RWANDA BANKERS' ASSOCIATION

"Together for a better banking environment"

WORKING PAPER SERIES

Volume 2, July 2025

Nos 5 -10

Published by:

Rwanda Bankers' Association Research Centre

Working Paper Series

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Working Paper Series

Volume 2, July 2025

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RBA/WPS/05-2025

Bank concentration, competition, and financial stability in Rwanda

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ABSTRACT

The Rwandan banking sector have been expanding in the last two decades. While the entry of new banks especially foreign led to an increase in number of banking institutions, earlier improvement in market concentration has been gradually reversing since 2016 and while previous analysis had pointed out improvement in competition on banking market, there are no empirical facts on recent evolution amid this increase in concentration. Considering the ongoing debates in the literature between the "competition stability hypothesis" and the "competition fragility hypothesis", the main objective of this study is to assess the evolution and relationship between concentration, competition, and financial stability in Rwanda.

Using data from all commercial banks in Rwanda from 2011 to 2021, this study revealed that similar to market concentration, banks have been gaining more market power in recent years as shown by evolution of Lerner index and H statistic. Furthermore, results from GMM estimations largely support the competition fragility hypothesis as both the increase in market power and market concentration lead to more stability and improvement in bank efficiency. Nevertheless, this relationship is nonlinear as there is an inflexion point beyond which more market power would be detrimental to banking stability. Besides, the inclusion of the interaction term between market power and concentration revealed that when they both increase, they negatively affect banking sector stability. Hence, policymakers should keenly monitor how competition and concentration evolve and also consider how these two may interact.

I. Introduction

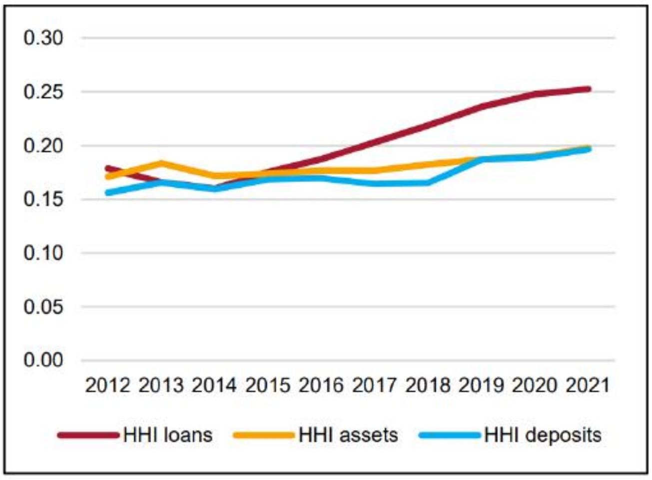
The financial sector across the globe has continuously expanded overtime driven by economic activities, initiatives to promote financial access and inclusion, financial innovations, and technological advancement, among others. In developing countries policy initiatives to increase financial deepening, access, and inclusion coupled with initiatives to protect users of financial services, to foster financial conduct and competition in financial markets have led tO improved financial services delivery and in some cases, more financial institutions. This trend has had positive implications on other sectors of the economy, mainly through the financial system playing its role of mobilizing and channelling funds where needed and risk sharing.

Nevertheless, there have also been some tendencies for concentration and issues related to competition in the banking industry in the last decades, with more interconnectedness and implications on the problem of too big to fail in the financial system (Narain et al., 2012). Following the 2008 Global Financial Crisis (henceforth, GFC), and on the backdrop of more stringent regulation measures, especially on bank capitalization, to cushion the financial system against risks and ensure the financial system's stability, concentration trends are still present in different economies, including Rwanda (see Figures 1 and 2 below). Important here to distinguish concentration and competition. The former refers to the number of market players and the extent to which their market shares are distributed, while competition refers to firms' (in)ability to influence pricing on the market.

It is argued that competition in an industry leads to more efficiency, better customer service and innovation (Weill, 2013; Claessens and Laeven, 2004). However, banking is a particular industry where competition may negatively affect financial stability (Allen and Gale, 2004). Indeed, Allen and Gale (2004) argued that the relationship between competition and financial stability is complex. Previous studies on the nexus between concentration, competition and financial stability have not yet reached a consensus. On one side, according to the charter value hypothesis (Keeley, 1990), bank market power increases its charter value and reduces incentives for excessive risk-taking, thus leading to more financial stability. On the other side, concentration or less competition can lead to banking system fragility. One argument behind this hypothesis is that banks with market power can boost bank's profit but also affect bank behavior, especially its ability to charge excessive interest rates to borrowers, who in turn would be incentivized to take more risks (Boyd and De Nicoló, 2005).

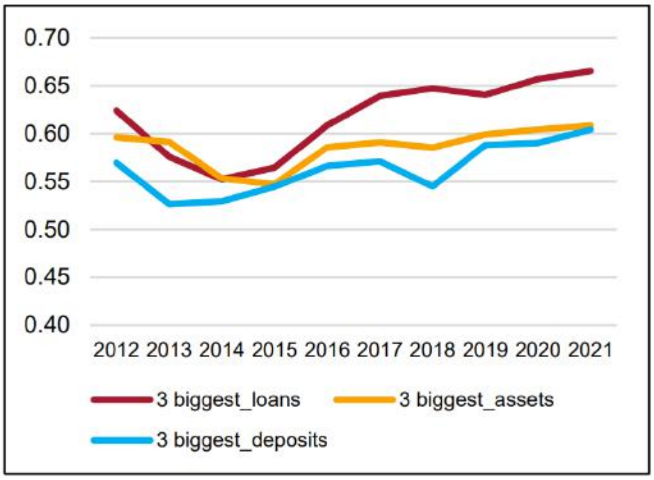
For Rwanda in particular, since the economic liberalization in the early 90s, the banking sector has been growing, although it is still relatively in the developing stage, with the ratio of credit to the private sector to GDP standing at 25.5% by the end 2021. While the banking sector has generally remained resilient in the last decades, there have been some episodes of risk increase on bank assets, primarily loans. Meanwhile, on the regulation and macroprudential policy side, ongoing implementation of banking sector regulations to protect the banking sector, such as the increase in banks capitalization, may likely incentivize bank consolidation given the relative size of the economy, while at the same time, recent regulations on market conduct and consumer protection tend to promote more competition in the Rwandan banking sector. Indeed, data show that concentration has recently increased, and various studies (e.g., Gaertner and Sanya, 2012) had shown that competition had been improving at the beginning of the last decade, but this trend has gradually been reversing in the recent period (Nyangu et al., 2022).

Figure 1: Evolution of different HHIs



Source: Author's calculation using NBR

Figure 2: Market share of 3 biggest banks



Source: Author's calculation using NBR

Previous analysis on bank competition and stability in Rwanda suggested that market power was associated with low-risk exposure. Still, this relationship was nonlinear, as there was a threshold above which excess market power would lead to instability in the financial sector. Considering conflicting theoretical and empirical debates on the relationship between bank concentration, competition and financial stability, as discussed in the previous section, and recent changes in banking sector activities and regulations in Rwanda, it is paramount to reevaluate this nexus. This would inform policymakers, notably those in charge of ensuring financial stability.

Therefore, this study sought to assess the evolution and relationship between concentration, competition and financial stability in Rwanda. Specifically, to evaluate on one side how bank concentration affects financial stability and, on the other side, how bank competition affects financial stability in Rwanda. In addition, this study assessed how competition on bankingnmarket affect bank lending and banks' efficiency.

Building from past literature and using data from all commercial banks in Rwanda (10 banks) from 2011 to 2021, this study evaluated how the competition has evolved in Rwanda's banking market via the Lerner index and Panzar Rosse H statistic (henceforth, H statistic). These indicators revealed that competition has recently declined, and banks have gained market power. Secondly, on the relationship between bank competition and banking sector stability, results from Generalized Methods of Moments (henceforth, GMM) estimation tend to a larger extent to support the competition fragility hypothesis as both the increase in market power proxied by the Lerner index and market concentration proxied by HHI for loans lead to more stability. Nevertheless, this relationship is nonlinear as there is an inflexion point beyond which more market power would be detrimental to banking stability.

Besides, bank market power is associated with more bank lending and improvement in banks cost efficiency and operation efficiency.

This study contributes to the empirical literature on this topic, especially in developing markets where empirical evidences have been relatively scanty. While previous studies had singled out either concentration or competition's effect on financial stability, this study adds another dimension by looking at the interaction of competition and concentration and how this affects banking system stability and banks efficiency. The inclusion of the interaction term between market power and concentration revealed that when they both increase, they negatively affect banking sector stability. Hence, this is an essential input for policymakers in charge of ensuring financial stability. It is paramount that they keenly consider the evolution of competition and concentration and how these two may interact.

This paper is structured as follows: the next chapter reviews the related literature, and chapter three outlines the methodology. Chapter four discusses the empirical results, and the last chapter concludes.

II. Literature review

II.1. Theoretical literature

Theoretical literature on bank market power and financial stability has not reached a consensus. On one side, the work by Allen and Gale (2004), based on various models of competition and financial stability, argue that concentration/market power enhances stability. Their arguments mainly revolve around three points. First, concentration enhances market power, leading to higher profit and buffer against adverse shocks. Secondly, they support the charter value hypothesis that concentration/market power increases the charter value and reduces incentives for risk-taking. Another related channel is via skin in the game, where banks without a charter value to lose (no skin in the game) have higher incentives to take more risks (Arping, 2019). Thirdly, few banks are easier to monitor; thus, this reduces the probability of contagion and systemic risks.

On the other side, contrary to this view, market power can be detrimental to financial stability, according to Boyd and De Nicoló (2005). They argued that market power allows banks to charge higher interest which may push banks to undertake more risks. Besides, less competition can lead to less credit rationing, larger loans and a higher probability of bank distress. Lastly, having fewer banks could lead to a market with big banks which are deemed too big to fail. This implicit insurance may intensify risk-taking leading to systemic fragility.

Important to note that frameworks and assumptions considered in theoretical studies were somewhat different. Thus, having fewer banks that are too big to fail could lead to moral hazard issues and more risk-taking in one framework, while in the other framework, this would allow the regulator to monitor them better. Building from Boyd and De Nicoló (2005) framework, Martinez-Miera and Repullo (2010) theoretical work brought another view that the trade-off between competition and financial stability could depend on the level of competition in the market. On one side, in line with Boyd and De Nicoló (2005), there is a risk-shifting effect where competition forces banks to charge lower lending rates, thus reducing the loan risks and leading to more bank stability. On the other side, the margin effect where these lower lending rates imply lower bank revenues and less healthy banks. This margin effect would dominate in more competitive markets, while the risk shifting would dominate in less competitive markets. Therefore, according to Martinez-Miera and Repullo (2010) the relationship between competition and stability is U shaped, and would depend on the level of market competitiveness.

This debate in theoretical studies is also present in the empirical literature, as discussed in the following sections

II.2. Empirical literature

Similar to the theoretical literature, empirical studies on the relationship between concentration, competition and financial stability have led to conflicting results, as previously alluded to. On one side, several studies (e.g. Keeley, 1990; Beck et al., 2006; Mirzaei et al., 2013; Danisman and Demirel, 2019; Phan et al., 2019; Adu, 2022, etc.) support the “competition fragility” hypothesis or alternatively “concentration stability” hypothesis (depending on whether authors measured market power via competition or concentration respectively), which postulates a tradeoff between competition/less concentration on banking market and financial stability. On the other side, there are empirical findings (e.g., Schaeck et al., 2009; Soedarmono et al., 2013; Schaeck and Cihák, 2014; Akins et al., 2016, etc.) supporting the “competition stability” or “concentration fragility” hypothesis that competition/less concentration on banking market would enhance financial stability.

In addition to these conflicting conclusions from empirical studies, crucial differences exist across those studies, including the methodologies adopted and country cases. Specifically, studies could differ mainly in terms of estimation methods and variables used, and one crucial difference is how authors measured bank market power. Some studies used indicators of concentration (usually measured via market shares) to measure competition (traditionally measured by the ability to influence market prices). In contrast, others separated the two but used alternative indicators. Yet, although both concentration and competition may portray market power, the two notions are different, and their relationship can sometimes be ambiguous.

II.2.1. Concentration and competition in the banking sector

Past literature has considered either or both concentration and competition to measure market power or competitiveness in the banking market. Yet, as highlighted in the previous section, the two notions are different, and their relationship is not always consistent across different markets. Claessens and Laeven (2004) investigated that issue and argued that market contestability, rather than concentration indicators, is a better measure of market competitiveness. Their cross-country study with bank-level data from 1994 to 2001 did not find evidence that higher concentration is associated with lower competition.

This possibility that more concentration does not necessarily imply less competition portrays the perils of confounding concentration and competition or even using a single indicator of competition instead of many in this area. Besides, there are several studies which included both competition and concentration indicators in their model and found that the two indicators had opposite effect on bank stability (e.g., Schaeck et al., 2009; Phan et al., 2019; Saif-Alyousfi et al., 2020). For instance, results from Saif-Alyousfi et al. (2020) study on banking system of Gulf Cooperation Countries indicate that more competition is associated with instability in the financial system while more concentration also adds to instability in the financial system.

In addition, concentration and competition were proxied by different variables in the literature, depending on the sample period and data availability. There was no significant difference regarding concentration indicators in the literature as those commonly across different studies are the HH index and the market share of 3 or 5 biggest banks. More diversity is in indicators of competition where some studies opted for firm behaviour indicators such as the Lerner index, H statistic and Boone indicator, while others considered the regulatory environment indicators such as the threat of entry, entry barriers, severity of activity restrictions, bank mergers, etc.

II.2.2. Bank concentration, competition and financial stability

While more empirical studies could not settle the debate on the relationship between concentration, competition and financial stability, authors further analysed other factors that may influence this relationship. Some assessed whether this relationship depends on bank characteristics such as liquidity, profitability, capitalization, or size (e.g., Saif-Alyousfi et al., 2020; Schaeck and Cihák, 2014). Others (e.g., Soedarmono et al., 2013; Danisman and Demirel, 2019) considered whether the relationship depends on the regulatory/institutional environment, or whether the relationship change during the crisis period (e.g., Soedarmono et al., 2013; Akins et al., 2016; Saif-Alyousfi et al., 2020).

Regarding how bank characteristics influence the relationship between concentration or competition and financial stability, empirical evidence indicates that bank characteristics matter, although the direction of their effect is still diverse. For instance, Schaeck and Cihák (2014) highlighted the influence of a bank's health (proxied by the Z score, which includes capitalization, profitability and volatility) as they argued that competition enhances financial stability, but this relationship holds more in healthy banks. Their study mainly sought to understand the mechanisms which induce competition to lead to financial stability. Using data from the European banking system, they hypothesized that the main channel is the efficiency caused by competition (proxied by Boone indicator). They found that efficiency was the primary channel via which competition enhanced financial stability.

Again, bank capital, in addition to bank liquidity and size, were critical determinants of how competition affected financial stability in the Gulf Cooperation Council (henceforth, GCC) banking sector, according to Saif-Alyousfi et al. (2020). On capitalization, lower competition decreases risks and enhances stability in highly capitalized banks. The same competition fragility hypothesis also holds for highly liquid and bigger banks. Competition fragility hypothesis holds in “healthy” banks for the case of GCC banks, contrary to findings by Schaeck and Cihák (2014) for European banking system. Important to recall that evidence from Saif-Alyousfi et al. (2020), support both the competition stability and competition fragility hypothesis. Their study considered alternatively the Boone indicator and Lerner index as measures of competition and HHI (henceforth, Herfindahl Hirschman Index) and five largest bank ratio as measures of concentration. Their findings from different GMM estimations are counterintuitive as the effect of higher competition/ lower market power on risk-taking and stability is quite the opposite of the effect of lower concentration.

Other empirical studies (e.g., Soedarmono et al., 2013; Danisman and Demirel, 2019) have underlined the influence of regulatory or institutional environment on the relationship between bank market power and financial stability. For instance, Soedarmono et al. (2013) considered the implications of too-big-to-fail policies and the resulting moral hazard issue in the Asian banking industry by including the interaction between the Lerner index and a too big to fail (henceforth, TBTF) indicator (assets of 3 largest bank to GDP). Their sample period runs from 1994 to 2009, thus including the period of the Asian financial crisis. While their findings suggest that bank market power had a destabilizing effect over the sample period except during the 1997 Asian crisis, where bank market power was associated with more financial stability, the existence of TBTF policies had an opposite effect on the linkages between competition and stability in the Asian banking system. During the crisis, market power enhanced stability only in countries with lower too-big-to-fail policies, suggesting a moral hazard issue.

Danisman and Demirel (2019) considered other aspects of regulation, such as capital requirement, bank activity restrictions and the power of supervisory authority in banks from 25 developed countries. Estimation results from different models, including interactions of competition indicator and regulatory indicators, suggest that competition increases varioustypes of banks' risks. Secondly, capital regulation reduces bank risks, which is stronger in banks with more market power. Thirdly, activity restrictions lead to higher bank risks except in banks with market power. Lastly, powerful supervisory institution increases bank risks, and the effect is more substantial in banks with market power. This study also had the particularity of considering various types of risks, including default risk, leverage risk, portfolio risk, credit risk, noninterest income risk, interest income risk, liquidity risk and operational risk.

The relationship between competition and financial stability could change when an economy is undergoing a financial crisis, as shown by some studies (e.g., Soedarmono et al., 2013; Saif-Alyousfi et al., 2020). Indeed, Soedarmono et al. (2013) analysis shows that while for the whole sample period of study, market power had rather a destabilizing effect, this changed during the 1997 Asian crisis as bank market power helped to stabilize the financial system in East Asian Countries. In the same vein, findings by Saif-Alyousfi et al. (2020) for GCC countries also pointed out to stabilizing effect of lower bank competition during the 2008 GFC. Nevertheless, results from Akins et al. (2016) for the case in the United States (henceforth, US), are quite the contrary, as more competition was associated with less risk-taking during the 2008 GFC. On this, it could be possible that differences in implicit guarantees for bailing out banks (TBTF policies) across these countries can also play a role in these differences in empirical findings.

Obviously, even considering different factors that could influence the relationship between concentration, competition and financial stability, empirical findings have not yet clearly settled how a given bank characteristic, a type of regulation, or the occurrence of financial crisis would influence that relationship.

Regarding the case of Rwanda in particular, a study by Nyangu et al. (2022) assessed the evolution of concentration and competition in the East African Community (henceforth, EAC) banking markets and how this affected efficiency. Concentration indicators (proportion of assets held by three and five largest banks, and HHI) suggest that concentration is still generally high, especially in Rwanda and Burundi, and has been declining between 2001, when the sample period began and 2016, but has been increasing again recently. The Lerner index almost portrays the same trend, where improvement in competition observed between 2007 and 2014, has been reversing afterwards, and on average, over the sample period, the level of competition is still low.

On the relationship between bank competition and financial stability in Rwanda, results from the previous study by NBR staff using panel estimation with bank-level data from 2006 to 2013, suggested that market power (proxied by Lerner index) is associated with low risk in the financial system. However, these insights were not fully conclusive given that this relationship held up to a certain level. The results from the quadratic model revealed a threshold beyond which more bank market power would be associated with financial instability. This study will differ from the existing literature on Rwanda (e.g. Nyangu et al., 2022) in twofold: first is to reassess how different measures of competition and concentration have recently evolved, amid the ongoing implementation of banking sector regulations to cushion the banking sector in line with Basel III which may favour more concentration, and recent regulations on market conduct and consumer protection with intent to promote more competition in the banking sector. Secondly, the study assesses the linkages between competition and concentration on the Rwandan banking market. Thirdly, it considers how both interact and impact different financial stability measures. Fourthly, we examine the relationship between competition and concentration with other key bank performance indicators namely bank lending and efficiency. Regarding the empirical literature in general, it contributes to the debate on the relationship between competition and stability in developing market.

One of its shortcomings is that it is not a cross-country study to take into account the effect of bank regulations and institutional framework on the relationship between competition and financial stability.

III. Paper Methodology

This section describes how indicators of concentration, competition and financial stability will be computed and discuss models and estimation methods used to achieve this study's primary objective, namely analysis of the relationship between bank concentration, competition and financial stability in Rwanda. Besides, we assess how competition and concentration impact bank lending, bank efficiency. Lastly, it outlines the variables needed.

III.1. Indicators of concentration on the banking market

Following the literature on bank concentration (Beck et al., 2006; Schaeck and Cihák, 2014; Mirzaei et al., 2013), two alternative indicators will be derived. Firstly, we calculate three measures of concentration on assets, deposits and loans markets in Rwanda respectively by calculating the share of assets, deposits and loans of 3 largest banks in total banking sector assets, deposits and loans. Secondly, the HHI as one of the most used indicators of market concentration in the literature (e.g. Beck et al., 2013; Wolfe and Amidu, 2013; Mirzaei et al., 2013, etc.) will also be derived on the three different markets namely banks assets, deposits and loans. The HHI for each of the three markets is derived as follows:

$$HHI = \sum_{i=1}^{N} s_i^2 \quad \dots \dots \dots (1)$$

With N as number of banks and s as market share for each bank

III.2. Indicators of competition in the banking market

In the literature on competition on the banking market, especially non-structural indicators, three are mostly used: the Lerner index and its variant, the H statistic and the Boone indicator. We propose to use the Lerner index as it can be derived per bank-level and be used in panel analysis. Alternatively, the H statistic will be derived to check further how competition has been evolving on the Rwandan banking market.

III.2.1. The Lerner index

The Lerner index measures competition from bank behaviour, specifically on how much a bank can set the price above the marginal cost. It is derived as the difference between the price and the marginal cost, divided by the price as follows:

$$Lerner\ index_{it} = \frac{P_{it} - MC_{it}}{P_{it}} \quad \ldots\ldots\ldots (2)$$

With P_{it} s the price for bank i in period t, derived as the ratio of total revenues of bank i to total bank i assets (Weill, 2013; Leon, 2014), while MC_{it} is the marginal cost for bank i in period t.

The marginal cost is obtained from the total cost function of the banking industry. Literature (e.g., Soedarmono et al., 2013; Wolfe and Amidu, 2013, etc.) has opted for a translog cost function as follows:

$$Ln\ Total\ cost_{it} = \beta_0 + \beta_1 \ln y_{it} + \frac{\beta_2}{2}\ln y_{it}^2 + \sum_{k=1}^{3} \alpha_{kt} \ln W_{k,it} + \frac{1}{2}\sum_{k=4}^{6} \alpha_{kt} \ln W_{k,it}^2 + \sum_{k=1}^{3} \gamma_k \ln y_{it} \ln W_{k,it} + \sum_{k \neq k'} \omega_k \ln W_{k,i} \ln W_{k',i} + \varepsilon_{i,t} \quad \ldots\ldots\ldots (3)$$

With $Total\ cost_{it}$ as total operating cost per bank i in period t, y_{it} as total bank i output in period t, proxied by total bank assets, $W_{k,it}$ the cost of banks inputs, namely funds, labour and fixed capital. These are derived as the ratio of bank interest expenses to deposits; bank staff cost to total assets and other operating expenses to total bank assets, respectively.

From the cost function, the marginal cost per bank in each period t () is derived as follows:

$$MC_{it} = \frac{Total\ cost_{it}}{y_{it}}\left[\beta_1 + \beta_2 \ln y_{it} + \sum_{k=1}^{3} \gamma_k \ln W_{k,it}\right] \ldots\ldots\ldots (4)$$

III.2.2. The Panzar Rosse H statistic

This is an alternative non-structural measure of competition, usually derived in many empirical studies on competition in the banking sector. According to Degryse et al. (2009), it captures the extent to which changes in input prices is reflected in banks specific revenues, for instance, interest revenues, as follows:

$$\ln Interest\ revenue_{it} = \alpha + \sum_f \beta_f \ln W_{f,it} + \sum_k \gamma_k X_{k,it} + \varepsilon_{it} \quad \ldots\ldots\ldots (5)$$

With $interest\ revenue_{it}$ as the ratio of interest revenue to total assets for bank i in period t, $W_{k,it}$ the cost of banks inputs, namely funds (interest expenses), labour (staff expenses) and fixed capital, all scaled to total assets and $X_{k,it}$ as control variables. Estimation of coefficients from equation 5 above are used to compute the H statistic as a sum of elasticities to input costs as follows:

$$H = \sum_f \beta_f \quad \ldots\ldots\ldots (6)$$

III.3. Indicators of financial stability

The concept of financial stability is complex and cannot be captured by a single indicator. Nevertheless, several empirical studies on competition and financial stability mostly opted for the Z-score (Berger et al., 2017; Wolfe and Amidu, 2013; Mirzaei et al., 2013, etc.), nonperforming loans, return on assets (henceforth, ROA), return on equity (henceforth, ROE) and capital ratio (Berger et al., 2017; Wolfe and Amidu, 2013) as indicators of bank stability or alternatively bank's risks.

