolio risk. As noted earlier, we measure revenue diversification as 1-Herfindahl-Hirschman index (HHI) of banks income, which we classify into three types: interest income, investment income and other income.

For institutional and macroeconomic variables, we control for quality of institutions, real interest rate, and GDP growth. According to Bermpei et al. (2018), well-functioning institutions can enhance lending terms, reduce adverse selection and borrowers' moral hazard, thus, leading to enhanced banking stability. Moreover, strong institutions can promote transparency and disclosure, which can reduce banks adverse selection and excessive risk-taking. As pointed out earlier, we construct a composite measure of the quality of institutions using PCA based on Kaufmann et al. (2011) six governance indicators. We anticipate the quality of institutions to have a negative effect on banks asset portfolio risk.

We find mixed evidence on the effects of real interest rates on banks risk. Ghosh (2015) suggests that an increase in real interest rates makes it more expensive for borrowers to service their debts, and this may lead to increased loan defaults. In contrast, Baselga-Pascual et al. (2015) show that low-interest rates make banks assume more risk in search of higher returns. We are therefore unsure about the direction of the relationship between real interest rates and banks asset portfolio risk. We measure real interest rate by adjusting the lending rate for inflation.

Finally, we use GDP growth to account for the effects of macroeconomic conditions on banks asset portfolio quality. According to Baselga-Pascual et al. (2015), lower rates of growth are associated with less stable economic conditions and thus higher probability of distress by banks. However, banks may tend to increase their lending during favourable economic conditions in search of higher returns, which may negatively affect their stability. Consequently, we are unsure about the expected sign for the coefficient of GDP growth. As stated earlier, we measure GDP growth as the annual percentage change in real GDP.

3.5.3 Robustness Test

We use two alternative measures of asset portfolio risk to check the robustness of our results. First, we employ the Z-score following previous studies by Laeven and Levine (2009), Berger

et al. (2014) and Ahamed and Mallick (2019), among others. We calculate the Z-score by dividing the sum of return on assets (ROA) ratio and the capital to assets ratio by the standard deviation of ROA, (ROA + E/A)/SDROA. The Z-score captures the likelihood of default by a bank by showing the number of standard deviations that a bank ROA has to decrease before it depletes its capital and becomes insolvent (Beck et al., 2013; Dwumfour, 2017). Therefore, lower values of the Z-score indicate increased volatility in assets returns hence higher risk. Because our Z-scores are highly skewed, we use the log of the Z-scores following past studies by Bermpei et al. (2018) and Teixeira et al. (2020).

Secondly, we use the "ratio of risk-weighted assets, to banks' total assets" (RWAtoTA). The risk-weighted assets ratio is a widely used proxy in the literature for measuring banks asset portfolio risk (Avery & Berger, 1991; Basel Committee on Banking Supervision, 2011; Stolz & Wedow, 2011). This ratio allocates risk across different assets categories, allowing inferences on the banks' portfolio risk structure. Moreover, Berger et al. (2014) note that this ratio is more likely to reflect the changes in the asset portfolio risk of banks.

3.5.4 Estimation Technique

We employ a dynamic two-step system Generalized Methods of Moments (GMM) estimator suggested by Arellano and Bover (1995), which has been applied in prior related studies (e.g., Tabak et al., 2012; Bermpei et al., 2018; Shim, 2019). The system GMM uses first difference transformation to eliminate fixed-effects and lagged values of the dependent and independent variables as instruments to handle possible endogeneity (Abuzayed et al., 2018; Radivojević et al., 2019). Thus, the system GMM addresses the possible endogeneity problems between our asset portfolio risk measures and our response to competition and bank-specific variables.

In addition, it accounts for the unobserved heterogeneity as well as the persistence of bank risk (Saif-Alyousfi et al., 2018). We prefer the two-step GMM because it is considered to be more robust compared to the alternative one-step GMM estimator (Louzis et al., 2012). Furthermore, we employ the two-step system GMM with robust adjusted standard errors in order to obtain inferences that are more accurate (Windmeijer, 2005). We opted for forward orthogonal deviations transformation because our data is unbalanced.

Similar to other studies (e.g., Álvarez et al., 2018; Shim, 2019; Teixeira et al., 2020), we treat as endogenous the lagged dependent variable and bank-specific controls and treat as exogenous macroeconomic controls. We use collapse option to avoid the proliferation of our instruments. We apply the Arellano-Bond test (AR) to detect the presence of first-order AR(1), and second-

order AR(2) serial correlation. The presence of second-order AR(2) serial correlation makes the GMM estimator to be inconsistent (Saif-Alyousfi et al., 2018). Finally, we test the validity of our instruments by using the Hansen test of over-identifying restrictions. Hansen test p-values of between 0.1 and 0.25 indicate that the GMM instruments are valid (Roodman, 2006).

3.6 Banking Industry Response to Competition for the Financial Inclusion Project and Social Performance

3.6.1 Model Specification and Estimation Technique

To estimate how the responses to financial inclusion affect the social performance of banks in Africa, we construct a linear regression model whereby we relate "banking industry response to competition" and social performance. The estimation equation is as follows:

$$SP_{\mathrm{jt}} = \propto \ + \beta_1 \ \mathrm{Response}_{\mathrm{jt}} + \sum_{k=2}^{k} \beta_{\mathrm{k}-1} \mathrm{X}_{\mathrm{jt}} + \ \acute{\epsilon}_{\mathrm{jt}} \qquad (3.9)$$

Where SP_{jt} is a measure of social performance of bank j at year *t.* Response is our measure of the banking industry response. $\propto$ is the y-intercept while X denote our set of control variables. $\mathrm{B}_1 \mathrm{to} \ \beta_k$ are the coefficients of the explanatory variables while $\acute{\epsilon}$ is the error term. We use four commonly used measures of social performance; breadth of outreach, depth of outreach, number of ATMs and the number of bank branches (Hartarska, 2005; Assefa et al., 2013; Cull et al., 2014; Gopalan & Rajan, 2018). We measure the breadth of outreach as the logarithm of the total number of borrowers from commercial banks at the end of each period. A higher number of borrowers will indicate deeper outreach.

On the other hand, we measure the depth of outreach as the loan size per borrower divided by the gross national income (GNI) following previous studies (e.g., Quayes, 2012; Cull et al., 2015; Bibi et al., 2018). We calculate the loan size per borrower as the ratio of outstanding commercial banks' loans to households and SMEs to the total number of borrowers. Higher average loan sizes show that banks are serving relatively lesser poor clients. Furthermore, we measure the number of ATMs as the log number of ATMs per 100,000 adults. Lastly, we calculate the number of bank branches as the ratio of the number of commercial bank branches per 100,000 adults. We estimate our equations using a fixed-effects models, following previous related studies by Mersland and Strøm (2009),Vanroose and D'Espallier (2013) and Beisland et al. (2017). We proxy our target independent variable using the "ratio of banks' households and SMEs loans, to banks' gross loans."

3.6.2 Control Variables

Following other studies (e.g., Assefa et al., 2013; Vanroose & D'Espallier, 2013; Cull et al., 2014), we control for bank-specific variables, and institutional and macroeconomic variables that may affect banking industry social performance (outreach). Under bank-specific variables, we include bank size, capital and age in our model. Large banks may enjoy scope and scale economies in providing financial services which can allow them to be more efficient, resulting in better outreach (Beck et al., 2005; Hermes & Hudon, 2018). Additionally, larger banking institutions may have better outreach due to their ability to cross-subsidize their revenues (Vanroose & D'Espallier, 2013). We thus anticipate a positive coefficient for bank size. As previously stated, we measure bank size as the log of total assets.

According to Berger and Bouwman (2013), capital is a source of economic strength and competitive advantage. Accordingly, banks that are highly capitalized can be able to increase their outreach more efficiently. We thus anticipate capital to be positively associated with our outreach measures. We measure capital as the ratio of total equity to total assets. Bank age controls for learning effects and management experience in the performance of a bank. Wijesiri et al. (2017) note that banks can be able to enhance their outreach performance as they gain increased market experience in implementing suitable outreach models. We thus expect bank age, which we measure as the log of the number of years since the inception of a bank, to have a positive coefficient.

For institutional and macroeconomic variables, we control for quality of financial development, quality of institutions, population, inflation, and GDP growth. Ahlin et al. (2011) and Vanroose and D'Espallier (2013) note that well-developed financial markets provide incentives for banks to advance financial services beyond the rich. In addition, developed financial systems are associated with higher competition in the provisioning of financial services and this may enable banks to increase their outreach (Hermes & Hudon, 2018). We, therefore, expect the coefficient of financial development to have a positive sign. As stated earlier, we use PCA to measure quality of financial development which comprises stock market capitalization to GDP, stock value traded to GDP and the ratio of private credit to GDP.

The surrounding institutional environment may influence the social performance of banks. For example, Im and Sun (2015) show evidence that increased institutional quality enhances trusting relationships between borrowers and lenders. This may increase the demand for financial services, which can encourage banks to increase their outreach. Consequently, we

anticipate a positive relationship between the quality of institutions and banks social performance. As indicated earlier, we construct a composite index for institutional quality using PCA comprising the six governance indicators of political stability, control of corruption, the rule of law, the absence of violence and regulatory quality.

Banks may have higher outreach in areas that are densely populated because of the larger customer base and lower operating costs (Nanayakkara & Mia, 2012; Ray & Mahapatra, 2016). Thus, we expect population, as measured by the log of a country's total population, to have a positive coefficient. According to Boyd et al. (2001) and Ahlin et al. (2011), higher inflationary environment makes it difficult for lenders and borrowers to contract, which may affect the outreach of banks. Accordingly, we anticipate a negative relationship between bank social performance and inflation. In contrast, growth in the economy can provide the appropriate conditions for households and SMEs to borrow and for banks to expand their services. We thus expect the coefficient of GDP growth to have a positive coefficient.

3.6.3 Robustness Tests

To check for robustness of our results, we use our two alternative measures of banking industry response to competition for the financial inclusion paradigm: The "ratio of banks' households and SMEs loans, to credit to the private sector," and the "ratio of banks' households, SMEs and agriculture loans, to the population living below the poverty line."

CHAPTER FOUR

ANALYSES AND DISCUSSIONS

4.1: Banking Industry Response to the Competition for the Financial Inclusion Paradigm

4.1.1 Introduction

In this section, we present the analyses results of the first research question**.** As indicated in the methodology chapter, we use the "ratio of MFIs' loans, to credit to the private sector" (MFIs loans to CPS) as the target-independent variable for the baseline regression model. This ratio relates to MFIs' market share (or likely influence) in the low-income market. For our dependent variable, we use the "ratio of banks' loans to households and SMEs, to credit to the private sector" (HHSMEs to CPS) to measure banking industry response to competition from the financial inclusion paradigm. As also stated earlier, we use two alternative measures of MFIs' market share (influence) and banking industry response to check the robustness of the baseline regression results.

First, we use the "ratio of MFIs' assets, to the population living below the poverty line" (MFIs assets to poverty) as the predictor variable and the "ratio of banks' loans to households, SMEs and agriculture, to the population living below the poverty line" (HHSMEs Agric loans to poverty) as the response variable. Secondly, we use the "ratio of MFIs' gross loans, to the total of banks' loans to household and SMEs" (MFIs loans to HHSMEs) and the "ratio of banks' loans to households and SMEs, to banks' gross loans" (HHSMEs to gross loans), as the independent and dependent variables, to measure MFIs' market share and banking industry response, respectively.

For the regression estimation, we include several control variables: banks' return on assets (banks ROA), banks' efficiency, Gini-coefficient, quality of financial development, quality of institutions, population, and GDP growth. Lastly, and as explained in our methodology chapter, we use 'differenced transformation' for the variables with unit root problem. We start our analyses by providing a summary of our descriptive statistics, followed by graphical trends in MFIs' market share and banking industry response proxy. We then show the results of our correlation analyses. And finally, we present the results of our regression analyses, including the associated robustness checks.

4.1.2 Summary Statistics of MFIs Market Share and Banking Industry Response Variables

Table 4.1a: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Dependent Variables					
HHSMEs loans to CPS	0.0003	0.0002	3.40E-07	0.001	1,368
HHSMEs Agric. loans to poverty	0.32	0.264	0.015	0.636	1,368
HHSMEs to gross loans	0.358	0.236	0.0004	0.914	1,368
Independent Variables					
MFIs loans to CPS	0.0001	8.07E-05	4.50E-08	0.0003	1,674
MFIs assets to poverty	0.009	0.010	0.00001	0.047	1,631
MFIs loans to HHSMEs	0.420	0.280	0.229	0.968	1,368
Banks-Specific Variables					
Banks ROA	0.014	0.025	-0.282	0.140	1,934
Banks efficiency	0.077	0.030	0.035	0.129	1,930
Institutional and Macro-economic variables					
Gini coefficient	0.423	0.088	0.298	0.680	1,622
Financial development	0.092	0.203	0.012	1.388	1,622
Quality of institutions	0.453	0.573	-0.723	1.875	1,699
population (millions)	52.4	42.4	11	190	1,699
Population (log)	7.582	0.371	6.027	8.281	1,699
GDP growth	0.052	0.028	-0.043	0.140	1,631

Notes: Table 2 above presents descriptive statistics of our test variables. HHSMEs loans to CPS is the "ratio of banks' loans to households and SMEs, to credit to the private sector." HHSMEs Agric. loans to poverty is the "ratio of the total of banks' loans to households, SMEs and agriculture, to the population living below the poverty line." HHSMEs to gross loans is the "ratio of banks' households and SMEs loans, to gross banks' loans." MFIs loans to CPS is the "ratio of MFIs loans to credit to the private sector." MFIs assets to poverty is the "ratio of MFIs assets to the population living below the poverty line." We define MFIs loans to HHSMEs as the "ratio of MFIs total loans to total banking industry loans to households and SMEs." Banks ROA is banks return on assets measured as commercial banks' profits divided by total assets while banks efficiency is commercial banks operating costs to gross loans ratio. Gini coefficient is the measure of wealth distribution. Financial development is calculated using principal component analyses (PCA), and it comprises stock market capitalization to GDP, stock market turnover to GDP and credit to the private sector to GDP. Similarly, the quality of institutions is calculated using PCA from the Kaufmann six indicators of governance (institutions). Population (log) is the logarithm of population and GDP growth is the change in GDP. Source: IMF financial access survey: Mix market; World Development Indicators.

Table 4.1a presents the summary statistics of the variables that we use in the first empirical estimations of our baseline model. Looking first at the proxies for the dependent variable, the mean value of "banks' loans to households and SMEs divided by credit to the private sector"

(the banking industry response variable) is 0.0003, suggesting that the banking industry's credits to clients they generally deem opaque/high risk, is relatively small in terms of overall credits extended to non-government agents by financial intermediaries (dominated by banks), perhaps mainly because it involves extending micro-small credit amounts to this group of typical "financially excluded" (Mersland & Strøm, 2010). For, the average "financial inclusion paradigm" proxy – i.e., "banking industry's loans to households and SMEs divided by credit to the private sector" – it is expectedly quite small, 0.0001. Furthermore, approximately a third of the loans issued by banks are channelled towards households and SMEs, as shown by the mean "ratio of household and SMEs loans to gross loans" of 0.358.

For our measures of MFIs market share, the average for MFIs loans divided by credit to the private sector is 0.0001. This suggests that the microfinance industry is relatively small, mainly because it involves making microcredit to the poor (Beisland et al., 2017). This is further shown by the low mean ratio of MFIs assets to the population living below the poverty line 0.009. Furthermore, the summary statistics in Table 4.1a indicate that banks offer almost twice as much loans to low-income earners in comparison to MFIs as evidenced by the average ratio of MFIs gross loans to the total of bank loans to household and SMEs of 42 %. This can be explained by the lower leverage ability of MFIs as compared to banks (Donou-Adonsou & Sylwester, 2017).

According to Table 4.1a, the banks in the countries that we included in our sample have an average ROA of 1.4% and a mean efficiency (inefficiency) of 7.7%. The low ROA may be due to the increasing competition in the African banking industry as shown by Sarpong-Kumankoma et al. (2017). Regarding our institutional and macroeconomic variables, the countries sampled show a high level of income inequality as highlighted by the average Gini coefficient of 42.4%. This is expected as African countries tend to exhibit consistently higher levels of inequality (Shimeles & Nabassaga, 2017). Unsurprisingly, there are wide variations in terms of financial development in our sample with the quality of financial development ranging between 0.012 and 1.388[30], while the quality of institutions has an average of 0.453.

The wide variation in financial development between different African countries can be attributed to a variety of diverse factors like political stability, income levels and resource endowments (Mecagni et al., 2015a). In contrast, Tunyi and Ntim (2016) observe that the low

[30] For instance, in terms of financial markets depth, South Africa is ranked at position 18 while Rwanda is ranked at position 145 (Svirydzenka, 2016).

quality of governance results due to poor governance both in resource endowment and developing countries in the region. Similarly, there is a high variation in the continent's population, as shown by the standard deviation of 0.371. This may be explained by a number of factors, including differences in country sizes, HIV prevalence and child mortality rate (Christiaensen & Hill, 2019). Finally, GDP growth has an average of 5.2% following earlier predictions by the World Bank (2014) of growth above 5% in Africa. Chummun and Ojah (2016) argue that the growth in GDP may be attributed to the increased access to finance.

4. 1.3 Trend in MFIs Market Share and Banking Industry Response

To evaluate banking industry response to competition for financial inclusion paradigm in Africa, we begin by presenting the trend in MFIs market share (influence) and banking industry response, using our three measures of MFIs market share and banking industry response, respectively. Figure 4.1a below shows the trend in MFIs market share and banking industry response as measured by MFIs loans to credit to the private sector and the ratio of bank loans to household and SMEs to credit to the private sector, respectively. The amount of loans issued by banks to households and SMEs roughly increase and decrease at the same rate except in 2016 when there was a drastic decrease in MFIs loans and an increase in bank loans to households and SMEs. According to Bartillat et al. (2017), the sharp decline in MFIs loans start from 2016 may be due to increased competition from banks.

Figure 4.1a: Trend in MFIs market share and banking industry response.

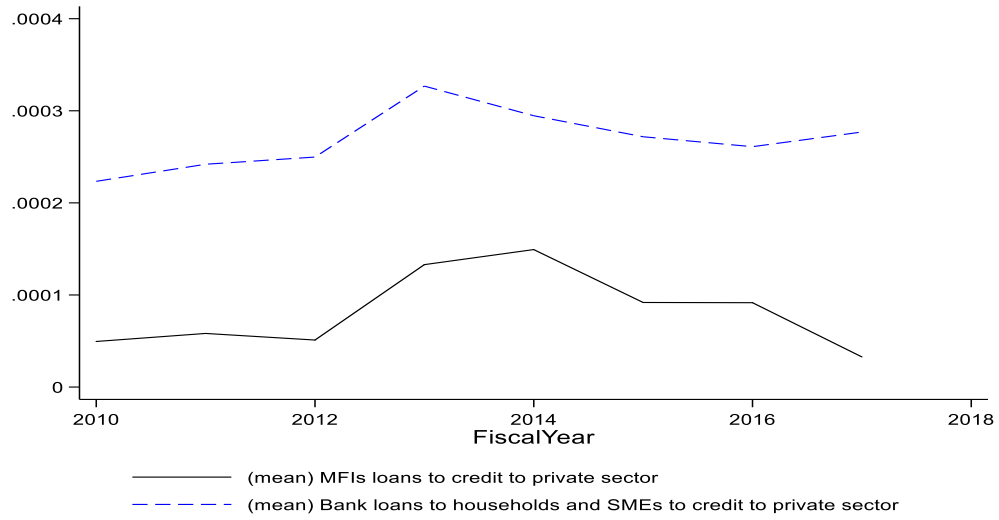
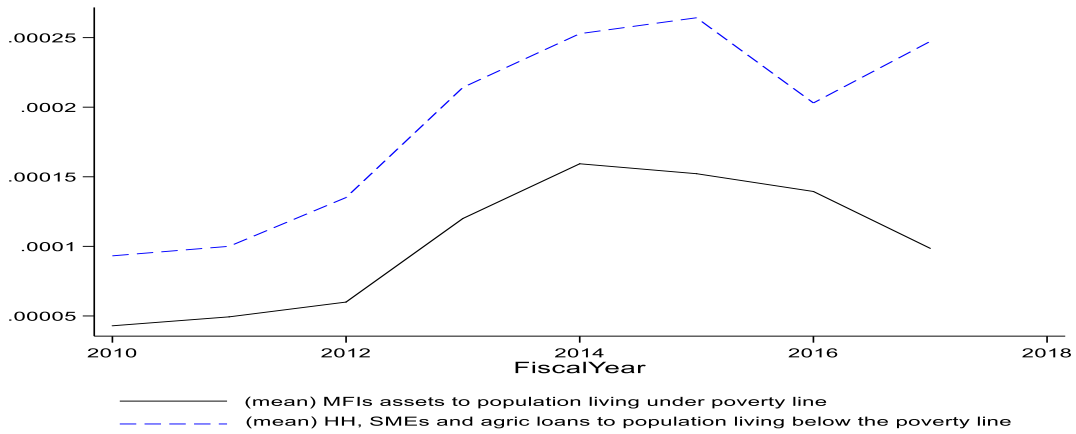


Figure 4.1a also shows that there was a rapid increase in the amount of loans to the low-income market between 2012 and 2014. This may be explained by efforts to promote financial

inclusion as well as the increased flow of funds to emerging and developing countries that made financial institutions to be more liquid (Garcia-Escribano & Han, 2015). However, from 2014 there is a notable decline in the amount of loans offered by both banks and MFIs. The uncertainty, mixed sentiments, and volatility in the global economy in 2014 could have contributed to the decline in the amount of credit extended to households and SMEs (PWC, 2016b).

In Figure 4.1b below, we show the trend in MFIs market share and banking industry response using the ratio of MFIs assets to the population living below the poverty line and the ratio of bank loans to households, SMEs and agriculture to the population living below the poverty line, respectively. We find a similar trend as in Figure 4.1a. The amount of loans given by banks to households, SMEs and agriculture, increased steadily from 2010 to 2015; however, there was a sharp decline between 2015 and 2016. Similarly, there was a gradual increase in the amount of MFIs assets between 2010 and 2014. However, from 2014, MFIs experienced a decline in their assets.