This study uses the Z-score per each bank as it provides the advantages of combining bank profitability, capitalization and returns volatility. Alternatively, the non-performing loans ratio will be a key indicator of bank risks.

Standard deviation is computed using three years rolling windows in line with other studies (Wolfe and Amidu, 2013; Soedarmono et al., 2013; etc.)

The Z-score for bank i in period t will be computed as follows:

$$Z\_score_{it} = \frac{ROA_{it} + Equity_{it}/Total\ assets_{it}}{\sigma ROA} \quad \ldots\ldots\ldots (7)$$

III.4. Other indicators of banks' performance

To enrich our analysis on how competition and concentration on bank market affect banking institutions in Rwanda, we considered other key banks performance indicators and evaluated how they are affected by competition and concentration. These are bank lending, the ratio of operating cost to income as indicator of bank cost efficiency and the ratio of bank operating cost to bank total asset as an indicator bank operation efficiency.

III.5. Models and estimation methods

Firstly, to assess the relationship between concentration and competition on the Rwandan banking market, this study will use simple correlation analysis, considering different indicators of concentration and competition discussed above.

In line with the literature, to assess the relationship between competition, concentration and financial stability in Rwanda, the following panel model with Rwandan banks as crosssectional will be estimated:

$$Financial\ stability_{it} = \beta_0 + \beta_1 Financial\ stability_{it-1} + \beta_2 Lerner_{it} + \beta_3 HHI_{it} + \sum_{j=4}^{M} \beta_j\ Bank\ specific_{it} + \sum_{j=N}^{R} \beta_j\ Macro\ indicators_{it} + \varepsilon_{it} \quad \dots\dots\dots (8)$$

The main financial stability indicator will be the Z-score and, alternatively the non-performing loans ratio. The Lerner index is used as proxy of competition. The main concentration indicator is the HHI for loans market. Bank-specific control variables and other control variables include bank size, loan exposure, proxy of credit risks, GDP growth, inflation, and exchange rate depreciation. These are chosen based on the literature, the availability of data in Rwanda, and the need for a parsimonious model.

We include the lerner index squared to check whether the relationship could be nonlinear and the interaction between the Lerner index and a concentration indicator to evaluate whether and/or how competition interacts with concentration in affecting the banking system's stability. Other authors have considered interaction with regulation indicators (Beck et al., 2006; Soedarmono et al., 2013; Saif-Alyousfi et al., 2020).

Alternatively, we estimate almost the same equation, but replacing successively the endogenous variables with other three indicator of bank performance namely indicator of bank lending, indicator of cost efficiency and indicator of operation efficiency as follows:

$$Indicator\ of\ bank\ performance_{it} = \beta_0 + \beta_1 indicator\ of\ bank\ performance_{it-1} + \beta_2 Lerner_{it} + \beta_3 HHI_{it} + \sum_{j=4}^{M} \beta_j\ Bank\ specific_{it} + \sum_{j=N}^{R} \beta_j\ Macro\ indicators_{it} + \varepsilon_{it} \quad \dots\dots\dots (9)$$

Regarding estimation methods, panel data estimation is used for the main model. Considering that (in)stability/ risk is usually persistent in the banking systems, we use a dynamic panel model as in other similar studies (e.g., Saif-Alyousfi et al., 2020) we estimate the model using GMM because of lagged variables included in the model as well as endogeneity issues and standard errors which are robust to heteroscedastic errors. One example of a possible endogeneity issue is that bank stability measures such as the Z score include capitalization measures which may influence bank market power. Different authors have argued that GMM addresses this endogeneity issue and the presence of lagged dependent variable. Following Beck et al. (2013), we used fixed effect estimation (with homogeneity constraint) to estimate the translog cost function for deriving the Lerner index and random effect for the revenues function used in deriving the H statistic.

III.6. Data

We use annual data at the bank level (10 banks) from 2014 to 2021, to calculate the above indicators and estimate the models. The selection of variables is based on the formula discussed above and past literature. These are:

a. Variables from banks balance sheets

For each of 10 banks in the sample, the following variables in the individual bank balance sheet are selected: total loans, total asset, total deposits, total equity and total liabilities. Firstly, total loans, assets and deposits per banks are used to derive concentration indicators (e.g., HHIs). Secondly these are used in the models to calculate the Lerner and H statistic in line with the past literature, as explained in the previous section.

c. Bank level financial soundness indicators:

We select each bank's return on average assets, net interest margin and non-performing loans ratio. These variables are mainly used as indicators of bank stability and in calculating composite indicators such as the Z score. As in most of reviewed studies, we selected the return on average assets to derive the main Z score used in estimation.

d. Bank performance indicators

We select three simple indicators namely bank lending, bank cost efficiency and bank operation efficiency. As highlighted in the previous section, they are obtained using data from individual bank balance sheets (Net bank lending, total assets) and income statement (bank operating costs)

e. Other control variables

These are selected mainly based on the past literature (e.g. Beck et al., 2013; Berger et al., 2017, etc.) and include bank-specific variables such as bank size (proxied by the log of assets), the loan exposure measured as the ratio of loans to total assets, credit risks measured as the provision to total interest income Besides, macroeconomic indicators such as GDP growth, inflation and exchange rate depreciation.

IV. Empirical analysis

IV.1. Measuring competition in the banking sector

Firstly, the estimation of competition indicators on the Rwandan banking market using both the Lerner index and the H statistic revealed that the degree of competition has declined in the last three years. Recall that the Lerner index indicates the extent to which a bank is able to price above the marginal cost. Banks' marginal cost (equation 4) were obtained using results from a translog cost function (equation 3). Following Beck et al. (2013) and Berger et al. (2017), the cost function is estimated for the whole banking system with bank-level data, using fixed effect panel estimation, with restrictions on the homogeneity of input prices, namely funds, labour and fixed assets. The detailed results of the cost function estimation are in the annex.

The H statistic was also derived as an alternative measure of competition, using the results from the random effect estimation of equation 5. Random effect estimation was chosen following results from the Hausman test. As outlined above, the H statistic is calculated as the sum of coefficients on input prices and totalled 0.56.

Figure 3: Evolution of Lerner index

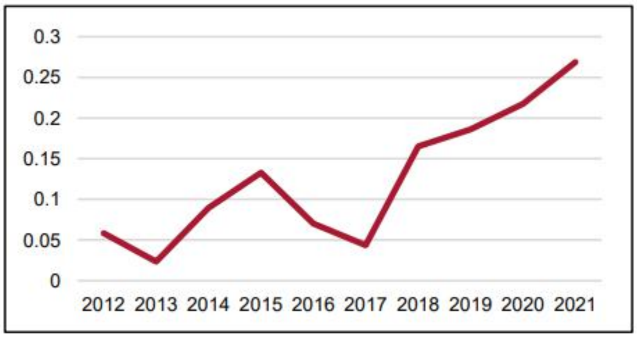
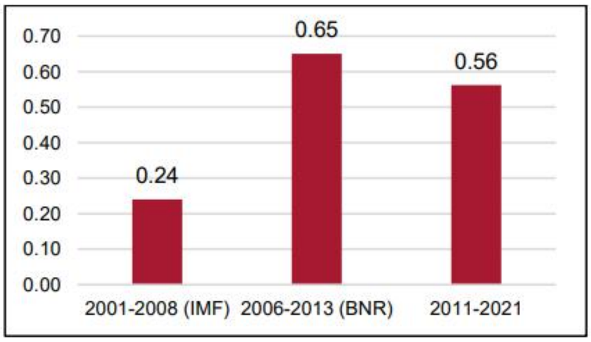


Figure 4: Evolution of H statistic



Source: Author's calculation using NBR data

The figures above depict the evolution of the Lerner index and H statistic. On the left, the average of the Lerner index from 10 banks included in the sample has been going up since 2018 implying a deterioration of competition. The H statistic also confirms these developments as the value obtained in this study (0.56) is lower than 0.65 earlier obtained in a study using a sample from 2006 to 2013. The lower the H statistic, the lower is the competition in the market.

IV.2. Other key banking markets indicators

In line with how market power in the Rwandan banking market has been evolving,concentration has been increasing, especially in loan markets, as shown by the evolution of HHIs and total share of the three biggest banks (see figure 1 and 2 above). One of the reasons is that the bigger banks are more likely to finance bigger projects with considerable amounts, and in developing markets like Rwanda, this can be salient in terms of market share.

Regarding the soundness of the banking system, The Z score, which a proxy of banking sector soundness, shows that this has improved compared to the onset of the last decades, and this has been more evident since 2019, driven mainly by the increase in ROA across banks combined by a decrease in the volatility of banks profitability measured by the standard deviation of the ROA.

A simple co-movement analysis between the Z score and the Lerner index shows some comovement between the two variables, with a correlation coefficient of 0.74. Nevertheless, this relationship is insufficient to conclude that increased market power would be associated with banking system stability. Furthermore, both variables include banks' income and profitability in their calculation. Thus, it cannot be excluded that their relationship may be mechanical and not economically meaningful, as Beck et al. (2013) argued. As specified in the methodology, further analysis in the next section shed more light on this relationship.

Figure 5: Evolution of Z score

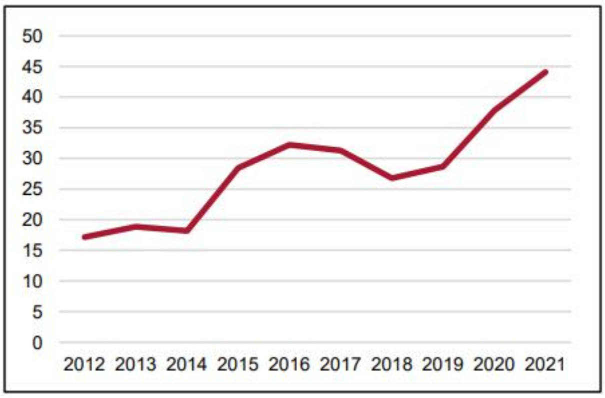
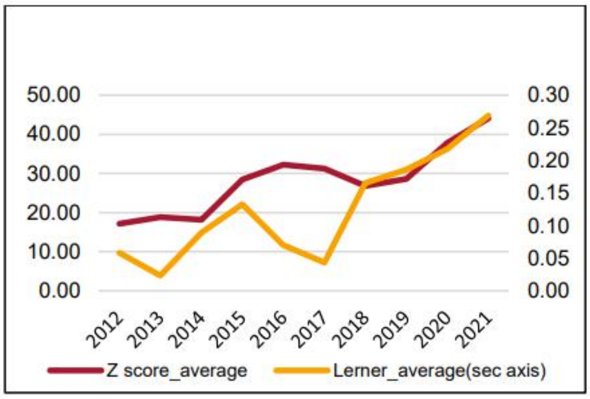


Figure 6: Z score and Lerner index



Source: Author's calculation using NBR data

The summary statistics in the table below provide some insights into the Rwandan banking markets. Overall, the Lerner index has remained positive, indicating that banks have had some degree of market power; however, disparities exist across banks and time, and one of the reasons is that some banks at the beginning of their operation had a negative Lerner index due to higher marginal cost and lower income. This is also one reason for disparities observed in ROA across banks. Banking institutions in Rwanda also have many similarities, especially in terms of asset structure and source of income, as shown in the summary statistics on the revenue and loanto-assets ratios. Recall that the loan ratio is the ratio of net loans to total assets per bank. The revenue ratio is the ratio of total revenue to total assets per bank.

Table 1: Key banking sector indicators

Variable		Mean	Standard Deviation	Min	Max	Observation
Lerner index	Overall	0.096	0.368	-3.195	0.404	110
	Between		0.151	-0.167	0.295	
	Within		0.339	-2.932	0.641	
Loan to assets ratio	Overall	0.515	0.140	0.026	0.851	110
	Between		0.095	0.304	0.611	
	Within		0.106	0.023	0.848	
Return to assets ratio	Overall	0.017	0.032	-0.125	0.159	110
	Between		0.021	-0.015	0.064	
	Within		0.025	-0.093	0.112	
Z index	Overall	27.074	20.199	0.505	92.658	110
	Between		8.554	16.017	41.399	
	Within		18.481	-7.022	86.511	
Revenue to asset ratio	Overall	0.138	0.028	0.012	0.208	110
	Between		0.016	0.113	0.157	
	Within		0.023	0.036	0.195	

Source: Author's calculation using NBR data

IV.3. Relationship between concentration and competition

Figure 7 below shows that the industry average Lerner index and HHI of loans, assets and deposits have been co-moving in the last decades. The correlation coefficient between the Lerner index and HHI of loans, assets and deposits between 2012 and 2021 stood at 0.85, 0.78 and 0.85, respectively, implying a strong co-movement between market power and market concentration on the banking market in Rwanda.

Figure 7: Co-movement between lerner index and different HHIs

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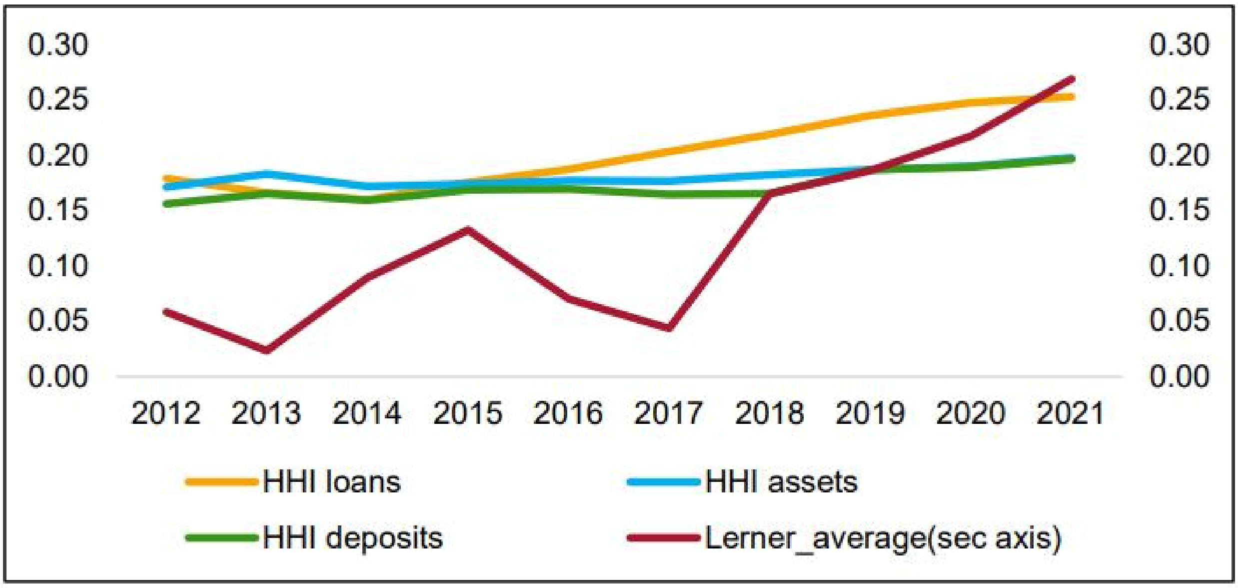

Source: author's calculation using NBR data .

Table 2: Cross-correlation between Lerner index and concentration indicators

	Lerner index	Share in total banking sector loans	Share in total banking sector asset	Share in total banking sector deposits
Lerner index	1.00			
Share in total banking sector loans	0.26	1.00		
Share in total banking sector asset	0.27	0.96	1.00	
Share in total banking sector deposits	0.28	0.96	0.96	1.00

Source: author's calculation using NBR data .

Considering that the HHI is measured at the whole banking sector level, we used the market share per each bank and analyzed whether it is correlated with its market power proxied by the Lerner index. The table below displays correlation coefficients and the level of significance. In short, there is some positive co-movement between market power in pricing and market share on loans, assets and deposits, however, the coefficients are lower (0.26, 0.26 and 0.28, respectively) compared to the overall correlations discussed in the previous paragraph. This may indicate that looking at the bank level, the link between the market power and the market share is not that strong. Further analysis via estimation will shed more light on this.

IV.4. Competition and financial stability

Evidence on the relationship between competition on the banking market and the stability of the Rwandan financial system is obtained via panel regression using Arellano– Bover/Blundell–Bond GMM estimation with robust standard errors. The choice of this method is motivated by addressing the endogeneity issues given variables selected as discussed in the methodology.

We estimated 4 different models, with the logarithm of the Z score as a dependent variable. These 4 models were almost similar except for a few additional variables as shown in the table below. We initially estimated the model including only one indicator of market power, namely the Lerner index, in addition to a set of control variables and progressively added indicator of market concentration, their interaction term to evaluate the implication of market concentration and the square of the Lerner index to gauge whether the relationship between bank market power and financial stability could be nonlinear. These different specifications are also a form of robustness check.

We selected the most parsimonious models where the diagnostic test of the models, namely the autocorrelation test and the Sargan test for instrument validity, were satisfactory (details in the appendix).

Table 3: Arellano–Bover/Blundell–Bond estimation results on competition and bank stability

	Model 4		Model 3		Model 2		Model 1	
Variables	Log of Z score		Log of Z score		Log of Z score		Log of Z score	
	Coeffi-cient	Robust st. errors	Coeffi-cient	Robust st. errors	Coeffi-cient	Robust st. errors	Coeffi-cient	Robust st. errors
Lag 1 log of Z score	0.13	0.15	0.08	0.15	0.10	0.16	0.09	0.16
Lag 1 log of Z score			-0.23**	0.11	-0.23**	0.11	-0.23**	0.10
Lerner index	11.95**	3.29	15.59**	2.42	3.30**	1.00	3.31**	0.97
Lerner indexsquared	-1.99**	0.79						
Lerner*HHI	-45.95**	16.35	-61.34**	13.89				
HHI loans	12.88**	4.84	15.12**	4.12	-0.92	3.42		
Log assets	-0.05	0.17	-0.06	0.16	-0.03	0.17	0.04	0.16
Loan to assets ratio	-1.99**	1.12	-1.79	1.23	-2.03	1.33	-1.96	1.26
Provision to interest income ratio	-0.12	0.83	-0.65	0.69	-0.53	0.69	-0.55	0.68
Per capita GDP growth	1.25	2.70	3.69	3.17	3.46	3.27	3.03*	1.80
Inflation	1.32	1.60	2.49	1.65	2.31	1.17	2.35	1.71
Exchange rate	1.68*	1.10	0.34	2.24	0.73	2.36	0.90	2.05
Constant	0.89	1.60	1.07	1.39	4.16	1.17	4.02	1.08

Source: author's estimation from Stata

In all four equations estimated, the coefficient of the Lerner index is positive and statistically significant, suggesting that bank market power would lead to more stability in the banking system in line with the competition fragility hypothesis. In particular, the coefficient is slightly larger compared to the previous analysis done for Rwanda using a sample of 6 commercial banks from 2006 to 2013. The coefficient of the interaction term is negative, implying that bank market power in a more concentrated market is detrimental to the banking system's stability.

When the square of the Lerner index is included in the model, its coefficient is negative and statistically significant, suggesting that the positive relationship between bank market power and banking system stability is not linear and it has an inflection point beyond which more market power would lead to a deterioration in the banking system stability.

Regarding the effect of concentration proxied by the HHI on the loans market on the banking sector stability, the table shows that the coefficient of HHI on the loan market is positive and statistically significant, suggesting that more market concentration leads to more stability in the banking system. However, as mentioned in the previous section, the interaction with the lerner index shows that a combination of lower market competition and higher market concentration is detrimental to banking system stability.

Other control variables included were not statistically significant in most cases, under different model specifications. Nevertheless, there are some worthy insights to highlight. First, on banks characteristics, in the main equation, the exposure to loan market proxied by loan to asset ratio negatively affects the banking system stability ceteris paribus, implying that though the earning assets structure in the Rwandan banking system and the level of development in the economy and financial markets oblige banks to rely on loans as source of income heavily, the overreliance on this could negatively affect the banking sector soundness. Therefore, the recent improvement in earning assets diversification will likely enhance the banking system soundness.

The coefficients of other bank's characteristics are not statistically significant. However, the consistent negative signs across different model specifications are worthy to notice, notably the bank size and credit risks proxied by the provision to interest income ratio. As expected, the latter seems to negatively influence Rwanda's banking system stability. Furthermore, the bank size does not have a significant effect, which is counterintuitive considering the market power and concentration results.

Secondly, regarding the macroeconomic environment variables, there is some evidence that per capita GDP growth would enhance the banking system stability as expected. Its coefficient is significant in only one model specification, but in other specifications, it is not the case though it is positive. Similarly, in the main model specification, the exchange rate depreciation leads to more banking system stability.

IV.5. Competition and bank efficiency

Similar to the analysis of the relationship between competition on the banking market and the stability, we used Arellano–Bover/Blundell–Bond GMM estimation with robust standard errors. The choice of this method is motivated by addressing the endogeneity and simultaneity issues notably between the lerner index and indicators of cost efficiency and operation efficiency. We selected parsimonious models by removing some independent variables which were not important for some estimations as shown in the next table. On bank lending, results indicate that market power and market concentration are positively associated with higher bank lending suggesting that competition could be detrimental bank lending. However, their interaction has a negative sign suggesting that as market get more concentrated, increase in competition lead to more bank lending. Besides, credit risks lead to lower bank lending as expected.

Regarding bank efficiency, results show that the lerner index has negative signs for both model 6 and 7, suggesting that more banks have market power, more that bank is efficient in terms of cost efficiency and operation efficiency. Nevertheless, there is no evidence of effect of market concentration on bank efficiency, although the interaction term in model 7 show that combination of both market power and market concentration lead lower operation efficiency. Besides, credit risks is associated with bank inefficiency. One puzzling result is the negative effect from the bank size on bank efficiency

Table 4: Arellano–Bover/Blundell–Bond estimation results on competition and bank efficiency

	Model 5		Model 6		Model 7	
Variables	Log of net lending		Operating cost to income ratio		Operating cost to assets ratio	
	Coefficient	Robust st. errors	Coefficient	Robust st. errors	Coefficient	Robust st. errors
Lag 1	0.57**	0.07	0.06***	0.02	0.22**	0.09
Lerner index	2.72***	0.85	-0.63**	0.35	-0.13***	0.03
Lerner index squared	0.91**	0.41	0.22***	0.07	0.02	0.02
Lerner*HHI	-13.7***	4.44	-0.02	1.60	0.24**	0.11
HHI loans	5.30***	1.47	0.15	0.46	0.06	0.06
Log assets			-0.07***	0.02	-0.03***	0.01
Loan to assets ratio			-0.09***	0.03	0.05***	0.02
Provision to interest income ratio	-0.23*	0.13	0.25**	0.10	0.06**	0.02
Per capita GDP growth	-0.80**	0.30	0.04	0.11	-0.01	0.02
Inflation	0.68**	0.32	0.22***	0.08	0.00	0.01
Exchange rate	-1.01	0.67	0.16	0.10	-0.08**	0.04
Constant	0.90***	0.33	0.99***	0.09	0.17***	0.05

IV.6. Robustness check

In addition to the consistency of results, especially on the positive relationship between market power and banking system stability and market concentration and banking system stability across different model specifications. We replaced the Z score with the non-performing loans ratio as an indicator of financial system (in)stability. To some extent, the results tend to support the competition fragility hypothesis as in the previous specification. In the parsimonious model with only the Lerner index as an indicator of market power, its coefficient is negative and statistically significant, suggesting that more bank market power leads to a reduction in nonperforming loans and, subsequently, more banking system soundness. However, when we add HHI for loans and the square of the Lerner index, the Lerner index is no longer statistically significant. In the main model, among key coefficients in this study, it is only the coefficient of the square of the Lerner which is statistically significant and is negative, whereas in the model excluding market concentration indicators, both coefficients on the Lerner index and its square are negative and statistically significant suggesting that more market power would lead to better loan performance, thus more soundness in the banking system. Detailed results are in the annex

IV.7. Discussion of results

While the preliminary analysis shows that both market power and banking sector stability have been increasing in the last decades and both are positively correlated, the GMM estimation results discussed above allow us to confirm that this relationship is economically meaningful. There are important insights to discuss. The increase in bank market power leads to bank stability, but this relationship is nonlinear. While it can be argued that the Z score itself does not reflect all aspect of banking sector stability, the alternative specification using the nonperforming loans ratio confirm this relationship.

Similarly, the effect of market concentration on banking system stability is positive. Although concentration and competition are not the same and some previous studies (e.g., Saif-Alyousfi et al., 2020) had found that they can have opposite effect, the two are usually strongly related as the more a bank gains the market share, the more it has the power to charge above the marginal cost. Preliminary analysis in the previous section had established the co-movement between concentration and competition. Overall, these results tend to support the competition fragility hypothesis.

Despite this evidence in favour of the competition fragility hypothesis, the existence of a nonlinear relationship between market power and banking stability as well as the negative coefficient on the interaction terms between the Lerner index and the HHI for the loans market is a sign that the ongoing increase in market power and concentration would not always be a recipe for banking system stability. Important to note that this nonlinear relationship was also found in the case of 23 developed countries by Berger et al. (2017).

Using the main equation and calculating the maximum point using derivatives reveals some essential details. Considering the average for the sample period of HHI for the loans market (0.21), the maximum Lerner index beyond which more market power would negatively affect stability is 0.57 higher than the 0.27 of 2021, implying that the situation is not that alarming. However, considering the average HHI on the loans market for the last four years (0.24), the maximum Lerner becomes 0.23, well below the 0.27 of 2021, which would imply that the current market power (Lerner of 0.27) is too high if combined with the currently increasing market concentration and this may be detrimental to banking sector stability. Thus, it is paramount that the central bank in charge of financial stability keenly monitors how the market power and concentration in banking is evolving.

Although our analysis could not establish the reason behind this nonlinearity, it can be argued that in an environment where the cost of borrowing is already high and in the absence of welldeveloped financial institutions to diversify sources of external finance or even to manage risk on the side of lenders, combined with some economic sectors at the onset of modernization, an additional increase in the price of loans may have negative implications, especially by increasing the debt burden of borrowers. This could also be a challenge for authorities as the central bank oversees financial system stability and the market conduct and consumer protection function. However, it can also be an opportunity to manage these two objectives under the same institutions, especially when they conflict, rather than having two public institutions pull in different directions.

Another critical insight to mention is the negative effect of loan ratio on stability, indicating the overreliance on loans as a source of income is detrimental to stability. The ongoing diversification in banking asset structure recently observed can enhance stability. One may wonder whether this could be linked to the fact that most of the studies that supported the competition stability hypothesis were on developed markets where banks usually have a welldiversified source of income.

Regarding the relationship between competition and bank efficiency, while results from the literature are mixed (some studies showing that competition improve efficiency while others point out that competition lead to deterioration of efficiency). Our results are largely in line with one recent cross country studies by Yin (2021) on 148 countries indicated that bank competition is detrimental to bank cost efficiency.

In a nutshell, evidence generally supports the competition fragility hypothesis despite the existence of nonlinearity and inflection point beyond which market power would no longer enhance stability. Nevertheless, this is a call for the central bank to keenly monitor how market power is evolving to ensure that excessive market power does not lead to instability while also being detrimental to market discipline and consumer protection. Furthermore, continue supporting the development of the financial sector to diversify the banking system's source of income is essential.

V. Conclusion

Following the debate on the effect of bank competition and financial stability, where past literature has found evidence supporting the competition fragility hypothesis in some cases and the competition stability hypothesis in other cases, this study sought to empirically analyses this relationship in the case of a developing country with shallow financial markets. The main objective of this study was to investigate the relationship between bank concentration, competition, and financial stability in Rwanda.

The methodology partly borrowed from the past literature (Beck et al., 2013; Berger et al., 2017, etc.) but added another dimension by considering the influence of competition and concentration individually and their interaction on Rwandan banking system stability.

Firstly, we assessed how bank competition has evolved in Rwanda. The derivation of the Lerner index and H statistic show that bank competition has deteriorated recently, especially since 2018. Simple correlation analysis shows that both market power and concentration comove. Secondly, on the relationship between competition and bank stability, the GMM estimation with data from 10 banks from 2011 to 2021 suggests that bank market power would lead to more stability in the banking system in line with the competition fragility hypothesis. Nevertheless, the inclusion of the squared term shows the existence of a nonlinear relationship between market power and banking stability. In addition, the negative coefficient on the interaction terms between the Lerner index and the HHI for the loans market may signal that the ongoing increase in market power and concentration would not always be a recipe for banking system stability.

Lastly, our results show that bank market power is positively associated with more bank lending and improvement in bank cost efficiency and banks operational efficiency.

The contribution of this study is to show that while both competition and concentration could have a similar effect in terms of direction on banking system stability, their excessive increase may reverse the initial relationship. Therefore, the close monitoring of the two and their interaction is paramount for authorities in charge of financial stability. This may also support the role of market function and consumer protection and show that this is not always at the expense of banking system profitability and stability.

Lastly, in line with some past studies, this study highlighted again the perils of confounding competition and concentration. Thus, ongoing research on the topic should consider distinguishing competition and concentration, the possibility that they may have or have not similar implications on stability and more importantly how the effect of their interactions.

REFERENCES

Adu, D.A., 2022. Competition and bank risk-taking in Sub-Saharan Africa countries. SN Bus. Econ. 2, 80. https://doi.org/10.1007/s43546-022- 00250-1

Akins, B., Li, L., Ng, J., Rusticus, T.O., 2016. Bank Competition and Financial Stability: Evidence from the Financial Crisis. J. Financ. Quant. Anal. 51, 1–28. https://doi.org/10.1017/S0022109016000090

Allen, F., Gale, D., 2004. Competition and Financial Stability. J. Money Credit Bank. 36, 453–480.

Arping, S., 2019. Competition and risk taking in banking: The charter value hypothesis revisited. J. Bank. Finance 107, 105609. https://doi.org/10.1016/j.jbankfin.2019.105609

Beck, T., De Jonghe, O., Schepens, G., 2013. Bank competition and stability: Cross-country heterogeneity. J. Financ. Intermediation 22, 218–244. https://doi.org/10.1016/j.jfi.2012.07.001

Beck, T., Demirgüç-Kunt, A., Levine, R., 2006. Bank concentration, competition, and crises: First results. J. Bank. Finance 30, 1581–1603. https://doi.org/10.1016/j.jbankfin.2005.05.010

Berger, A.N., Klapper, L.F., Turk-Ariss, R., 2017. Bank competition and financial stability, in: Handbook of Competition in Banking and Finance. Edward Elgar Publishing, pp. 185–204.

Boyd, J.H., De Nicoló, G., 2005. The Theory of Bank Risk Taking and Competition Revisited. J. Finance 60, 1329–1343. https://doi.org/10.1111 j.1540-6261.2005.00763.x

Claessens, S., Laeven, L., 2004. What Drives Bank Competition? Some International Evidence. J. Money Credit Bank. 36, 563–583.

Danisman, G.O., Demirel, P., 2019. Bank risk-taking in developed countries: The influence of market power and bank regulations. J. Int. Financ. Mark. Inst. Money 59, 202–217. https://doi.org/10.1016/j.intfin.2018.12.007

Degryse, H., Kim, M., Ongena, S., 2009. Microeconometrics of Banking: Methods, Applications, and Results. Oxford University Press.

Gaertner, M., Sanya, S., 2012. Assessing Bank Competition within the East African Community.

Keeley, M.C., 1990. Deposit Insurance, Risk, and Market Power in Banking. Am. Econ. Rev. 80, 1183–1200.

Leon, F., 2014. Measuring competition in banking: A critical review of methods. Work. Pap., Working Papers.

Martinez-Miera, D., Repullo, R., 2010. Does Competition Reduce the Risk of Bank Failure? Rev. Financ. Stud. 23, 3638–3664. https://doi.org/10.1093/rfs/hhq057

Mirzaei, A., Moore, T., Liu, G., 2013. Does market structure matter on banks' profitability andstability? Emerging vs. advanced economies. J. Bank. Finance 37, 2920–2937. https://doi.org/10.1016/j.jbankfin.2013.04.031

Narain, A., Ötker, I., Pazarbasioglu, C., 2012. Building a More Resilient Financial Sector: Reforms in the Wake of the Global Crisis, in: Building a More Resilient Financial Sector. International Monetary Fund.

Nyangu, M., Marwa, N., Fanta, A., Uwe, L.-L., 2022. The Dynamics of Bank Concentration, Competition and Efficiency in the East African Community. J. Ind. Compet. Trade 22, 21–49. https://doi.org/10.1007/s10842-022-00379-7

Phan, H.T., Anwar, S., Alexander, W.R.J., Phan, H.T.M., 2019. Competition, efficiency and stability: An empirical study of East Asian commercial banks. North Am. J. Econ. Finance 50, 100990. https://doi.org/10.1016/j.najef.2019.100990

Saif-Alyousfi, A.Y.H., Saha, A., Md-Rus, R., 2020. The impact of bank competition and concentration on bank risk-taking behavior and stability: Evidence from GCC countries. North Am. J. Econ. Finance 51, 100867. https://doi.org/10.1016/j.najef.2018.10.015

Schaeck, K., Cihák, M., 2014. Competition, Efficiency, and Stability in Banking. Financ. Manag. 43, 215–241. https://doi.org/10.1111/fima.12010

Schaeck, K., Cihak, M., Wolfe, S., 2009. Are Competitive Banking Systems More Stable? J. Money Credit Bank. 41, 711–734. https://doi.org/10.1111/j.1538-4616.2009.00228.x

Soedarmono, W., Machrouh, F., Tarazi, A., 2013. Bank competition, crisis and risk taking: Evidence from emerging markets in Asia. J. Int. Financ. Mark. Inst. Money 23, 196– 221. https://doi.org/10.1016/j.intfin.2012.09.009

Weill, L., 2013. Bank competition in the EU: How has it evolved? J. Int. Financ. Mark. Inst. Money 26, 100–112. https://doi.org/10.1016/j.intfin.2013.05.005

Wolfe, S., Amidu, M., 2013. Does bank competition and diversification lead to greater stability? evidence from emerging markets. Rev. Dev. Finance 3, 152–166. https://doi.org/10.1016/j.rdf.2013.08.002

Annex

1. Fixed effect estimation of translog cost function

Variables	Log of total cost		
	Coefficient	Robust st. errors	Probability
In _assets	1.038	0.046	0.000
In_assets_squared	-0.005	0.005	0.306
In_cost of funds	0.301	0.091	0.001
In_cost of labor	-0.011	0.122	0.929
In_cost of fixed assets	0.710	0.105	0.000
In_cost of funds*In_cost of labor	-0.054	0.037	0.146
In_cost of funds*In_cost of fixed assets	-0.024	0.041	0.568
In_cost of funds*In_cost of fixed assets	0.077	0.028	0.007
In_cost of fund_squared	0.041	0.009	0.000
In_cost of labor_squared	-0.036	0.040	0.369
In_cost of fixed assets_squared	0.002	0.042	0.957
In_assets*In_cost of funds	-0.011	0.014	0.435
In_assets*In_cost of labor	0.018	0.030	0.554
In_assets*In_cost of fixed assets	-0..006	0.031	0.834
Cons	0.875	0.105	0.000

2. Fixed effect results of revenue function

Variables	Log of ratio of interest revenue to assets		
	Coefficient	Robust st. errors	Probability
In_cost of funds	1.112	0.060	0.063
In_cost of labor	0.217	0.121	0.074
In_cost of fixed assets	0.233	0.034	0.000
In_assets	0.050	0.024	0.036
In_equity to asset ratio	-0.032	0.074	0.664
In_loan to asset ratio	0.350	0.106	0.001
Cons	-0.201	0.358	0.574

3. Diagnostic tests for the main models

3.1. Arellano Bond test for autocorrelation (Ho: no autocorrelation)

Arellano Bond test for zero auto-correlation	Ho: no autocorrelation		
	Order	Z	Prob
Model 1	1	-2.314	0.021
	2	-1.049	0.294
Model 2	1	-2.246	0.025
	2	-1.115	0.265
Model 3	1	-2.365	0.018
	2	-1.018	0.309
Model 4	1	-2.505	0.012
	2	-1.134	0.257

3.2. Sargan test for instrument validity (Ho:overidentifying restrictions are valid)

Sargan test for oveidentifying restrictions		
Model 1	chi2(53)	56.900
	Prob >chi2	0.264
Model 2	chi2(51)	55.734
	Prob >chi2	0.301
Model 3	chi2(50)	50.213
	Prob >chi2	0.465
Model 4	chi2(52)	59.683
	Prob >chi2	0.217

4. Models with Non-performing loans ratio as dependent variable

4.1. Simple model with non performing loans ratio as dependent variable

Variables	Non performing loans ratio		
	Coefficients	Robust Std. errors	Probability
Lag 1	0.106	0.138	0.443
Lag 2	0.189	0.094	0.043
Lag 3	-0.263	0.109	0.016
Lerner index	-0.130	0.079	0.097
hhi for loans market	0.169	0.208	0.416
log of assets	0.000	0.012	0.995
loan to asset ratio	-0.060	0.040	0.136
percapita GDP growth	0.021	0.319	0.947
inflation	-0.106	0.110	0.335
exchange rate depriciation	0.406	0.135	0.003
constant	0.047	0.095	0.616

4.2. Arellano Bond test for autocorrelation (Ho: no autocorrelation)

Order	Z	Prob >z
1	-2.8811	0.004
2	1.437	0.1507

4.3. Sargan test for instrument validity (Ho:overidentifying restrictions are valid)

chi2(45)	50.36897
prob	0.2694

4.4. Model with non-performing loans as dependent variable (with the lerner index squared included in independent variables)

Variables	Non performing loans ratio		
	Coefficients	Robust Std. errors	Probability
Lag 1	0.078	0.110	0.480
Lag 2	0.046	0.063	0.469
Lerner index	-0.205	0.047	0.000
Lerner index squared	-0.200	0.047	0.000
log of assets	0.013	0.012	0.277
loan to asset ratio	-0.065	0.038	0.091
percapita GDP growth	0.312	0.203	0.124
inflation	-0.029	0.099	0.766
exchange rate depriciation	0.256	0.126	0.043
constant	0.013	0.070	0.855

4.5. Arellano Bond test for autocorrelation (Ho: no autocorrelation)

Order	Z	Prob >z
1	-2.8704	0.0041
2	1.0943	0.2738

4.6. Sargan test for instrument validity (Ho:overidentifying restrictions are valid)

chi2(45)	59.584
prob	0.143

RBA/WPS/06-2025

Empowering MSME Financing in Rwanda: A Pragmatic Framework for Domestic Credit Market Development

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ABSTRACT

Expanding MSME access to finance is a national imperative for Rwanda's inclusive and sustainable development. Yet, despite strong policy commitments and a growing digital ecosystem, financing for small and medium enterprises remains constrained by structural inefficiencies, regulatory limitations, and risk aversion in the banking sector. This paper evaluated the current situation and gives a potential proposal for a pragmatic framework to strengthen Rwanda's domestic credit market through reforms in data infrastructure, capital allocation, risk-sharing instruments, and institutional practices. Combining international best practices and local innovations, the paper emphasizes intelligent risk sharing, performance-oriented incentives, and outcome-based impact measurement. The paper includes policy recommendations tailored to Rwanda's current capabilities and development priorities, while adding scalable mechanisms—such as a co-financing SME Risk Sharing Platform and ESG-aligned data collection—that can align with the country's Vision 2050 agenda for commercial sustainability and national development goals.

1. Introduction

Micro, Small and Medium-Sized Enterprises (MSMEs) are widely recognized as the engine of job creation, economic diversification, and innovation. In Rwanda, they account for the vast majority of registered businesses and play a critical role in agriculture, trade, manufacturing, and services ((AFR), 2024). Despite their significance, MSMEs face persistent challenges in accessing formal finance due to high perceived risk, limited credit histories, lack of collateral, and underdeveloped risk assessment systems. Over the past decade, Rwanda has made major strides in improving its financial infrastructure and policy frameworks. However, the domestic credit market still struggles to serve the "missing middle" viable SMEs that are too large for microfinance yet too small or informal for traditional banking. This paper responds to these gaps by evaluating alternative methods and presenting a comprehensive and actionable framework to strengthen MSME financing. In the sections that follow, we review the relevant literature, analyze Rwanda's current credit market conditions, identify key enablers and constraints, and propose a structured implementation pathway. The goal is to combine academic and theoretical recommendations and offer actionable solutions tailored to Rwanda's unique context.

2. Literature Review and Theoretical Framework

Access to finance for MSMEs has long been recognized as a critical driver of inclusive growth and job creation in emerging markets. Numerous studies have identified MSMEs as vital contributors to GDP, employment, and innovation, while also pointing to structural financing gaps that persist globally and particularly in Africa. In Rwanda, MSMEs constitute over 90% of private enterprises (UNDP, 2021), yet their contribution to GDP and employment remains below potential (IFC, 2025), primarily due to limited access to appropriate financial services (UNDP, 2021).

Theoretical frameworks informing this discussion include credit market segmentation theory, which explains how informational asymmetries and high transaction costs lead to the exclusion of smaller borrowers. (Weiss, 1981) Financial intermediation theory and risk-based pricing frameworks also offer insights into how risk based pricing forces MSMEs towards financing in the informal sector as opposed to the banking market (Tschach, 2003).

Recent literature also points to the evolving role of fintech in addressing MSME credit gaps. The literature presents that while digital platforms, mobile technologies, and alternative data offer promising avenues for expanding access, limitations in scalability, risk assessment, and client onboarding remain (Ibitola, 2024). The academic discourse reflects two competing perspectives on this dynamic: one view argues that fintech disrupts traditional banking models, increasing risk-taking and financial instability (Zins, 2021); the other sees fintech as a stabilizing force that reduces information asymmetry and enhances institutional resilience. In practice, outcomes depend on the broader financial architecture and the degree of integration between digital innovations and regulatory frameworks (Thakor, 2020).

This paper builds on the above frameworks by presenting a more pragmatic, implementation-focused approach that prioritizes local context, institutional capacity, and long-term systemic change over technological or policy quick fixes.

3. Rwanda’s MSME Credit Market Landscape

Despite regulatory reforms and economic growth, Rwanda’s credit market remains small and underdeveloped in terms of depth, inclusion, and diversity of financial instruments. According to data from the World Bank, credit to the private sector stands at under 25% of GDP well below regional comparators (Trading Economics, 2025). MSMEs remain particularly underserved, constrained by short tenors, high collateral requirements, and limited product diversification (Azimut, 2022).

3.1.Status

The 2024 FinScope Survey ((AFR), 2024)provides further clarity: only 24% of adults (1.8 million) in Rwanda had formal credit, up only slightly from 22% in 2020. Among selfemployed individuals, 42% of those who borrowed did so to expand or invest in their businesses. However, a significant unmet demand persists - 37% of adults (around 3 million people) expressed a desire to start or invest in a business, while an additional 15% intended to acquire agricultural and business inputs. Despite these aspirations, 32% of adults are doing nothing to meet these financial goals, and 31% resort to non-financial means such as saving in-kind or informally.

Mobile money services, with 86% of adult usage, have helped close access gaps, but the integration of credit functionality remains limited. Fintechs and MFIs continue to face challenges related to scale, capital sustainability, and regulatory clarity. Furthermore, while banks are capitalized, they remain risk-averse and focused on large-scale borrowers.

Notably, a document from the World Bank underscores a significant mismatch in the financial ecosystem: while financial institutions express readiness to lend, MSMEs fail to meet the standard documentation and collateral requirements. The majority of MSMEs are informal and lack financial records, which prevents credit scoring and product tailoring. As a result, MFIs have grown in outreach but remain shallow in financial depth, with limited long term credit or investment capacity (The World Bank, 2023).

The following table shows the MSME Finance Gap as described by the IFC in 2025 (IFC, 2025)

MSME FINANCE GAP 2025 — IFC International Finance Corporation WORLD BANK GROUP

SUMMARY	
Country	Rwanda
Region	Sub-Saharan Africa
Income Group	Low income
MSME FINANCE GAP - FORMAL MSMEs	
MSME Current Supply of Finance (millions, US$)	291.85
MSME Potential Demand (millions, US$)	1,513
MSME Finance Gap (millions, US$)	**1,221**
Formal MSME Finance Gap as % of GDP	12.87%
MSME FINANCE GAP - GENDER DISAGGREGATED	
Men-led MSME Finance Gap (millions, US$)	1,193
Women-led MSME Finance Gap (millions, US$)	27
Women-led MSME Finance Gap as % of GDP	0%
Women-led MSME Finance Gap as % of Overall MSME Finance Gap	2%
INFORMAL MSME SECTOR	
Potential Demand in Informal Sector	531
Informal MSME Demand for Finance as % of GDP	6%
CREDIT CONSTRAINED MSMEs	
MSMEs Constrained (% of total)	55%
MSMEs Fully Constrained (% of total)	17%
MSMEs Partly Constrained (% of total)	38%
MSMEs UnConstrained (% of total)	45%
CREDIT CONSTRAINED MSMEs - GENDER DISAGGREGATED	
Share of Men-Led MSMEs (% of total)	81%
Men-led MSMEs Constrained (% of M-MSMEs)	56%
Men-led MSMEs Fully Constrained (% of M-MSMEs)	16%
Men-led MSMEs Partly Constrained (% of M-MSMEs)	40%
Men-led MSMEs Unconstrained (% of M-MSMEs)	44%
Share of Women-Led MSMEs (% of total)	19%
Women-led MSMEs Constrained (% of W-MSMEs)	50%
Women-led MSMEs Fully Constrained (% of W-MSMEs)	22%
Women-led MSMEs Partly Constrained (% of W-MSMEs)	29%
Women-led MSMEs Unconstrained (% of W-MSMEs)	50%

This disconnect between liquidity and risk-bearing appetite is a core issue that must be resolved through better tools, guarantees, and data infrastructure. If properly structured, Rwanda's ambition to promote Kigali as a financial hub (Kigali International Financial Center – KIFC) could be leveraged to increase domestic long-term funding sources and risk-sharing mechanisms.

4. Key Drivers and Constraints: Technology, Regulation, and Competition

Rwanda's MSME financing ecosystem operates at the intersection of three powerful forces:technology, regulation, and market competition. Each of these elements offers opportunities for innovation and expansion but also presents critical constraints that must be addressed for the ecosystem to function at scale.

4.1.Technology: Fintech's Promise and Reality

The past decade has seen a surge in fintech innovation across Africa, with Rwanda emerging as one of the more digitally forward-leaning markets. Digital wallets, mobile lending, e-KYC platforms, and credit scoring tools have all gained traction, enabling more seamless access to financial services for the unbanked and underserved populations.

However, while the promise of fintech remains substantial, the reality has been more complex. Many early stage fintechs failed to achieve sustainability, highlighting a growing survivorship bias in the fintech narrative (Kodongo, 2024). The solutions that remain in operation today often represent only the small percentage of ventures that survived intense capital constraints, customer acquisition hurdles, and regulatory ambiguity.