Figure 4.1b: Change in MFIs market share and banking industry response

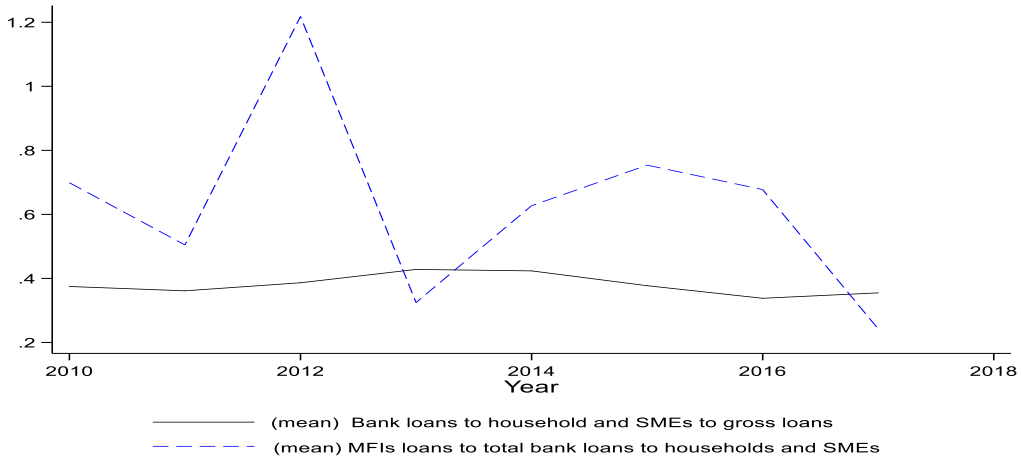


Notes: HHSMEs and Agric loans to the population living below the poverty line is the "ratio of banks' households, SMEs and agriculture loans, to the population living below the poverty line." This ratio has been scaled down by 10000 to aid comparability.

Finally, Figure 4.1c presents the trend in MFIs market share and banking industry response as measured by the "ratio of banks' loans to household and SMEs as a proportion of banks' gross loans," and the "ratio of MFIs total loans to total bank loans to households and SMEs," respectively. Overall, we find a similar trend as in Figure 4.1a and 4.1b above except in 2013

and the period between 2014 and 2016, where the trend in MFIs loans and bank loans move in opposite directions.

Figure 4.1c: Change in banking industry loans to households and SMEs and MFIs loans



As indicated earlier, the reduction in MFIs loans as compared to bank loans to households and SMEs in 2013 may be due to increased liquidity in the banking sector and increased competition for financial inclusion which saw banks increase their lending activities to the low-income market. As stated previously, the decline in bank loans to households and SMEs in 2014 can be associated with the uncertainty and volatility in the global economy during that period. This uncertainty could be expected to affect the financing of banks more than MFIs (due to the social mission focus of MFIs) leading to a decline in loans issued by banks, particularly to the low-income market.

4.1.4 Correlation Analyses of Banking Industry Response and MFIs Market Share Variables

Having presented the trend in MFIs market share and banking industry response in Figure 4.1a, 4.1b, and 4.1c, we proceed further and present our correlation analyses results in Table 4.1b below. Our main measures of banking industry response and MFIs market power (influence) show a low correlation. Nonetheless, most of them indicate a significantly positive coefficient. Notably, is the "ratio of banks' loans to households and SMEs, to credit to the private sector" and the "ratio of MFIs loans, to credit to the private sector."

Table 4.1b: Correlation analyses

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1	HHSMEs loans to CPS	1												
2	HHSMEs Agric. loans to poverty	0.056*	1											
3	HHSMEs to gross loans	0.187***	0.744***	1										
4	MFIs loans to CPS	0.237***	0.023	0.016	1									
5	MFIs assets to poverty	-0.182***	0.442***	0.490***	0.100***	1								
6	MFIs loans to HHSMEs	0.095***	0.048*	0.037	0.780***	0.149***	1							
7	Banks ROA	0.04	-0.013	0.001	0.028	0.001	0.031	1						
8	Banks efficiency	-0.081***	-0.378***	-0.157***	0.001	-0.036	-0.012	0.249***	1					
9	Gini coefficient	0.032	-0.117***	-0.073**	-0.023	-0.146***	-0.064**	-0.004	0.034	1				
10	Financial development	0.161***	0.414***	0.492***	0.025	-0.078***	0.014	-0.080***	-0.210***	-0.008	1			
11	Quality of institutions	0.005	0.524***	0.609***	-0.025	0.238***	-0.060**	-0.033	-0.056**	-0.068**	0.567***	1		
12	Population (log)	0.070**	-0.034	-0.138***	-0.013	-0.074***	0.071**	0.001	-0.158***	0.104***	0.081***	-0.388***	1	
13	GDP growth	-0.070**	-0.396***	-0.332***	0.008	-0.084***	0.026	0.095***	0.240***	0.106***	-0.353***	-0.122***	0.077***	1

Notes: Table 4.1b shows the correlation between the "ratio of banks' loans to household and SMEs, to credit to the private sector" (HHSMES loans to CPS), the "ratio of banks' loans to households, SMEs and agriculture to the population living below the poverty line" (HHSMEs Agric. to poverty), the "ratio of banks' loans to household and SMEs, to banking industry gross loans" (HHSMEs to gross loans), "MFIs loans to credit to the private sector" (MFIs loans to CPS), "MFIs assets to the population living below the poverty line" (MFIs assets to poverty), the "ratio MFIs loans to bank loans" (MFIs loans to HHSMEs), banks ROA, banks efficiency, Gini coefficient, quality of financial development and quality of institutions, population (log) and GDP growth. ***, ** and * indicate statistical significance at 1%, 5% and 10% correspondingly. The variables are defined as per Table 2. Source: Author calculations.

We find a weak relationship between our bank specific variables (banks ROA and efficiency) and our banking industry response variables. However, the coefficients for banks efficiency are negative and significant. This is perhaps because of the higher transaction and information costs associated with serving low-income clients that may be a source of inefficiencies (Le et al., 2019) Gini coefficient has a largely negative and significant coefficient, suggesting that lending by banks is considerably affected by inequalities in income. This can be expected since providing financial services to low-income earners is costly, hence the borrowing capacity of the poor may decline as a result of high levels of inequality (Baumann, 2004).

According to the results in Table 4.1b, financial development and quality of financial institutions have a positive and significant association with our banking industry response measures. This is perhaps because banks are able reach more clients including low-income earners in countries that have more developed financial sectors (Vanroose & D'Espallier, 2013). Conversely, high-quality institutions facilitate enforcement of contracts and reduction of intermediation costs which increases the confidence of banks, particularly in lending to opaque borrowers (Churchill, 2019). Population has a mainly negative relationship with our banking industry response measures.

Vanroose (2008) observes that MFIs are more developed in areas with high population of micro-borrowers, hence the demand for banks may not be present. Lastly, we find a significantly negative correlation between GDP growth and our banking industry response variables, implying that lending by banks to households and SMEs declines with growth in the economy. This is possibly because the demand for small microloans may decline in a higher growth economy due to a shift in low-income borrowers wealth as shown by Ahlin et al. (2011). Our results in Table 4.1b show a low correlation between our independent variables, suggesting that our model would not have a concerning multicollinearity problem.

4.1.5 Regression Analyses of Banks Response to Financial Inclusion Paradigm

Table 4.1d presents the regression results of our baseline model. We find a positive and statistically significant relationship between the "ratio of banks' households and SMEs loans, to credit to the private sector" and the "ratio of MFIs loans, to credit to the private sector" (i.e., proxy for financial inclusion) (with coefficients of 0.155, and t-stats of 5.15 and 4.90 for models 1 and 2, respectively). This suggests that increased attention to (or competition) for financial inclusion, induces banks to increase lending to previously under-served segments of the market.

Table 4.1d: Regression of financial inclusion, using the "ratio of banks' households and SMEs loans, to credit to the private sector" as banks" response variable.

VARIABLES	HHSMEs loans to CPS (1)	HHSMEs loans to CPS (2)
MFIs loans to CPS	0.155*** [5.15]	0.155*** [4.90]
	(0.030)	(0.032)
Banks ROA	5.80e-05 [0.96]	5.80e-05 [0.86]
	(6.07e-05)	(6.76e-05)
Banks efficiency	6.14e-05 [0.75]	6.14e-05 [0.69]
	(8.17e-05)	(8.88e-05)
Gini coefficient	0.0001 [1.56]	0.0001* [1.65]
	(6.87e-05)	(6.50e-05)
Financial development	0.0001*** [13.15]	0.0001*** [9.00]
	(8.20e-06)	(1.20e-05)
Quality of institutions	6.16e-05*** [4.36]	6.16e-05*** [6.27]
	(1.41e-05)	(9.83e-06)
Population (log)	-0.001*** [-6.52]	-0.001*** [-3.37]
	(0.0002)	(0.0002)
GDP growth	-5.13e-07 [-0.00]	-5.13e-07 [-0.01]
	(0.0001)	(8.82e-05)
Constant	0.008*** [6.50]	0.008*** [3.35]
	(0.001)	(0.002)
Observations	1,084	1,084
F-test	0.000	0.000
R-squared	0.197	0.334
Hausman test (p-value)	0.000	
Time fixed effects	Yes	Yes
Number of bank_id	177	

Notes: In this Table, we regress the "ratio of banks' loans to household and SMEs, to credit to the private sector" (HHSMES loans to CPS), and the "ratio MFIs loans, to credit to the private sector (MFIs loans to CPS)." We control for banks ROA, banks efficiency, Gini coefficient, financial development, institutional quality, population (log) and GDP growth. We employ a fixed-effects model (FE) with year dummies based on the results of the Hausman test and the time fixed effects test. We also report the R-squared after incorporating the effects of the dummy variables in model 2. T-statistics are in brackets, and Heteroscedastic robust standard errors are in parentheses. *** and * indicate statistical significance at 1% and 10% correspondingly. Source: Author calculations.

This finding supports the "market power hypothesis," which argues that competition prompts banks to reduce their lending costs and increase the availability of funds to relatively opaque borrowers, which ordinarily would not have been considered worthy of receiving banks' credit. Our results are in line with prior related studies (e.g., Vanroose & D'Espallier, 2013; Cull et

al., 2014; Pham et al., 2019; Leon & Baraton, 2021), which documented evidence that competition pushes financial institutions to increase their loan output in order to grow and/or sustain their market share.

It is noteworthy that not only does the financial inclusion paradigm proxy elicit positive statistically significant response from the banking industry, its statistical impact is among the highest (with only the level of financial development and institutional quality, expectedly, among control variables to record similarly high statistical impacts). Furthermore, their coefficients are also the most economically important amongst all independent variables of our baseline model. Moreover, the overall model fit is significant, with our independent variables explaining 20-33.4% of the variation in the banking industry's response to financial inclusion paradigm (according to the R-squared of models 1 and 2 in Table 4.1d).

For the bank-specific variables, which constitute part of our model's control variables, ROA and banking efficiency are both positively but insignificantly related to our measure of banks' response to the financial inclusion paradigm; thus, suggesting that the amount of loans extended to the under-served and/or often financially excluded groups – i.e., households and SMMEs – is not affected by banks' profitability. This is perhaps because, per the intermediation theory of banking, banks depend on deposits to fund their loan creation activity rather than their own financial performance by way of undistributed profits (Sanfilippo-Azofra et al., 2019). The efficiency of banks, depending on the nature of competition in the market, could have bank efficiency relate either positively or natively to a bank's production activity (Godspower-Akpomiemie & Ojah, 2021).

Turning to the other variables that would naturally influence banks' credit extension activity (i.e., control variables), income inequality, measured by the Gini coefficient, is positive and marginally associated with bank's response to financial inclusion competition. Interestingly, income inequality is one of the factors responsible for demarcating low-income earners and micro-small businesses, from the traditional 'financially included' (Alhassan, 2015; Lessmann, 2016). Therefore, it can be said to provide a large target market for banks that now decide to reach out to the traditional "financially excluded" by participating in the financial inclusion project.

Expectedly, two of the factors that are arguably traditional determinants of effective banking activity – e.g., level of financial development and quality of institutions – are positively related to banks' response to the call of the financial inclusion paradigm. High financial development,

by its very definition, implies a national financial system where financial institutions and markets are 'well-networked' to enable effective: financial intermediation, payments services mechanism, and the like, in support of producing firms and government units. Therefore, our result reflects the complementarity of other financial institutions and markets in fostering banks' credit extension activity (Ojah & Kodongo, 2015; Donou-Adonsou & Sylvester, 2016; Gyeke-Dako et al., 2018; and Hermes & Hudon, 2018).

Similarly, quality institutions have been shown to be important prerequisites for cost-effective banking; and this is particularly so in developing and emerging market economies where there is immense need for financial markets to become fuller spanned by assorted financial services firms, most of which need robust banks as an important partner, in their operations (Baselga-Pascual et al., 2015, Godspower-Akpomiemie & Ojah, 2021; and others). Population has a negative and statistically significant relationship with banks' response to the financial inclusion paradigm. This confirms recent findings by Im and Sun (2015), which reinforce the near empirical regularity that banks tend to gain competitive advantage in areas, such as cities, that have a high population density, and not necessarily in populous countries with its people mainly distributed across many sparsely populated rural dwellings – as is the case in many African countries.

This may also suggest that competition may push MFIs to the fringes of the market as banks locate themselves in the characteristic banking-beneficial densely populated areas, such as cities. Interestingly and contrary to our expectations, we find a negative association between GDP growth and banking industry response variable. According to Ahlin et al. (2011) and Lassoued (2017), an increase in GDP reflects higher income flows for small borrowers and, therefore, better solvency, hence lower demand for loans.

4.1.6 Regression Analyses Using Alternative Banking Industry Response and MFIs Market Share Measures

In Table 4.1e, we undertake additional estimation using the "ratio of MFIs assets, to the population living below the poverty line" as our target independent variable, and the "ratio of banks' loans to households, SMEs and agriculture, to the population living below the poverty line" as our dependent variable (i.e., reflecting banks' response to the financial inclusion paradigm). The rationale behind the use of MFIs' assets is because MFIs are involved primarily in the business of providing financial services to the poor and micro-small ventures. Therefore, the expansion of their assets (almost all of which are naturally interest-earning assets) can be

considered as an indicator of their competitiveness in the low-income market (Liñares-Zegarra & Wilson, 2018). Additionally, focusing on the 'population living below the poverty line', engages quite directly with the segment of society from which the most "financially excluded" groups emanate. Similar to our previous empirical analysis, we estimate the regression model using fixed effects (per the Hausman test outcome).

Table 4.1e: Regression of financial inclusion, using the "ratio of banks' households, SMEs and agriculture loans to the population living below the poverty line" as bank's response variable

VARIABLES	HHSMEs Agric. to poverty (1)	HHSMEs Agric. to poverty (2)
MFIs assets to poverty	2.870*** [10.76]	2.870*** [10.76]
	(0.267)	(0.234)
Banks ROA	-0.079 [-1.34]	-0.079 [-1.34]
	(0.059)	(0.050)
Banks efficiency	0.098 [1.06]	0.098 [1.06]
	(0.092)	(0.082)
Gini coefficient	0.362*** [6.84]	0.362*** [6.84]
	(0.053)	(0.043)
Financial development	0.022*** [2.65]	0.022*** [2.65]
	(0.008)	(0.008)
Quality of institutions	0.085*** [7.37]	0.085*** [7.37]
	(0.012)	(0.007)
Population (log)	-0.757*** [-3.73	-0.757*** [-3.73]
	(0.203)	(0.182)
GDP growth	-0.191*** [-4.46]	-0.191*** [-4.46]
	(0.043)	(0.051)
Constant	6.025*** [3.88]	6.025*** [3.88]
	(1.552)	(1.396)
Observations	1,084	1,084
F-test	0.000	0.000
R-squared	0.448	0.992
Hausman test (p-value)	0.000	
Time fixed effects	Yes	Yes
Number of bank_id	177	

Notes: Table 4.1e above shows the regression results of the "ratio of bank loans to households, SMEs and agriculture, to the population living below the poverty line" (HHSMEs Agric. to poverty) and the "ratio of MFIs assets, to the population living below the poverty line" (MFIs assets to poverty). The control variables include: banks ROA, banks efficiency, Gini coefficient, financial development, quality of institutions, population (log) and GDP growth. South Africa has been eliminated from the analyses since agriculture in South Africa is mainly undertaken on a large-scale basis. As stated earlier, we report the R squared provided after including the effects of the dummy variables in model 2. T statistics are in brackets. Standard errors in parentheses are heteroscedastic robust. *** indicate statistical significance at 1%.

Our results are largely consistent with our baseline model's results. Table 4.1d shows that our model explains 61.7% of the variations in assets that banks dedicate to provisioning financial services to the poorer segment of the population (i.e., proxy of banks' response to the financial inclusion paradigm). The coefficient of the relations between our measure of financial inclusion and banking industry's response to it, remains statistically significant, with a positive coefficient (2.87 for both models 1 and 2, with corresponding t-stats of 10.76 for both models). This finding provides further evidence that increased competition for financial inclusion forces banks to increase lending to the low-income market.

Similar to our baseline results, the coefficients for banks ROA and banks efficiency remain insignificant in explaining changes in banking industry loans to households and SMEs. However, Table 4.1e shows that the positive coefficient of the "Gini coefficient" becomes more statistically important at the 1% significance level, further confirming that low-income earners offer a large market for banks as a result of the financial inclusion paradigm shift. Consistent with our baseline findings, both financial development and quality of institutions have a significant and positive coefficient.

Likewise, the coefficient for population remains negative and significant in line with our findings in Table 4.1d. Lastly, GDP growth now becomes statistically significant (and still negatively) related to banks' extension of credit to the financial inclusion paradigm targets. This further confirms our earlier argument that households and SMEs may be able to finance their projects from profits in periods when the economy is growing, and this can in turn reduce the demand for loans from MFIs and other financial intermediaries (such as banks) in general.

4.1.7 Further Test of Robustness

We consider another robustness test of our baseline model about banks' response to competition for financial inclusion, by using yet another alternative measure of MFIs market share and banking industry response proxy. We use the "ratio of MFIs loans, to bank loans to households and SMEs", to measure MFIs market share since MFIs can be able to exert more competitive influence and prevent banks from crowding them out if they offer more loans to low-income earners vis-à-vis the loans to low-income earners by commercial banks (Vanroose & D'Espallier, 2013). In other words, this proxy for the financial inclusion paradigm, matches the overall activity of the financial institution representative of the financial inclusion paradigm (i.e., MFIs) against the credit activities of commercial banks that are more specifically targeted

at the typical audience of the financial inclusion paradigm. We measure banking industry response by using the "ratio of banks' household and SME loans, to banks' gross loans".

Table 4.1f: Regression of financial inclusion, using the "ratio of banks' loans to households and SMEs, to banking industry gross loans" as banks' response variable

VARIABLES	HHSMEs to gross loans (1)	HHSMEs to gross loans (2)
MFIs loans to HHSMEs	0.074*** [4.88]	0.074*** [5.81]
	(0.015)	(0.013)
Banks ROA	0.363** [2.47]	0.363*** [2.93]
	(0.147)	(0.124)
Banks efficiency	0.341* [1.81]	0.341** [2.01]
	(0.188)	(0.170)
Gini coefficient	0.630*** [3.44]	0.630*** [3.40]
	(0.183)	(0.185)
Financial development	-0.027 [-0.57]	-0.027 [-0.68]
	(0.047)	(0.039)
Quality of institutions	0.096*** [4.95]	0.096*** [5.17]
	(0.019)	(0.019)
Population (log)	-5.620*** [-3.92]	-5.620*** [-4.34]
	(1.432)	(1.295)
GDP growth	-0.130** [-2.18]	-0.130 [-1.17]
	(0.060)	(0.112)
Constant	43.22*** [3.95]	43.22*** [4.36]
	(10.96)	(9.909)
Observations	1,073	1,073
F-test	0.000	0.000
R-squared	0.291	0.940
Hausman test (p-value)	0.000	
Time fixed effects	Yes	Yes
Number of bank_id	174	

Notes: In Table 4.1f we present the regression results of the "ratio of bank loans to households and SMEs, to total banking industry loans" (HHSMEs to gross loans) and the "ratio of MFIs' loans, to total banking industry loans to households and SMEs" (MFIs loans to HHSMEs). The control variables include: banks ROA, banks efficiency, Gini coefficient, financial development, quality of institutions, population (log) and GDP growth. As stated earlier, we report the R squared provided after including the effects of the dummy variables in model 2. T statistics are in brackets. Standard errors in parentheses are heteroscedastic robust. ***, ** and * indicate statistical significance at 1%, 5% and 10%. Source: Author calculations.

Again, our results are largely similar to the findings in Tables 4.3d and 4.3e; and thus provide strong robustness support for the findings of our baseline model. Consistent with our prior results, we find a positive coefficient for our measure of banking industry response (with

coefficient of 0.074 for models 1 and 2, and corresponding t-stats of 4.88 and 5.81, respectively). Interestingly, the bank-specific control variables of profitability and efficiency remain positively related to banks' response variable, but they now become statistically significant at the 1% significance levels. Financial development has a negative and insignificant coefficient in contrast to our findings in Tables 4.3d and 4.3e. This inconsistent is likely since in well-developed financial systems households and SMEs may substitute their loans from banks for loans from MFIs as shown by Hermes et al. (2018).

4.2 Efficiency Effects of Banks' Response to the Financial Inclusion Paradigm

4.2.1 Introduction

In this section, we present the analyses results for our second research question. As described in the methodology chapter, we use a two-stage approach to determine the efficiency effect of banking industry response to competition for financial inclusion. In the first stage, we estimate our cost efficiency scores using Data Envelopment Analyses (DEA) under the variable returns to scale assumption. We model banks as multi-product units that employ 3 inputs; labour, physical capital and purchased funds (deposits and borrowed funds) to produce 4 outputs: total loans, off-balance sheet items, deposits and other earning assets. We also estimate the cost efficiency scores whereby we do not include deposits as part of the outputs in the DEA estimation.

Additionally, we employ translog Stochastic Frontier Analyses (SFA) technique, and Simar and Wilson bootstrapping technique to generate robust cost efficiency scores. As noted in the previous section, the SFA technique allows random noise to be isolated from management inefficiency. On the other hand, the Simar and Wilson bootstrapping technique simulates the DEA cost efficiency scores to generate bias-corrected efficiency scores which have a true distribution (Simar & Wilson, 2007; Badunenko & Tauchmann, 2019). In the second stage, we regress the efficiency scores obtained from the first stage against our explanatory variables.

Similar to our previous analyses, we measure banking industry response to competition in financial inclusion paradigm, using the "ratio of banks' households and SMEs loans, to gross loans" (HHSMEs to gross loans), the "ratio of banks' households and SMEs loans, to credit to the private sector" (HHSMES loans to CPS), and the "ratio of banks' households, SMEs and agriculture loans, to the population living below the poverty line" (HHSMEs Agric loans to poverty). As also indicated earlier, we employ fractional probit regression model (FRM) since the DEA efficiency scores are censored between 0 and 1.

For the SFA and the Simar and Wilson bias-corrected DEA efficiency scores, we use maximum likelihood estimation technique (MLE), following relevant past studies (e.g., Huang et al., 2018; Badunenko & Tauchmann, 2019; Jiménez-Hernandez et al., 2019; Cabrera-Suárez & Pérez-Rodríguez, 2020) to estimate the truncated regression model. We begin our analyses by presenting the descriptive statistics for the first stage analyses, followed by a summary of the proportion of efficient and inefficient banks, together with the mean efficiency per year. We then present the descriptive statistics, and the correlation analyses results for the second stage analyses, and we conclude by showing our regression analyses results, including our robustness checks.

4.2.2 Summary Statistics for the Cost Efficiency and Banking Industry Response Variables

Table 4.2a: Descriptive statistics for the efficiency estimation

Variable	Mean	Std. Dev.	Min	Max	Obs
Inputs (Millions 'USD')					
Staff expenses	53.251	180.091	0.052	1,863.740	1,935
Fixed assets	51.049	131.909	0.033	1,244.058	1,935
Deposits and borrowed funds	2,892.215	9,282.375	0.386	90,000	1,935
Outputs (Millions 'USD')					
Gross loans	1783.124	6,738.733	39.895	77,000	1,935
Off balance sheet items	715.270	3,561.376	14.904	126,000	1,935
Deposits	2,766.931	9,002.301	385.771	90,000	1,935
Investment in securities	928.502	3,340.591	33.535	40,900	1,935
Price of inputs					
Price of labour	0.024	0.017	0.0003	0.159	1,935
Price of physical capital	3.997	6.723	0.015	104.091	1,935
Price of funds	0.048	0.087	0.001	2.759	1,935

Notes: Table 4.2a shows the descriptive statistics for our first stage analyses. Staff expenses is the total of personnel costs. Fixed assets is the value of non-current assets of the banks sampled. Deposits and borrowed funds is the total of customer deposits and borrowed funds. Gross loans is the total loans disbursed by the banks included in the sample. Off-balance sheet items is the total of guarantees, acceptances and documentary credit, contingent liabilities and securitized assets. Investment in securities is the value of the total investment in financial assets. We calculate the price of labour as personnel expenses divided by total assets. Price of physical capital is calculated as non-interest expenses divided by fixed assets. Lastly, price of funds is the ratio of interest expenses to total deposits. Source: BankFocus.

Table 4.2a presents the descriptive statistics for our cost efficiency estimation variables. Staff expenses have a mean of 53.251 with a maximum of 1,863.74. The high personnel costs may

be explained by the need for specialized and skilled human resources required to assist banks with IT transformations, and also to help meet evolving compliance requirements and cyber risks (PWC, 2018). Fixed assets have an average of 51.049 with a minimum of 0.033. Furthermore, we find a high variation in the amount of deposits and borrowed funds of the sampled banks as shown by the standard deviation of 9282.375. This may be attributed to the disparities in banking industry depth and cost of funding[31] in different countries in the region (Nyantakyi & Sy, 2015; Chironga et al., 2018).

Similarly, we find a high variation in the amount of loans issued by the sampled banks as shown by the standard deviation of 6,738.733 with a minimum and a maximum of 39.875 and 77,000, respectively. According to Beck and Cull (2014), the high variation in gross loans may be due to differences in the demand for credit and banking development in the continent.[32] The mean for off-balance sheet items is 715.270, suggesting increased focus on non-traditional sources of income by banks in Africa. Deposits have a mean of 2,766.931, which is approximately twice the amount of loans issued by the studied banks, while the average for investment in securities is 928.502.

The high gap between deposits and loans, and the substantial investment in securities, confirms the preference for banks in the region to invest in safer government securities at the expense of private sector lending as shown by Allen et al. (2011) and Ojah and Kodongo (2015). According to Table 4.2a, personnel expenses comprise 2.4% of the total assets of the banks sampled. This is probably because of the continued efforts by banks to move-staff to higher value work by deploying digital and artificial intelligence labour (PWC, 2018). The ratio of non-interest expenses to fixed assets has a mean of 3.997, reflecting inefficiency in African banks cost management. Lastly, interest expenses comprise 4.8% of the total deposits of the banks studied. The low deposit rate confirms previous findings by Stijns and Pelletier (2018) that banking markets in Africa are characterized by high lending rates and low rates for deposits.

Table 4.2b shows the distribution of efficient and inefficient banks together with mean efficiency score per year (see Figure A1 in the Appendix for detailed graphical presentation of

[31] For instance, the interbank rate in the Gambia for 2016 was 13.67 as compared to 6.75 for Egypt for the same year (Central Bank of Egypt, 2016; Central Bank of the Gambia, 2016). Consequently, the high funding cost in the Gambia necessitates banks to mobilize more deposits so as to fund their lending activities.

[32] Smaller and poorer countries like Central African Republic and Burundi, for example, have shallow banking systems that offer limited credit compared to countries like South Africa and Mauritius that have a developed banking system that offers significant credit denominations to the private sector (Mlachila et al., 2013).

the distribution of cost efficiency scores). In general, we find an increase in the number of efficient banks and the mean efficiency from 2010 to 2017. This may be due to increased focus on structural cost-reduction programmes like migrating customers to digital channels and investing in information technology aimed at enhancing efficiency and simplifying banks business process (Chironga et al., 2018).

Table 4.2b: Ratio of efficient and inefficient banks and mean efficiency

	Proportion		
Year	Efficient	Inefficient	Mean
2010	0.063	0.936	0.471
2011	0.084	0.916	0.509
2012	0.088	0.912	0.562
2013	0.089	0.911	0.553
2014	0.088	0.912	0.560
2015	0.085	0.915	0.590
2016	0.094	0.906	0.591
2017	0.098	0.902	0.576

Notes: This Table presents the proportion of efficient and inefficient banks and the mean efficiency score per year based on the DEA results. We categorize a bank as efficient if it has a cost-efficiency score equal to one and inefficient if the efficiency score is less than one. Source: Author calculations.

Table 4.2c shows the descriptive statistics for our second stage analyses. The DEA cost efficiency has a mean of 0.552, which suggests that banks in the region have a substantial potential to improve their cost management. This is further supported by the mean of the robust cost efficiency score of 0.467. The mean for SFA cost efficiency is 0.317 with most of the SFA parameter estimation variables having a significant coefficient (see Table A2 in Appendix). This indicates that our SFA cost efficiency scores are reliable. Furthermore, we find a high variation between the cost efficiency scores estimated using DEA and those estimated using SFA. According to Silva et al. (2017), the difference between the DEA and the SFA efficiency results is due to the fact that the DEA does not incorporate random shocks (error term) when establishing the efficient frontier.

Table 4.2c: Descriptive statistics of second stage analyses

Variable	Mean	Std. Dev.	Min	Max	Obs
Dependent variables					
DEA cost efficiency	0.552	0.238	0.098	1	1,935
DEA robust cost efficiency	0.467	0.255	0.007	1	1,935
SFA cost efficiency	0.317	0.105	0.089	0.915	1,929
Simar & Wilson bootstrapped cost efficiency	0.010	0.008	0.001	0.057	1,935
Independent variables					
HHSMEs to gross loans	0.359	0.237	0.0004	0.914	1,420
HHSMES loans to CPS	0.0003	0.0002	3.40E-07	0.001	1,416
HHSMEs Agric loans to poverty	0.325	0.245	0.057	0.606	1,390
Bank specific variables					
NPLstoGLs	0.080	0.083	0.0002	0.563	1,766
Total assets (millions 'USD')	3.60	11.9	0.004	124.00	1,935
Bank size	5.819	0.746	3.651	8.094	1935
Profitability	0.026	0.032	-0.282	0.135	1,908
Liquidity	0.333	0.143	0.001	0.875	1,935
Revenue diversification	0.450	0.132	0.000	0.906	1,889
Boone index	0.010	0.098	-1.107	1.494	1,598
Institutional and Macroeconomic variables					
Quality of financial development	0.101	0.217	0.009	1.388	1,811
Inflation	0.081	0.055	-0.018	0.333	1,935
GDP growth	0.050	0.028	-0.043	0.140	1,935

Notes: In Table 4.2c, we present the descriptive statistics for the second stage analyses. DEA cost efficiency is the cost efficiency of banks calculated using DEA. We compute DEA robust cost efficiency by excluding deposits in the DEA output matrix. SFA cost efficiency is the efficiency of banks calculated using translog stochastic frontier analyses (SFA). Simar & Wilson bootstrapped cost efficiency scores are obtained by bootstrapping the DEA cost efficiency scores over 1000 interactions. HHSMEs to gross loans is the "ratio of banks' households and SMEs loans, to banks' gross banks loans. HHSMEs loans to CPS is the "ratio of banks' loans to households and SMEs, to credit to the private sector. HHSMEs Agric loans to poverty is the "ratio of the total of banks' loans to households, SMEs and agriculture, to the population living below the poverty line." NPLstoGLs is the ratio of banks' non-performing loans to gross loans. We calculate bank size as the log of total assets. Profitability is income before taxes divided by total assets. Liquidity is the ratio of cash and marketable securities to total assets. We compute revenue diversification as 1-Herfindahl-Hirschman index (HHI) of banks income classified into three types of incomes: interest income, investment income and other income. Boone index is a measure of banking industry competitiveness. We use principal component analyses (PCA) to calculate the quality of financial development, and it comprises stock market capitalization to GDP, stock market turnover to GDP and credit to the private sector to GDP. Inflation is the average change in the consumer price index, while GDP growth is the annual growth rate of GDP. Source: Author calculations; IMF financial access survey; BankFocus; World Development Indicators.

Similarly, the mean for the Simar and Wilson bootstrapped cost efficiency of 0.010 is significantly lower compared to the mean efficiency score of 0.552 estimated under the DEA approach. This may be explained by the systematic underestimation of inefficiency under the DEA approach since it excludes some production possibilities that are not observed from the

sample (Badunenko & Tauchmann, 2019).[33] Looking at our banking industry response variables, the mean for "banks' households and SMEs loans to banks' gross loans is 0.359, with a minimum and a maximum of 0.004 and 0.914, respectively.

Furthermore, the "ratio of banks' households and SMEs loans, to credit to the private sector" has a mean of 0.0003, which reflects the high credit constraints faced by households and SMEs in the region as shown by Stijns and Pelletier (2018). Table 4.2c, shows a high heterogeneity in the amount of loans issued to households, SMEs and for agricultural purposes as shown by the standard deviation of 0.245. As noted earlier, this is perhaps because of variations in banking markets development with lower share of bank loan portfolios being provided to households, SMEs and agricultural sector in countries having poorly developed banking markets (Christiaensen & Demery, 2017).

Regarding our control variables, the NPLs ratio has a mean of 8%, indicating low asset quality of the assets held by the sampled banks. According to Chironga et al. (2018), the low asset quality may be attributed to dwindling credit risk management practices by banks in the region across the major steps of credit value chain including defining risk appetite, loan monitoring and loan collection. The average size of the assets of banks sampled is 5.819, which suggests increased opportunities for banks in the region to improve financial inclusion and benefit from economies of scale. Profitability has a mean of 2.6%, which highlights the higher profitability of banks in the continent as reported by Stijns and Revoltella (2016) and Amidu and Harvey (2016).

As indicated earlier, the higher profitability maybe attributed to the growing banking market in the region, increased innovation and the preference of banks to invest in risk-free government securities (Chironga et al., 2018; Stijns & Pelletier, 2018). We find a high variation in liquidity as indicated by the standard deviation of 0.143. This is perhaps because of the differences in capital market development in the continent, whereby banks in countries with less developed capital markets are forced to hold more liquid assets to accommodate liquidity shocks since they may not be able to raise funds on a moment notice (Nketcha & Samson, 2014).

[33] The DEA estimate of the efficiency frontier is based on the banks sampled. Accordingly, some efficiency production possibilities may not be factored in the sample (Stewart et al., 2016).

Alternatively, the high variation in liquidity may be explained by disparities in deposit volatility[34] with banks in countries with lower deposit volatility holding less reserves for precautionary motive.[35] The mean for revenue diversification is 0.450, suggesting high income diversification of the banks sampled. According to Boadi (2018), regulatory changes and financial reforms in many African countries have forced banks to shift their focus towards the generation of income from non-traditional activities. Boone index has a mean of 0.010, which confirms the low competitive banking environment in Africa, as documented by Beck and Cull (2014).

Table 4.2c shows a significant heterogeneity in quality of financial development of the countries studied, as reflected by the standard deviation of 0.217. This may be as a result of disparities in population densities and infrastructural development in different countries in the region (Allen et al., 2013; Ojah & Kodongo, 2015).[36] Lastly, inflation and GDP growth have a mean of 0.081 and 0.050, respectively. According to World Bank (2018), the modest economic growth in Africa may be attributed to improvements in commodity prices, favourable global financing conditions and slowing inflation that has helped to increase demand by households.

4.2.3 Correlation Analyses of the Banking Industry Response Variables and Cost Efficiency

We present the results of our correlation analyses in Table 4.2d. The coefficients for our banking industry response variables vis-à-vis efficiency variables show a largely positive sign, suggesting cost efficiency benefits associated with increasing financial inclusion. Particularly, we find a positive and a significant association between the "ratio of banks' households and SMEs loans, to banks' gross loans and both the DEA cost efficiency and the robust DEA cost efficiency. Similarly, the coefficients for the relationship between the "ratio of banks' households and SMEs loans, to credit to the private sector" and the DEA cost efficiency, robust DEA cost efficiency and Simar & Wilson bootstrapped cost efficiency have a positive sign.

[34] Deposit volatility refers to the standard deviation of daily deposits in commercial banks less withdrawals (Choudhary & Limodio, 2017).

[35] Banks in countries like South Africa and Botswana have low deposit volatility hence they also hold the lowest levels of bank reserves as compared to banks operating in countries like Malawi and Congo which have high deposit volatility and are associated with larger bank reserves (Nketcha & Samson, 2014).

[36] Allen et al. (2013) and Allen et al. (2014) find evidence that population and infrastructure are important factors in explaining financial development in Africa. Larger population and good infrastructure spur economies of scale and networking that make provision of financial services more efficient. For example, Nigeria and Egypt which are among the most populous countries in Africa have relatively better developed financial markets.

Table 4.2d: Correlation matrix

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	DEA cost efficiency	1															
2	DEA robust cost efficiency	0.898***	1														
3	SFA cost efficiency	0.685***	0.739***	1													
4	Simar & Wilson bootstrapped cost efficiency	0.595***	0.499***	0.428***	1												
5	HHSMEs to gross loans	0.102***	0.071**	0.012	0.045	1											
6	HHSMES loans to CPS	0.045	0.006	-0.023	0.011	0.582***	1										
7	HHSMEs Agric loans to poverty	0.502***	0.429***	0.302***	0.417***	0.044	0.02	1									
8	NPLstoGLs	-0.057**	-0.050**	-0.054**	-0.025	0.007	-0.016	0.034	1								
9	Bank size	0.373***	0.309***	0.250***	0.092***	0.056**	0.110***	0.285***	-0.043*	1							
10	Profitability	-0.027	-0.027	-0.011	-0.079***	0.042	0.04	-0.034	-0.170***	0.209***	1						
11	Liquidity	0.021	0.011	-0.005	0.009	0.169***	0.097***	-0.135***	-0.069***	0.024	0.108***	1					
12	Revenue diversification	-0.214***	-0.221***	-0.171***	-0.177***	-0.076***	0.017	-0.334***	-0.039*	0.019	0.022	-0.032	1				
13	Boone index	-0.006	0.009	0.022	-0.006	0.028	0.033	-0.110***	0.014	-0.036	-0.035	-0.043*	0.024	1			
14	Quality of financial development	0.279***	0.237***	0.335***	0.306***	-0.100***	0.04	0.409***	-0.067***	0.172***	-0.076***	-0.210***	0.006	-0.044*	1		
15	Inflation	-0.028	-0.041*	-0.110***	-0.071***	0.344***	0.199***	-0.247***	-0.001	0.001	0.156***	0.318***	0.044*	-0.024	-0.185***	1	
16	GDP growth	-0.289***	-0.304***	-0.279***	-0.173***	0.034	-0.033	-0.400**	-0.076***	-0.298***	0.061***	0.182***	0.149***	0.024	-0.355***	0.119***	1

Notes: Table 4.2d presents the correlation results between DEA cost efficiency, DEA robust cost efficiency, SFA cost efficiency, Simar & Wilson bootstrapped cost efficiency, the ratio of households and SMEs loans to banks' gross loans (HHSMEs to gross loans), the "ratio of banks' loans to households and SMEs, to credit to the private sector" (HHSMES loans to CPS), the "ratio of banks' loans to households, SMEs and agriculture, to the population living below the poverty line" (HHSMEs Agric to poverty), non-performing loans to gross loans (NPLstoGLs), bank size, profitability, liquidity, revenue diversification, Boone index, quality of financial development, inflation and GDP growth. ***, ** and * indicate statistical significance at 1%, 5% and 10%, correspondingly. Source: Author calculations.

Again, we find a significantly positive association between our banking industry efficiency measures and the "ratio of banks' households, SMEs and agriculture loans, to population living below the poverty line." Expectedly, the coefficient for the association with NPLs ratio is mostly negative and significant probably because the non-performing loans deteriorate the quality of banks assets resulting to increased cost inefficiency (Partovi & Matousek, 2019). Bank size has a strong and a significant positive association with our cost efficiency measures, and this may be explained by the economies of scale and scope that large banks enjoy because they have a wider deposit and lending base (Nguyen, 2018). Furthermore, we observe a negative correlation between profitability and our banking industry efficiency indicators. A possible explanation is that higher profits reduces bank managers incentives to control costs as shown by Phan et al. (2016).

The coefficient for liquidity is mainly positive suggesting efficiency advantages associated with holding liquid assets. This is possibly because holding liquid assets is relative cost-effective for banks since they have lower maturities (Sarmiento & Galán, 2017). Surprisingly, revenue diversification has a negative and a significant relationship with our indicators of banking industry cost efficiency. As indicated earlier, this is probably because of the increased cost consequences that result as banks try to operate in areas outside their expertise (Louzis et al., 2012; Nguyen, 2018). We find mixed results, in terms of signs, on the correlation between competition and our banking industry efficiency measures. Nonetheless, the coefficient for the Boone index is insignificant perhaps because of the limited competition in the African banking industry.

According to Table 4.2d, quality of financial development is positively and significantly associated with our measures of banking industry efficiency. One possible explanation is that developed financial markets are characterized by presence of well-functioning credit markets and institutions that can benefit banks funding costs and recovery rates, both of which may lead to reduced costs and improved efficiency (Ahlin et al., 2011). The coefficient for inflation is largely negative and significant, implying that rise in price level decreases the efficiency of banks. This may be explained by the higher costs of funds associated with higher inflation (Ngo & Le, 2019).

Lastly, GDP growth is significantly and negatively associated with banking efficiency perhaps because growth in the economy increases the demand and price of banking services and this may make managers to be less careful in controlling costs leading to a decline in efficiency

(Tan & Anchor, 2017). Table 4.2d shows pairwise correlation coefficients of less than 0.4 for all our independent variables, suggesting the absence of multicollinearity issues in our data.

4.2.4 Regression Analyses of Banking Industry Response and Cost Efficiency

Table 4.2e: Regression of banking efficiency, using the "ratio of banks' households and SMEs loans, to banks' gross loans" as banks' response measure

Variables	(1)	(2)	(3)	(4)
HHSMEs to gross loans	0.435***	0.437***	0.132***	0.005***
	(0.098)	(0.104)	(0.016)	(0.001)
NPLstoGLs	-0.209***	-0.187**	-0.010***	-0.003
	(0.074)	(0.082)	(0.037)	(0.003)
Bank size	0.084***	0.071***	-0.002	0.001**
	(0.011)	(0.012)	(0.004)	(0.0003)
Profitability	-0.468*	-0.306	-0.249***	-0.003
	(0.240)	(0.232)	(0.092)	(0.007)
Liquidity	0.208***	0.162***	0.198***	0.007***
	(0.056)	(0.063)	(0.024)	(0.002)
Revenue diversification	-0.211*	-0.202*	-0.003	-0.007*
	(0.115)	(0.123)	(0.052)	(0.003)
Boone index	-0.023	0.0004	-0.009	0.002
	(0.034)	(0.034)	(0.026)	(0.002)
Quality of financial development	0.185***	0.158***	0.072***	0.009***
	(0.038)	(0.040)	(0.015)	(0.001)
Inflation	-0.549***	-0.813***	-0.243***	-0.022***
	(0.132)	(0.140)	(0.059)	(0.004)
GDP growth	-1.981***	-2.121***	-0.634***	-0.030***
	(0.262)	(0.301)	(0.145)	(0.011)
Constant			0.274***	0.001
			(0.030)	(0.002)
Observations	1,025	1,025	1,033	1,034

Notes: This Table presents the regression results of the relationship between our measures of banking industry efficiency and the "ratio of banks' households and SMEs loans, to banks' gross loans" (HHSMEs to gross loans). We estimate marginal effects in model 1 and 2 using fractional probit regression model with DEA cost efficiency and DEA robust cost efficiency scores as the dependent variables, respectively. We use maximum likelihood estimation (MLE) technique in model 3 and 4 with SFA cost efficiency, and Simar & Wilson bootstrapped cost efficiency scores as the dependent variables. We control for non-performing loans, bank size, profitability, liquidity, revenue diversification, Boone index, quality of financial development, inflation and GDP growth. Standard errors are robust and in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10%, correspondingly. Source: Author calculations.

Table 4.2e reports the estimation results of our regression analyses with the main objective of assessing possible impact of banks' response to competition for financial inclusion paradigm on banking efficiency. We find that the coefficient for the "ratio of banks' households and SMEs loans, to banks' gross loans" is consistently positive and significant across our four estimation models (i.e., coefficients of 0.435, 0.437, 0.132 and 0.005 for models 1-4, all at the significance level of 1%).