Several recurring challenges have emerged according to Mutati (Mutati, 2024):

- Insufficient demand-side traction: Many fintechs were built on compelling technologies but failed to gain enough users, particularly in rural or informal markets where trust, digital literacy, and data reliability remained barriers.
- Lack of stable, long-term debt capital: Fintechs focusing on lending needed access to predictable, patient capital to grow responsibly. However, many depended on short-term equity or soft funding, which constrained their ability to manage risk across lending cycles.
- Limited integration with traditional institutions: Fintechs often operated as standalone entities, disconnected from banks and MFIs, missing opportunities for scale and systemic impact.
- Weak unit economics: Transaction costs, acquisition spending, and high default rates among digitally underwritten loans eroded financial viability.

These experiences underline that technology alone cannot solve MSME credit gaps. Without scalable business models, institutional partnerships, and sound risk management frameworks, digital lenders risk replicating the same exclusionary dynamics they aim to disrupt.

Going forward, Rwanda's fintech ecosystem could evolve toward collaborative models, where innovation is embedded into core financial sector infrastructure-rather than running in parallel to it. This includes integrated APIs, shared risk tools, and cross-institutional data standards that allow fintechs to complement, rather than compete with, traditional lenders.

4.2.Regulation: Enabler and Constraint

Rwanda's regulatory landscape has made important strides in strengthening financial sector stability, including the adoption of the Basel II framework, the rollout of IFRS 9, and the implementation of internal capital adequacy processes (ICAAP). These developments have increased prudential oversight and aligned Rwanda with global standards.

However, certain aspects of this regulatory architecture present unintended obstacles for MSME financing – particularly the application of Basel II's standardized approach to credit risk modeling. Under the standardized framework, MSME loans are typically assigned a 100% risk weight, regardless of underlying risk characteristics, collateral quality, or repayment performance. This uniform treatment imposes disproportionately high capital requirements on banks for extending credit to small businesses, compared to safer sovereign or corporate exposures. For instance:

- A loan to a small-scale poultry farmer with a strong repayment history and a partial guarantee is treated with the same capital charge as a completely unsecured microenterprise loan.
- In contrast, an investment in OECD government bonds carries a 0% risk weight, making it significantly more capital-efficient for banks to just park their resources as, it results in an infinite marginal return on investment.

This regulatory bias, while conservative in nature, discourages banks from expanding into MSME segments, even when those segments are commercially and developmentally promising. It also limits the incentives for banks to invest in better risk models, because the standardized approach offers no capital benefit for doing so.

Moreover, as international experience has shown, only large, globally active banks typically implement the more advanced internal ratings-based (IRB) approaches that allow for differentiated risk treatment. Most small and medium-sized banks lack the capacity and regulatory clearance to use internal models (McBride, 2018).v

4.3.Competition: Traditional Banks vs Fintechs

The competitive landscape for MSME financing in Rwanda is evolving but remains fragmented. Traditional commercial banks continue to dominate in terms of asset size, branch networks, and deposit mobilization, while fintechs and MFIs are more active in niche segments such as microloans, mobile credit, and rural outreach. However, true competition in the MSME segment is still underdeveloped, constrained by structural imbalances and operational limitations.

Asymmetries in Scale, Trust, and Capital

Traditional banks enjoy structural advantages that fintechs and MFIs often lack. These include:

- Established customer relationships and brand trust
- Access to low-cost, stable deposit funding
- Large-scale distribution networks and infrastructure

In contrast, fintechs and smaller institutions must operate with leaner resources and face significant hurdles in acquiring customers, achieving scale, and accessing affordable long-term capital. Many rely on external donor support or venture capital, which may not be sustainable or consistent.

This asymmetry has created a form of “two-speed” competition, where established players hold most of the market power, and newer entrants struggle to gain traction despite technological agility. The competition between the traditional banks and fintechs and MFIs could become shallow and inefficient unless there were deliberate strategies to level the playing field. Such strategies could include data sharing protocols.

The Case for Collaborative Models

A more constructive path forward lies in collaborative competition, where different institutions leverage their respective strengths through structured partnerships. Examples would include:

- Co-lending arrangements, where banks originate and service loans while partnering with fintechs or funds to share risk and scale reach.
- Embedded finance, where MSMEs access financing directly through digital platforms or supply chain partners, with banks acting as capital providers.
- White-label solutions, where fintechs offer their technology to banks or MFIs to digitize loan origination, risk scoring, or customer engagement.

These models could allow for both innovation and prudence-maximizing outreach while managing risk effectively. In addition, they can improve the economics of MSME lending by spreading fixed costs and utilizing complementary capabilities.

Risks of Fragmented Competition

Unregulated or poorly coordinated competition can also create new risks, such as:

- Over-indebtedness when multiple lenders target the same MSMEs without credit visibility.
- Market distortions from subsidized capital that undermines commercial pricing.
- Reputational risk if aggressive or unethical lending practices emerge from unsupervised actors.

To mitigate these risks, Rwanda could continue to prioritize regulatory clarity, including tiered licensing regimes, mandatory data reporting, and consumer protection standards that apply uniformly across financial service providers.

Strategic Role for Regulators and Industry Bodies

To ensure that competition fosters innovation rather than instability, the BNR and the RBA can play strategic roles by:

- Creating frameworks for responsible innovation, including digital lender regulation and cross-sector supervision.
- Supporting interoperability standards and shared data infrastructure (e.g., credit registries, KYC platforms).
- Promoting collaborative sandboxes and pilot programs that bring together banks, fintechs, and MFIs around shared goals (e.g., rural SME lending, youth entrepreneurship, climate finance).

By shifting the narrative from "bank vs. fintech" to "financial sector partnerships for inclusion", Rwanda can catalyze a more resilient and dynamic MSME finance market, one that fosters both innovation and institutional strength.

5. A Pragmatic Framework for MSME Financing Development

Rwanda's efforts to enhance financial inclusion and develop a domestic capital market could now translate into a coherent framework for MSME financing. Based on the gaps identified in the previous sections, we show a potential pragmatic, implementation-oriented roadmap structured around four core pillars: Data Infrastructure, Risk-Sharing Mechanisms, Institutional Transformation, and Regulatory Alignment.

5.1.Strengthening Data Infrastructure for Risk Assessment

The ability to assess credit risk reliably remains one of the most persistent obstacles to scaling MSME lending in Rwanda. Most MSMEs operate informally, with limited financial records, inconsistent documentation, and minimal collateral-making traditional risk assessment approaches difficult to apply. The result is a credit market that is both under penetrated and risk-averse, particularly for smaller and younger enterprises.

To overcome these challenges, the financial sector in Rwanda must invest in the development of a robust, interoperable data infrastructure that supports effective, responsible, and inclusive credit decision-making.

Data systems for MSMEs Credit Risk Management

Characteristics	Digital Credit Registries	Sector-specific Data	Alternative Data Systems	ESG Data Collection
Data Focus	Borrower financial obligations and repayment history	Sector-specific performance trends and benchmarks	Operational data like mobile money and invoices	Environmental, Social, and Governance performance
Key Benefits	Reduces over-indebtedness and fraud risk	Enables context-sensitive credit models	Expands credit access for thin-file borrowers	Supports climate finance and sustainability initiatives
Data Integration	Real-time data integration	Input-output ratios and cash flow patterns	Mobile money, utility payments, and e-commerce	Self-assessment questionnaires based on frameworks

Figure 1 - Data Systems for MSME Credit Risk Management

This includes building:

Digital credit registries

A comprehensive digital credit registry consolidates data on borrowers' financial obligations, repayment history, and credit behavior. In Rwanda, enhancing the current system to include MFIs, SACCOs, and licensed fintechs would provide a more complete picture of borrower exposure and reduce the risk of over-indebtedness or fraud. Real-time data integration would further strengthen credit assessments and portfolio monitoring.

Sector-specific data repositories

Different MSME sectors carry distinct risk profiles. Dedicated data repositories tailored to sectors such as agriculture, manufacturing, trade, and services would enable financial institutions to benchmark clients, understand sectoral performance trends, and apply more context-sensitive credit models. These repositories could include indicators like input-output ratios, seasonal cash flow patterns, or employment intensity-enabling better credit structuring and risk classification.

Alternative data systems

MSMEs often lack audited financial statements but generate valuable data through their everyday operations. Alternative data sources – including mobile money transactions, utility payment history, supplier invoices, and e-commerce/e-invoicing activity – can provide powerful proxies for assessing capacity and willingness to repay. Integrating these data sources into underwriting models helps expand access to credit for “thin-file” borrowers and improves the accuracy of credit scoring for informal or early-stage businesses.

ESG Data Collection and Self-Assessment Tools

As financial institutions and investors increasingly seek to align portfolios with Environmental, Social, and Governance (ESG) standards, MSMEs must be empowered to understand and communicate their ESG performance. Structured self-assessment tools can guide MSMEs through tailored questionnaires based on international frameworks, adjusted by sector and business size. When aggregated anonymously, ESG data can also support climate finance initiatives, policy design, and broader efforts to embed sustainability in Rwanda’s financial sector. It adds a non-financial dimension to credit risk management and enables more informed product development and risk pricing strategies.

Collectively, these systems can reduce information asymmetries, expand lender confidence, and enable tailored product design for different MSME segments.

One particularly promising development is the emergence of portable, verifiable digital credentials-such as those championed by international initiatives like the UNDP’s Universal Trusted Credentials (UTC) framework 1 . These efforts aim to give individuals and small businesses a digital identity linked to a standardized set of verified information, allowing them to securely share their data across institutions. For financial institutions in Rwanda, such frameworks can streamline onboarding, reduce fraud, and improve segmentation without undermining their autonomy in applying proprietary risk models.

Crucially, the objective is not to enforce a centralized credit scoring system, but to enable shared access to reliable, consistent, and comparable data. Each institution should retain the flexibility to design and apply its own risk models, while benefiting from higher-quality inputs. This shared foundation promotes trust, reduces duplication of effort, and improves efficiency across the lending ecosystem.

Enabling Systemic Risk Management and Policy Insight

Beyond individual credit decisions, a national data infrastructure also enhances Rwanda’s capacity for systemic financial oversight and policy design. By aggregating data across institutions and sectors, policymakers and regulators can monitor trends in credit distribution, identify early signs of portfolio stress, and develop targeted interventions to support financial stability and inclusion.

A Coordinated Approach to Implementation

Establishing such an infrastructure will require coordinated action. Financial institutions, fintechs, regulators, and development partners each bring complementary capabilities.

Public-private partnerships will be essential to:

- Define common data standards and interoperability protocols.
- Finance infrastructure development and institutional upgrades.
- Provide incentives for early adoption and sustained participation.

The RBA can play a leading role by convening working groups to harmonize definitions, establish sector-specific reporting templates, and build capacity across its members. This coordination will reduce fragmentation and ensure that data systems evolve in line with both market needs and regulatory expectations.

Importantly, all data collection must adhere to robust consumer protection standards, ensuring that MSMEs retain control over their information and are not excluded or penalized by data-driven processes.

Linking Data to Impact and Strategic Steering

Well-structured data infrastructure is not just about risk management. It is also about accountability and strategic steering. Financial institutions, regulators, and policymakers all need visibility into the outcomes of MSME financing efforts, not just inputs and volumes.

This report proposes a dedicated framework for tracking impact indicators-including access, employment creation, gender inclusion, ESG adoption, and portfolio performance-which is outlined in detail in the 7.1 “Measuring Impact and Outcomes of MSME Financing”. These indicators can guide financial product development, inform capital allocation, and support Rwanda’s broader policy priorities under Vision 2050.

Ultimately, investing in data is an investment in institutional intelligence, policy effectiveness, and trust. Rwanda has already demonstrated leadership in digital governance; the next step is to translate this strength into a financial data ecosystem that supports inclusive, sustainable, and risk-informed credit market development.

5.2.Integrating Risk Appetite Frameworks in MSME Lending

As Rwanda strengthens its MSME credit infrastructure, institutions must move beyond data collection and analytics to real, risk-informed lending decisions. This transition requires an operational bridge between raw data and institutional strategy-built on the foundation of credit risk modeling and formalized through a Risk Appetite Framework (RAF).

From Risk Modeling to Risk Appetite: A Strategic Pathway

Modern credit risk modeling enables financial institutions to assess and manage MSME risk with greater accuracy.

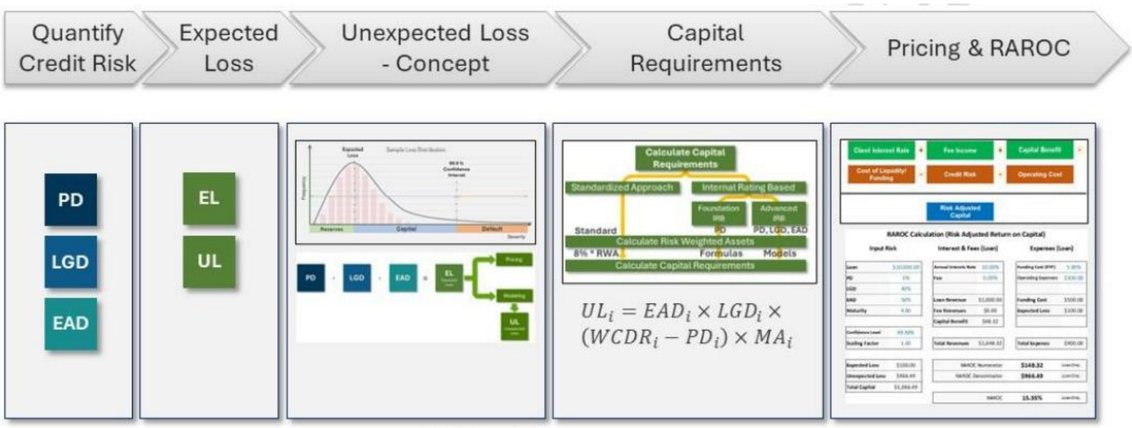

Figure 2 - Steps in Credit Risk Modeling

Core parameters include:

- Probability of Default (PD) – the estimated likelihood of borrower default.
- Loss Given Default (LGD) – the share of exposure that will likely be unrecoverable in case of default.
- Exposure at Default (EAD) – the outstanding amount at the point of borrower failure.

These elements are used to compute:

- Expected Loss (EL) = PD × LGD × EAD – representing the average anticipated credit loss.
- Unexpected Loss (UL) – reflecting the uncertainty or volatility around expected outcomes. This is used to estimate the amount of Risk Capital the institution must hold to absorb losses under stress scenarios.

Once risk capital is quantified, it feeds into the calculation of RAROC (Risk-Adjusted Return on Capital):

$$\text{RAROC} = (\text{Net Income} - \text{Expected Loss}) / \text{Risk Capital}$$

RAROC helps financial institutions evaluate whether lending activities generate sufficient returns relative to the capital consumed. This is especially relevant in MSME finance, where higher perceived risk and thinner margins require careful capital allocation. These tools form the analytical basis for a RAF. See the attachment 7.2 “Basic Concepts of Credit Risk Modeling” for more details on how to use Credit Risk Modeling as an elementary input for the Risk Appetite Framework.

Defining the Risk Appetite Framework

A Risk Appetite Framework articulates the amount and types of risk a financial institution is willing to accept in pursuit of its business objectives. It translates risk analytics into strategic guidelines that govern day-to-day operations, investment decisions, and institutional growth.

Figure 3 - Components of a Risk Appetite Framework

A well-designed RAF will:

- Set exposure limits by product, sector, geography, or client size.
- Define thresholds and triggers that require additional review or credit committee escalation.
- Allocate capital based on the risk-return profile of different segments.
- Justify differentiated pricing, provisioning, or risk mitigation strategies.
- Guide portfolio composition, ensuring concentration risk and diversification are actively managed.

For MSME lending in particular, the RAF supports institutions in moving beyond blanket risk aversion by segmenting risk types, embedding controls, and identifying “smart” opportunities within risk tolerance.

Applying RAF in the Rwandan Context

In Rwanda, MSME finance has often remained on the margins of institutional portfolios due to its perceived volatility, thin documentation, and higher transaction costs. However, with the evolution of credit risk models and better data infrastructure, these barriers could be addressed. A clearly articulated RAF would enable Rwandan banks, MFIs, and fintechs to:

- Systematically grow MSME exposure in segments where risk can be controlled.
- Use risk-based pricing and guarantees to manage low-margin but high-impact loans.
- Engage confidently with regulators and investors, demonstrating that MSME lending is not undisciplined risk-taking but guided by structured governance.
- Support compliance with the Internal Capital Adequacy Assessment Process (ICAAP) and stress-testing obligations under regulatory frameworks.

This alignment between institutional objectives and risk understanding builds resilience, transparency, and long-term value creation.

Embedding the RAF in Institutional Practice

For the RAF to be effective, it must be more than a document. It must be a living framework embedded into the institution’s culture and operations.

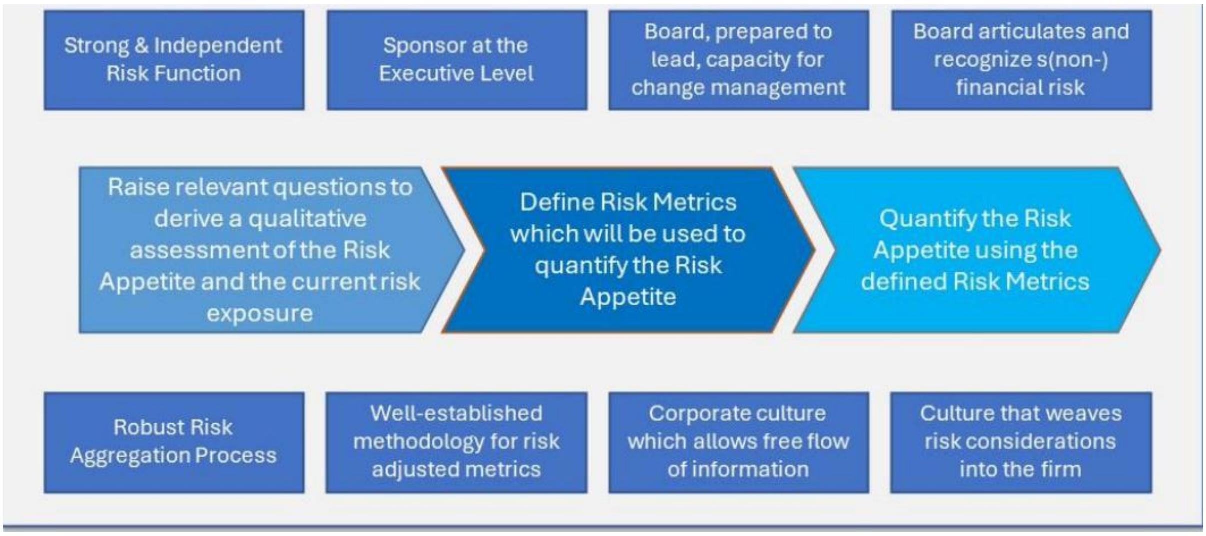

Figure 4 - Development of a Risk Appetite Framework

This includes:

- Alignment across risk, finance, business development, and compliance teams.
- Integration into credit workflows, approval hierarchies, and management dashboards.
- Regular review and recalibration, especially in response to macroeconomic shifts or portfolio changes.
- Training and communication across all levels, ensuring buy-in from frontline officers to board members.

Institutions that embed RAF into operational decision-making are better positioned to allocate capital efficiently, meet regulatory expectations, and expand responsibly into underserved markets.

5.3.Embedding Customer Centric Business Models

As Rwanda's financial institutions seek to expand MSME financing, a fundamental shift is needed-from a transactional, product-focused approach to a customer-centric business model. This evolution is not just about improving service quality; it is a strategic transformation that enhances profitability, strengthens risk management, and builds longterm institutional resilience.

Customer centricity means placing the client – not the product-at the center of all business decisions. For financial institutions, it requires a deep understanding of MSME clients' needs, behaviors, risks, and growth trajectories. Rather than pushing pre-defined products, banks must co-create integrated financial solutions that are aligned with the business realities of their MSME customers.

Why Customer Centricity Matters

- Improved Risk Management: When institutions understand their clients more deeply – how they generate income, manage costs, deal with seasonality, and interact with suppliers-they can make better lending decisions and reduce defaults. Knowing a client well is the first step to assessing their real risk profile.
- Stronger Business Performance: Customer-centric institutions enjoy higher client retention, increased cross-selling, and more sustainable portfolio growth. Relationship-based banking leads to greater loyalty and better word-of-mouth, especially critical in informal or semi-formal MSME segments.
- Increased Relevance: MSMEs often fall through the cracks of traditional banking systems. Customer centricity enables institutions to reach these clients with tailored products, value-added services, and digital channels that meet them where they are.
- Support for Impact and ESG Goals: Institutions focused on inclusion, gender equity, or green finance can only achieve results by truly understanding client barriers and motivations.

Core Components of a Customer-Centric Business Model

To build a customer-centric model, institutions must integrate several elements across their operations:

Figure 5 - Components of a Customer Centric Model

- Client Segmentation: Not all MSMEs are the same. Segmentation based on business size, formality, sector, gender, location, and digital readiness enables institutions to develop differentiated solutions for distinct client groups.
- Needs-Based Product Design: Financial solutions should align with cash flow cycles, business goals, and risk capacity. This includes appropriate loan tenors, grace periods, collateral flexibility, and bundled services (e.g., financing + insurance + training).
- Integrated Service Channels: Combining digital onboarding with personalized relationship management ensures both efficiency and trust. Mobile apps, agent networks, and call centers must work alongside relationship managers and field staff.
- Customer Journey Mapping: Understanding and optimizing every touchpoint-from first contact to loan renewal-enhances customer satisfaction and reduces drop-off.
- Financial Capability Support: MSMEs benefit from basic business literacy, financial planning tools, and guidance on navigating formal financial systems. Providing these services builds stronger borrowers.
- Feedback Loops: Institutions should regularly collect and act on client feedback through surveys, complaints mechanisms, and usage analytics to improve products and processes continuously

For Rwandan financial institutions ready to adopt this model, the following steps provide a practical implementation framework:

- Conduct Client Research: Use surveys, interviews, and behavioral data to understand MSME segments, needs, and pain points. Leverage existing data from sector associations, fintechs, and mobile money providers.
- Develop Segment-Specific Value Propositions: Based on insights, create differentiated offerings for key segments (e.g., smallholder agribusinesses, youthowned startups, women-led enterprises, informal traders).
- Train Staff and Adjust Incentives: Equip relationship managers, credit officers, and call center agents with tools and training to listen to clients, diagnose needs, and build long-term relationships. Align KPIs and incentives with customer satisfaction and client growth, not just loan disbursements.
- Digitize Thoughtfully: Use digital tools to lower costs and enhance access, but maintain human support for trust-building, especially for first-time borrowers. Prioritize simple, intuitive user interfaces that match MSMEs' digital capabilities.
- Bundle Non-Financial Services: Partner with business development providers, NGOs, or government programs to offer training, market access, and advisory services alongside finance.
- Institutionalize Feedback Mechanisms: Regularly capture customer experience data and build it into management dashboards. Use feedback to refine offerings, anticipate churn, and innovate responsively.
- Monitor Results and Adapt: Track usage, satisfaction, repayment behavior, and customer lifetime value across segments. Use these metrics to steer portfolio strategy and risk appetite.

Role of Regulators and Industry Associations,

Regulators such as the BNR and coordination platforms like the RBA can support customer centric MSME finance by:

- Encouraging transparent disclosure of terms and pricing.
- Promoting responsible lending codes.
- Facilitating shared research on MSME needs and digital inclusion.
- Supporting sector-wide financial literacy and complaint resolution infrastructure.

Embedding customer centricity is not a one-time project – it is a long-term cultural shift. But for institutions serious about scaling MSME finance, it is an essential step toward delivering value to clients, maintaining portfolio health, and fulfilling their role in Rwanda's broader economic transformation.

5.4.Implementing Risk Sharing Tools and Guarantee Schemes

Expanding access to finance for MSMEs requires more than institutional willingness or good product design — it also requires an enabling financial architecture that aligns risk, return, and incentives. One of the most effective mechanisms to achieve this alignment is the use of risk-sharing tools, including partial credit guarantees and co-lending platforms.