These results support the efficiency structure hypothesis and are similar to previous related studies (e.g., Chortareas et al., 2011; Hartarska et al., 2013; Bos & Millone, 2015; Mia et al., 2019; Saha & Dutta, 2020), which suggest that higher financial inclusion is related to greater banking efficiency. We can offer two alternative insights/views for these findings. First, growing financial inclusion due to active participation of households and SMEs in the formal financial system may lead to expansion of banks' lending activities (Le et al., 2019). This may in turn enable banks to realize economies of scale and reduce loan costs leading to improved cost efficiency.

Secondly, commercial banks tend to focus on better-off low income earners due to their profit orientation as shown by Cull et al. (2014) and Caserta et al. (2018). This may lead to higher loan portfolio quality and lower default rates, hence improved cost efficiency. NPLs have a largely negative and significant effect on bank efficiency, consistent with earlier studies by Sun and Chang (2011) and Partovi and Matousek (2019). The negative and significant coefficient for NPLs may be attributed to increased costs[37] that banks incur while dealing with NPLs as shown by Berger and DeYoung (1997) and Ghosh (2018). We may also argue that banks with bad management may have inadequate loan evaluation and monitoring skills, and thus resulting to increased NPLs and reduced cost efficiency (Podpiera & Weill, 2008).

The coefficient for bank size is mostly positive and significant, suggesting that bigger banks are more efficient. These findings do not contradict previous studies by Wijesiri et al. (2017) and Sapci and Miles (2019), which show that large banks have higher cost efficiency due to economies of scale benefits. The positive coefficient for bank size may also be attributed to the ability of large banks to diversify their assets, funding sources and to use sophisticated technologies in their operations which can greatly reduce their costs. Similar to previous studies

[37] Berger and DeYoung (1997) term the extra costs that banks incur in administering NPLs, and that lead to reduction in cost efficiency, as bad luck hypothesis.

by Batir et al. (2017) and Tan et al. (2017) and our earlier expectations, we find a negative relationship between profitability and efficiency across our four estimation models.

This profitability result is possibly because of the high monitoring and personnel costs associated with higher profitability due to large scale production (García-Herrero et al., 2009; Alhassan et al., 2016). Consistent with our earlier prediction, liquidity has a positive and significant effect on banking industry efficiency across all our estimation models. Our results are supported by previous findings by Bitar et al. (2019) and Triki et al. (2017) who show that higher liquidity enhances bank efficiency. This may be explained by preference of depositors and investors for banks with healthy liquidity ratios (Johnes et al., 2014). The higher deposits and investors funds can help such banks avoid liquidity shortages and reduces the necessity to raise expensive equity, particularly on short notice, hence the resulting reduced cost inefficiency.

We may also argue that higher liquidity reduces banks operating costs by decreasing the expenses involved in originating, servicing and monitoring loans (Sufian et al., 2017). This may in turn lead to higher cost efficiency. In line with earlier studies of Nguyen (2018) and Ammar and Boughrara (2019), revenue diversification has a largely significant and negative coefficient. This suggests that income diversification increases banks cost inefficiency. We can offer two plausible explanations for this observation. First, diversification increases learning costs and operating expenses as banks venture in areas where they have less expertise and competitive advantage (Louzis et al., 2012; Meslier et al., 2016).

Secondly, diversification may lead to higher agency costs due to challenges and complexities involved in coordinating and monitoring different activities leading to lower cost efficiency (Berger et al., 2010; Subramaniam & Wasiuzzaman, 2019). The coefficient for the Boone index is insignificant across our four models, suggesting that competition has no impact on banking industry efficiency in Africa. As noted earlier, this is perhaps because of the limited competition in the African banking market, as shown by Banya and Biekpe (2018). Nonetheless, the direction of the relationship between competition and banking industry cost efficiency is rather unclear.

Consistent with our earlier predictions and previous studies (e.g., Chan & Karim, 2010; Luo et al., 2016; Hermes et al., 2018), quality of financial development has a positive and significant effect on banking industry cost efficiency. One reason for these findings is that greater financial development is associated with lower frictions and information asymmetry (Gyeke-Dako et al.,

2018). This may in turn lead to increased efficiency via lower intermediation costs. We may also argue that well developed financial systems are characterized by effective regulatory and supervisory environment which may lead to more efficient banking systems.

According to Table 4.2e, inflation has a significant effect on bank efficiency with the coefficient having a negative sign across all our four models. This is consistent with earlier studies by Chen (2009); Triki et al. (2017) and Azad et al. (2017), which suggest that higher inflation increases bank costs by adjusting asset and liability gap, resulting to increased inefficiency. The negative coefficient may also be explained by inability of bank managers to predict inflation and appropriately adjust deposit and lending rates, which may in turn lead to higher banking costs (Perry, 1992; Batten & Vo, 2019). A further argument is that inflation increases default rates and this can increase cost inefficiency since banks have to incur additional costs in managing the bad debts (Chan & Karim, 2010).

Lastly, we find a significantly negative association between GDP growth and bank efficiency, contrary to our a priori expectations and previous studies (e.g., Thi My Phan et al., 2016; Alqahtani et al., 2017; Azad et al., 2017). This suggests that favourable economic growth reduce bank cost efficiency, possibly because of banks inability to control costs in expanding markets in good times as shown by Haque and Brown (2017) and Batir et al. (2017).

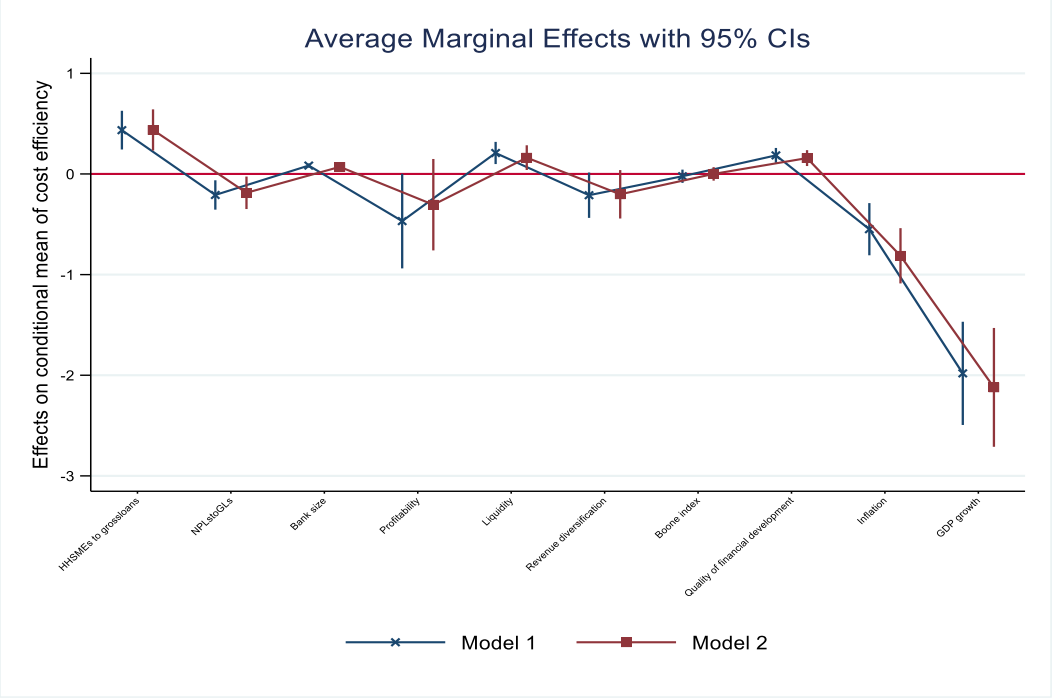


Figure 4.2a: Marginal effects plot of households and SMEs loans to gross loans on average cost efficiency.

Figure 4.2a presents the margins plot, using the "ratio of banks' households and SMEs loans, to banks' gross loans," as our target independent variable. According to Figure 4.2a, the probability that an increase in banks cost efficiency due to a 1% increase in the amount of loans to households and SMEs is about 50 %. This supports our baseline findings that increased financial inclusion has a positive impact on the banking industry cost efficiency. Furthermore, Figure 4.2a shows that the cost efficiency of banks is largely impacted negatively by profits, revenue diversification, inflation and GDP growth.

4.2.5 Regression Using Alternative Response Measure

As indicated in our introductory section, we re-estimate our models using the "ratio of banks' households and SMEs loans, to credit to the private sector," as our alternative measure of banking industry response to competition for financial inclusion. We present the results of our estimations in Table 4.2f. We find a significant relationship between the "ratio of banks' households and SMEs loans, to credit to the private sector' and our efficiency indicators with the coefficients having a positive sign in all our models. These findings support the results of our main analyses that suggest that financial inclusion enhances banking industry cost efficiency.

The coefficient for NPLs has a largely significant and negative effect on banking industry efficiency across our estimation models. This is consistent with the results of our baseline models which indicate that non-performing loans increase banks monitoring and underwriting expenditures which ultimately drives down the cost efficiency of banks as shown by Berger and DeYoung (1997). Bank size has a largely positive and significant coefficient which confirms our findings in Table 4.2e that larger banks benefit from economies of scale as a result of offering more loans at a lower cost.

Consistent with our earlier findings, the coefficient for profitability remains mostly negative suggesting that higher profits reduce the cost efficiency of banks. This is probably because highly profitable banks may lack the incentive to invest in innovative ways thereby reducing their efficiency (Akhisar et al., 2015). According to Table 4.2f, liquidity has a positive and significant effect on banking industry efficiency. This supports the results of our baseline finds that higher liquidity reduces banks financing costs.

Table 4.2f: Regression of banking efficiency, using the "ratio of banks' households and SMEs loans, to credit to the private sector" as banks' response measure

Variables	(1)	(2)	(3)	(4)
HHSMEs loans to CPS	0.034***	0.035***	0.014***	0.001**
	(0.003)	(0.003)	(0.002)	(0.0001)
NPLstoGL	-0.251***	-0.233***	-0.103***	-0.003
	(0.072)	(0.081)	(0.037)	(0.003)
Bank size	0.077***	0.065***	-0.004	0.001***
	(0.011)	(0.012)	(0.004)	(0.0003)
Profitability	-0.527**	-0.369	-0.177*	0.0005
	(0.246)	(0.235)	(0.092)	(0.007)
Liquidity	0.319***	0.270***	0.190***	0.007***
	(0.057)	(0.064)	(0.024)	(0.002)
Revenue diversification	-0.148	-0.163	0.006	-0.004
	(0.117)	(0.122)	(0.05)	(0.004)
Boone index	-0.007	0.016	-0.017	0.002
	(0.033)	(0.034)	(0.026)	(0.002)
Quality of financial development	0.159***	0.136***	0.111***	0.010***
	(0.038)	(0.040)	(0.014)	(0.001)
Inflation	-1.914***	-2.031***	-0.200***	-0.021***
	(0.252)	(0.291)	(0.058)	(0.004)
GDP growth	-0.373***	-0.607***	-0.751***	-0.034***
	(0.131)	(0.140)	(0.145)	(0.011)
Constant			0.460***	0.009***
			(0.034)	(0.002)
Observations	1,032	1,032	1,031	1,032

Notes: In Table 4.2f, we show the regression results between the "ratio of banks' loans to household and SMEs, to credit to the private sector" (HHSMES loans to CPS) and our measures of banking industry efficiency. As stated previously, we estimate models 1 and 2 using fractional probit regression model with DEA cost efficiency and DEA robust cost efficiency scores as the dependent variables. Models 3 and 4 are estimated using maximum likelihood estimation (MLE) technique with SFA cost efficiency and Simar & Wilson DEA bootstrapped cost efficiency scores as the dependent variables. Similar to our prior analyses, we control for non-performing loans, bank size, profitability, liquidity, revenue diversification, Boone index, quality of financial development, inflation and GDP growth. Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% correspondingly. Source: Author calculations.

Contrary to our results in Table 4.2e, revenue diversification has no substantial effect on banking industry cost efficiency. This is likely since the cost benefits of diversification maybe offset by higher overheads, adverse selection and poor monitoring of different activities (Acharya et al., 2006). Nonetheless, the coefficient for revenue diversification has a negative

sign confirming our earlier findings that income diversification reduces cost efficiency of banks in Africa. Similarly, and consistent with our baseline findings, competition has no effect on banking industry efficiency as shown by the insignificant coefficient for the Boone index.

The coefficient for quality of financial development is positive and significant. This is consistent with our earlier findings that suggest that financial development increases banking intermediation activities and this may help to reduce banks costs. Table 4.2f shows a consistently negative and significant association between inflation and banking industry efficiency. These findings corroborate our earlier findings indicating that inflation reduces bank cost efficiency by increasing interest rates leading to an increase in banks cost structure. Again, GDP growth has a significantly negative coefficient consistent with our baseline findings.

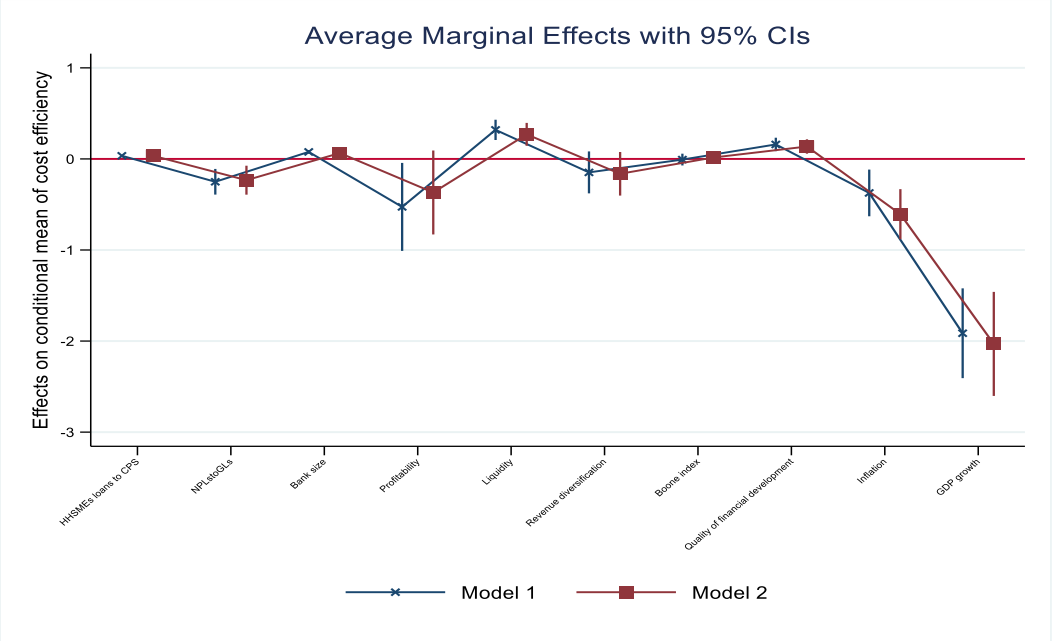


Figure 4.2b: Marginal effects plot of households and SMEs loans to credit to the private sector on average cost efficiency.

Figure 4.2b shows the marginal effects plot using the "ratio of banks' households and SMEs loans, to credit to the private sector" as our measure of banking industry response to competition from financial inclusion paradigm. Similar to Figure 4.2a, we see a positive likelihood that an increase in the amount of loans to households and SMEs will lead to an increase in banks' cost efficiency.

4.2.6 Further Robustness Test

Table 4.2g: Regression of banking efficiency, using the "ratio of banks" households, SMEs and agriculture loans to the population living below the poverty line" as banks' response measure

Variables	(1)	(2)	(3)	(4)
HHSMEs Agric loans to poverty	0.393***	0.364***	0.165***	0.005***
	(0.028)	(0.031)	(0.014)	(0.001)
NPLstoGL	-0.311**	-0.281**	-0.131***	-0.003
	(0.0697)	(0.080)	(0.037)	(0.003)
Bank size	0.057***	0.047***	-0.012**	0.001***
	(0.010)	(0.012)	(0.006)	(0.0003)
Profitability	-0.526**	-0.361*	-0.175*	0.001
	(0.211)	(0.209)	(0.090)	(0.007)
Liquidity	0.261***	0.202***	0.167***	0.006***
	(0.054)	(0.061)	(0.024)	(0.002)
Revenue diversification	-0.173	-0.161	-0.0003	-0.003
	(0.107)	(0.115)	(0.054)	(0.004)
Boone index	0.059	0.074*	0.009	0.001*
	(0.039)	(0.040)	(0.025)	(0.002)
Quality of financial development	0.113***	0.098**	0.095***	0.010***
	(0.036)	(0.040)	(0.014)	(0.001)
Inflation	0.043	-0.252***	-0.043	-0.013***
	(0.110)	(0.123)	(0.059)	(0.004)
GDP growth	-0.827***	-1.014***	-0.313***	-0.016
	(0.246)	(0.298)	(0.151)	(0.001)
Constant			0.300***	0.001
			(0.029)	(0.002)
Observations	1,008	1,008	1,007	1,008

Notes: In Table 4.2g, we regress the "ratio of banks' loans to households, SMEs and agriculture, to the population living below the poverty line" (HHSMEs Agric to poverty) against our measures of banking industry efficiency. We use fractional probit regression model to estimate marginal effects in models 1 and 2 with DEA cost efficiency and DEA robust cost efficiency scores as the dependent variables, respectively. Similar to our previous analyses, we use MLE with SFA cost efficiency and Simar & Wilson estimated bootstrapped cost efficiency scores as the dependent variables in model 3 and 4, respectively. Our control variables include non-performing loans, bank size, profitability, liquidity, revenue diversification, Boone index, quality of financial development, inflation and GDP growth. Standard errors are robust and in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% correspondingly. Source: Author calculations.

As indicated earlier, we conclude our analyses by further testing the robustness of our results using the "ratio of banks' households, SMEs and agriculture loans, to people living below the poverty line" as our proxy for banking industry response to competition from the financial

inclusion paradigm. We present our estimation results in Table 4.2g. Overall, the coefficients for our banking industry response variables remain largely positive and significant, confirming our findings in Table 4.2e and Table 4.2f that increased loans to households and SMEs enhances banking industry cost efficiency. The NPLs ratio has a mostly negative and significant effect on banks cost efficiency. These findings support the results of our earlier analyses that show NPLs increase banks costs, leading to higher cost inefficiency.

Similar to our results in Tables 4.2e and 4.2f, we find a mostly positive and significant association between bank size and cost efficiency, suggesting economies of scale benefits associated with larger banks. Furthermore, the coefficient for profitability has a largely negative sign, supporting our earlier findings. Consistent with our baseline findings, liquidity has a significantly positive effect on banking industry efficiency. According to the regression results in Table 4.2g, revenue diversification is negatively related to banks cost efficiency. These results support our earlier findings that diversification reduces banking industry cost efficiency.

However, the coefficient for revenue diversification is largely insignificant, in contrast to our baseline findings but consistent with our results in Table 4.2f. Consistent with our baseline findings, the Boone index has no significant effect on banking industry cost efficiency. Moreover, and in line with our earlier analyses, quality of financial development has a positive and significant effect on banking industry efficiency. The coefficient for inflation is negative and significant, which supports our earlier findings. Lastly, GDP growth has a largely negative and significant effect on banking industry efficiency consistent with our findings in Table 4.2e and 4.2f.

In Figure 4.2c, we present the marginal effects plot using the "ratio of banks' households, SMEs and agriculture loans, to people living below the poverty line" as our dependent variable. As shown in Figure 4.2c, the likelihood that a one percent increase in the proportion of loans to households, SMEs and for agricultural purposes will enhance the cost efficiency of banks is approximately 0.1%. The positive effect is consistent with the marginal effects plot in Figure 4.2a and Figure 4.2b.

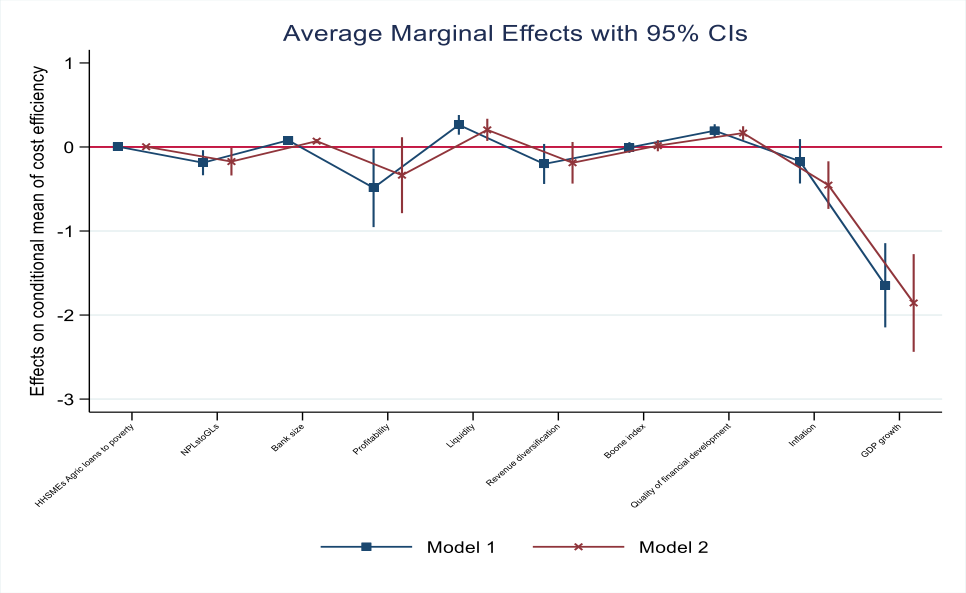


Figure 4.2c: Marginal effects plot of households, SMEs and agriculture loans to people living below the poverty line on average cost efficiency.

4.3 Banking Industry Response to Competition for Financial Inclusion and Asset Portfolio Risk

4.3.1 Introduction

For our third research question, we analyse how the response to competition for financial inclusion paradigm affects the asset portfolio risk of banks in Africa. As discussed in the methodology section, we estimate our main regression model using the "ratio of non-performing loans, to gross loans" (NPLstoGLs) as our dependent variable to measure banks asset portfolio risk. Additionally, we test the robustness of our results using the Z-score (log)[38] and the "ratio of risk-weighted assets, to total assets" (RWAtoTA) as our alternative measures of banks asset portfolio risk.

Consistent with our prior analyses, we use the "ratio of banks' household and SMEs loans, to banks' gross loans" (HHSMEs to gross loans), the "ratio of banks' households and SMEs loans, to credit to the private sector" (HHSMEs loans to CPS) and the "ratio of banks' households, SMEs and agriculture loans, to people living below the poverty line" (HHSMEs Agric loans to poverty), to measure banking industry response to competition for financial inclusion paradigm. We employ a two-step system generalized method of moments (GMM) estimator in

[38] The Z-score is an inverse measure of risk; therefore, higher Z-score values indicate increased banking industry stability.

our regression models. We begin our analyses by providing a summary of the descriptive statistics, followed by correlation analyses. And conclude by presenting the results of our baseline regression model, together with the results of our robustness tests.

4.3.2 Summary Statistics of Asset Portfolio Risk and Banking Industry Response Variables

Table 4.3a: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Dependent variables					
NPLstoGLs	0.082	0.084	0.0002	0.563	1,907
Z-score (log)	3.023	0.975	-3.227	7.801	2,224
RWAtoTA	0.644	0.231	0.095	5.016	1,590
Independent variables					
HHSMEs to gross loans	0.367	0.241	0.0004	0.914	1,643
HHSMES loans to CPS	0.0003	0.0002	3.40E-07	0.001	1,637
HHSMEs Agric loans to poverty	0.337	0.247	0.070	0.625	1,591
Bank specific variables					
Loan reserve ratio	0.055	0.064	0.0003	0.574	2,058
Total assets (millions 'USD')	3.600	11.3	0.004	124.00	2,245
Bank size (log)	5.823	0.758	3.608	8.095	2,245
Capital ratio	0.147	0.094	-0.161	0.927	2,244
Loan ratio	0.493	0.187	0.004	0.967	2,235
Profitability	0.025	0.033	-0.324	0.159	2,213
Revenue diversification	0.463	0.148	0.000	0.906	2,209
Institutional and Macroeconomic variables					
Quality of institutions	0.635	0.778	-0.723	2.852	2,360
Real interest rate	0.061	0.071	-0.264	0.236	2,232
GDP growth	0.049	0.027	-0.043	0.140	2,360

Notes: In Table 4.3a, we present the descriptive statistics of our variables. NPLstoGL is the "ratio of non-performing loans, to gross loans." Z-score (log) is a measure of banks' risk calculated as the log of return on assets (ROA) plus capital, to assets ratio divided by the standard deviation of ROA. RWAtoTA is risk-weighted assets, to total assets ratio. HHSMEs to gross loans is the "ratio of banks' households and SMEs loans, to banks' gross loans." HHSMEs loans to CPS is the "ratio of banks' loans to households and SMEs, to credit to the private sector." HHSMEs Agric loans to poverty is the "ratio of the total of banks' loans to households, SMEs and agriculture, to the population living below the poverty line." Loan reserve is the ratio of bank's loan loss reserves to gross loans. Bank size is the log of the sampled banks total assets. We calculate capital as total equity divided by total assets. Loan ratio is the ratio of gross loans to total assets. Profitability is the ratio of earnings before tax to total assets. Revenue diversification is calculated as 1-Herfindahl-Hirschman index (HHI) of banks income classified into three types of incomes: interest income, investment income and other income. We use principal component analyses (PCA) to calculate a composite index for the quality of institutions comprising the six governance indicators by Kaufmann et al. (2011). Real interest rate is the lending interest rate which has been adjusted for inflation. Lastly, GDP growth is the annual growth rate of GDP. Source: BankFocus; IMF financial access survey; World Development Indicators.

Table 4.3a presents summary statistics of our variables. As shown in Table 4.3a, non-performing loans (NPLs) represent 8.2 % of the total loans issued by the banks sampled. This is more than two times the world average of approximately 3.74%, and it may be attributed to poor processes for assessing credit, strained economic performance, and political uncertainties in the region (Stijns & Pelletier, 2018). Nonetheless, the Z-score mean of 3.022 suggests that banks in Africa are relatively stable with a low probability of default, similar to previous findings by Chavula et al. (2017). The risk-weighted assets (RWAs) represent 64.6% of the total assets, indicating the high-risk profile of the assets held by the banks studied. Additionally, we find a high variation in the RWAs, as shown by the standard deviation of 0.231 with a maximum of 501.6%. According to Santos et al. (2020), the significant heterogeneity of the RWAs may be due to differences in assessing risk and variations between regulatory measures of risk across different markets.[39]

In relation to the banking industry response variables, we find a high variation in terms of loans issued by banks to households and SMEs, as shown by the standard deviation of household and SMEs loans to gross loans of 0.241. This is perhaps because of the substantial discrepancies in the use of formal financial services in Africa, as shown by Beck and Cull (2014).[40] Furthermore, banking industry loans to households and SMEs constitute approximately 0.03% of the total credit issued to the private sector. According to Calice et al. (2012), obstacles like poor regulations, challenges in harmonizing risk assessment procedures, models and products can be attributed to the low lending to households and SMEs segments in Africa.

Table 4.3a shows the amount of loans issued by banks to households, SMEs and for agricultural purposes to be approximate twice the number of people living below the poverty line. This may be explained by efforts to increase access to finance so as to reduce poverty (Demirgüç-Kunt et al., 2008). Looking at the bank-specific variables, the ratio of loan loss reserves to gross loans has a mean of 5.5 %, suggesting that banks in the region anticipate low deterioration in their loan quality and a decrease in their risk-taking behaviour. However, it may also indicate under-provisioning for bad loans given the high percentage of NPLs in the continent, as shown

[39] Legal differences for instance, may affect how loan losses are recognized between different countries, to the extent that the differences are reflected in market assessment of risk. This could lead to a variation in RWAs of greater than one. Moreover, market perceptions about the riskiness of some banks; for example, too big to fail, may lead to underestimation of the riskiness of such banks (Mariathasan & Merrouche, 2014; Santos et al., 2020).

[40] For example, only 23% of adults hold an account at a formal financial institution in Tanzania as compared to 89% in Mauritius (Demirguc-Kunt et al., 2018).

by Ozili (2018).[41] According to Table 4.3a, there is high variation in the size of banks studied as indicated by the standard deviation of 0.758.

As stated earlier, the high variation in bank size may be due to the significant differences in financial development across different countries in the region (Beck & Cull, 2014). Capital has a mean of 14.7%, which is higher in comparison to an average of 13.3% held by banks outside the African continent. This is perhaps because of the regulatory environment in the region that pushes banks to hold more capital cushion (Allen et al., 2011). Furthermore, the average amount of loans issued by the banks sampled is 49.3% of the total assets. The low loan ratio confirms the dysfunctional intermediation process by banks in Africa that makes them to be over-liquid and to prefer investments in government securities at the expense of private sector credit provisioning as highlighted by Beck et al. (2011).

Profitability has a mean of 2.5% which confirms earlier observations by Beck and Cull (2014) and Chironga et al. (2018) that banks in Africa are more profitable compared to banks in other continents.[42] The higher profitability may be attributed to the growing banking market, increased innovations, and higher interest rate spreads. Income diversification has a standard deviation of 0.148, suggesting high diversification heterogeneity across the sampled banks. This is perhaps because of the differences in the level of competition between banks in different African countries (Nguyen et al., 2016).[43]

Similarly, we find a high variation in terms of quality of institutions among the countries sampled as shown by the standard deviation of 0.778. This could be due to disparities in development levels and geopolitical factors that make some countries to have weak governance structures (Mbaku, 2018).[44] The real interest rate has a mean of 6.1%, suggesting higher lending rates in the continent, which can be explained by higher operating costs and risk in Africa (Beck & Cull, 2014). Lastly, economic growth across the continent remains uneven, as

[41] For more information see https://www.businessdailyafrica.com/IMF-says-Kenyan-banks-exposed-to-bad-loans-danger/-/539552/2613532/-/apcc8h/-/index.html and https://www.theindependent.co.zw/2012/08/31/loan-loss-provisions-are-banks-underproviding/.

[42] For example, in 2017 return on equity (ROE) for African banks stood at 14.9% compared to 6% for banks in developed markets (Chironga et al., 2018). For more information see https://www.mckinsey.com/industries/financial-services/our-insights/african-retail-bankings-next-growth-frontier

[43] Banks in highly competitive markets may be forced to identify new growth opportunities in non-traditional banking business. For instance, the South African banking sector which is considered to be the most competitive in the region, is characterized by increased diversification across different financial products (PWC, 2016a).

[44] Countries like Somali, South Sudan and Libya remain burdened by poor-functioning structures of governance while countries like Botswana, Ghana and Mauritius have continued to build on their governance achievements.

shown by the minimum GDP growth of -4.3% and a maximum of 14%. The differences in GDP growth can be linked to the recession in larger commodity-driven economies like Nigeria and South Africa. In comparison, smaller non-commodity driven economies like Ethiopia and Ghana continue to record strong economic performance (Muzima & Mazivila, 2018).

4.3.3 Correlation Analyses of Banking Industry Response and Asset Portfolio Risk

Table 4.3b presents the results of our correlation analyses. We find mixed results for the relationship between our banking industry response variables and asset portfolio risk. Furthermore, the coefficients of the relationship between our banking industry response measures and asset portfolio risk proxies are generally weak and insignificant. This suggests that financial inclusion has a weak effect on the stability of the banking industry in Africa. In terms of the bank-specific variables, loan reserve ratio has a mainly positive coefficient in relation to our asset portfolio risk measures, suggesting that the risk levels assumed by banks in the region are driven by the expected losses in their asset portfolios.

Bank size has a significantly negative effect on banks' asset portfolio risk. This is perhaps because large banks may benefit from better monitoring, which can reduce their risk (Beccalli et al., 2015). Furthermore, we find a largely positive correlation between capital and our indicators of portfolio risk, implying that banks with higher capital assume more risk. The coefficient for the loan's ratio is mainly significant. Specifically, our results show a positive and significant correlation between RWAs and the loans to total assets ratio. This is probably because banks may lower their credit standards to increase their loans which may lead to higher risk (Dimitrios et al., 2016).

Similarly, we find the coefficient of the relationship between our asset portfolio risk proxies and profitability to be mostly positive and significant. We can argue that highly profitable banks are associated with efficient management which is skilled in identifying and controlling risk. Unsurprisingly, the coefficient for revenue diversification is mainly negative, suggesting that diversification improves banking industry stability. Looking at the macroeconomic variables, we find a generally negative relationship between the quality of institutions and banks' asset portfolio risk, as shown by the negative and positive coefficients for NPLs and the Z-score, respectively. This is possibly because strong institutions promote good governance that may make banks to engage in prudent lending practices (Boubakri et al., 2020).

Table 4.3b: Correlation matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1.NPLstoGLs	1														
2.Z-score (log)	-0.156***	1													
3.RWAtoTA	0.040	0.002	1												
4.HHSMEs to gross loans	0.011	-0.033	-0.033	1											
5.HHSMES loans to CPS	-0.007	-0.004	-0.041	0.577***	1										
6.HHSMEs Agric loans to poverty	0.007	0.139***	0.072**	0.055**	0.042	1									
7.Loan reserve ratio	0.032	-0.002	0.013	0.041	-0.018	-0.024	1								
8.Bank size	-0.058**	0.124***	-0.045*	0.068**	0.119***	0.315***	0.002	1							
9.Capital ratio	0.026	0.174***	0.022	-0.047*	-0.081***	-0.167***	0.013	-0.421***	1						
10.Loan	-0.019	0.040*	0.348***	-0.109***	-0.110***	0.211***	-0.007	0.173***	-0.219***	1					
11.Profitability	-0.144***	0.266***	0.105***	0.052*	0.072***	-0.048*	-0.011	0.210***	-0.047**	0.086***	1				
12. Revenue diversification	-0.001	0.017	0.021	0.033	0.073***	-0.007	-0.078***	-0.030	0.079***	0.005	-0.049**	1			
13.Quality of institutions	-0.024	0.017	0.120***	-0.093***	-0.053**	0.555***	-0.015	0.034*	-0.106***	0.175***	-0.097***	0.012	1		
14.Real interest rate	0.061***	-0.141***	0.057**	-0.082***	0.068**	-0.151***	0.000	-0.179***	0.057***	-0.031	0.008	-0.012	-0.027	1	
15.GDP growth	-0.067***	-0.031	-0.012	0.052**	-0.013	-0.401***	0.008	-0.293***	0.119***	-0.121***	0.051**	-0.012	-0.125***	0.089***	1

Notes: Table 4.3b shows the correlation between Non-performing loans to gross loans (NPLstoGL), Z-score (log), Risk-weighted assets to total assets (RWAtoTA), the "ratio of banks' loans to household and SMEs, to banks' gross loans" (HHSMEs to gross loans), the "ratio of banks' loans to household and SMEs, to credit to the private sector" (HHSMES loans to CPS), the "ratio of banks' loans to households, SMEs and agriculture, to the population living below the poverty line" (HHSMEs Agric to poverty), loan reserve, bank size, capital, loan ratio, profitability, revenue diversification, deposits, quality of institutions, real interest rate and GDP growth. ***, ** and * indicate statistical significance at 1%, 5% and 10% correspondingly. The definition of the variables is as per Table 4.3a. Source: Author calculations.

According to Table 4.3b, the real interest rate has a mostly positive and significant effect on banks' risk-taking. This suggests that higher interest rates encourage banks to take more risk, perhaps to make up for the possible squeeze on spread. According to Gizycki (2001), higher interest rates reduce the current value of banks, which may persuade them to undertake more risk so as to increase their value. Finally, the coefficient for GDP growth is mainly negative, probably because higher GDP growth is associated with a more stable economic environment and thus, lower risk exposure for banks (Boubakri et al., 2020). Generally, our correlation matrix Table shows a weak correlation between our explanatory variables, indicating that their inclusion does not present any multicollinearity problem.

4.3.4 Regression Analyses of Banking Industry Response and Asset Portfolio Risk

In Table 4.3c, we present the results of our baseline regression analyses, using the "ratio of non-performing loans, to gross loans" (NPLtoGL) as the dependent variable. Our lagged dependent variable (L.NPLtoGL) has a positive and significant coefficient across our three models, which provides evidence of the persistence of bank risk and justifies the use of system GMM estimation technique (Bermpei et al., 2018; Teixeira et al., 2020). According to Table 4.3c, all our GMM estimation models are valid as indicated by the absence of second-order autocorrelation, AR(2). Moreover, the p-values of the Hansen test of over-identifying restrictions are within the acceptable levels (0.1-0.25), suggesting that our instruments are valid.

We find a mainly positive and insignificant relationship between our banking industry response variables and NPLs (i.e., coefficients of 0.004, 24.71 and 0.050 for models 1-3). These results are consistent with previous studies (e.g., Dwumfour, 2017; Saha & Dutta, 2020) which show evidence that credit financial inclusion contributes negatively to banking industry stability in low and middle-income countries, whereas the result is opposite in high-income countries. We can argue that expanding credit to households and SMEs may lead to increased loan defaults and higher NPLs because they are considered to be more financially constrained. An alternative argument is that the information asymmetries associated with providing credit to households and SMEs may lead to an increase in the amount of NPLs as shown by Ahamed and Mallick (2019).

Table 4.3c: Regression of portfolio risk, using the "ratio of non-performing loans" as the dependent variable

VARIABLES	(1)	(2)	(3)
L.NPLstoGLs	0.653*** [8.56]	0.616*** [8.43]	0.616*** [8.55]
	(0.076)	(0.073)	(0.072)
HHSMEs to gross loans	0.004 [0.19]		
	(0.022)		
HHSMES loans to CPS		24.71 [0.69]	
		(36.07)	
HHSMEs Agric loans to poverty			0.050 [1.38]
			(0.036)
Loan reserve ratio	0.171*** [3.82]	0.159*** [3.69]	0.156*** [3.76]
	(0.045)	(0.043)	(0.042)
Bank size	-0.040*** [-2.81]	-0.052*** [-3.32]	-0.049*** [-3.52]
	(0.014)	(0.016)	(0.014)
Capital ratio	0.125* [1.84]	0.133** [2.01]	0.125** [1.87]
	(0.068)	(0.066)	(0.067)
Loans	0.017 [0.46]	0.005 [0.16]	0.003 [0.07]
	(0.037)	(0.032)	(0.037)
Profitability	-0.423*** [-2.71]	-0.420*** [-2.96]	-0.448*** [-2.80]
	(0.156)	(0.142)	(0.160)
Revenue diversification	-0.038 [-1.22]	-0.045 [-1.30]	-0.043 [-1.33]
	(0.031)	(0.035)	(0.032)
Quality of institutions	-0.013* [-1.69]	-0.015* [-1.70]	-0.024** [-2.05]
	(0.008)	(0.009)	(0.012)
Real interest rate	0.021 [0.70]	0.009 [0.28]	0.034 [1.09]
	(0.031)	(0.032)	(0.031)
GDP growth	-0.349*** [-2.90]	-0.388*** [-2.74]	-0.306** [-2.32]
	(0.121)	(0.142)	(0.132)
Constant	0	0.373*** [3.94]	0.333*** [3.58]
	(0)	(0.105)	(0.093)
Time fixed effect	Yes	Yes	Yes
Number of instruments	112	112	113
Number of groups	179	167	176
AR(1) (p-value)	0.000	0.000	0.000
AR(2) (p-value)	0.531	0.545	0.504
Hansen (p-value)	0.130	0.154	0.301
Observations	962	950	941
Number of Banks	179	167	176

Notes: This Table presents our regression results using the "ratio of non-performing loans, to gross loans" (NPLstoGLs) as the dependent variable. For our independent variable, we employ the "ratio of banks' loans to household and SMEs, to banks' gross loans" (HHSMEs to gross loans) in model 1, the "ratio of banks' loans to household and SMEs, to credit to the private sector" (HHSMES loans to CPS) in model 2, and the "ratio of banks' loans to households, SMEs and agriculture, to the population living below the poverty line" (HHSMEs Agric to poverty) in model 3. We control for loan loss reserves, Bank size, capital, loans ratio, profitability, revenue diversification, quality of institutions, real interest rate and GDP growth. We employ a two-step system GMM. T statistics are in box brackets. Robust standard errors are in round parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% correspondingly. Source: Author calculations.

Our results support the competition-fragility hypothesis which argues that higher competition undermines banking industry stability by encouraging banks to take more risk in order to increase their returns. We may explain the insignificant coefficient for our banking industry response variables in the following ways. First, the low outreach of the banking industry in Africa may result to smaller amounts of loans to household and SMEs, as shown by Beck and Cull (2014) and Neaime and Gaysset (2018). Accordingly, bank loans to low-income earners may not have a significant effect on the risk profile of the banks in the region. Second, the discriminatory lending practices by banks in the low-income market may contribute to lower rates of loan defaults (Caserta et al., 2018; Ozili, 2018). These two explanations seem most plausible in respect of our empirical results, as all our estimated coefficients for the "banking industry response to competition for financial inclusion" are statistically insignificant.

In line with previous studies (e.g., Ahamed & Mallick, 2019; Boubakri et al., 2020) and our earlier predictions, we find a significantly positive association between loan loss reserves and NPLs. An explanation for this is that banks with poor quality credit portfolios have moral hazard incentives to assume more risk in order to compensate for increased loan loss reserves, which may result in higher NPLs (Ghosh, 2015). Bank size has a negative and significant coefficient, suggesting that larger banks assume less risk. This confirms earlier findings (e.g., Bougatef & Mgadmi, 2016; Jin et al., 2017; Teixeira et al., 2020) that larger banks are more able to diversify their loan portfolios, leading to lower risk of default.

Larger banks also tend to be exposed to less risk because they are associated with skilled and efficient management which is more proficient in managing risk (Baselga-Pascual et al., 2015). Consistent with previous studies (e.g., Basher et al., 2017; Boubakri et al., 2020), we find capital to be positively and significantly related to NPLs across our three specifications. This is probably because banks with higher capital have a low probability of insolvency, which may encourage them to take more risk (Jiang et al., 2020). We may also argue that higher capital reduces banks portfolio size, and this may make them invest in risky assets in the hope of earning higher returns and preserving their value.

The loans to total assets ratio has a positive effect on NPLs across our three estimations. This confirms our earlier expectations and previous empirical evidence (e.g., Vithessonthi, 2016; Bermpei et al., 2018) that banks may soften their credit standards in order to increase their loan volumes which can lead to an increase in loan defaults. However, the coefficient for the loans ratio is not significant, perhaps because of the stringent lending and supervisory controls following the financial crisis. Profitability has a significantly negative coefficient, consistent

with our earlier expectations and previous empirical evidence of Baselga-Pascual et al. (2015), Ashraf (2017) and Teixeira et al. (2020).

A possible explanation is that profitable banks have good management quality with respect to lending activities which may mitigate higher NPLs (Louzis et al., 2012). An alternative explanation is that highly profitable banks are likely to have a higher franchise value which may discourage them from assuming excessive risk (Jiménez et al., 2013; Mili & Abid, 2017). Similar to previous studies (e.g., Shim, 2013; Teixeira et al., 2020), we find a negative association between revenue diversification and NPLs. This may be attributed to the decrease in banks overall risk due to an increase in the number of independent risk investments (Köhler, 2015; Shim, 2019).

However, the coefficient for revenue diversification is not significant. This is probably because of the possible drawbacks of diversification that can make banks not to gain a competitive advantage as a result of diversifying in activities where they are less experienced as shown by Stiroh (2004) and Louzis et al. (2012). A further explanation is that diversification may generate inefficiency due to the agency problems that may arise as managers cross-subsidize poor-performing investments with well-performing investments (Shin & Stulz, 1998; Shim, 2019).

Table 4.3c shows a significant association between the quality of institutions and NPLs with the coefficient between the two variables having a negative sign. These findings are generally consistent with our expectations and prior studies (e.g., Bermpei et al., 2018; Danisman & Demirel, 2019) which show that strong institutions reduce borrower moral hazard and adverse selection; and this in turn can improve loan repayment and banks stability. We may also argue that good governance can enhance bank supervision and regulation mechanisms, both of which can improve lending terms and reduce loan defaults.

In contrast to the previous empirical findings of Baselga-Pascual et al. (2015) and Teixeira et al. (2020), the real interest rate has a positive effect on NPLs across our three estimations. We may argue that a rise in real interest rates increases the value of debts and makes it expensive for borrowers to repay their loans (Ghosh, 2015). Additionally, higher interest rates increase the cost of funds which may, in turn, encourage banks to adopt more risk-taking behaviour in search of higher yields (Brewer et al., 2014). However, the coefficient for the real interest rate is not significant perhaps because lending rates in Africa tend to be sticky; hence, they may not have a substantial effect on the risk-taking behaviour of banks in the region (Kasekende & Brownbridge, 2011).