While guarantee schemes have long been used to de-risk SME lending, their success has been mixed. Many operate with low utilization due to complex procedures, unclear eligibility criteria, or weak alignment between guarantors and lenders. Traditional models tend to treat guarantees as static insurance policies rather than integrated financial structures that shape behavior and enable scale.

To address these limitations, more dynamic approaches to risk-sharing are emerging. One such model currently under development in Rwanda is an SME Risk Sharing Platform, a structured co-financing mechanism that directly partners with financial institutions to share credit risk, enhance lending capacity, and crowd in private capital.

Key Limitations of Traditional Guarantee Schemes

- Limited Coverage: Partial risk coverage (often capped at 30–50%) may not be enough to shift risk appetite significantly.
- Operational Complexity: Burdensome documentation and long claim timelines discourage usage
- Low Leverage: Many guarantees support only a small volume of additional lending relative to the capital committed.
- Misaligned Incentives: Financial institutions may not improve underwriting practices if risk is outsourced without co-responsibility.
- Fragmentation: Guarantees are often applied inconsistently across institutions, limiting scalability and coordination.

These shortcomings highlight the need for modern, performance-oriented risk-sharing mechanisms.

Toward a Modern SME Risk-Sharing Platform:

A moder SME Risk-Sharing Platform can address these challenges through a co-lending structure rather than a traditional contingent guarantee. Under this model, the fund investors participate alongside the financial institutions in eligible MSME loans — sharing both the risk and return on a proportional basis.

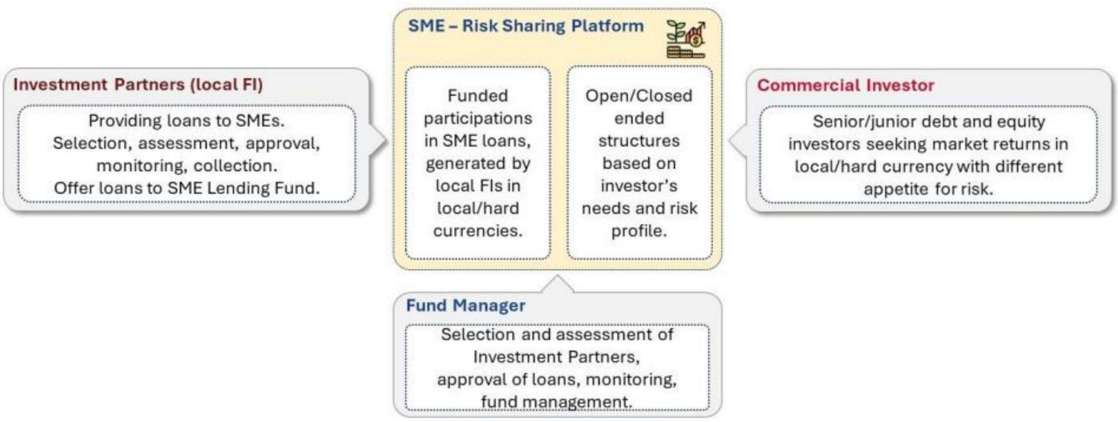

Figure 6 - Schema of the Risk Sharing Platform

Key features of the platform include:

- Standardized Legal and Operational Framework: A unified co-lending agreement and operational playbook ensure consistency across participating institutions. Clear definitions of eligible sectors, loan sizes, tenors, and risk bands improve transparency and predictability.
- Deal-by-Deal or Portfolio-Based Participation: Financial institutions can submit individual loans or pools of loans for co-financing approval. Participation is flexible, allowing banks to scale gradually based on comfort and performance.
- Proportional Risk and Return Sharing: The investors and the financial institution share losses and gains on the same terms, ensuring aligned incentives. This model avoids moral hazard and promotes better underwriting compared to back-end-only guarantee models.
- No Interference in Client Relationships: The originating financial institution retains full control over client interaction, loan servicing, and relationship management. This ensures operational efficiency and protects institutional branding and accountability.
- Embedded Monitoring and Learning Tools: A centralized reporting and feedback system allows for ongoing portfolio monitoring, analytics, and refinement. Lessons learned across partners are aggregated and shared to promote continuous improvement and peer learning.
- Flexible Finance Structure: The platform can be structured on a fully commercial basis. Based on specific policy goals it can also include capital from development finance institutions, philanthropic donors, and private investors
- ESG and Inclusion Criteria: The platform prioritizes loans that advance social, environmental, and inclusive finance objectives — such as lending to women-owned businesses, youth entrepreneurs, or green MSMEs. Impact metrics are tracked as part of performance evaluation.

Strategic Benefits for Rwanda's Financial Sector

This type of platform addresses several structural issues currently holding back MSME finance in Rwanda:

- It provides capital relief by offloading a portion of portfolio risk.
- It enables banks and MFIs to expand into new segments with greater confidence.
- It catalyzes market discipline by aligning underwriting incentives with shared outcomes.
- It attracts external capital by offering a transparent, replicable, and scalable risk sharing mechanism.
- It creates an ecosystem for data sharing, impact tracking, and knowledge transfer across financial institutions.

Role of Stakeholders

For the SME Risk Sharing Platform to succeed, strong engagement is needed by all actors:

- Financial Institutions must commit to originating high-quality MSME loans and maintaining credit discipline.
- Investors and Development Partners can contribute concessional and catalytic capital to support the Fund's risk-bearing capacity.
- Regulators should facilitate enabling guidelines, particularly regarding riskweighting of co-lent exposures.
- Industry Associations can support knowledge sharing and policy alignment.

This model has the potential to serve as a blueprint for regional replication, positioning Rwanda as a leader in innovative SME finance architecture. It moves beyond piecemeal interventions toward a systemic solution that connects capital supply, institutional capabilities, and market demand.

Practical Example:

A commercial financial institution (FI) in Rwanda has a strong and longstanding relationship with an established SME operating in the agribusiness sector. The SME has demonstrated solid repayment behavior and consistent cash flows over several years. Based on this relationship, the FI has a high level of comfort with the SME's credit risk profile.

The SME approaches the FI to request a capital expenditure loan of USD 400,000 to expand its processing facilities and scale production. After conducting its internal due diligence, the FI confirms the economic viability of the project and the creditworthiness of the borrower. However, due to internal risk appetite constraints and limited Tier 1 and Tier 2 capital, the institution is only able to assume USD 100,000 of the total credit exposure.

Rather than rejecting or scaling down the loan, the FI contacts the SME Risk Sharing Platform to request co-financing support. Under the terms of a pre-established framework agreement between the two parties, the Platform evaluates the proposal through a streamlined internal approval process and agrees to participate in the deal.

Once approved:

The FI remains the sole point of contact with the SME and structures the full USD 400,000 loan in its own name.

Upon disbursement of the loan, the SME Risk Sharing Platform deposits USD 300,000 in cash collateral with the FI, corresponding to its share of the risk. Risk and return on the loan are shared proportionally, based on the participation amounts.

- The FI continues to manage the loan, monitor performance, and report periodic updates to the platform.
- This arrangement allows the FI to serve its client fully, support business expansion, and optimize its use of capital — without breaching internal exposure limits or overextending its risk tolerance. Simultaneously, the Fund achieves its mandate of expanding access to finance for high-potential MSMEs while relying on the FI's origination and risk management capacity.

This example demonstrates the SME Risk Sharing Platform's ability to unlock constrained lending capacity, build institutional confidence, and crowd in capital to underserved market segments — all while ensuring operational simplicity and aligned incentives between partners.

5.5.Institutional Transformation and Capacity Building

Transforming Rwanda's MSME financing landscape requires more than new products and capital instruments. It demands a comprehensive institutional shift. Financial institutions must evolve from traditional, transaction-based lenders into agile, learning-driven organizations capable of understanding and addressing the unique needs of diverse SME clients.

This transformation requires several foundational elements:

- Capacity Building: Staff at all levels-from branch officers to risk managers-must receive training in SME-specific lending techniques, financial analysis for informal enterprises, and customer relationship management. Tailored capacity-building programs, supported by development partners or national training institutions, can accelerate this process.
- Process Reengineering: Institutions must move away from rigid, siloed lending procedures and embrace integrated workflows that enable faster, more tailored credit decisions. This includes digitizing core processes, enabling remote onboarding, and fostering cross-functional collaboration.
- Governance and Incentives: Boards and senior management must articulate a clear vision for SME engagement and align internal performance metrics accordingly. Incentive systems should reward responsible risk-taking, portfolio diversification, and long-term client value-not just loan volumes.
- Technology Adoption: The use of core banking systems, credit analytics platforms, and customer engagement tools must be harmonized to support smarter, real-time decision-making. Adoption of low-code and AI-driven tools can reduce cost and accelerate innovation.
- Cultural Shift: Successful SME finance requires a mindset change-viewing small businesses not as marginal clients but as central to the institution's growth strategy. Promoting this culture internally and publicly is essential for sustained transformation.

Public institutions such as the RBA and the Rwanda Academy of Finance can act as facilitators for institutional transformation by developing standardized curricula, certification programs, and industry-wide benchmarks. Development partners should support this agenda through technical assistance and results-based funding mechanisms.

Ultimately, the goal is to build a financial sector that is not only capable of delivering credit to MSMEs, but also of doing so efficiently, inclusively, and responsibly. Only through institutional transformation can the sector fully capitalize on innovations in policy, data, and finance mechanisms outlined in this paper.

5.6.Addressing Regulatory Risk Weights and Capital Allocation

Expanding MSME finance at scale in Rwanda requires more than increasing liquidity or improving credit processes. A core constraint lies in how banks allocate regulatory capital to their lending activities, particularly under current prudential frameworks. Capital requirements that are misaligned with actual risk can disincentivize lending to SMEs — especially those lacking traditional collateral or formal documentation (Supervision, 2006).

Capital Allocation Under the Standardized Approach

Today, Rwandan financial institutions calculate credit risk capital under the Standardized Approach of the Basel II framework.

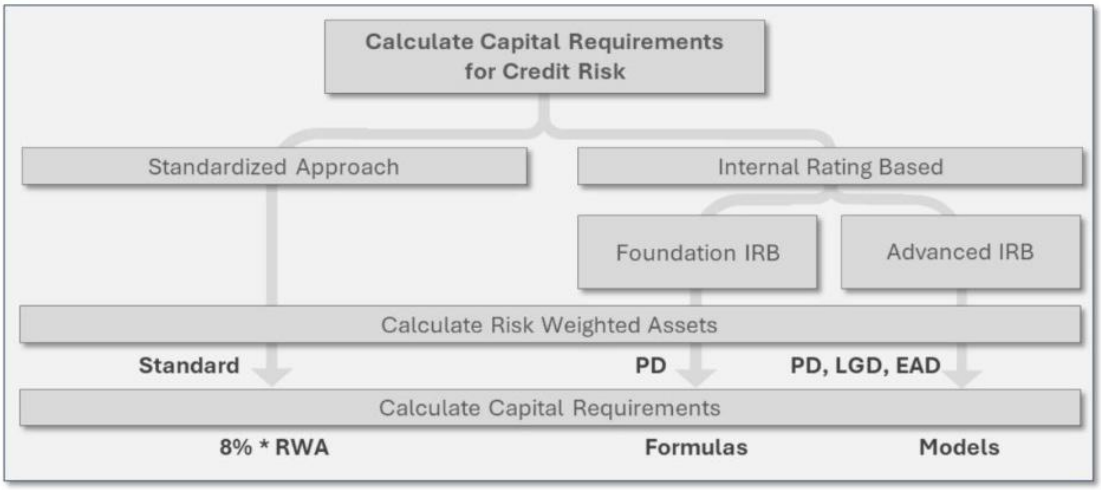

Figure 7 - Schema - Capital Allocation for Credit Risk

This approach assigns fixed risk weights based on external ratings or borrower type. For example:

- Unsecured SME loans without external ratings typically receive a 100% risk weight, regardless of actual credit quality;
- Government securities or exposures to highly rated sovereigns receive 0% or low risk weights, consuming no capital.

This structure creates a risk-weight asymmetry:

- MSME loans – even performing ones – tie up substantial capital.
- "Safe" investments with low social impact are favored due to minimal capital charges.

As a result, banks – especially those with thin equity bases – are reluctant to scale MSME lending, even when there is strong business rationale.

The Case for Transitioning Toward Risk-Based Capital Models

As Rwanda's financial sector matures, it has an opportunity to evolve toward more risksensitive capital frameworks. One potential path is the Foundation Internal Ratings-Based (FIRB) Approach under Basel II/III, which allows banks to:

- Develop internal models to estimate the Probability of Default (PD) for borrowers, including MSMEs.
- Use regulatory-defined estimates for Loss Given Default (LGD) and Exposure at Default (EAD).
- Compute capital requirements based on empirical credit risk, rather than fixed external categories.

This evolution introduces more flexibility and accuracy in capital allocation, particularly for well-managed institutions with robust data systems.

Benefits of F-IRB for MSME Financing

Risk Differentiation: Banks can assign lower capital to higher-quality SME exposures, enabling them to lend more without breaching capital adequacy ratios.

- Capital Efficiency: Reduces the cost of MSME loans that meet underwriting and performance thresholds – making these loans more commercially viable.
- Incentivizes Better Risk Management: Institutions are rewarded for improving credit assessment, monitoring, and portfolio analytics – creating a feedback loop of quality improvement.
- Supports Strategic Portfolio Steering: Enables more granular capital planning by sector, product, or geography, aligned with the institution's risk appetite.

Pre-conditions for F-IRB Implementation in Rwanda

Transitioning to F-IRB is a multi-year undertaking and must be phased and proportionate tonational priorities.

Key pre-conditions include:

- Robust Internal Data: Institutions must demonstrate the ability to collect, store, and validate data on defaults, recoveries, exposures, and risk drivers across time.
- Model Governance and Validation: Strong internal control over model development, calibration, backtesting, and governance procedures is essential.
- Regulatory Supervision Capacity: The BNR would need to provide the supervisory tools and capacity to review and validate internal models.
- Tiered Implementation Strategy: Larger or systemically important banks could pilot the IRB framework, while smaller institutions continue under the Standardized Approach until ready.
- Industry Alignment: The RBA can play a coordinating role in sharing methodologies, developing model validation protocols, and training staff.

Intermediate Steps and Risk-Sensitive Adjustments

Recognizing the significant investment required to move to F-IRB, Rwanda can adopt intermediate steps in the near term:

- Introduce differentiated risk weights for MSMEs, based on criteria such as loan size, business registration, or repayment history.
- Provide capital relief for co-financed MSME loans with recognized risk-sharing facilities (e.g., the SME Risk Sharing Platform).
- Expand the scope of eligible collateral under prudential regulation to include warehouse receipts, mobile money statements, and digitally recorded transaction flows.
- Incentivize behavioral data and alternative scoring models, as precursors to full internal model approval.

These measures would reduce capital constraints on MSME lending and build institutional readiness for more advanced Basel implementation.

5.7.Regulatory Reform and Market Coordination

While Rwanda has made significant progress in modernizing its regulatory framework, further alignment would further encourage innovation without compromising stability. Regulatory sandboxes, proportionate capital requirements, and incentives for long-term lending should be considered.

Moreover, effective MSME finance requires coordination across ministries, regulators, and private actors. A national task force or MSME finance council could help align priorities, track progress, and ensure accountability.

Taken together, these pillars offer a practical and context-sensitive roadmap to unlock credit for Rwanda's MSMEs. They shift the emphasis from high-level aspirations to tangible actions and from isolated interventions to a systemic approach. The next section outlines how these principles can be translated into actionable policy and institutional recommendations.

6. Conclusion

Unlocking the potential of MSMEs in Rwanda is both a developmental necessity and a financial opportunity. This paper has outlined a pragmatic roadmap that tackles the foundational barriers to MSME financing—from data asymmetries and inflexible capital regulation, to limited risk-sharing mechanisms and insufficient customer-centric practices.

A successful transformation will require systemic interventions at multiple levels. Financial institutions must build internal capabilities, adopt risk-based lending practices, and embed customer-centric models. Regulators must provide enabling guidance on capital treatment, digital data integration, and co-lending arrangements. Development partners and investors must support blended finance vehicles and impact-aligned investment strategies. And platforms such as the SME Lending Fund can act as catalytic instruments that demonstrate viability and build trust across stakeholders.

Perhaps most importantly, Rwanda must treat MSME finance not as a niche or concessionary segment but as a core pillar of its economic resilience and competitiveness. With targeted reforms, coordinated leadership, and scalable infrastructure, the country can position itself as a continental leader in inclusive financial systems—anchored in sustainability, digital innovation, and shared prosperity

Policy Recommendations

1. Strengthen Data Infrastructure

o Establish standardized, interoperable data frameworks that support risk assessment, policy design, and financial innovation.

o Promote the adoption of tools such as ESG self-assessment platforms and trusted digital credentials.

2. Clarify and Calibrate Risk Appetite

o Encourage financial institutions to define MSME-specific Risk Appetite Frameworks aligned with their strategic goals and operational capacities.

o Incorporate risk appetite thinking into ICAAP and internal performance management.

3. Foster Customer-Centric Business Models

o Incentivize product and process innovations that reflect the realities of MSME clients.

o Promote knowledge management platforms that enable continuous learning and service customization.

4. Mobilize Risk-Sharing Capital

o Expand the toolkit beyond traditional guarantees by piloting co-lending and blended finance structures.

o Support initiatives such as the SME Risk Sharing Platform through blended capital and policy support.

5. Enable Institutional Transformation

o Develop sector-wide capacity-building programs in SME finance.

o Support process modernization and digital transformation at the institutional level.

6. Review Regulatory Capital Treatment

o Explore differentiated risk-weighting for qualifying MSME exposures to improve capital efficiency.

o Facilitate ongoing dialogue between the BNR, financial institutions, and development partners to align prudential oversight with developmental priorities

Rwanda has the institutional credibility, policy momentum, and entrepreneurial energy to lead the next generation of inclusive finance. By embedding these reforms into the strategic direction of the financial sector, Rwanda can ensure that its credit markets not only expandbut do so equitably, responsibly, and in service of its broader development vision.

Bibliography

(AFR), A. t. (2024). Rwanda Finscope 2024 Survey. Kigali: Access to Finance Rwanda (AFR).

Azimut. (2022). MSMEs and access to finance in Rwanda. Brussels: Azimut.

Ibitola, J. (2024, May 2). Why Fintechs Should Prioritise Customer Risk Assessment for LongTerm Success. Retrieved from Flagright: https://www.flagright.com/post/whyfintechs-should-prioritise-customer-risk-assessment-for-long-term-success

IFC. (2025). MSME Finance Gap. Washington DC: IFC.

Kodongo, O. (2024). The Fintech Ecosystem and Financial Inclusion: Evidence from Kenya. Nairobi: AERC Working Paper DFSP-CCS-002.

Mutati, C. M. (2024, August 30). www.connectingafrica.com. Retrieved from https://www.connectingafrica.com/fintech/understanding-african-fintech-startupfailures?utm_source=chatgpt.com

Thakor, A. V. (2020). Fintech and banking: What do we know? Journal of Financial Intermediation, Vol 41.

The World Bank. (2023). Project Paper on a Proposed Additional Credit . Washington DC: World Bank.

Trading Economics. (2025, 05 31). Trading Economics. Retrieved from https://tradingeconomics.com/rwanda/domestic-credit-to-private-sector-bybanks-percent-of-gdp-wb-data.html

Tschach, I. E. (2003). The Theoretical Derivation of Credit Market. Frankfurt: Johann Wolfgang Goethe-Universität.

UNDP. (2021). Unblockin Rwanda's entrepreneurial potential. Kigali.

Weiss, J. E. (1981). Credit Rationing in Markets with Imperfect Information. The American Economic Review, 393-410.

Zins, A. &. (2021). Fintech credit and bank stability: Empirical evidence. International Review of Financial Analysis, Vol 78.

7. Attachments

7.1.Measuring Impact and Outcomes of MSME Financing

Expanding MSME finance is not only a question of volume – it is about generating measurable, but sustainable outcomes also that benefit businesses, financial institutions, and the broader economy. An impact-driven approach supports strategic alignment, guides resource allocation, and enables financial institutions to track whether their activities are producing meaningful results.

While Rwanda may not yet have a fully established, industry-wide dataset for impact measurement in MSME finance, this should not be a deterrent. On the contrary, building such a data foundation going forward is essential. It will promote accountability, support risk management, and enable institutions to steer their MSME strategies with greater clarity and confidence.

Why Impact Measurement Matters

A structured approach to impact measurement serves several purposes:

- Accountability and Transparency: Reliable outcome data helps regulators, investors, and policymakers understand how capital is being deployed and whether it is achieving stated development objectives. This transparency enhances trust in the financial sector and creates incentives for responsible lending.
- Investor Alignment: With global investors increasingly emphasizing ESG integration and alignment with the Sustainable Development Goals (SDGs), institutions that demonstrate measurable impact are more likely to attract finance and open up new funding sources for long-term investment.
- Internal Risk and Strategy Management: Even beyond external incentives, it is simply good practice. Measuring impact helps institutions better understand their client segments, monitor performance, identify early warning signals, and align operations with institutional goals. Impact metrics can complement traditional financial KPIs and improve overall portfolio quality.

Core Impact Dimensions and Indicators for MSME Financing

To operationalize impact measurement for MSME financing, a starting point is tracking indicators across five dimensions.

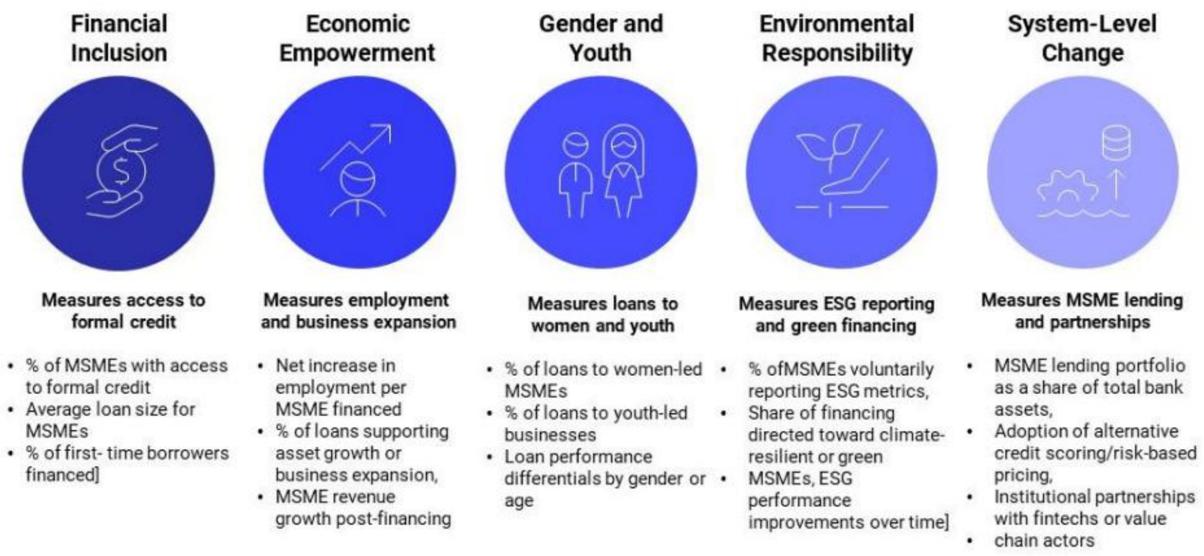

Figure 8 - Sample Indicators for MSME Financing

These indicators can be disaggregated over time by geography, sector, institution type, or target group. While actual data may not yet be available for all metrics, initiating data collection now sets the stage for more sophisticated analysis and better decision-making in the future.

Tools, Sources and Institutional Coordination

The effective implementation of impact measurement depends on the availability and quality of data, which must be collected systematically from multiple sources. In the current Rwandan context, where many institutions are still formalizing data collection practices, a phased approach is both realistic and effective. The goal should be to progressively develop a system where impact data becomes as integral to institutional operations as financial reporting.