Lastly, we find the coefficient for GDP growth to be negative and significant across all our specifications. These results are in line with previous evidence (e.g., Louzis et al., 2012; Kjosevski & Petkovski, 2017; Teixeira et al., 2020), which suggests that improved economic conditions reduce borrowers' loan defaults. We can offer two alternative explanations for this observation. First, higher GDP growth is associated with more stable economic conditions which may lead to lower risk of NPLs as shown by Baselga-Pascual et al. (2015) and Dimitrios et al. (2016). Secondly, a well-performing economy provides more channels of diversifying loan portfolios which can improve banks credit quality (Anderson et al., 2015).

As detailed in our introductory section, we re-estimate our main analyses using the Z-score as an alternative measure of banks asset portfolio risk. We present the results of that estimation in Table 4.3d, and they are generally consistent with our baseline findings. The lagged coefficient of the Z-score remains positive and significant, which confirms the persistence of bank risk and again supports the use of GMM estimation technique. Furthermore, the Hansen test and AR(2) test p-values suggest that our models are valid and consistent.

Our banking industry response measures show a negative and insignificant relations with the Z-score across the three specification models. These results confirm our baseline findings, suggesting that increased loans by banks' to households and SMEs reduces the stability of the banking industry in Africa, although this effect is not significant. Loan reserve ratio has a negative effect on the Z-score, which corroborates the results of our earlier analyses. However, the coefficient of the relationship between the two variables is not significant, possibly because of the conservative approach by bank managers to under-estimate loan reserves in order to signal favourable risk prospects (Bushman & Williams, 2012).

Bank size has a positive and significant coefficient across all our specifications. These results are consistent with our baseline findings that large banks are able to generate more funds which reduce their probability of default. In contrast with the results of our baseline analyses, we find a significant and positive relationship between capital and the Z-score. This may be expected since higher capital provides a buffer against adverse shocks which can reduce the risk of financial distress (Shim, 2013; Basher et al., 2017). Likewise, the loans to total assets ratio has a mostly significant and positive effect on the Z-score, contrary to our preliminary analyses. This inconsistency is likely since an increase in loans may increase earnings which may enhance the stability of banks (Teixeira et al., 2020).

4.3.5 Regression Analyses using Alternative Measure of Bank Asset Portfolio Risk

Table 4.3d: Regression of portfolio risk using the "Z-score" as the dependent variable

VARIABLES	(1)	(2)	(3)
L.Z-score (log)	0.368*** [4.20]	0.410*** [5.68]	0.810*** [11.91]
	-0.088	(0.072)	(0.068)
HHSMEs to gross loans	-0.009 [-0.08]		
	(0.107)		
HHSMES loans to CPS		-18.94 [-0.07]	
		(279.7)	
HHSMEs Agric loans to poverty			-0.215 [-1.16]
			(0.185)
Loan reserve ratio	-0.293 [-0.97]	-0.469 [-1.49]	-0.280 [-0.78]
	(0.303)	(0.315)	(0.361)
Bank size	0.453*** [3.72]	0.448*** [3.10]	0.166** [2.21]
	(0.122)	(0.144)	(0.075)
Capital ratio	3.298*** [4.82]	3.080*** [5.56]	1.422**[2.59]
	(0.684)	(0.554)	(1.548)
Loan	0.623* [1.86]	0.918** [2.29]	0.257 [1.36]
	(0.336)	(0.401)	(0.189)
Profitability	4.414*** [2.64]	3.600** [2.51]	-0.494 [-0.40]
	(1.672)	(1.434)	(1.234)
Revenue diversification	0.097 [0.61]	0.241 [1.34]	0.934 [1.34]
	(0.158)	(0.180)	(0.695)
Quality of institutions	0.180** [2.57]	0.192** [2.12]	0.097* [1.86]
	(0.070)	(0.091)	(0.052)
Real interest rate	-0.432* [-1.68]	-0.550** [-2.34]	-0.376** [-2.48]
	(0.257)	(0.235)	(0.152)
GDP growth	2.407** [2.50]	2.789** [2.38]	0.767 [1.07]
	(0.964)	(1.172)	(0.720)
Constant	0	0	-0.704 [-1.28]
	(0)	(0)	(0.551)
Time fixed effect	Yes	Yes	Yes
Number of instruments	69	100	88
Number of groups	198	186	195
AR(1) (p-value)	0.054	0.030	0.006
AR(2) (p-value)	0.272	0.212	0.178
Hansen (p-value)	0.103	0.108	0.200
Observations	1,057	1,045	1031
Number of Banks	198	186	195

Notes: In Table 4.3d, we present the regression results between banks' Z-score (log), the "ratio of banks' loans to household and SMEs, to banks' gross loans" (HHSMEs to gross loans), the "ratio of banks' loans to household and SMEs, to credit to the private sector" (HHSMES loans to CPS) and the "ratio of banks' loans to households, SMEs and agriculture, to the population living below the poverty line" (HHSMEs Agric to poverty). Similar to our preliminary analyses, we control for loan loss reserves, Bank size, capital, loan ratio, profitability, revenue diversification, quality of institutions, real interest rate and GDP growth. As indicated previously, we employ a two-step system GMM with bank-specific variables as instruments. T statistics are in box brackets. Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% correspondingly. Source: Author calculations.

The coefficient for profitability has a largely positive sign which confirms our baseline findings that larger banks have less incentive to engage in risky activities. This is perhaps because their shareholders tend to lose more in case of default (Martynova et al., 2020). According to Table 4.3d, revenue diversification has a positive and insignificant coefficient. This corroborates our prior findings that banks may gain limited benefits from diversification because they may lack the necessary expertise in selecting risk efficient portfolios. Again, we find the quality of institutions to have a significant and positive impact on the stability of the banking industry. The real interest rate has a negative effect on the Z-score, suggesting that an increase in interest rates increases banks asset portfolio risk.

However, we find the coefficient for the real interest rate to be statistically significant, in contrast to our earlier findings. This may be expected given the high-interest rates in the continent that can substantially affect the ability of borrowers to repay their loans (Allen et al., 2011). Additionally, high-interest rates may affect banks cost of funds that may in turn encourage them to take more risk (Ghosh, 2015). Finally, we find a positive association between GDP growth and the Z-score. These results are consistent with the findings of our earlier analyses and provide further evidence that a growing economy may lead to higher returns and more retained earnings, and this can reduce banks' probability of default.

4.3.6 Further Robustness Check

As described in our introductory section, we also check the robustness of our empirical findings using the "ratio of risk-weighted assets, to total assets" (RWAtoTA) as a further alternative measure of banking industry portfolio risk. Our results in Table 4.3e below are broadly consistent with those presented in our earlier analyses. The lagged coefficient of the dependent variable remains significant, which further confirms the persistence of bank risk. We again find the coefficient of our banking industry response variables to be mainly positive and insignificant, in line with the findings of our baseline analyses.

Consistent with the results of our earlier analyses, the loans reserve ratio has a positive relationship with RWA. Furthermore, the coefficient for bank size has a negative sign. This confirms the findings of our earlier analyses, suggesting that large banks take less risk, hence they are more stable. In contrast to our main results, capital has an insignificant coefficient. This can be expected since banks with higher capital ratios have a lower probability of default, and they may lack the incentive to invest in risky lending practices, as shown by Ghosh (2015).

Table 4.3e: Regression of portfolio risk, using the "ratio of risk-weighted assets, to total banks' assets" as the dependent variable

VARIABLES	(1)	(2)	(3)
L.RWAtoTA	0.778*** [5.15]	0.839*** [4.28]	0.673*** [5.08]
	(0.151)	(0.196)	(0.133)
HHSMEs to gross loans	0.223 [1.03]		
	(0.217)		
HHSMES loans to CPS		358.8 [0.66]	
		(542.3)	
HHSMEs Agric loans to poverty			0.093** [1.05]
			(0.093)
Loan reserve ratio	0.295 [0.69]	0.378*** [4.19]	0.360*** [3.07]
	(0.430)	(0.090)	(0.117)
Bank size	-0.048 [-0.88]	-0.015 [-0.39]	-0.035 [-0.74]
	(0.055)	(0.0381)	(0.048)
Capital ratio	-0.246 [-0.49]	0.332 [0.77]	0.008 [0.03]
	(0.498)	(0.434)	(0.323)
Loan	0.342** [2.37]	0.150 [0.96]	0.320** [2.22]
	(0.144)	(0.157)	(0.144)
Profitability	-0.298 [-0.17]	-0.332 [-0.46]	-0.505 [-0.59]
	(1.784)	(0.716)	(0.855)
Revenue diversification	-0.074 [-0.26]	0.462*** [3.28]	0.370 [2.27]
	(0.290)	(0.141)	(0.163)
Quality of institutions	-0.016 [-1.42]	-0.012 [-0.89]	-0.043 [-1.57]
	(0.011)	(0.013)	(0.028)
Real interest rate	-0.020 [-0.20]	-0.075 [-0.64]	-0.018 [0.19]
	(0.102)	(0.116)	(0.098)
GDP growth	-0.026 [-0.07]	0.312 [0.79]	0.203 [0.62]
	(0.390)	(0.396)	(0.326)
Constant	0	0.084 [0.30]	0.270 [0.80]
	(0)	(0.279)	(0.336)
Time fixed effect	Yes	Yes	Yes
Number of instruments	44	39	53
Number of groups	160	147	155
AR(1) (p-value)	0.008	0.005	0.002
AR(2) (p-value)	0.413	0.216	0.286
Hansen (p-value)	0.181	0.122	0.273
Observations	857	844	839
Number of Banks	160	147	155

Notes: Table 4.3e shows regression results between Risk-weighted assets (RWA), the "ratio of banks' loans to household and SMEs, to banks' gross loans" (HHSMEs to gross loans), the "ratio of banks' loans to household and SMEs, to credit to the private sector" (HHSMES loans to CPS) and the "ratio of banks' loans to households, SMEs and agriculture, to the population living below the poverty line" (HHSMEs Agric to poverty). We control for loan loss reserves, Bank size, capital, loans ratio, profitability, revenue diversification, quality of institutions, real interest rate and GDP growth. As indicated earlier, we use a two-step system GMM with bank-specific variables as instruments. T statistics are in box brackets. Robust standard errors are in round parentheses. *** and * indicate statistical significance at 1% and 10% correspondingly. Source: Author calculations.

4.4 Banking Industry Response to Competition for Financial Inclusion and Social Performance

4.4.1 Introduction

This section presents the results of our analyses for our last research question**.** As indicated previously, we use breadth and depth of outreach, and the number of ATMs and bank branches as our response variables in measuring the degree of banking industry's social performance. Similar to our previous analysis, we use the "ratio of banks' households and SMEs loans, to banks' gross loans" (HHSMEs to gross loans), as our explanatory variable in measuring banking industry response. As indicated in our methodology chapter, we check the robustness of our results by using our two alternative measures of banking industry response to competition for financial inclusion: the "ratio of banks' households and SMEs loans, to credit to the private sector" (HHSMES loans to CPS), and the "ratio of banks' households, SMEs and agriculture loans, to the population living below the poverty line" (HHSMEs Agric loans to poverty).

We include controls for both bank-specific variables and macroeconomic variables. For bank-specific variables, we include bank size, capital and bank age. Regarding macroeconomic variables, we control for quality of financial development, quality of institutions, population, GDP growth and inflation. We begin our analysis by providing a summary of our descriptive statistics, followed by correlation analysis and the test for multicollinearity. We conclude by presenting the results for the main regression analysis, including the test of robustness of the regression results.

4.4.2 Summary Statistics of Banking Industry Social Performance and Response Variables

The descriptive statistics in Table 4.4a show that the average number of borrowers from commercial banks in Africa is 1,860,000, with a maximum of 7,810,000. This suggests that the outreach of the banking industry to households and SMEs in Africa is still limited, as shown by Beck and Cull (2014). The low outreach may also be explained by the fact that low-income earners in developing countries like Africa rely mostly on informal credit (Demirguc-Kunt et al., 2018). Depth of outreach has a mean of 0.0001, which provides further evidence that countries in Africa still lag in most financial inclusion metrics as compared to other regions (Čihák et al., 2012; Sha'ban et al., 2020).

Table 4.4a: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Dependent Variables					
Number of borrowers (millions)	1.860	2.090	0.037	7.810	2024
Breadth	5.963	0.560	4.552	6.893	2,024
Depth	0.0001	0.0002	0.000	0.002	1,757
Number of ATMs	15.912	16.129	0.298	68.926	2,336
Number of ATMs (log)	2.277	1.092	-1.212	4.233	2,336
Bank branches	7.660	6.255	1.044	24.827	2,360
Bank branches (log)	1.773	0.697	0.043	3.212	2,360
Independent Variables					
HHSMEs to gross loans	0.367	0.241	0.0004	0.914	1,643
HHSMES loans to CPS	0.0003	0.0002	0.000	0.001	1,637
HHSMEs Agric loans to poverty	0.337	0.247	0.070	0.625	1,591
Bank specific Variables					
Total assets (millions 'USD')	3.600	11.300	0.004	124.00	2245
Bank size	5.825	0.758	3.608	8.095	2,245
Capital	0.145	0.758	-0.161	0.927	2,244
Age	35.889	33.886	1.000	180	2,249
Age (log)	3.157	0.991	0.000	5.193	2,249
Institutional and Macro-economic variables					
Quality of financial development	0.096	0.202	0.009	1.388	2,118
Quality of institutions	0.635	0.778	-0.723	2.852	2,360
Population (millions)	45.700	42.200	1.065	191	2360
Population (log)	7.422	0.556	6.027	8.281	2,360
Inflation	0.078	0.054	-0.018	0.333	2,360
GDP growth	0.049	0.027	-0.043	0.141	2,360

Notes: In this Table, we present the descriptive statistics of our variables. Breath is the log of the total number of commercial banks' borrowers. Depth is the average loan size per borrower, calculated as the "ratio of outstanding commercial banks' loans to households and SMEs, to the total number of borrowers divided by gross national income (GNI)." Number of ATMs is the number of commercial banks' automated teller machines per 100,000 adults, while bank branches is the number of commercial banks branches per 100,000 adults. HHSMEs to gross loans is the "ratio of banks' households and SMEs loans, to gross banks' loans". HHSMEs loans to CPS is the "ratio of banks' loans to households and SMEs, to credit to the private sector." HHSMEs Agric loans to poverty is the "ratio of the total of banks' loans to households, SMEs and agriculture, to the population living below the poverty line." Bank size is the log of banks total assets. Capital is calculated as total equity divided by total assets while bank age is the log of total years of operation since a bank was established. We calculate the quality of financial development using principal component analysis (PCA), and it comprises stock market capitalization to GDP, stock market turnover to GDP and credit to the private sector to GDP. Likewise, the quality of institutions is calculated using PCA and it comprises Kaufman six governance indicators. Population is the log of a country's total population. GDP growth is the annual growth rate of GDP. Lastly, inflation is the average change in the consumer price index. Source: IMF financial access survey; BankFocus; World Development Indicators.

For geographic penetration, our sample shows that there are approximately 16 ATMs and 8 bank branches per 100,000 adults. This represents a 75% increase in the number of branches from around 2 in 2008, which may be credited to banking industry expansion programs to

previously unbanked populations (Leon & Zins, 2020). Indeed, Beck (2016) finds that there has been an apparent increase in branch penetration over time in sub-Saharan Africa, Eastern and Central Europe, and Latin America, as compared to other regions. On the other hand, the rise in the number of ATMs may also be explained by the growth in ownership and use of debit cards in the continent (Demirguc-Kunt et al., 2018).

As shown in the Table 4.4a, households and SMEs loans account for about 36.7% of the total banking industry loans and approximately 0.03% of the total credit issued to the private sector. As indicated in the earlier section, this can be attributed to efforts to increase credit access to households and small enterprises by banks. Equally, banks are scaling up financing for agriculture as shown by the sizeable maximum "ratio of banks' households, SMEs and agriculture loans, to people living below the poverty line" of 62.5%. One reason for this is that improved financial access to households is also associated with a higher probability of adoption of mechanized agricultural technologies (Bachewe et al., 2018).

The average size of the sampled banks is approximately $5.8 million. The large size may be associated with economies of scale and banking industry concentration in Africa (Banya & Biekpe, 2018). We also find that capital represents 14.5% of the total banks' assets. This is similar to findings by Beck and Cull (2014) who show that banks in Africa have become better capitalized with a ratio of equity to assets of around 14.3%. Further, we see high age variation among the sampled banks, as shown by the standard deviation of 33.886 years with the minimum and the maximum age being 1 year and 180 years, respectively. Nonetheless, the average age of 35.889 years suggests that most of the banks included in our sample have the necessary know-how and experience in their operations.

Looking at the institutional and macro-economic variables, quality of financial development has an index average of 0.096, indicating low development of the African financial sector, as also reported by Otchere et al. (2017). Moreover, the quality of institutions has a mean of 0.635, which represents steady progress in governance improvement over the last decade (Atiase et al., 2018; Coulibaly, 2020).[45] According to Table 4.4a, a substantial market for financial services exists in Africa as shown by the average population of 45.7 million. In contrast, the country with the largest population has a total of 191 million people. Finally, our sample shows an average inflation rate of 7.8% while the average GDP growth is 5.93%.

[45] For instance, fragile countries like the Democratic Republic of Congo, Central African Republic, Togo, Côte d'Ivoire and Eritrea have recorded continuous improvement in their overall governance score (Office of the Chief Economist for the Africa Region, 2019).

4.4.3 Correlation Analyses of Banking Industry Social Performance and Response Variables

Table 4.4b: Correlation analysis

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1.Breadth	1														
2.Depth	-0.358***	1													
3.Number of ATMs	0.258***	-0.421***	1												
4.Bank branches	-0.022	-0.323***	0.763***	1											
5.HHSMEs to gross loans	0.128***	-0.105**	-0.005	-0.067**	1										
6.HHSMES loans to CPS	0.005	-0.099*	0.032	0.095***	0.577***	1									
7.HHSMEs Agric loans to poverty	0.045	0.088***	0.307***	0.445***	0.003	0.255***	1								
8.Bank size	0.333***	-0.341***	0.318***	0.340***	0.068**	0.119***	0.169***	1							
9.Capital	-0.029	0.074***	-0.168***	-0.215***	-0.048*	-0.083***	-0.109***	-0.421***	1						
10.Age	0.175***	-0.076**	0.306***	0.260***	-0.005	0.014	0.168***	0.464***	-0.233***	1					
11.Quality of financial development	0.164***	-0.320***	0.471***	0.309***	-0.095***	0.037	0.397***	0.176***	-0.103***	0.206***	1				
12.Quality of institutions	-0.383***	-0.009	0.543***	0.671***	-0.093***	-0.053**	0.317***	0.037*	-0.129***	0.161***	0.395***	1			
13.Population	0.511***	-0.024	-0.433***	-0.529***	0.117***	0.102***	-0.03	0.152***	0.119***	-0.052**	0.040*	-0.682***	1		
14.Inflation	-0.309***	-0.114***	-0.593***	-0.432***	0.052**	-0.013	-0.274***	-0.294***	0.116***	-0.237***	-0.338***	-0.125***	0.136***	1	
15.GDP growth	0.111***	0.188***	-0.287***	-0.407***	0.313***	0.178***	-0.187***	-0.033	0.050**	-0.129***	-0.181***	-0.311***	0.356***	0.143***	1

Notes: Table 4.4b shows the correlation between breadth, depth, log number of ATMs and log bank branches per 100, 000 adults, the "ratio of banks' loans to household and SMEs, to banks' gross loans" (HHSMEs to gross loans), the "ratio of banks' loans to household and SMEs, to credit to the private sector" (HHSMES loans to CPS), the "ratio of banks' loans to households, SMEs and agriculture, to the population living below the poverty line" (HHSMEs Agric to poverty), bank size, capital, liquidity, age, quality of financial development, quality of institutions, population, inflation and GDP growth. ***, ** and * indicate statistical significance at 1%, 5% and 10%, correspondingly. The variables are defined as per Table 4.4a. Source: Author calculations.

We present the results of our correlation analyses in Table 4.4b. We find mixed results regarding the relationship between banking industry response measures and our outreach indicators. In particular, we find a significantly positive association between the "ratio of banks' household and SMEs loans, to gross loans" and the breadth of outreach, and a negative association between the "ratio of banks' household and SMEs loans, to banks' gross loans" and both the number of ATMs and bank branches.[46] Moreover, the coefficient between our outreach variables and banking industry response is mainly weak. This is especially the case for the correlation between the "ratio of banks' households, SMEs and agriculture loans, to people living below the poverty line" and both the depth and breadth of outreach.

The coefficient for bank size is mainly positive and significant, suggesting economies of scale advantages are associated with increased outreach (Wijesiri et al., 2017). However, the correlation between capital and our outreach indicators is mostly negative probably because higher capital may translate to less lending, hence low outreach (Bibi et al., 2018). We find the association between bank age and our outreach indicators to be mostly positive and significant. Since age indicates experience and management ability, banks may enhance their outreach over time (Talavera et al., 2018).

Concerning the institutional and macro-economic variables, the coefficients for both quality of financial development and the quality of institutions are mainly significant. Notably, there is a strong positive correlation between the quality of institutions and banking industry geographic penetration. This may be explained by the business-friendly policies associated with good governance that can facilitate the expansion of banking services (Hermes & Hudon, 2018). In contrast, population has a mostly negative and significant coefficient with most of our outreach indicators. The negative coefficient may be due to the inability of banks to achieve minimum scale economies in populated low-income areas in Africa (Beck & Cull, 2014).

Similarly, we find both inflation and GDP growth to be largely significantly and negatively correlated with most of our banking industry outreach measures. In particular, inflation has a strong negative association with both the number of ATMs and bank branches. According to Cull et al. (2015), the increase in cost associated with inflation may make it hard for banks to contract with borrowers, and this may affect their outreach. In contrast, the demand for loans

[46] We use log transformation since our measures of geographic outreach (number of ATMs and bank branches) are distributed with fat tails.

from the formal sector may increase in a growing economy, and this may in turn hinder banking outreach to the poor.

Table 4.4b shows a low correlation between most of our independent variables except for the relationship between age and bank size and quality of institutions and population. As a result, we perform a multicollinearity test of these four explanatory variables. We report the VIF scores for these variables that are highly correlated in Table 4.4c. Our results show that all our variables are within the acceptable levels of VIF of less than 10.

Table 4.4c: Test for multicollinearity

Variable	VIF	1/VIF
Age	1.48	0.674
Bank size	2.16	0.463
Population	3.96	0.253
Quality of institutions	4.63	0.216

Notes: Table 4.4c presents the multicollinearity test results for the highly correlated variables. The variables are defined as per Table 4.4a. Source: Author calculations.

4.4.4 Regression Analysis of Banks Response to Financial Inclusion Shift

In Table 4.4d, we present the results of our baseline regression estimation, using the "ratio of banks' households and SMEs loans, to banks' gross loans" as our target-independent variable, deploying a fixed-effects model. Similar to previous studies (e.g., Cull et al., 2009; Cull et al., 2015; Im & Sun, 2015; Leon & Zins, 2020), we find a positive and significant association between households and SMEs loans and depth of outreach and a negative and significant relationship with the breadth of outreach(i.e., coefficients of -0.425, 0.0002, for models 1 and 2, all at 1% significant level). This may be explained by the preference of commercially oriented financial institutions to make larger loans to fewer but best among low-income clients, as shown by Cull et al. (2014).

Since small loans are associated with higher costs, banks may find it attractive to lend to a relatively more well-off clients in the low-income market who demand larger loan sizes which have higher returns (Caserta et al., 2018; Kar & Swain, 2018). Although this may reduce banks costs and increase profits, it may come at the expense of lower outreach to the poor.

Additionally, banks' preference for wealthier micro-traders and households may be due to their ability to take individual loans as compared to poorer clients who are mainly served by group liability programs (which are largely available via informal set-ups).

Table 4.4d: Regression of social performance, using the "ratio of banks' households and SMEs loans, to banks' gross loans" as banks response measure

VARIABLES	Breadth	Depth	Number of ATMs	Bank branches
HHSMEs to gross loans	-0.425***	0.0002***	0.093***	0.293***
	(0.085)	(4.22e-05)	(0.028)	(0.066)
Bank size	0.025	4.98e-06	0.028	0.070*
	(0.044)	(2.48e-05)	(0.033)	(0.041)
Capital	0.047	-2.19e-05	0.019	0.018
	(0.111)	(1.78e-05)	(0.063)	(0.071)
Age	-0.040	3.88e-07	0.064**	0.018
	(0.035)	(1.78e-05)	(0.033)	(0.040)
Quality of financial development	-1.325***	-0.001**	-0.169***	-0.048
	(0.356)	(0.0005)	(0.033)	(0.033)
Quality of institutions	0.336***	4.18e-05	-0.167***	-0.145
	(0.025)	(2.58e-05)	(0.027)	(0.031)
Population	-2.136	-0.002	0.298	-0.138
	(1.928)	(0.001)	(0.899)	(1.081)
Inflation	-0.305**	0.0002**	1.316***	-0.098
	(0.128)	(9.32e-05)	(0.074)	(0.074)
GDP growth	1.251***	-0.001***	-0.985***	-0.018
	(0.216)	(0.0001)	(0.222)	(0.241)
Constant	21.970	0.015	-0.647	2.1650
	(14.650)	(0.010)	(6.794)	(8.106)
Observations	1,163	966	1,341	1,341
F-test	0.000	0.000	0.000	0.000
R-squared	0.532	0.199	0.739	0.232
Hausman test (p-value)	0.002	0.000	0.000	0.000
Time fixed effects	Yes	Yes	Yes	Yes
Number of Banks	188	159	214	214

Notes: Table 3d presents the regression results of commercial banks' breadth, depth, number of ATMs and bank branches and the "ratio of banks' households and SMEs loans, to banks' gross loans" (HHSMEs to gross loans), as our target independent variable. We control for bank size, capital, bank age, quality of financial development, quality of institutions, population (log), GDP growth and inflation. We estimate the models using fixed effects. Standard errors are in parentheses and are heteroscedastic-robust. *** and * indicate statistical significance at 1% and 10% respectively. Source: Author calculations.

Regarding the geographic penetration, we find a positive and significant association between banking industry response and the number of ATMs and bank branches (with coefficients of 0.093 and 0.293 for models 3 and 4, respectively). A possible explanation is that households and SMEs rely more heavily on personal contact which may persuade banks to set-up more branches so as to increase client interaction and also to enhance their competitive advantage (Cull et al., 2014; Kondo, 2018; Coulibaly & Yogo, 2019). Importantly, branches are effective tools for reaching new clients. On the other hand, the significantly positive coefficient for the number of ATMs may be explained by the need for banks to attract new clients as well as enable existing customers to effectively and reliably (conveniently) deposit and withdraw cash (Demirguc-Kunt et al., 2018; Natarajan et al., 2019).

Bank size has a positive association with both the breadth and depth of outreach. These results confirm our earlier expectations and are in line with previous studies by Vanroose and D'Espallier (2013) and Gutierrez-Goiria et al. (2017). However, the coefficient for the two variables is not significant, suggesting that banks in Africa do not benefit from the potential economies of scale associated with increasing outreach to households and SMEs. As noted earlier, this may be because the loan sizes issued to the low-income earners may not be large (i.e., widespread) enough to enable banks to enjoy cost-saving benefits that are usually associated with serving more clients.

Similarly, we find a positive relationship between bank size and both the number of ATMs and bank branches. However, only the coefficient for the number of bank branches is significant. One reason for this is the fact that bank branches offer more services compared to ATMs which are mainly used to withdraw cash and check account balances (Rewilak, 2017). The wide range of services provided by branches may provide banks with economies of scale discount in serving low-income clients. Table 3d further shows that capital is insignificant in explaining banking industry outreach in Africa.

These findings confirm previous evidence (e.g., Ediz et al., 1998; Kar, 2012; Werner, 2014; Fang et al., in press) that capital serves to predominantly strengthen banks' ability to absorb losses without altering their lending decisions. The positive coefficient for the number of ATMs and bank branches may be explained by the investment cost required to establish and operate ATMs (Sathye & Sathye, 2017). We find the coefficient of bank age to be largely insignificant in explaining banking outreach in Africa. These age-related findings are similar

to prior related literature (e.g., Cull et al., 2015; Afrifa et al., 2019; Leon & Zins, 2020) which suggests that experience (inexperience) does not impact banks' outreach performance.

We can argue that banks' outreach to households and SMEs is largely influenced by their market and profit strategy rather than their experience (Olivares-Polanco, 2005; Chikalipah, 2019). Conversely, we find the coefficient between age and the number of ATMs to be significantly positive, suggesting that banks may gain cost efficiency benefits associated with establishing more ATMs over time (Ledgerwood, 1998; Zamore et al., 2019). Banks may also be able to earn reputation, improve their technology and accumulate clientele information gradually, which may enable them to offer a number of their services using ATMs (Khachatryan et al., 2017).

Still according to Table 4.4d, quality of financial development has a significantly negative coefficient with breadth and depth of outreach. We can offer several arguments for this outcome. First, in countries with developed financial systems, most SMEs and households are already incorporated in the formal financial services sector (Vanroose & D'Espallier, 2013). This may enable MFIs to reduce their lending costs leading to a decline in the demand for banking services from low-income earners. Secondly, MFIs located in developed financial systems, can access funding opportunities more easily. Accordingly, they may be able to serve the low-income market more effectively reducing the demand for financial services from banks.

Similarly, we observe a negative association between quality of financial development and banking industry geographical penetration. However, only the number of ATMs has a statistically significant coefficient. This is in contrast to findings by Hossain et al. (in press) who document that financial development promotes inclusive access to financial services by facilitating banks' geographical expansion. We may argue that financial development offers borrowers more flexibility and choice in accessing financial services. Accordingly, low-income earners may substitute financial services from banks for those from MFIs, which may in turn cause a substantial decline in the use of ATMs (Hermes & Hudon, 2018).

Consistent with previous studies (e.g., Beck et al., 2007b; Le et al., 2016; Mia & Lee, 2017), we find the quality of institutions to have a significantly positive impact on the breadth of outreach. According to Ahlin et al. (2011), better institutions enhance borrower discipline, which can increase banks' willingness to provide financial services to low-income earners. Further, we see no significant association between the quality of institutions and depth of

outreach. A possible explanation is that improved institutional quality increases the pool of clients that can be served by banks but does not influence the loan sizes granted. This is especially evident in respect of SMEs, where the loan size mostly depends on the borrower-lender relationship and the quality of information (Durguner, 2017; Nakamura & Roszbach, 2018).

In contrast, our results in Table 4.4d show a negative and significant association between the quality of institutions and the number of ATMs. We may argue that improvement in governance, particularly in Africa can promote trust in the use of alternative channels for delivering financial services like mobile phones and agent banking that may result to limited use of ATMs (Chironga et al., 2018). Moreover, we find the quality of institutions to be irrelevant in explaining the number of bank branches. This may be due to the fact that investment decisions are not easily reversible as a result of fluctuations in governance, as shown by Kodongo (2016).

Interestingly, the potential market opportunities for financial services do not influence the outreach of the banking industry, as shown by the insignificant coefficient for population. This is in contrast to studies by Ahlin et al. (2011) and Chmelíková et al. (2019) who find evidence that high population increases banking efficiency and market potential for financial services. However, a high population may not necessarily translate to higher profitability and financial sustainability for banks, as shown by Lopez and Winkler (2018). The outreach of the banking industry may thus be largely driven by the commercial viability of the target market, not the mere size of the market.

In line with our prediction, we find inflation to have a significantly negative effect on the breadth of outreach. As stated earlier, reaching poor clients is costly and less efficient due to the lower loan sizes (Adhikary & Papachristou, 2014). Because inflation increases operating costs, banks may opt to reduce their outreach during periods of high inflation so as to lessen their expenses and increase efficiency. We may also argue that the demand for loans, particularly by the poor, may decline during periods of high inflation. This is because banks may add a large inflation premium on their interest rates, increasing the cost of funds (Ahlin & Lin, 2006; Ahlin et al., 2011).

In contrast to prior studies (e.g., Allen et al., 2014; Aluko & Ajayi, 2018), we find the coefficient for the relationship between inflation and the depth of outreach to be positive and significant. This is perhaps because banks may respond to higher inflation by offering larger

loans to the relatively wealthier clients in the low-income market, as poor customers are more susceptible to inflation risk and higher borrowing costs (Xu et al., 2016). We further find inflation to be significantly positive in explaining variations in the number of ATMs. This may be explained by the need for banks to adopt financial technologies in order to reduce the welfare cost of inflation (Attanasio et al., 2002).

On the other hand, the number of bank branches has a negative and insignificant relationship with inflation. The negative coefficient may be due to a decline in banking operations as a result of the reduction in lending activities and capital formation owing to higher inflation (BenNaceur & Ghazouani, 2005; Kakar & Daniels, 2019). Additionally, we observe a significant positive association between GDP growth and breadth of outreach and a negative and significant coefficient for the depth of outreach, similar to findings by Churchill (2019). These results suggest that improved economic conditions enhance bank lending to a larger number of borrowers, but does not necessary expand the pool of banks' loanable funds.

A well-performing economy may provide wealthier borrowers with alternative sources of financing. Consequently, banks may be forced to increase their outreach to poorer households, leading to a decrease in loan sizes. Similarly, we find a significantly negative coefficient for the number of ATMs which could be explained by the limited use of ATMs by poorer households who hold lower account balances. Finally, GDP growth has no significant effect on the number of bank branches in Africa, similar to previous observations by Mersland et al. (2011) and Cull et al. (2014). This is probably because the marginal effects associated with changes in a country's economic performance may not be large enough to influence banks decisions to establish new branches.

4.4.5 Regression of Alternative Response Measure

As indicated in the introductory section, we re-estimate our model using an alternative measure of banking industry response to competition for financial inclusion paradigm. Specifically, we use the "ratio of banks' households and SMEs loans, to credit to the private sector" (HHSMES loans to CPS). Table 4.4e shows the results of our analyses, which are broadly consistent with our findings in Table 4.4d. We find the interaction between the "ratio of banks' households and SMEs loans, to credit to the private sector" and both depth and breadth of outreach to be statistically significant at the 1% level, with the two variables having a negative and a positive coefficient, respectively. This confirms our earlier findings that the commercial logic of banks

makes them cherry-pick and offer large loans to fewer and less poor households and micro-entrepreneurs.

Table 4.4e: Regression of social performance, using the "ratio of banks' households and SMEs loans, to credit to the private sector" as banks' response measure

VARIABLES	Breadth	Depth	Number of ATMs	Bank Branches
HHSMEs loans to CPS	-692.0***	0.405***	-115.4***	825.6***
	(161.2)	(0.063)	(33.43)	(200.2)
Bank size	0.032	2.02e-06	0.025	0.069*
	(0.046)	(2.47e-05)	(0.033)	(0.039)
Capital	0.017	-1.80e-05	0.005	0.038
	(0.115)	(1.69e-05)	(0.063)	(0.064)
Age	-0.044	1.03e-06	0.066**	0.014
	(0.035)	(1.77e-05)	(0.033)	(0.039)
Quality of financial development	-1.029***	-0.001***	-0.177***	-0.136***
	(0.362)	(0.001)	(0.033)	(0.022)
Quality of institutions	0.315***	5.00e-05**	-0.162***	-0.005
	(0.022)	(2.46e-05)	(0.027)	(0.028)
Population	-0.697	-0.003**	0.396	-0.880
	(1.998)	(0.001)	(0.922)	(0.838)
Inflation	-0.371***	0.001*	1.379***	-0.113*
	(0.124)	(9.29e-05)	(0.079)	(0.060)
GDP growth	1.088***	-0.001***	-0.886***	-0.039
	(0.207)	(8.57e-05)	(0.213)	(0.243)
Constant	11.07	0.021**	-1.411	7.814
	(15.23)	(0.010)	(6.987)	(6.270)
Observations	1,148	951	1,326	1,326
F-test	0.000	0.000	0.000	0.000
R-squared	0.536	0.218	0.738	0.290
Hausman test (p-value)	0.000	0.001	0.000	0.000
Time fixed effects	Yes	Yes	Yes	Yes
Number of Banks	173	144	199	199

Notes: In Table 3e, we regress commercial banks breadth, depth, number of ATMs and bank branches with the "ratio of banks' households and SMEs loans, to credit to the private sector" (HHSMEs to CPS) using fixed effects. We control for both bank-specific variables and macroeconomic variables. For bank-specific variables, we control for bank size, capital and bank age. In relation to institutional and macro-economic variables, we control for quality of financial development, quality of institutions, population (log), GDP growth and inflation. Standard errors are heteroscedastic-robust and are in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively. Source: Author calculations.

We further find a significant coefficient for geographical penetration. However, the coefficient for the number of ATMs has a negative sign which is inconsistent with our earlier findings.

This may be expected since lending mostly occurs at the bank branches. Similar to our results in Table 4.4d, we find bank size to be relevant in explaining the number of bank branches. Nonetheless, our results show a positive and significant association between bank size and depth of outreach. This contrasts with our previous findings, and it may be explained by the possible economies of scale that can arise because of providing fewer borrowers with larger loans that are less costly to monitor.

Consistent with our findings, capital has no significant influence on banking industry outreach. This confirms our earlier argument that capital mainly serves as a buffer against adverse economic conditions. We further find the coefficients for both Bank age and financial development to be mostly in line with our previous results. However, the quality of institutions has a positive and significant effect on the depth of outreach, in contrast to earlier findings. This may be anticipated since banks incentives to lend to poorer clients can increase with strong institutions. Moreover, population has a largely insignificant effect on banking industry outreach in Africa, confirming our earlier findings.

Similar to our results in Table 4.4d, we find inflation to be negatively and significantly related to the breadth of outreach and positively related to both depth of outreach and the number of ATMs. However, the coefficient between inflation and the number of bank branches is significantly negative at the 10% level, in contrast to our earlier findings. This inconsistency is possible since inflation increases price and reduces the capacity of borrowers to take up loans which can adversely affect the ability of banks to set-up more branches (Mia & Lee, 2017). Lastly, GDP growth has a significantly positive association with the breath of outreach and a negative and significant relationship with both the depth of outreach and the number of ATMs, which confirms our prior findings.

4.4.6 Further Robustness Test

Having presented our baseline results, we test the robustness of our findings by using the "ratio of banks' households, SMEs and agricultural loans, to the population living below the poverty line" as our target-independent variable. Our findings reported in Table 4.4f are generally consistent with the results in Table 4.4d and Table 4.4e. We find a significantly negative coefficient for the breadth of outreach and a positive and significant coefficient for the depth of outreach (i.e., -1.372 and 0.001 for both models 1 and 2, with a 1% significance level). This is consistent with our earlier findings suggesting that banks respond to the competition for financial inclusion by providing larger loans to few but less poor clients.

Table 4.4f: Regression analysis of social performance, using the "ratio of banks' households, SMEs and agriculture loans to population living below the poverty line" as banks' response measure

VARIABLES	Breadth	Depth	Number of ATMs	Bank branches
HHSMEs Agric to Poverty	-1.372***	0.001***	0.051***	0.071***
	(0.219)	(0.0001)	(0.014)	(0.016)
Bank size	0.040	3.74e-05*	-0.044	0.064**
	(0.045)	(2.11e-05)	(0.035)	(0.031)
Capital	0.100	-1.69e-05	-0.015	0.018
	(0.132)	(5.17e-05)	(0.078)	(0.056)
Age	-0.065	1.44e-05	0.066*	0.022
	(0.041)	(1.89e-05)	(0.036)	(0.040)
Quality of financial development	1.582***	-0.003***	-0.120***	-0.136***
	(0.552)	(0.001)	(0.038)	(0.033)
Quality of institutions	0.368***	-3.33e-06	-0.103***	-0.018
	(0.024)	(1.45e-05)	(0.030)	(0.021)
Population	-5.254**	0.002	-1.889*	-3.289***
	(2.374)	(0.003)	(0.989)	(0.777)
Inflation	-0.745***	0.0003***	1.476***	0.252***
	(0.139)	(0.0001)	(0.069)	(0.051)
GDP growth	1.047***	-0.001***	0.487***	1.171***
	(0.206)	(8.82e-05)	(0.178)	(0.237)
Constant	46.00***	-0.019	16.42**	26.26***
	(18.23)	(0.019)	(7.515)	(5.866)
Observations	961	961	1,113	1,113
F-test	0.000	0.000	0.000	0.000
R-squared	0.488	0.205	0.704	0.205
Hausman test (p-value)	0.000	0.000	0.000	0.000
Time fixed effects	Yes	Yes	Yes	Yes
Number of Bankid	172	172	198	198

Notes: In Table 4.4f above, we present the regression results between commercial banks breadth, depth, number of ATMs and bank branches with the "ratio of banks' households, SMEs and agriculture loans, to the population living below the poverty line" (HHSMEs Agric to Poverty) using a fixed-effects model. We include controls for both bank-specific variables and, institutional and macroeconomic variables. For bank-specific variables, we control for bank size, capital and bank age. In relation to macro-economic variables, we control for quality of financial development, quality of institutions, population (log), GDP growth and inflation. Standard errors are heteroscedastic-robust and are in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively. Source: Author calculations.

We find a significant and positive relationship between both the number of ATMs and bank branches and the "ratio of banks' households, SMEs and agricultural loans, to people living below the poverty line," consistent with our findings in Table 4.4d. This is expected since expansion through branches and ATMs provides banks with an important avenue to provide financial services to a larger population base (Natarajan et al., 2019). Consistent to our baseline findings, we find a largely insignificant association between bank size and our outreach variables.

Comparable to our results in Table 4.4d, capital has no significant effect on our outreach variables. Similarly, we find the coefficient of age to be insignificant in explaining changes in both the number of bank branches and depth of outreach, which confirms our prior findings. However, age has a negative and significant coefficient with the breadth of outreach, contrary to our baseline findings. This is possible since older banks may be susceptible to competition from younger peers in reaching new clients which may adversely affect their outreach, as shown by Ayayi and Wijesiri (2018). Moreover, older banks may be less aggressive and growth-oriented than their younger counterparts and this may explain their poor outreach performance.

Furthermore, the quality of financial development has a significant effect on our outreach measures, consistent with our baseline results. Nevertheless, the coefficient for quality of financial development and breadth of outreach has a positive sign which is contrary to our previous findings. This is possibly because financial development may lead to increased competition in the provisioning of financial services which can force banks to increase their outreach to more poor clients. Similar to our earlier analysis, we find a significant association between the quality of institutions and both depth and breadth of outreach, as well as the number of ATMs.

Contrary to our earlier results, the coefficient between depth and quality of institutions has a negative sign. This results are likely given that well-developed institutions reduce the opportunities to circumvent costly government procedures (Hermes & Hudon, 2018). Therefore, the demand for loans by households and SMEs may decline in countries with a good institutional environment due to their inability to follow procedures and access government services. Likewise, the relation between population and our outreach measures is mostly negative and significant, in contrast with our previous findings.

A possible explanation is that population sprawl may significantly increase the number of clients served, especially when banks may already be developed in areas with a high population (Tirtiroğlu et al., 2005). Contrary to our prior results, we find inflation to have a significantly positive association with depth of outreach and the number of bank branches. This can be expected since banks may aim to reduce costs and reach more borrowers during periods of high inflation by offering large loans and establishing more branches (Mia & Lee, 2017; Bibi et al., 2018). Finally, and in contrast to our baseline results, GDP growth has a positive and significant coefficient. This is possible because better economic conditions, improve the borrowing ability of the poor and stimulate the demand for micro-loans as well as monetary transactions (Mia & Soltane, 2016).

CHAPTER FIVE

CONCLUSIONS, POLICY IMPLICATIONS AND SUGGESTIONS FOR FUTURE STUDIES

5.1 Introduction

The recent paradigm shift from microfinance to financial inclusion has created conditions for expanding financial services to low-income earners. Accordingly, commercial banks, particularly in Africa, are expanding their services to households and SMEs they traditionally/previously ignored (Mader, 2018). On the other hand, MFIs have experienced impressive growth over the last few years owing to increased funding from commercial and public sources and the ongoing commercialization of the microfinance industry (Liñares-Zegarra & Wilson, 2018). This has, in turn, led to stiff competition in the low-income market segment as banks and MFIs contest to attract and provide financial services to more households and SMEs (Cull et al., 2014; Leon & Baraton, 2021).