Primary data sources include:

- Administrative and transactional data from banks, MFIs, and SACCOs, which includes borrower profiles, loan performance, sectoral classifications, and digital usage metrics. These are foundational and should be routinely collected and reported.
- Borrower self-assessments and surveys, particularly relevant for capturing qualitative outcomes such as business expansion, job creation, or satisfaction with financial services. These can be conducted by financial institutions themselves or through third-party evaluators.
- Digital platform analytics, especially where institutions use loan origination systems, mobile banking apps, or ESG assessment tools. These systems can provide real-time insights into customer behaviors, product usage, and areas of attrition.
- Regulatory data, including reports submitted to the BNR, which can be expanded to incorporate structured impact indicators beyond traditional prudential metrics.

To ensure consistency and comparability across institutions, it is critical to adopt standardized definitions and reporting formats for all key indicators. These standards should address, for example, what qualifies as a "woman-led business," how to define a "first-time borrower," or how employment creation is attributed to a specific loan.

This is where the RBA can play a transformative role. As a convening body for the country's financial institutions, RBA is ideally positioned to:

Set data standards and reporting protocols through consultative processes involving commercial banks, MFIs, fintechs, and regulators.

Organize thematic working groups, e.g., on MSME lending, ESG reporting, or digital finance, to develop common methodologies and address operational challenges in implementation.

Develop industry-wide training modules to build internal capacity for data analysis, impact monitoring, and reporting.

Act as an intermediary for aggregating anonymized sectoral data, allowing benchmarking across institutions while protecting client privacy.

The RBA can also facilitate engagement with international best practices and align local reporting systems with global impact management frameworks such as the SDG Impact Standards, the Global Impact Investing Network (GIIN) IRIS+ system, or the IFC's Operating Principles for Impact Management.

To institutionalize these efforts, a collaborative approach involving RBA, the BNR, the Ministry of Finance and Economic Planning, and development partners should be adopted. A national roadmap for data governance and impact reporting in the financial sector could help synchronize these initiatives and align them with Rwanda's digital transformation and financial inclusion goals.

Toward a National MSME Finance Impact Dashboard

In order to make impact measurement a practical and actionable tool, Rwanda should consider the development of a National MSME Finance Impact Dashboard. This would serve as a centralized monitoring and learning tool that aggregates, analyzes, and disseminates progress across the sector. The rationale for such a dashboard is threefold:

- Strategic Policy Alignment: A consolidated view of national-level impact indicators helps ensure that MSME finance initiatives are contributing effectively to Rwanda's Vision 2050 goals, the National Strategy for Transformation (NST1/2), and relevant SDGs.
- Operational Visibility: Financial institutions can benchmark their performance against sector peers, identify gaps, and refine their business models accordingly.
- Investor and Stakeholder Communication: Development partners, DFIs, and private investors increasingly require transparent reporting on development outcomes. A national dashboard can streamline communication and improve Rwanda's profile as a credible investment destination.

Key design features of the dashboard might include:

- A clear indicator framework, covering the five core dimensions outlined earlier (inclusion, growth, gender/youth, ESG, and market development), with disaggregation by region, sector, and institutional type.
- Integration with regulatory and supervisory systems, allowing BNR to incorporate impact indicators into routine data collection and supervisory review.
- A tiered structure, where different institutions report at levels commensurate with their size and capacity, ensuring that smaller MFIs or SACCOs are not overburdened.
- Open-access summaries for the public, while providing granular, secure data access for policymakers and financial institutions.
- The dashboard should not merely be a reporting tool-it must support decisionmaking. For example, policy adjustments to SME support programs can be guided by impact trends; training interventions can be targeted where ESG or gender inclusion scores are lagging; and risk-sharing mechanisms can be adjusted based on credit performance patterns.

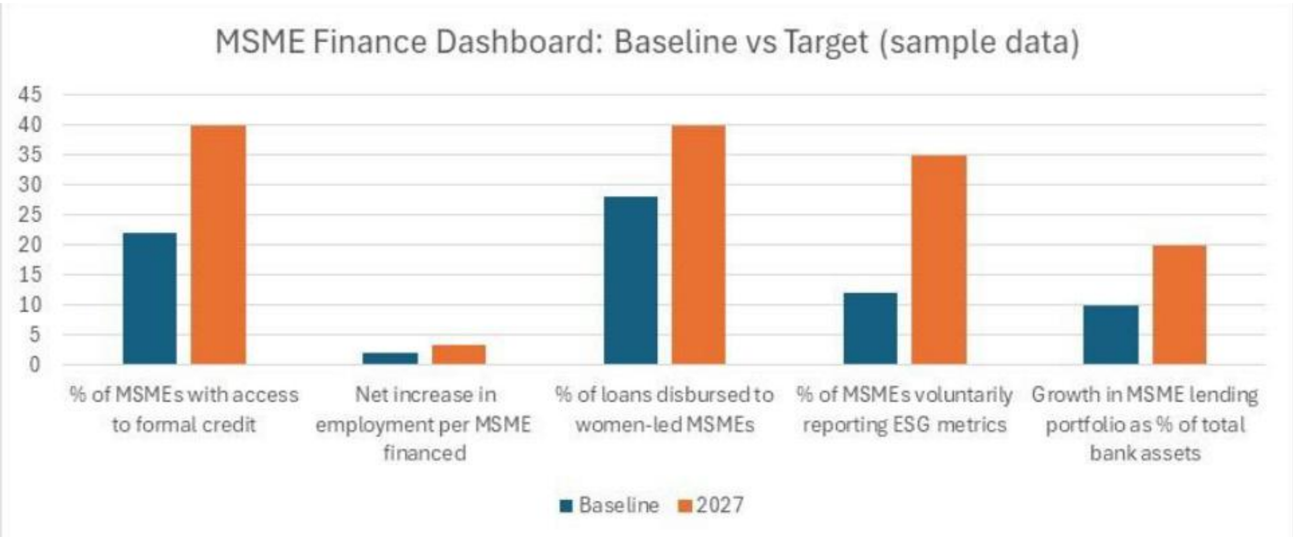

Figure 9 - Conceptual Mockup of an MSME Finance Dashboard

Governance and Oversight

The success of a national impact dashboard depends on clear governance and multistakeholder coordination. We recommend establishing a steering committee that includes representatives from the RBA, BNR, Ministry of Trade and Industry, Rwanda Development Board (RDB), and selected financial institutions and development partners.

The RBA can lead the technical coordination and facilitate engagement with its members, while BNR ensures alignment with regulatory priorities. The committee would be responsible for:

- Approving indicator frameworks and reporting standards.
- Overseeing data quality and dashboard functionality.
- Guiding periodic reviews and refinements based on sector feedback.

To build momentum, the dashboard can start with a pilot phase involving volunteer institutions, gradually expanding to full coverage. Development partners can support this process through funding, technical assistance, and independent evaluation. This governance structure ensures that impact measurement remains relevant, credible, and integrated into national financial sector strategy.

7.2.Basic concepts of Credit Risk Modeling

Credit risk is the most fundamental risk type faced by lending-focused financial institutions. It encompasses the risk of borrower default and is central to product pricing, portfolio management, capital planning, and institutional sustainability. This concept note focuses specifically on credit risk modeling, moving beyond qualitative analysis to offer a structured quantitative framework for risk-informed decision-making.

The objective is to bridge theoretical rigor with operational relevance—ensuring financial institutions can apply the concepts effectively within day-to-day lending, particularly in environments like Rwanda's MSME finance landscape.

Core Components of Credit Risk Modeling

Credit risk can be quantified using three foundational metrics:

- Probability of Default (PD): The likelihood that a borrower will default within a given time frame, typically one year. PD is influenced by credit history, business performance, macroeconomic factors, and sectoral risk.
- Loss Given Default (LGD): The proportion of the loan not recovered if a borrower defaults. LGD is influenced by collateral value, legal recovery processes, and seniority of the loan in the capital structure.
- Exposure at Default (EAD): The outstanding amount the bank is exposed to at the moment of default. This may include undrawn loan portions and accrued interest.

Together, these components form the basis for calculating:

Expected Loss (EL):

$$EL = PD \times LGD \times EAD$$

This represents the average loss a lender expects over time and should be covered by pricing and provisioning.

Unexpected Loss (UL):

Reflects the potential deviation from the expected loss under stress conditions. It is critical to determine how much capital a financial institution must hold to remain solvent during adverse scenarios.

UL forms the quantitative basis for regulatory capital requirements. Institutions must hold sufficient capital to absorb unexpected losses at a defined confidence level (often 99.9%).

This is central to the Basel regulatory framework, particularly under:

• Standardized Approach (SA): Uses fixed risk weights based on external ratings.

• Foundation Internal Ratings-Based (F-IRB) Approach: Allows banks to use internal models to estimate PD while using regulatory values for LGD and EAD. Understanding UL also enables institutions to calculate economic capital, which in turn informs Risk-Adjusted Return on Capital (RAROC)—a performance metric that links credit risk to profitability.

RAROC = Net Income / Risk Capital

RAROC measures whether a given loan or portfolio justifies the economic capital it consumes. It serves multiple purposes:

• Pricing individual loans based on their risk profile.

• Comparing the profitability of business units.

• Supporting strategic asset allocation decisions.

RAROC enables institutions to prioritize high-value, low-risk lending and avoid underpricing risk — especially relevant for MSME portfolios where perceived volatility is often high.

Stress Testing and the Role of the Risk Appetite Framework

Building on credit risk modeling, institutions can perform stress testing by adjusting PD, LGD, or EAD assumptions under adverse scenarios. This helps them:

• Understand tail risk.

• Identify portfolio vulnerabilities.

• Plan capital buffers in line with their Risk Appetite Framework (RAF).

The RAF sets tolerance thresholds for credit risk, including limits by sector, geography, or product type. It ensures that lending strategies are aligned with institutional capacity and market dynamics.

Application in MSME Lending Contexts

Although credit risk modeling originated in large corporate banking, it is increasingly relevant to MSME finance—especially as:

• Digital data availability improves.

• Alternative data sources (e.g., mobile money, utility payments) offer new signals for PD estimation.

• Institutions can pool data across sectors or regions to build simplified internal scoring models.

Even smaller financial institutions in emerging markets can begin applying basic versions of these models to differentiate risk within their MSME portfolios and develop tiered pricing or lending strategies accordingly.

Practical Considerations for Implementation

To operate credit risk modeling, institutions should:

• Start simple: Use risk buckets or scorecards before building full statistical models.

• Build data incrementally: Begin collecting performance data now to enable model development over time.

• Align with business strategy: Embed risk concepts in product design, pricing, and customer segmentation.

For Rwanda, these principles can support efforts to develop MSME-specific underwriting practices, more transparent loan pricing, and scalable risk-sharing arrangements that link institutional sustainability with inclusive finance.

RBA/WPS/07-2025

Fintech Evolution, Banks' Market Power and Risk-Appetite Nexus among Rwandan Commercial Banks

David. M. Ndwiga & Eric Niyongira

Abstract

The study examines the nexus between fintech evolution, banks' market power, and risk-taking behaviour among Rwandan commercial banks. The study is motivated by contrasting views in existing literature with one supporting the complimentary relationship between fintechs and other financial players on one hand, and the other citing the competing relationship between fintechs and other financial players. Specifically, the study seeks to investigate the effect of fintech entrance on market power and subsequent changes in banks' risk appetite. Using data from seven commercial banks in Rwanda over the period 2010 to 2024, the study analyze market power before and after the adoption of mobile banking. The results reveal no statistically significant difference in banks' market power between the two periods, suggesting a co-evolution rather than competition between fintechs and banks. The panel GMM result find the banks market power positively and significantly affect bank net interest margin and NPL ratio. However, at industry level, fintech adoption by banks was found to have positive but insignificant effect on bank net interest margin and NPL ratio. Yet, adopting bank specific fintech adoption years, panel GMM results reveal that fintech adoption at bank has positively and significant effect on banks risk appetite and consequently credit risk.

1.0 Motivation of the study

The evolution of the fintech in the financial services sector has elicited a contemporary debate regarding whether fintech firms and dominant financial sector players are complementary: - coevolve together, or competitors. Conclusiveness into this debate is contextual in nature, varying across countries and even from one bank to another. Practice and literature consents to crucial role by fintechs in enhancing access to financial services - thus complementing commercial banks in this role. In many cases, commercial banks have leveraged on the fintechs to develop digital financial products as well as reach the unbanked population. This presents a co-evolution scenario.

However, to the contrary, fintechs could be perceived to have infiltrated into banks' market power by offering alternative financial products and services to the public. Particularly, fintech has accelerated innovation and competition across core banking services, including payments, lending, deposit-taking, and advisory services. The entry of new fintech-based service providers has expanded access to financial services and put pressure on the market share and pricing power of incumbent banks. This presents a dilemma, into what is the net effects of fintechs evolution in so far as banks' market power and risk appetite is concerned?

In the context of the credit markets, fintech evolution does play a crucial role in influencing efficiency in the credit allocation, perhaps the supportive role of the fintech in augmenting credit allocation dynamics (Liberti & Petersen, 2017 and Boot & Thakor, 2000). However, other proponents assert that the growing competition from fintech companies presents a challenge to traditional banks. Many fintech firms enter specific niches within the broader multi-product financial industry, often operating with business models that contrast sharply with those of universal banks. They operate in single and lightly regulated segments of the industry, and try to customers will incline to fintech with few or no layers of intermediation due to flexibility associated with the fintech in offering basic utilities - thus adversely affecting banks market power (Ariss, 2010b). This is the competing angle of fintechs in so far as the operations of the incumbent financial services providers are concerned.

Therefore, it is worth noting that the extent to which financial technology will reshape the banking industry depends largely depends on the nature of competition for banking services – whether driven by innovation from incumbent banks or the entry of new market players. According to Basel Committee on Banking Supervision (2018), credit markets' future is dependent on whether banks will retain their traditional roles in managing client relationships, the execution of transactions, and risk taking, or whether these functions will be partially or full taken over by fintechs.

Fintech evolution and banks' operation literature, indicates that competition from fintechs to banks could reduce cost of payments and put pressure on fees (Jonker and Kosse 2022). However, this literature fails to elucidate how this has affected commercial banks given that banks have also been engaged in innovation - in addition to providing much of the underlying infrastructure for digital payments. Within credit markets scope, fintechs are potentially changing how banks compete for deposits and with whom. Abrams (2019) notes that online deposit-taking has the potential to increase the geographical reach of banks and therefore reduce market power that banks derive from having a physical presence in deposit markets. On operational front, partnership between fintechs and financial institutions is key in enhancing operational efficiency, product development and enhanced customer relations (Petralia et al, 2019; Wang, Xiuping, and Zhang, 2021).

A review of the Sub-Saharan financial landscape reveals that Fintech has of recently been an eminent major force that is shaping the financial sector structure in the region (IMF, 2019). This change has been viewed to be in terms of market competition, disruption of the traditional financial structures. With fintech entrance, SSA has been ranked to be a global leader in mobile money transfer (Lukonga, 2018). However, just as it has been noted on the global review, the growth has been uneven within the region, with East Africa leading in mobile money adoption and usage. Through this, fintechs in the regions have been seen to provide a panacea for improving efficiency, increased access to credit with the help of new technologies and lowering the cost of cross border funds transfers.

A closer lens review in Rwanda reveals that the economy has witnessed unprecedented development in fintech landscape. More recently, year 2024 witnessed the launch of Rwanda National Fintech Strategy (2024-2029). The 5 years strategy seeks to buttress the development of the FinTech ecosystem - thus maximising the potential that FinTechs hold for economic growth and socio-economic transformation while mitigating potential risks. Further, review does point out the government's reliance on the strategy to position Rwanda as a regional finance centre and promote financial inclusion, which has already reached 96 percent (Finscope, 2024).

2.0 Problem statement

It is notable that whereas globally studies on the banking industry and fintech nexus have allude to this relationship being complementary in nature. The complementarity arises from the fact that it allows fintech to operate by riding on the incumbent financial services providers clients base, while traditional banks benefit from fintech-driven innovations that enhance their competitive edge. However, there exists some exceptions into the nature of this relationship. Such exceptions can be elicited from the fact that though some fintechs have ventured into credit and payment system provisions, they have not been capable of fully unbundling or replacing the profitable services by the incumbent financial services providers.

Further, the benefits to the incumbent financial services providers in terms of the competitive edge arising from the fintech entrance may be mutually exclusive. This could be from the fact that the incumbent financial services providers that are first in accessing and adopting the fintech technology may have an upper hand in dominating market share at the expense of those that are reluctant in adoption. Such development may lead to changes in the market structure of the financial services. The alteration in the market structure could be characterized by the number and the size of the market players, market barriers to market entry and exit, and information and technology access amongst all market players. Further, this aspect poses some market risks by leading to the creation of "too big to fail" entities in the market among the incumbent financial services providers. Such development could have a long-run effect on the financial market and system stability. This, therefore, warrants the need for an examination into the firm-level analysis of the nexus between market power and stability among the incumbent financial services providers (banking industry) in pre- and post-fintech entrance.

The effect of fintech on the financial sector's health is a fundamental aspect that cannot be undermined. This argument stems from the fact that, in supporting the National Fintech Strategy(2024–2029), Rwanda seeks to have 300 active fintech players by 2029 and attain a top-30 position in global fintech rankings, as well as the top position in Africa. Further, the strategy envisages achieving an 80 percent fintech adoption rate. This ambitious strategy comes at a time when the current state of the banking industry in Rwanda reflects an evolving landscape shaped by the strategic objectives of market players responding to competitive dynamics (Rwanda Bankers Association, 2024). Competition-wise, the Herfindahl-Hirschman Index shows that the market is becoming less concentrated even as mergers and acquisitions continue. However, remarkably, while the extent of market concentration is decreasing despite ongoing mergers and acquisitions, the small-bank versus big-bank dichotomy remains relevant in understanding the potential systemic risks that may arise from clusters of banks.

The risk appetite profile indicates that the banks' cost of funding, as reflected in the stable cost of deposits, has over the past two years been on a gradual decline on the back of stable net interest margins. This performance could infer the potential for more risk appetite amid stable net interest margins. This poses a pertinent question: how will the banking industry look by 2029, considering the current industry state and the expected outcome of the National Fintech Strategy (2024–2029)? This calls for an empirical examination into the inquiry, much needed to offer insights and evidence for or against the co-evolution or competitor paradigm, in so far as banks and fintech operations in Rwanda are concerned.

Therefore, it would be somewhat correct to postulate that the entrance of more fintechs will further disrupt the credit market through changes in the banks' business models in Rwanda. Accordingly, commercial banks will have to evaluate their business models amidst the changing operating environment. However, how this disruption will unfold in terms of market power and risk appetite calls for an empirical examination. Against this backdrop is the need to examine how fintech evolution has impacted commercial banks' market power and, consequently, banks' risk-taking behaviour. Undertaking this examination in the Rwandan context is timely, as the economy pursues positioning itself as a financial hub within the East African region.

3.0 Objectives of the study

The specific objectives of the study were:

i. To determine the effect of fintechs on the overall banking industry and the individual bank's market power in Rwanda.

ii. To examine the effect of fintechs on the banks' risk-taking behavior in Rwanda.

4.0 Summary of empirical studies

Fintech's impact on banks is dynamic, thus non-uniform. Fintechs' negative effect on bank profitability is reported by Naceur et al. (2023). The negative impact on profitability is primarily due to a reduction in interest incomes and a rise in operational costs. Notably, their study finds banks' efforts to diversify their revenue streams as inadequate to offset the profitability reduction linked to fintechs' entry. Additionally, the fintechs' business model will have differing effects on banks. Larger banks benefit from partnerships with P2P platforms offered by fintechs through increased non-interest income (Naceur et al., 2023).

The substitutional effect of fintech is reported by Gopal and Schnabl (2022). Amid the 2008 financial crisis, which called for tighter regulatory requirements within the global financial sector, fintechs played a crucial role in filling the void created by reduced bank lending to small and medium-sized enterprises. Further, competition from fintechs has reduced banks' profitability within the United States mortgage market (IMF, 2022). Moreover, evidence of reduced interest income among banks operating in environments with a higher fintech presence has been reported recently in Latin America (Bejar et al., 2022).

On the market power front, though fintechs are more vulnerable to systemic shocks compared to traditional financial institutions, there is insufficient evidence to support the claim that banks' market power diminishes with the growth of fintechs (Saklain, 2024).

5.0 Research methodology

The study employs quantitative analysis in examining the nexus between fintech evolution, banks' market power, and risk-taking behaviour among Rwandan commercial banks. The study adopts a comparative research design in its analysis. This implies that two periods will be reviewed in the study, namely: the pre-fintech entrance and the post-fintech entrance, in order to inform the conclusion. Within the study, the pre-fintech period will be defined as the period before the first mobile banking adoption among banks in Rwanda, with the post-fintech period being defined as the period after the first mobile banking adoption among banks in Rwanda. The methodology to be adopted in the study is discussed as follows:

To measure the market power of individual banks, the study applies the Lerner Index. This index measures the ability of a firm to set its price above marginal cost (i.e., market power). The advantage of using the Lerner Index to measure the market power of a bank lies in its basis in economic principles, as opposed to using market share (e.g., a bank's assets relative to total industry assets). The index is capable of illustrating how and whether imperfectly competitive markets diverge from the perfect competition benchmark, which highlights its economic relevance. Berger et al. (2009) assert that the Lerner Index is a direct measure of competition because it focuses on pricing power, shown by the difference between price and marginal cost, thereby capturing the extent to which a firm can raise its price above marginal cost. The index will be computed as follows:

$$LI_{it} = \frac{P_{it-} MC_{it}}{P_{it}} \ldots \ldots \ldots \ldots \ldots (1)$$

Where:

P_{it} s the price of banking outputs for bank i at time t,

MC_{it} is the marginal costs for bank i at time t.

P_{it} is the price of total assets proxied by the ratio of total revenues (interest and noninterest income) to total assets for bank i at time t. MC_{it} is derived from the translog cost function. The cost function is specified as follows:

$$LnTc = \alpha_0 + \alpha_1 lnTA + \frac{1}{2}\alpha_2(lnTA)^2 + \sum_{j=1}^{3} \beta_j lnx_j + \sum_{j=1}^{3}\sum_{k=1}^{3} lnx_j lnx_k + \sum_{j=1}^{3} \gamma_j lnTA lnx_j + \varepsilon \ldots \ldots \ldots (2)$$

Where:

TC denotes total costs, TA bank's total assets, xjk (x1, x2 and x3) indicate three input prices (labor, capital and funds). x1 is the price of labor, which is the ratio of personnel expenses to total assets, x2 is the price of physical capital, which is the ratio of other non-interest expenses to fixed assets and x3 is the price of borrowed funds, which is the ratio of interest expenses to total funds. Total cost is the sum of personnel expenses, other non-interest expenses and interest expenses. The estimated coefficients of the cost function are then used for computing the marginal cost. Therefore, marginal cost is equal to the first derivative of the logarithm of total cost function with respect to output multiplied by the ratio of total cost to output. The derivative of the logarithm of the total cost with respect to the logarithm of output is computed using the cost function specified in Eq. (4). The marginal cost is based on the estimation of the cost function. We estimate a translog cost function with one output and three input prices.

The estimated coefficients of the cost function are then used to compute the marginal cost using the function below:

$$MC = \frac{TC}{TA}\left(\alpha_1 + \alpha_2 lnTA + \sum_{j=1}^{3} \gamma_j lnX_j\right) \ldots \ldots \ldots \ldots \ldots (3)$$

Lerner index closer to one indicates more market power for the firm. Generally, an index equal to 0 it indicates perfect competition, while an index equal to 1 indicates monopoly. Thus, the greater Lerner index the lower the market competition.

To investigate the fintech entrance – market power hypothesis on the industry and individual bank market power (hypothesis 1), parametric analysis on the market powers for the two period pre and post fintech entrance will be performed. In this case, both the industry analysis is undertaken.