The increased competition in providing financial services to low-income earners is perceived as a sustainable market-driven incentive for banks to improve their efficiency and broaden financial access. However, there are concerns in the financial inclusion literature that this competition may push banks towards risky borrowers and affect the overall stability and efficiency of the banking industry. Yet, the outcome of the increased competition for financial inclusion in the banking industry, as well as access to financial services remains unclear. Most studies on competition and financial access focus on the effect of competition between banks and access to finance; the effect of competition between MFIs on outreach to the poor; and the effect of banking sector development on MFIs outreach.

The motivation for this study, therefore, is to shed more light and fill the literature gap on the broader issue of competition between banks and MFIs and how the competition affects the banking industry and access to finance by the low-income earners. Specifically, we investigated four issues in this study. First, we examined how the banking industry in Africa is responding to the competition for financial inclusion. Secondly, we assessed how the response to competition for financial inclusion affects the efficiency of the banking industry in Africa. Third, we analysed the extent to which the response to competition for financial inclusion has changed the asset portfolio risk of these banks. Lastly, we investigated how the response affected the degree of social performance (outreach) of the banking industry in Africa. We present our findings in the following sections in accordance to our research questions.

5.2 Banking Industry Response to Competition for Financial Inclusion Paradigm

Our analysis is based on a sample comprising all banks and MFIs across 16 countries (Ethiopia, Kenya, Rwanda, Tanzania, Uganda; Egypt, Morocco, Tunisia; Botswana, Namibia, South Africa, Swaziland, Zambia; Ghana, Nigeria and the Gambia) in Africa for the period 2010-2017. Bank-specific data was obtained from the Bankfocus database, while MFI-specific data was sourced from the MIX database. Furthermore, data on bank loans to households and SMEs was extracted from the IMF financial access survey database and the Central banks of the countries sampled. Finally, institutional, and macroeconomic data were sourced from the Kaufman governance indicators and the World Bank WDI database, respectively.

To investigate how the banking industry in Africa is responding to the competition for financial inclusion, we used a fixed-effects model following extant related studies (e.g., Assefa et al., 2013; Vanroose & D'Espallier, 2013). Since competition for financial inclusion is arising from MFIs, we constructed our proxy for the competition for financial inclusion using the "ratio of MFIs' loans divided by credit to the private sector." On the other hand, we used the "ratio of banks' loans to households and SMEs, to credit to the private sector," as our proxy for the banking industry response to competition for the financial inclusion paradigm.

We found evidence that banks in Africa are responding to the competition for financial inclusion by increasing the amount of loans to households and SMEs. These findings support the argument that competition pushes financial institutions to supply more credit to opaque borrowers in order to grow and/or sustain their market share in accordance with the "market power hypothesis." To check the robustness of our results, we employed two alternative measures for both competition for financial inclusion and the banking industry response. First, we used the "ratio of MFIs' assets, to the population living below the poverty line" as our proxy for competition for financial inclusion.

For our banking industry response variable, we constructed our proxy using the "ratio of banks' loans to households, SMEs and agriculture, to the population living below the poverty line." Secondly, we used the "ratio of MFIs gross loans divided by the total of banks' loans to household and SMEs" as our measure for competition for financial inclusion, and the "ratio of banks' loans to households and SMEs, to banks' gross loans" as our proxy for banking industry response. We employed a fixed-effects model for our first robustness check and a random-effects model for our second robustness check, based on the Hausman test results. Our results remained consistent with our baseline findings, confirming that increased competition for

financial inclusion prompts banks to increase lending to households and SMEs, so as to grow their market share in the low-income market.

5.3 Banking Industry Response to Competition for the Financial Inclusion Paradigm and Efficiency

Competition is viewed in the banking industry literature as having a positive impact on banks' cost efficiency by fostering expansion and diversification of banks' lending activities (Hossain et al., 2020; Li & Li, 2020). However, competition, particularly for low-income earners, may shorten lending relationships and intensify information asymmetry, and thus increasing banks' cost inefficiency due to higher screening and monitoring costs. Accordingly, to determine the efficiency effect of banking industry response to competition for financial inclusion, we employed a two-stage approach. In the first stage, we generated the cost efficiency scores using four alternative techniques.

First, we used the DEA approach with 3 inputs (labour, capital and purchased funds) and 4 outputs (total loans, off-balance sheet items, deposits and other earning assets) to generate the cost efficiency estimates of the banks sampled. Second, we generated robust cost efficiency estimates using the DEA approach, whereby we did not include deposits as part of the outputs in the input-output matrix. Third, to generate more robust cost efficiency scores, we employed the SFA technique since it accounts for statistical noise and measurement errors (Alhassan & Biekpe, 2016). Lastly, to correct the bias in the cost efficiency scores, we bootstrapped the DEA cost efficiency estimates generated in the first approach using the Simar and Wilson double bootstrap technique.

In the second stage, we regressed the efficiency scores obtained from the first stage against the "ratio of banks' households and SMEs loans, to banks' gross loans" as our proxy for the banking industry response to competition for financial inclusion paradigm. For the models with DEA efficiency scores, we employed a fractional logistic estimation technique following previous studies (e.g., De Abreu & Kimura, 2020; Nguyen & Pham, 2020b). In contrast, we used maximum likelihood estimation technique for the models with SFA and the Simar and Wilson bias-corrected DEA efficiency scores, similar to previous studies by Huang et al. (2018) and Cabrera-Suárez and Pérez-Rodríguez (2020).

We found that increased lending by banks to households and SMEs in response to the competition for financial inclusion, has a positive and significant effect on the banking industry's cost efficiency in Africa across our four estimation models. These results support

earlier findings by Mia et al. (2019) and Saha and Dutta (2020) that higher credit financial inclusion enhances banking industry's cost-efficiency. We attribute these findings to the economies of scale advantages that banks gain as a result of expanding their output to the large market of low-income earners in the continent. It is also possible that the higher cost efficiency levels result due to lower loan costs and scale economies associated with banks' preference for providing large loans to few but relatively well-off households and SMEs in the low-income market.

We performed further robustness checks using our two alternative measures of banking industry response. First, we regressed our cost efficiency scores against the "ratio of banks' households and SMEs loans, to credit to the private sector." Secondly, we used the "ratio of banks' households, SMEs and agriculture loans, to the population living below the poverty line" as our explanatory variable and the cost-efficiency estimates as our predictor variables. Our results were consistent with the findings of our earlier estimation that showed that increased banks' lending to households and SMEs contributes positively to banking industry cost-efficiency.

5.4 Banking Industry Response to Competition and Asset Portfolio Risk

The literature on bank risk taking shows that competition may encourage banks to lower their screening and lending standards in an attempt to grow their market share (Jiménez et al., 2013; Saif-Alyousfi et al., 2018). This can attract low-quality borrowers and deteriorate banks' asset portfolio quality. However, via competition for financial inclusion, banks can grow their lending in the low-income market by lowering their loan rates (Albaity et al., 2019). This may lower default rates and provide banks with an opportunity to diversify their loan portfolios, leading to enhanced banking stability. As a result, we investigated the effect of 'banking industry response to competition for financial inclusion' on banks' assets portfolio risk.

We employed the "ratio of non-performing loans, to gross loans ratio" to measure banks' asset portfolio risk in Africa. And, we used the "ratio of banks' household and SMEs loans, to banks' gross loans," the "ratio of banks' households and SMEs loans, to credit to the private sector," and the "ratio of banks' households, SMEs and agriculture loans, to people living below the poverty line" to measure banking industry response to competition for the financial inclusion paradigm. Using a two-step system GMM estimator following earlier studies by Abuzayed et al. (2018), Bermpei et al. (2018) and Teixeira et al. (2020), we found that increased lending to

households and SMEs has a positive but insignificant effect on the asset portfolio risk of banks in Africa across our three estimation models.

These results support the competition-fragility hypothesis and confirm earlier findings by Dwumfour (2017) and Saha and Dutta (2020) that increased lending due to competition may attract low-quality borrowers, which may lower banking industry stability. We used two alternative measures of assets portfolio risk for our robustness checks: The Z-score and the risk-weighted assets to total assets ratio. The results were mostly consistent with the findings of our baseline models, confirming that growing credit financial inclusion in response to competition for financial inclusion has a deleterious and insignificant effect on the stability of the banking industry.

5.5 Banking Industry Response to Competition and Social Performance (Outreach)

A distinct feature of the financial inclusion paradigm is that it invites mainstream commercial banks to look "downward" and consider providing financial services to the poor (Mader, 2018). However, the microfinance literature (e.g., Assefa et al., 2013; Cull et al., 2014; Hossain et al., 2020) shows that competition may lead to reduced focus on outreach by commercialized MFIs because it is cheaper to provide large loans to relatively well-off clients than providing small-loans to poorer borrowers. Accordingly, we investigated the banking industry social outreach (performance) as a result of the response to the competition for financial inclusion paradigm. We used four alternatives measures of banking industry social performance: the breadth of outreach, the depth of outreach, and the number of ATMs and bank branches per 100,000 adults, in line with previous studies by Im and Sun (2015), Churchill (2019) and Hossain et al. (2020), among others.

For our baseline regression model, we deployed the "ratio of banks' households and SMEs loans, to banks' gross loans" as our proxy for the banking industry response to competition for financial inclusion paradigm. Using a fixed-effects model, we found a positive and significant relationship between banking industry response to competition for financial inclusion paradigm and depth of outreach, and both the number of bank branches and ATMs. However, we found a negative and significant relationship between our banking industry response variable and breadth of outreach, suggesting that competition makes banks to target wealthier borrowers in the low-income market.

These findings support the view that profit-oriented financial institutions prefer to make larger loans to few but relatively well-off low-income clients in order to increase their returns and

reduce both loan costs and default rates. For our robustness check, we used the "ratio of banks' households and SMEs loans, to credit to the private sector," and the "ratio of banks' households, SMEs and agriculture loans, to the population living below the poverty line," as our alternative measures of banking industry response to competition for financial inclusion paradigm. The results were consistent with the findings of our main analysis. These findings also confirm our efficiency estimation results that banks can gain cost efficiency advantages by offering relatively large loans to few but wealthier households and SMEs.

5.6 Policy Recommendations

We can draw several implications from the findings of this study that can help policymakers and practitioners in the fields of banking, microfinance, and financial inclusion. First, from the perspective of the banking industry response to the competition for financial inclusion paradigm, our results underline the importance of competition in driving the financial inclusion agenda in Africa. Accordingly, governments, regulators, and international institutions interested in financial inclusion should provide policy pathways to promote competition in the low-income market and thus generate market-based and sustainable incentive in advancing financial inclusion.

This may involve easing regulatory impediments to attract more financial sector actors to provide financial services to the poor and drive competition in the low-income market. Additionally, enabling access to borrowers' information combined with a policy framework to support the development of financial market infrastructures like lending technologies and information sharing can further promote competition for low-income earners. Secondly, our analysis shows the significance of MFIs in pushing the financial inclusion agenda in Africa. Accordingly, with the increasing competition for financial inclusion, regulators need to develop the necessary policies to ensure that MFIs can access the required funding and support to facilitate their growth and ensure that they remain competitive and sustainable. And consequently, keep steady the productive competition outcomes from commercial banks.

Secondly, looking at the results of our efficiency estimations, we recommend that in the presence of potential economies of scale, regulators should support pro-competitive policies in the low-income market as a means of enhancing efficiency in the banking industry and improving social welfare. Our findings suggest that as banks compete for higher market share, they can gain cost efficiency advantages due to economies of scale associated with increased lending to households and SMEs. Furthermore, our results suggest that banks can gain scale

efficiencies and reduce intermediation costs by expanding their loan output through increased outreach to low-income earners.

Therefore, to enable banks to increase their productivity, regulators should adopt policies that encourage banks to expand their services to the low-income market. This may help in boosting banking industry efficiency and increasing financial outreach to the poor. However, policymakers also need to take into consideration the potential detrimental effects of competition on efficiency. Our results indicate that banks may prefer to focus on more profitable (relatively more well-off) clients in the low-income market as they seek to enhance their cost efficiency in the face of competition. Accordingly, governments and regulators need to develop policies that can enable banks to deliver financial services at a lower cost while providing financial services to the broader population segment of the poor.

Third, from the banking industry portfolio risk results, our analysis shows that increasing the amount of loans to households and SMEs can deteriorate banks credit quality. Therefore, central banks and regulators need to design appropriate regulatory measures to ensure that competition for financial inclusion does not compromise the stability of the banking industry. This may involve supporting initiatives to establish credit bureaus, centralised risk management systems, and promote information-sharing culture between financial institutions in the low-income market. This can help to reduce information asymmetry and lower banking industry risk exposure.

Furthermore, regulatory authorities should ensure that competition policies in the low-income market do not compromise banking stability. This may involve designing regulations that improve both competition and stability and create appropriate conditions for low-income earners to access credit. Moreover, improved supervisory measures may play an essential role in ensuring that banks do not take excessive risk as they compete to grow their market share in the market for low-income earners. Lastly, there is also potential for banks to improve their stability by increasing financial inclusion. Policies on broadening banking services to a larger spectrum of low-income earners can help banks maximize the benefits of assets diversification and reduce the risk of instability.

Finally, our social performance results show that increased competition for financial inclusion may make banks to ration credit to poorer and less credit worthy borrowers. Therefore, efforts to encourage competition for financial inclusion should take into consideration the resulting decline in the breadth of outreach. This calls for regulators in the banking sector to develop

policies that encourage banks to increase financial access to the poor. Some of the policies may involve providing funding and conditional subsidies, like tax reduction, to encourage banks to increase their outreach to poorer borrowers. This can assist in achieving greater financial inclusion in the current competitive low-income market.

Furthermore, creating an enabling environment for innovation and use of technology like ATMs and telephony money and related transactions, to reach more lower-income clients can help banks lower the costs and risk involved in providing financial services to the poor. Lastly, policies that improve the competitiveness of banks in the low-income market can have positive spill-over effects in prompting MFIs to increase their outreach to poorer borrowers. Our banking industry social performance results indicate that competition for financial inclusion makes banks to focus on wealthier clients among a pool of low-income borrowers. Increased competition for profitable clients can push MFIs towards poorer borrowers, which can in turn promote more widespread financial inclusion.

5.7 Contributions to the Literature

Our study makes several significant contributions to the literature. First, we add to the literature on market structure matters and financial inclusion paradigm effects by reporting how the banking industry is responding to the competition from the financial inclusion paradigm in Africa, where access to finance is notably limited. Importantly, whereas previous studies have mainly centred on competition external to MFIs and access to finance, our study provides new evidence by focusing on competition between banks and MFIs and employing unique measures of banking industry response and competition for financial inclusion.

Second, we extend the literature on banking efficiency by considering the sparsely researched issue of the effect of competition for financial inclusion on banking industry cost-efficiency. We use different cost-efficiency estimation methods, thus providing more robust results. Furthermore, our study contributes to the currently growing literature on financial inclusion and banking industry stability by examining the impact of banking industry response to competition for financial inclusion paradigm on banks' asset portfolio risk in Africa. And lastly, we add to the limited research on competition and its consequence on financial institutions outreach by providing evidence on the effect of competition for financial inclusion on banking industry social performance.

5.8 Suggestions for Future Studies

Our study is limited to credit financial inclusion. Accordingly, an avenue for future studies is to explore the impact competition in the low-income markets on other financial inclusion parameters (other kinds of financial product). For instance, future studies can examine how the banking industry is responding to the competition for financial inclusion by focusing on price, quality of banking services and loan conditions to households and SMEs. Additionally, future studies can investigate whether banks are able to attract more deposits from households and SMEs, and in turn increase their outreach to women with the increased competition for financial inclusion.

Future studies can also assess the implications of the response to competition for financial inclusion on banking industry profitability. Furthermore, our study focused on the nexus between competition and financial inclusion from the supply-side perspective. Therefore, an opportunity for future research is to look at how the increased competition for financial inclusion affects the usage of banking services by households and SMEs from the demand-side perspective. Lastly, future studies can analyse the optimal level of competition in the low-income market that maximizes access to finance, without hurting financial inclusion.

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Appendix

Table A1: Distribution of Commercial banks

List of ample countries	No of banks
Botswana	10
Egypt	23
Eswatini	3
Ethiopia	14
Gambia, The	3
Ghana	21
Kenya	33
Malawi	5
Morocco	14
Namibia	6
Nigeria	18
Rwanda	8
South Africa	14
Tanzania	30
Uganda	18
Zambia	15
Total	**235**

Figure A1: Distribution of cost efficiency and mean efficiency from 2010-2017.

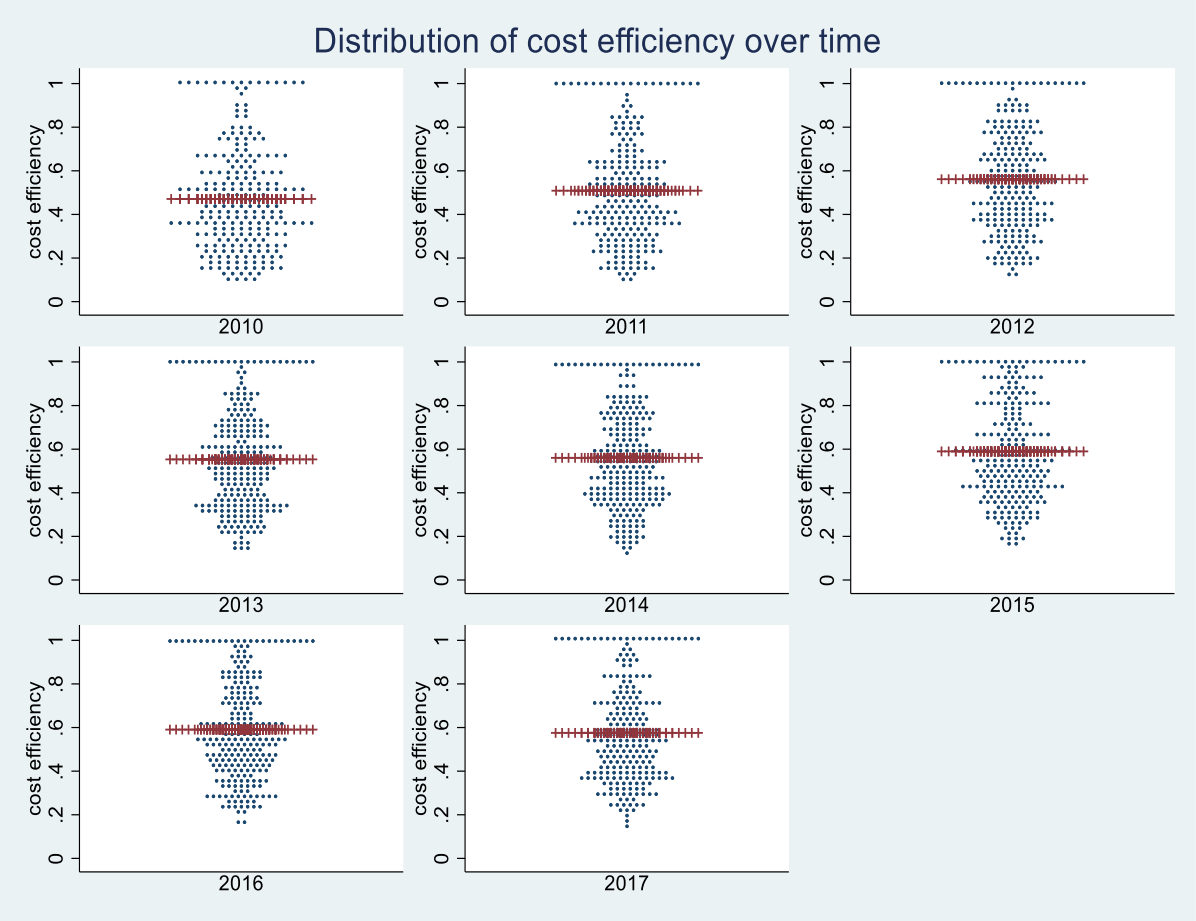

Figure 4.2d presents the distribution of the cost efficiency scores of the sampled banks from 2010 to 2017 using the DEA model.

Table A3: SFA parameter estimates

Variable	Co-efficient
Off-balance sheet items (ln)	0.195*** (0.0463)
Gross loans (ln)	0.783*** (0.787)
Deposits (ln)	-1.328*** (0.094)
Investment in securities (ln)	0.449*** (0.054)
Price of fixed assets to price of labour (ln)	0.541*** (0.079)
Price of funds to price of labour (ln)	0.202** (0.081)
0.5 * Off-balance sheet items (ln)^2	-0.003 (-0.003)
Off-balance sheet items (ln) * Gross loans (ln)	0.004 (0.006)
Off-balance sheet items (ln) * Deposits (ln)	-0.016** (0.007)
Off-balance sheet items (ln) * Investment in securities (ln)	0.001 (0.004)
0.5 * Gross loans (ln)^2	0.047*** (0.009)
Gross loans (ln) * Deposits (ln)	-0.031*** (0.004)
Gross loans (ln) * Investment in securities (ln)	-0.035*** (-0.007)
0.5 * Deposits (ln)^2	0.147***(0.010)
Deposits (ln) * Investment in securities (ln)	0.003 (0.008)
0.5 * Deposits (ln)^2	0.010***(0.004)
0.5 * Price of fixed assets to price of labour (ln)	-0.065*** (0.008)
Price of fixed assets to price of labour (ln) * Price of funds to price of labour (ln)	0.030*** (0.008)
0.5 * Price of fixed assets to price of labour (ln)	0.115*** (0.015)
Off-balance sheet items (ln) * Price of fixed assets to price of labour (ln)	-0.003(0.005)
Off-balance sheet items (ln) * Price of funds to price of labour (ln)	0.018*** (0.005)
Gross loans (ln)^2 * Price of fixed assets to the price of labour (ln)	-0.095*** (-0.010)
Gross loans (ln)^2 * Price of funds to the price of labour (ln)	-0.011(-0.011)
Deposits (ln)^2 * Price of fixed assets to price of labour (ln)	0.114*** (0.008)
Deposits (ln)^2 * Price of funds to price of labour (ln)	-0.026** (0.010)
Investment in securities (ln) * Price of fixed assets to price of labour (ln)	-0.031*** (0.005)
Investment in securities (ln) * Price of funds to price of labour (ln)	0.0001 (0.0001)
Equity (ln)	0.104*** (0.013)
Constant	4.591*** (0.603)
Observations	1,932
Number of banks	258

Table 4.2e shows the cost efficiency parameter estimates based on the stochastic frontier analysis (SFA) model.