Econometric model

In modelling the effect of fintech entrance on the market share and the risk appetite of commercial banks, the study applies the Panel Generalized Method of Moments (GMM). The application of this model is informed by the need to address endogeneity and unobserved heterogeneity issues common in panel data. In practice, a bank's risk appetite in the current period is largely determined by its risk appetite in the previous period. Furthermore, the quality of assets in the previous period informs current-period bank lending, which subsequently influences current-period lending decisions. Therefore, when considering bank lending, the quality of lending, and risk appetite, it is evident that past lending behaviour and asset quality largely determine the current period's outcomes in practice. Within the panel GMM estimation, one way to determine whether a dynamic model is appropriate is by adding lagged dependent variables and testing their statistical significance. If the lagged dependent variables are significant, then a dynamic panel GMM model and estimator are most appropriate. However, if the lagged dependent variables are not significant, then a standard panel (fixed effects) GMM estimator is more suitable.

The advantage of using the GMM estimation, which justifies its application in this study, is that the model does not require distributional assumptions such as normality. Unlike other estimation methods, such as maximum likelihood estimation, GMM naturally accommodates non-normality, eliminating the need for additional diagnostic testing. Secondly, the model can accommodate heteroskedasticity of an unknown form. In this case, the effects of heteroskedasticity can be addressed using a "robust" estimator.

However, it is important to note that under the GMM estimation approach, the assumption of uncorrelated error terms must hold. If the error terms are autocorrelated, then the lagged error terms cannot be independent of the instruments, and the validity of the GMM instruments is compromised. Therefore, before interpreting GMM estimation results, it is necessary to test the validity of the instruments, including checks for autocorrelated error terms, as proposed by Arellano and Bond (1991). The Arellano-Bond test is used to assess the consistency of the GMM estimates. In addition, the Sargan or Hansen test is used to evaluate the validity of over-identifying restrictions.

From the general model, the specific model is defined as follows:

$$\begin{aligned} Risk\ appetite_{it} = {} & \beta' Risk\ appetite_{i,t-1} + \gamma Learner\ Index_{i,t} + \lambda' Bankfactors_{i,t} + \rho' Macrofactors_t \\ & + \mu_i + \varepsilon_{i,t} \ldots\ldots\ldots\ldots\ldots\ldots (1) \end{aligned}$$

The econometric models are defined as follows:

$$\begin{aligned} NIM_{it} = {} & \beta_0 + \beta_1 NIM_{it-1} + \beta_2 Learner\ Index_{it} + \beta_3 Operational\ Efficieny_{it} + \beta_4 Liquidity_{it} \\ & + \beta_5 Market\ Share_{it} + \beta_6 Bank\ Size_{it} + \beta_7 Mobil\ banking\ Dummy_t + \beta_8 Inflation_t \\ & + \beta_9 Tbill\ rate_t + \beta_{10} GDP_t + \mu_i + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots (2) \end{aligned}$$

$$\begin{aligned} Credit\ Risk_{it} = {} & \beta_0 + \beta_1 Credit\ Risk_{it-1} + \beta_2 Learner\ Index_{it} + \beta_3 Operational\ Efficieny_{it} \\ & + \beta_4 Liquidity_{it} + \beta_5 Market\ Share_{it} + \beta_6 Bank\ Size_{it} + \beta_7 Mobil\ banking\ Dummy_t \\ & + \beta_8 Inflation_t + \beta_9 Tbill\ rate_t + \beta_{10} GDP_t + \mu_i + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots (3) \end{aligned}$$

The Net Interest Margin and credit risk were computed as follows:

$$NIM = \left({Loan\ Interest\ Income - Deposit\ Interest\ Income} \big/ {Total\ Assets} \right) \ldots\ldots\ldots\ldots (6)$$

$$Credit\ Risk = \left({Non-Performing\ Loans} \big/ {Total\ Loans\ and\ Advances} \right) \ldots\ldots\ldots\ldots (7)$$

To account for individual bank's adoption of mobile banking and its effect on risk appetite, the study includes bank specific dummies based on the year each bank adopted mobile banking platform. Upon developing the dummies, the two econometric models are re-run eliminating the mobile banking dummy that is industry level dummy.

Study data

Commercial banks specific data is obtained from the audited financial statements over years from respective banks' websites and Rwanda Bankers' Association where applicable. Data on the macroeconomic control variables will be obtained from the National Bank of Rwanda published reports. Banks' market power is computed from the bank related data as defined by equation 1, 2 and 3. The study utilises data from seven banks for 2010 – 2024 period.

6.0 Results and findings

To examine the effect of fintech on banks market power, a chow test was undertaken for pre mobile banking and post mobile banking among Rwandan banks. The chow test results indicate that banks' market power in pre and post mobile banking periods are not significantly different. Therefore, the study concludes that the entrant of fintechs through mobile banking platform does not significantly alter commercial banks' market power. This finding could be interpretated to imply that fintechs and commercial banks do co- evolve together in Rwandan financial sector, thus complementary as opposed to competitors.

Table 1.0: Chow test results

Chow test	
F (1, 103) = 1.60	F (1, 103) = 1.60 Prob > F = 0.2086

To determine the effect of fintechs on banks risk appetite, a panel GMM model was fitted. Two models were fitted. First, is the model with mobile banking dummy for the entire banking industry. In this model, the mobile banking dummy took value 1 in post 2013 given that the first bank adopted mobile banking in year 2013. This implies that the dummy took value 0 for period 2010 to 2012. The second model drops the industry mobile banking dummy and adopts individual banks' dummies where dummies indicate specific year the bank adopted mobile banking. In this case, the model has seven dummies each for every commercial bank. For each model, two models are fitted: - one for net interest margin and second for the credit risks.

Panel GMM results for net interest margin, using industry fintech dummy (mobile banking dummy) indicates that previous year's NIM positively and significantly affects current year's NIM. Similarly, bank market power, bank level characteristics and macroeconomic factors except treasury bill rates increases bank risk appetite. Industry mobile banking dummy has a positive effect on the bank risk taking. However, the effect of industry mobile banking dummy is insignificant.

Table 2.0: Panel GMM for NIM model

Nim	Coef.
Nim (-1)	0.339***
	(0.061)
Learner index	1.291***
	(0.476)
Liquidity	0.021***
	(0.007)
Efficiency	0.008***
	(0.002)
Market share	0.077***
	(0.034)
Bank size	0.703***
	(0.159)
Mobile banking dummy	0.227
	(0.226)
Inflation	0.044***
	(0.016)
TB Rate	-0.05
	(0.04)
GDP	0.057***
	(0.015)
Constant	6.843***
	1.106
Mean dependent var 6.784	SD dependent var 1.106
Number of Obs 98	Chi-square
Arellano-Bond test for AR(1) in first differences: z= -2.35 Pr >z= 0.190	
Arellano-Bond test for AR(2) in first differences: z= -2.45 Pr >z= 0.146	
Sargan test of overid. restrictions: chi2(64) = 82.29 Prob > chi2 = 0.452	

*** p<.01, ** p<.05, * p<.1, Standard errors in parenthesis

However, after dropping the industry mobile banking dummy and adopting individual banks' mobile banking dummies, the panel GMM model results indicate that fintech adoption at the bank level has a positive effect on banks' risk appetite, except for one bank. These results suggest that, at the individual bank level, fintech adoption positively and significantly influences banks' risk-taking behaviour. This could be explained by the provision of digital credit facilities through mobile banking channels. The implication of these results is that the adoption of fintech by banks via mobile banking channels affects banks' net interest margins differently, given the heterogeneity and diversity in their operations.

Table 3.0: Panel GMM for NIM model

Nim	Coef.
L	0.171**
	(0.073)
Learner index	1.343**
	(0.681)
Liquidity	0.003
	(0.008)
Efficiency	0.01**
	(0.003)
Market share	0.205***
	(0.055)
Bank size	1.566***
	(0.408)
Dummy bank 1	0.369
	(0.253)
Dummy bank 2	0.734**
	(0.353)
Dummy bank 3	0.225**
	(0.282)
Dummy bank 4	0.843**
	(0.362)
Dummy bank 5	0.307**
	(0.282)
Dummy Bank 6	0.538*
	(0.285)
Dummy bank 7	0.944***
	(0.295)
Inflation	0.031*
	(0.017)
TB Rate	-0.181***
	(0.065)
GDP	0.076***
	(0.018)
Constant	12.871***
	(1.798)
Mean dependent var 6.784	SD dependent var 2.110
Number of Obs 98	Chi-square 9792.675
Arellano-Bond test for AR(1) in first differences: z= -1.58Pr >z= 0.113	
Arellano-Bond test for AR(2) in first differences: z= -2.62 Pr >z= 0.527	
Sargan test of overid. restrictions: chi2(64) = 82.83 Prob > chi2 = 0.716	

*** p<.01, ** p<.05, * p<.1, Standard errors in parenthesis

Turning to the credit risk model, the panel GMM results indicate that the previous year's NPL ratio positively and significantly affects the current year's NPL ratio. Further, the bank's market power is found to have a positive and significant effect on credit risk. At the bank level, liquidity, market share, and bank size positively affect the bank's NPL ratio. However, the bank's operating efficiency has a negative effect on NPLs. Regarding fintech adoption at the industry level, the mobile banking dummy has a positive effect on the bank's NPL ratio. However, the effect of fintech adoption at the industry level on bank NPLs is found to be insignificant.

Credit risk model

Credit risk	Coef.
Credit risk (-1)	0.378***
	(0.076)
Learner index	1.293*
	(0.661)
Liquidity	0.001
	(0.009)
Efficiency	-0.003
	(0.003)
Market share	0.147**
	(0.061)
Bank size	0.978***
	(0.28)
Mobile banking dummy	0.226
	(0.323)
Inflation	-0.075***
	(0.023)
TB Rate	0.136**
	(0.056)
GDP	0.023
	(0.025)
Constant	6.358***
	(1.692)
Mean dependent var 4.138	SD dependent var 2.117
Number of Obs 98	Chi-square 2058.632
Arellano-Bond test for AR(1) in first differences: z= -3.83 Pr >z= 0.628	
Arellano-Bond test for AR(2) in first differences: z= -0.85 Pr >z= 0.395	
Sargan test of overid. restrictions: chi2(64) = 84.96 Prob > chi2 = 0.486	

*** p<.01, ** p<.05, * p<.1, Standard errors in parenthesis

However, after dropping the industry mobile banking dummy and adopting individual bank's mobile banking dummy, panel GMM model results indicate that fintech adoption at bank level has a positive effect on bank's NPL ratio. These results posit that at individual bank level, fintech adoption positively and significantly influences bank's NPL ratio. This could be explained by provision of digital credit facilities through mobile banking channels. The implication for these results are that adoption of fintech by banks via mobile banking channel affects banks NPL ratio differently given banks' heterogeneity and diversity in their operations.

Table 5.0: Panel GMM for NIM model

Nim	Coef.
Credit risk (-1)	0.58**
	(0.099)
Learner index	1.578**
	(0.735)
Liquidity	0.014
	(0.011)
Efficiency	-0.002
	(0.004)
Market share	0.223**
	(0.088)
Bank size	1.783***
	(0.585)
Dummy bank 1	0.121*
	(0.385)
Dummy bank 2	0.073**
	(0.462)
Dummy bank 3	0.217***
	(0.418)
Dummy bank 4	0.448*
	(0.494)
Dummy bank 5	0.623**
	(0.416)
Dummy Bank 6	0.228**
	(0.4)
Dummy bank 7	1.234***
	(0.413)
Inflation	-0.099***
	(0.026)
TB Rate	0.119
	(0.081)
GDP	0.001
	(0.027)
Constant	7.463***
	(2.47)
Mean dependent var 4.138	SD dependent var 2.117
Number of Obs 98	Chi-square 1793.390
Arellano-Bond test for AR(1) in first differences: z= -4.28 Pr >z= 0.742	
Arellano-Bond test for AR(2) in first differences: z= -5.56 Pr >z= 0.575	
Sargan test of overid. restrictions: chi2(64) = 83.80 Prob > chi2 = 0.486	

*** p<.01, ** p<.05, * p<.1, Standard errors in parenthesis

6.0 Conclusion and recommendations

The study sought to examine the effect of fintechs on bank risk taking behaviour among commercial banks in Rwanda. Fintech adoption within the banking industry in the study was defined by embedding of mobile banking channels among the banks. Therefore, the years of adoption dummy was used in the analysis. The study analysis finds that and industry level, the banks market power in pre and post mobile banking channel adoption are not statistically different implying the banks and fintechs co-evolve rather than competing. The panel GMM result find the banks market power positively and significantly affect bank net interest margin and NPL ratio. However, at industry level, fintech adoption by banks was found to have positive but insignificant effect on bank net interest margin and NPL ratio. However, adopting bank specific fintech adoption years, panel GMM results reveal that fintech adoption at bank has positively and significant effect on banks risk appetite and consequently credit risk.

Based on the study findings, there is need for commercial banks to keenly evaluate their risk appetite especially when it comes to offering fintech linked financial products. However, there is need for banks to leverage on existing fintech platforms but keenly develop rigorous model for evaluating fintech linked financial products from their risk perspective.

Further, the findings call for proper regulation of fintech in Rwanda. Fintechs have been praised for their achievement in financial inclusion in Rwanda among other economies. However, a balance between financial inclusion and banking industry stability is core as the country gears towards being a regional financial hub. This therefore calls for formal regulation of fintechs as well as fintech models applied by the banks in offering financial inclusion as well as automation of financial services.

References

Abrams, E. (2019). Assessing Bank Deposit Market Power Given Limited Consumer Consideration, University of Chicago - Booth School of Business, 2019.

Berger, A.N., Hasan, I., Zhou, M., (2009). Bank ownership and efficiency in China: What will happen in the world's largest nation? Journal of Banking & Finance, 33, 113-130.

Boot, A. W. A. and A. V. Thakor (2000). Can Relationship Banking Survive Competition? Journal of Finance, 55, 679–713.

Finscope (2024). Rwanda FinScope 2024 report

Grossmann, A., Love, I., & Orlov, A. G. (2014). The Dynamics of Exchange Rate Volatility: A Panel VAR Approach. Journal of International Financial Markets, Institutions and Money. 3, 1-27.

International Monetary Fund. (2019). Fintech in Sub-Saharan African Countries: A game changer?, IMF Policy Paper No. 19/04, Washington, DC, October.

Jonker, N., and Kosse, A. (2022). The Interplay of Financial Education, Financial Inclusion and Financial Stability and the Role of Big Tech. Contemporary Economic Policy, 40 (2022), 612-635.

Liberti, J.M and Petersen, M.A. (2017): "Information: Hard and Soft," Working Paper, Northwestern University.

Lukonga, I. (2018). Fintech, Inclusive Growth, and Cyber Risks: Focus on MENAP and CCA Regions. IMF Working Paper 18/201, International Monetary Fund, Washington, DC.

Rwanda Bankers Association (2024). State of Banking Industry Report.

Naceur, S., Candelon, B., Elekdag, S., and Emrullahu, D. (2023). Is FinTech Eating the Bank's Lunch?, IMF Working Papers, Washington DC.

Saklain, M. (2024). FinTech, systemic risk and bank market power – Australian perspective, International Review of Financial Analysis, 95

Bibliography

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RBA/WPS/08-2025

Optimal Credit Growth Path for Rwanda

Jared Osoro * & Josea Kiplangat **1

"Instead of being a servant, finance had become the economy's master".
Marttin Wolf (2009)

Abstract

This paper seeks to assess whether credit growth in Rwanda is on an optimal path. Deploying a reduced-form specification with a second-order polynomial in credit growth, we confirm that private sector credit growth is on a path that does not pose the risk of instability. However, while that path fulfils the necessary condition of growth with limited instability risk, it falls sort of fulfilling the sufficient condition of yielding maximum economic benefits. The credit growth path is accompanied by a generally declining loan-to-deposit ratio even as the banking system's loan loss provisions as a share of core capital is on the declining trend in line with the low Non-Performing Loans. This liquidity leaning path is therefore deemed suboptimal, there being scope for its upward shift towards optimality. The upward shift is premised on the understanding that continued investment in a better functioning financial system that allows innovative and efficient resource allocation. A key source of innovation stems from digital financial services that have a strong relationship with financial depth and ultimately economic growth. Sustaining the optimal credit path will necessitate the evolution of a hybrid financial system that blends the entrenched bank-based market with aspects of a market-based system. That way intermediation of foreign savings will support long-tenor liabilities that will support the optimal domestic credit path.

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Introduction

This paper seeks to answer the question: is credit growth in Rwanda on an optimalpath? We explore the question on the backdrop of the intellectual debate on the finance-growth nexus, both in a general sense and in the case of Rwanda, being alive and well. The general consensus that financial depth has a causal effect on growth established over the past five decades is nonetheless largely intact even as the subject is often revisited (King and Levine, 1993; 2000; and Levine, 2005). Recent studies in the case of Rwanda not only confirm the causal relation (Karekezi, Owolabi, Ogbebor and Nduka, 2024) but also establish its bi-directional nature (Mikebanyi and Kigabo, 2021).

Rwanda's financial system is bank-led in the Demirgüç-Kunt and Levine (2004) sense. That means that banks play a dominant role in mobilising saving that they channel to investments, thus providing risk management avenues for households and corporations. The contrast is a market-led financial systems where securities markets are dominant. This implies that the banking system in Rwanda plays a critical role in financing the economy, thus being an engine of the economic growth. Credit availability from the banking system enables households' consumption and corporations' investment to exceed what their own funds will enable. Acknowledging the reality of moral hazard and adverse selection problems, banks play an important role of capital optimal capital allocation.

Underneath the general consensus around the causal relationship between finance and economic growth is an acknowledgement of the complexities that infuse perspectives that challenge the direction of influence of the interaction. This dimension of the debate was initially subtle (Minsky, 1974, 1982 and 1986; Kindleberger, 1978; and Rajan, 2005), with the core arguments being:

- One, even a robust banking system could face endogenous transformation to fragility given that extended periods of stability induce enhanced risk-taking in pursuit of profit maximization.
- Two, the more a financial system develops and becomes sophisticated, the heighted the probability of a meltdown. This is on account of the argument sophistication could come with some neglected tail risks financial innovations that could engender fragility even when devoid of leverage.

The bridge between the subtle and the vocal dimension of the new phase of finance - growth relationship debate was then deemed controversial but in hindsight prophetic insights of Rajan (2005) that large and sophisticated financial systems would boost the implicit transition from thin tails to fat tails that point to possible financial meltdown. Even without the benefit of being prescriptive on timelines, this was predictive of the 2008 – 2008 Global Financial Crisis (GFC) that has been characterised as the point of a 'paradigm shift' in the finance and growth literature. In the period subsequent to the GFC, there is more a nuanced tone, in instances less exuberant, in the influence of finance on growth.

The messaging of the limits of finance is now more prominent (Reinhart and Rogoff, 2013; Arcand, Berkes, and Panizza, 2015; Loayza, Ouazad and Rancière, 2018; and Sufi and Taylor, 2021). The core of the message is that:

- One, the complexity of the relationship between finance and economic growth is that its concavity nature implies the existence of a point beyond which economies could potentially experience "too much finance" where financial depth starts exhibiting "vanishing effects" as described in Arcand, et. al., (2015).
- Two, the indirect transmission channel of the complexity finance to economic growth is by way of banking crises arising from episodes of "credit booms gone bust", an argument prominently espoused by Schularick and Taylor (2012).

The estimates of the threshold beyond which the "vanishing effects" kick in when credit to the private sector as a share GDP is in the 80% - 100% range (Arcand, et. al., 2015), with earlier studies coming up with a point target of 100% (Easterly, Islam, and Stiglitz, 2000). A cursory inference from these empirical results for an economy such as Rwanda where the banking system's combined assets as a share of GDP and the private sector credit as a share of GDP are less than 40% and 30% respectively, there is abundant headroom before finance becomes "too much of a good thing". That however does not preclude the possibility of the credit boom-bust episodes based on the pace of credit expansion.

The foregoing background therefore motivates the thrust of this paper on is optimal credit growth, which we define as the rate of credit expansion that supports maximisation of economic benefits without increasing the risk of financial stability. The non-accelerating credit risk aligned with optimal credit growth path is not necessarily a self-equilibrating process but one that is presumed to reconcile the business imperatives of banks managing risks in a manner that obviates the acceleration of non-performing loans (NPLs), accompanied by regulatory safeguards at microprudential and macroprudential levels.

Deploying a reduced-form specification with a second-order polynomial in credit growth, we confirm that private sector credit growth is on a path that does not pose the risk of instability. However, while that path fulfils the necessary condition of growth with limited instability risk, it falls sort of fulfilling the sufficient condition of yielding maximum economic benefits. The credit growth path is accompanied by a generally declining loan-to-deposit ratio even as the banking system's loan loss provisions as a share of core capital is on the declining trend in line with the low NonPerforming Loans. This liquidity leaning path is therefore deemed suboptimal, there being scope for its upward shift towards optimality.

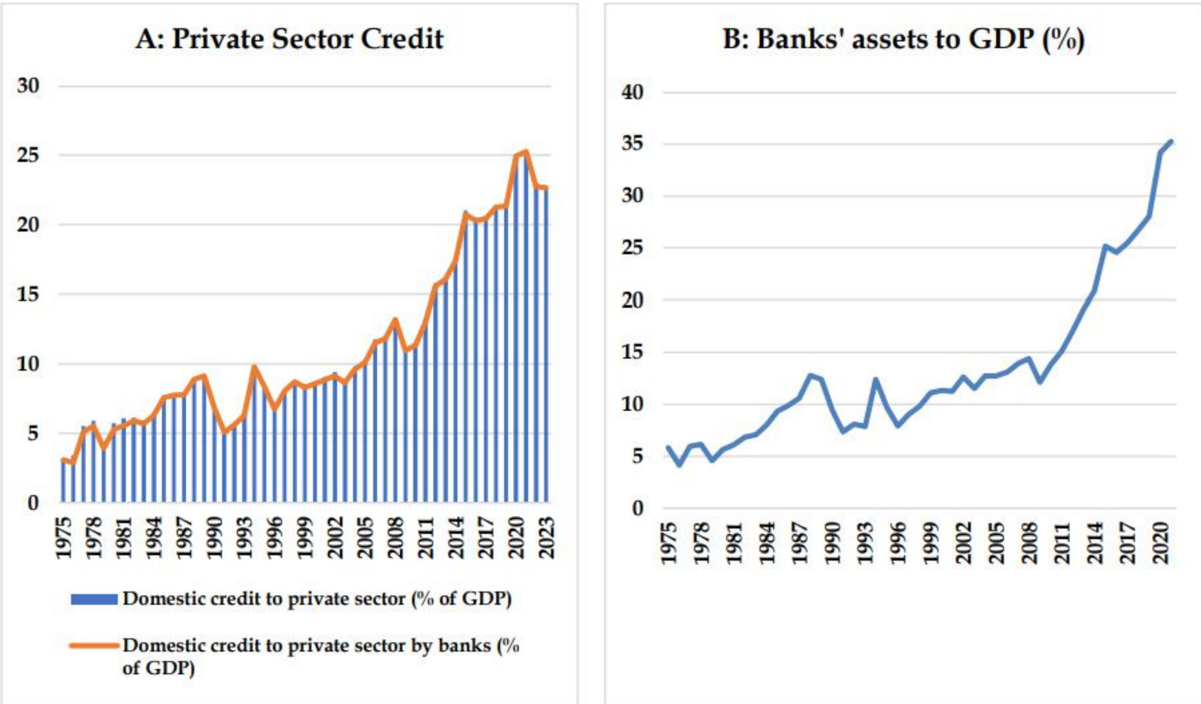
The rest of the paper is organized as follows: The next section of the paper presents a set of stylized facts that ground the subsequent section's empirical assessment. The concluding section highlights the key inferences from the empirical findings and draws implications on markets and policy.

2.0. Stylized facts

In the empirical backdrop of this is paper are two stylised facts.

The first one is that there is a two-regime characteristic in the evolution of private sector credit in Rwanda over the past five decades, the first being a gradual growth tend to 2008 subsequently and a steady pace (Figure 1). The consistent attribute of the entire period though is that private sector credit provision leans almost entirely on the banking industry as depicted by the neath overlap of the total domestic private sector credit and the domestic private sector credit by the banking industry.

Figure 1: Evolution of Private Sector Credit and Banking Sector Assets in Rwanda

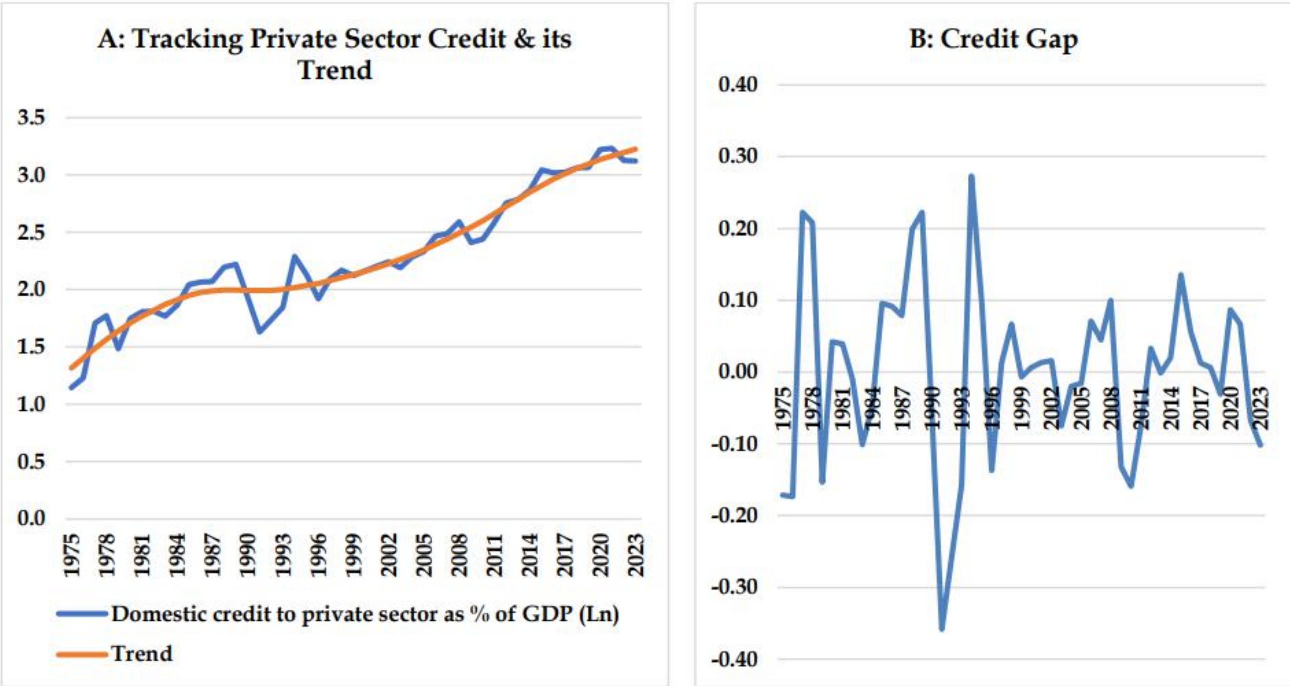


Source: World Bank's World Development Indicators (WDI).

The bank-led financial system in Rwanda as confirmed by the trend in Figure 1 implies that the fortunes of the economy and that of the banking industry are intertwined. The strong banking industry asset growth seen in the post 2008 period is supportive of economic growth in line with the findings of Karekezi, et al., (2024), with the growth anchoring the banking industry's progress in line with Mikebanyi and Kigabo (2021).

The second one is that the credit gap, that we dime as the deviation of the domestic private sector credit from its Holdrick-Prescott (HP) filtered trend, follows the aforementioned two regimes. The amplitude of the swings between negative and positive being more pronounced prior to than post 2008 (Figure 2).

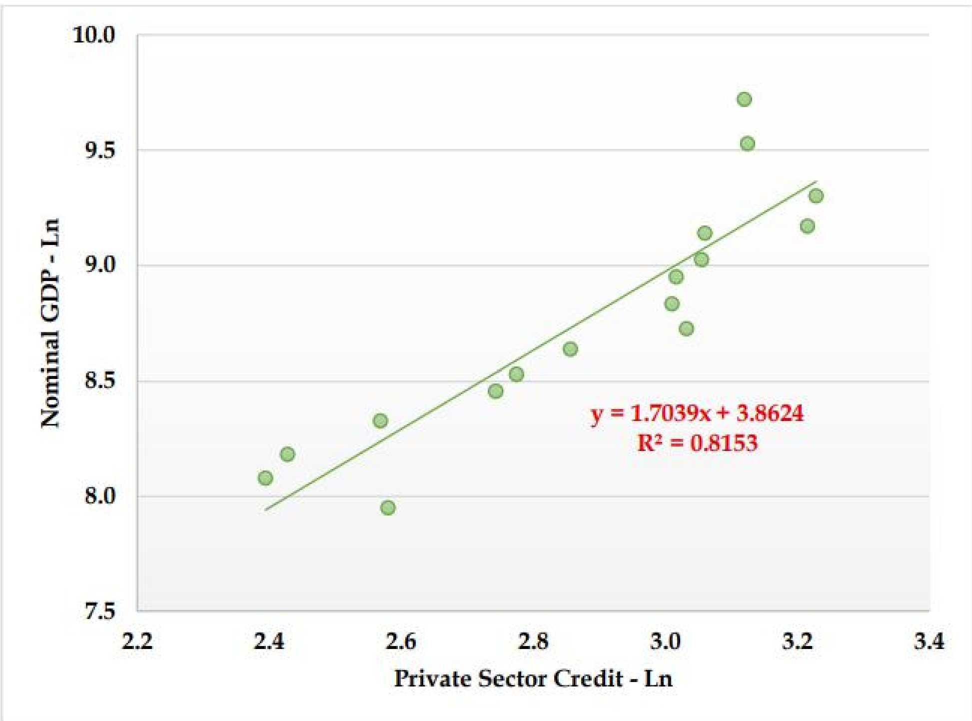
Figure 2: Private Sector Credit and Its Trend in Rwanda



Source: World Bank's World Development Indicators (WDI).

It is instinctual that fast slow-paced private sector credit should be associated with narrow a narrow credit gap and not, as depicted above, vice versa. The fact that the credit gap is less erratic when the domestic private sector credit regime has a very strong association with the economy's nominal GDP (Figure 3) call for scrutiny of the underlying dynamics that the assumption of linearity could be masking. Hence the empirical analysis that this paper undertakes.

Figure 3: Association between Private Sector Credit (Ln) and Nominal GDP (Ln): 2008 - 2023



The estimation of the credit gap is central in our analysis give our hypothesis that adjustment around the trend has a connection with asset quality and consequently informs perspectives on Rwanda's optimal credit path. The HP filter is foundational to this analysis, notwithstanding the critique that the arising series has spurious dynamic relations with no basis in the underlying data-generating process and that the filtered values at the end of the sample differ from those in the middle (Hamilton, 2018).

We find the HP filter approach still persuasive at two levels. First, the Hamilton (2018) alternative suffers the key drawbacks it finds in the HP filter in the form of the filterinduced dynamics in the estimated cycles and arbitrariness in the choice of a filterdefining parameter (Moura, 2024). Two, Drehmann and Yetman (2018) argues that in the absence of clear theoretical foundations, all proposed gaps are but indicators whose suitability is an empirical question. Its suitability as an early warning indicator for crises is confirmed in the credit gap analysis.

3.0. Empirical Analysis

3.1. The model

We begin by estimating a reduced-form specification that includes a second-order polynomial in credit growth:

$$AQ_t = \alpha + \beta_1 PSCG_t + \beta_2 PSCG_t^2 + X'_t y + \varepsilon_t \qquad (1)$$

AQ_t is the dependent variable the asset quality measured by the NPLs as a ration of gross loans. The primary explanatory variable, private sector credit-to-GDP $PSCG_t$, along with its squared term, $PSCG_t^2$, tests for a hypothesized nonlinear (inverted-U) effect. X'_t is a vector of exogenous controls and includes real GDP growth, inflation, and the lending-deposit interest rate spread.

Real GDP growth is hypothesized to reduce NPLs via improved repayment capacity, while inflation may reduce the real debt burden but also reflect macroeconomic volatility, implying an ambiguous or mildly negative relationship. The interest rate spread is expected to be positively associated with NPLs, reflecting underlying credit risk. Finally, a positive private sector credit gap, defined as the deviation of credit-toGDP from its HP-filtered trend captures procyclical lending beyond fundamentals. Positive gaps are expected to correlate positively with NPLs. ε_t is a mean-zero error term satisfying $E[\varepsilon_t|X_t] = 0$.

The empirical analysis uses annual data for Rwanda from 2000 to 2024, sourced from the World Bank's World Development Indicators (WDI). The dependent variable, bank nonperforming loans (NPL) as a percentage of total gross loans, is directly available from WDI for the period 2008–2024. To ensure temporal coverage from 2000 onward, backward extrapolation is applied for the earlier years (2000–2007). Specifically, we estimate a quadratic polynomial regression of the NPL ratio on a linear trend and its squared term using observed data from 2008–2024, subsequently predicting the NPL values backward for the missing period.

Domestic credit to the private sector (% of GDP), the threshold variable capturing financial intermediation depth, is fully available for the entire analysis period. The domestic credit-to-GDP gap as computed by way of the HP filter procedure uses a smoothing paramete $\lambda = 100$. The annual real GDP growth captures the broader economic environment, the lending-deposit rate spread proxies financial intermediation efficiency and risk premium, and consumer price inflation reflects macroeconomic stability and the real cost of borrowing.

Equation (1) is estimated by Ordinary Least Squares (OLS), with standard errors robust to heteroskedasticity and autocorrelation using the Newey-West covariance matrix estimator (Newey and West, 1987). The optimal credit growth threshold (turning point) — interpreted as the point above which further credit expansion begins to adversely affect asset quality—is computed as:

$$\gamma^* = -\frac{\beta_1}{2\beta_2}.$$

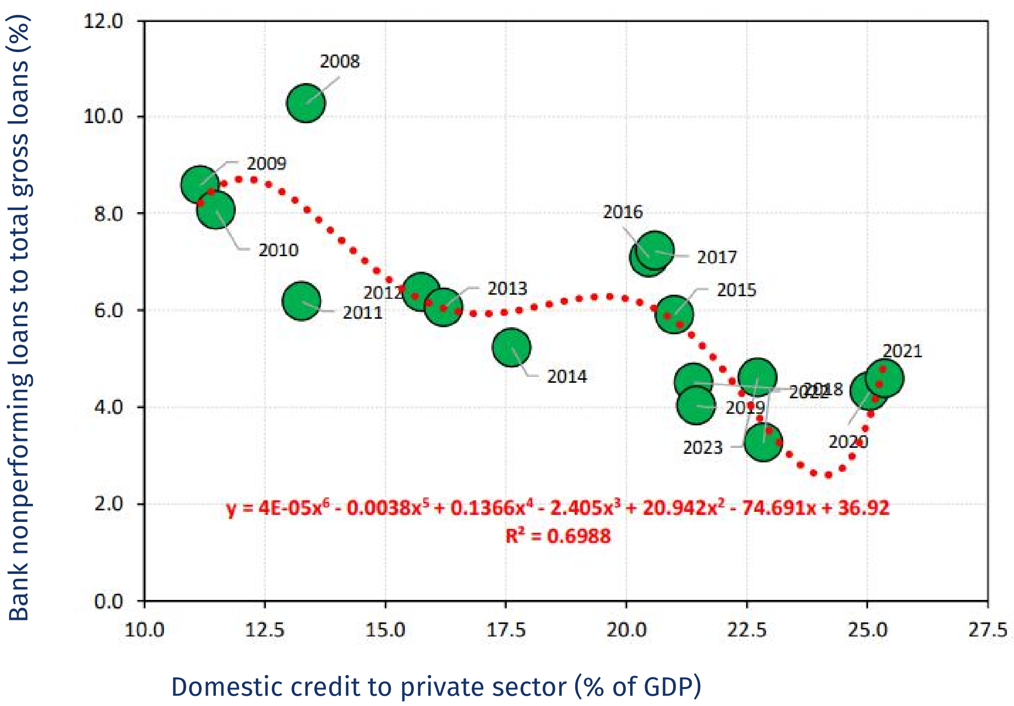
The null hypothesis of linearity, $\beta_3 = 0$, is tested using a standard Wald test.

3.2. Scatter Plot of Private Sector Credit and Asset Quality

Figure 4 depicts scatter plot with a polynomial regression fit, illustrating a pronounced nonlinear relationship between domestic credit to the private sector (% of GDP) and bank nonperforming loans (% of total loans). The fitted polynomial regression indicates multiple nonlinear (inverted-U) relationship, suggesting asset quality initially improves as credit-to-GDP increases but subsequently deteriorates after surpassing a critical threshold.

Notably, two distinct turning points emerge: an initial threshold at approximately 18% of credit-to-GDP, beyond which asset quality improves significantly, and a subsequent turning point around 22.8%, after which asset quality begins to deteriorate. This suggests that moderate financial deepening initially enhances banking sector resilience, but excessive credit growth eventually leads to higher asset quality risks.

Figure 4: Scatter plot of Private Sector Credit (% GDP) and Bank Asset Quality (NPL Ratio)



Notes: The scatter plot depicts the empirical relationship between Domestic Credit to the Private Sector (as a percentage of GDP) and Bank Nonperforming Loans (NPLs, as a percentage of total gross loans). The polynomial regression line (red dotted curve) illustrates a clear nonlinear (inverted-U) pattern, indicating that asset quality initially improves as credit deepens, reaching an optimal rage of 22% - 25% of GDP, beyond which further increases in credit are associated with a deterioration in asset quality.

3.3. Descriptive Statistics

Table 1 reports summary statistics for variables utilized in the analysis, providing essential context for interpreting empirical results. The mean nonperforming loan (NPL) ratio is 8.59%, with considerable variation (standard deviation of 3.65%), indicating substantial fluctuations in banking sector asset quality over the period. Domestic credit to the private sector averages 14.71% of GDP, ranging notably from a low of 6.81% to a high of 25.36%, reflecting gradual financial deepening and variability in credit market expansion.

The credit-to-GDP gap, by construction, averages zero, with a relatively narrow dispersion, illustrating balanced cyclical fluctuations around its long-term trend. GDP growth averages 7.81%, but shows sizable volatility (standard deviation 3.46%), including negative episodes (minimum of -3.37%), underscoring the economy's exposure to growth shocks. Lending-deposit rate spreads have an average of 8.12%, varying moderately from 6.38% to 10.24%, suggesting stable but variable interest rate margins. Inflation averages approximately 7.03% with substantial variability (standard deviation of 5.58%), indicative of occasional macroeconomic instability.

Table 1: Summary Statistics of Asset Quality, Credit Growth, and Macroeconomic Indicators

	Obs	Mean	Std. Dev.	Min	Max
Bank nonperforming loans to total gross loans (%)	28	8.588	3.645	3.26	15.63
Domestic credit to private sector (% of GDP)	28	14.711	5.954	6.81	25.36
Domestic credit to private sector gap (% of GDP)	28	0	1.129	-2.248	2.356
GDP growth (annual %)	28	7.806	3.464	-3.37	13.85
Lending -deposit rate spread (%)	28	8.123	1.142	6.38	10.24
Inflation, consumer prices (annual %)	28	7.03	5.575	-2.41	19.79

3.4. Pairwise Correlation Analysis

Table 2 presents the pairwise correlation coefficients among the key variables. Asset quality, measured by bank nonperforming loans (NPLs) as a percentage of total loans, exhibits a significant negative correlation (−0.897, $p < 0.1$) with domestic credit to the private sector (% of GDP), suggesting that deeper financial intermediation associates with improved asset quality. Furthermore, the lending-deposit rate spread correlates negatively and significantly (−0.483,$p < 0.1$) with asset quality, indicating that higher interest rate spreads are associated with reduced NPL ratios, potentially reflecting higher risk premiums charged by banks in riskier environments.

Table 2: Pairwise Correlation Matrix of Asset Quality, Credit, and Macroeconomic Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Bank nonperforming loans to total gross loans (%)	1.000					
(2) Domestic credit to private sector (% of GDP)	-0.897*	1.000				
(3) Domestic credit to private sector gap (% of GDP)	0.025	0.228	1.000			
(4) GDP growth (annual %)	0.326	-0.304	-0.052	1.000		
(5) Lending -deposit rate spread (%)	-0.483*	0.434*	0.083	-0.128	1.000	
(6) Inflation, consumer prices (annual %)	-0.091	0.086	-0.202	0.006	-0.114	1.000

*** p<0.01, ** p<0.05, * p<0.1

3.5. Econometric estimations and findings

The empirical estimates from the quadratic polynomial regression, presented in Table 3, robustly support a nonlinear relationship between private sector credit expansion and bank asset quality, measured by the ratio of non-performing loans (NPLs). Specifically, the coefficient on domestic credit-to-GDP ratio is significantly negative (−1.904, $p < 0.01$), while the squared term is significantly positive (0.0417, $p < 0.01$). These results substantiate an inverted-U shaped relationship, indicating that initial increases in credit-to-GDP are beneficial for asset quality, possibly reflecting enhanced financial deepening, improved credit allocation, and strengthened borrower repayment capacity. However, beyond a critical threshold (turning point at approximately 22.83%[2]), further expansion in credit leads to a deterioration in asset quality, likely due to increased risk-taking.

Furthermore, the credit-to-GDP gap significantly positively relates to the NPL ratio (0.587, $p < 0.05$), confirming that cyclical deviations of credit growth from its sustainable trend are associated with rising financial vulnerabilities. However, that vulnerability will only be a concern if the deviations are sustained. This underscores the economic intuition that periods of excessive lending—captured by positive credit gaps—heighten systemic credit risk. Control variables—lending-deposit rate spread, GDP growth, and inflation—do not exhibit statistically significant effects, implying that credit dynamics predominantly drive asset quality fluctuations during the sample period. Overall, the model explains approximately 93.7% of the variation in asset quality ($R^2 = 0.937$), highlighting the explanatory power of credit dynamics.

The optimal credit growth threshold (turning point) — interpreted the point above which further credit expansion begins to adversely affect asset quality—is computed as:

$$\gamma^* = -\frac{\beta_2}{2\beta_3} = -\frac{-1.904}{2(0.0417)} = 22.83.$$

To formally assess the validity of the quadratic specification and thus the presence of nonlinearities in the credit-growth–asset-quality nexus, we conduct a Wald test of the null hypothesis of linearity ($\beta_3 = 0$). The results strongly reject this null hypothesis ($F(1,21) = 31.46$ $p < 0.001$), providing compelling statistical evidence that the relationship between domestic credit-to-GDP and the bank nonperforming loans (NPL) ratio is indeed nonlinear.

Table 3. Quadratic Regression estimation of the relations between credit growth and asset quality

	(1) Bank nonperforming loans to total gross loans (%)
Domestic credit to private sector (% of GDP)	-1.904***
	(0.237)
Domestic credit to private sector (% of GDP) squared	0.0417***
	(0.00744)
Domestic credit to private sector (% of GDP) gap	0.587**
	(0.159)
Lending-deposit rate spread (%)	0.0776
	(0.180)
GDP growth (annual %)	0.0502
	(0.0646)
Inflation	0.0285
	(0.0302)
Constant	24.92***
	(1.939)
N	28
R^2	0.937
Adj. R^2	0.919
Wald-Test	F(1,21)= 31.46***

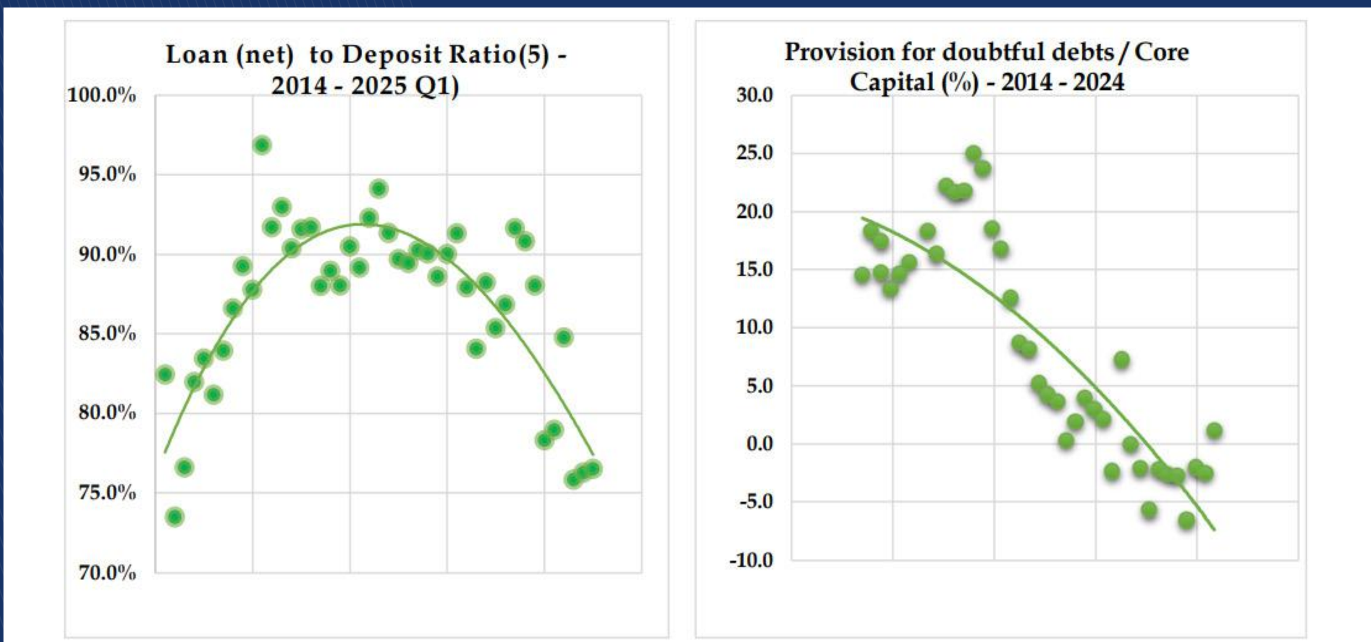
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Conclusion

This paper establishes that there is a threshold in the non-linear relationship between credit expansion and asset quality in Rwanda beyond which the sensitivity of the latter to the former is evident. Over the study's sample period, we estimate at 22.8% as the share of domestic private sector credit to GDP beyond which NPL's start rising. Noteworthy though is the fact that al that level, the NPLs ratio is below 5%, only gradually rising but within single digit level even as the share of domestic private sector credit to GDP increase beyond 25%.

Our empirical findings confirms that Rwanda's private sector credit growth is on a path that does not pose the risk of instability. We however make a further argument that while the credit growth path fulfils the necessary condition being associated with limited instability risk, it falls sort of fulfilling the sufficient condition of credit growth yielding maximum economic benefits. That is because the credit growth path is accompanied by a generally declining loan-to-deposit ratio even as the banking system's loan loss provisions as a share of core capital is on the declining trend in line with the low NPLs (Figure 5). The liquidity leaning credit growth path is therefore deemed suboptimal, there being scope for its upward shift towards optimality.

Figure 5: Liquidity Leaning Credit Growth Trend



Source: RBA Database

The upward shift towards a sustainable an optimal path is premised on the understanding that the cyclical deviations of credit growth from its sustainable trend are a function of the banking system's business imperatives as anchored in the risktaking behaviour of individual market players. With neither inflation nor GDP growth having any statistically significant relationship with banks asset quality, the National Bank of Rwanda's price-based monetary policy only influences is by way of the credit channel that doesn't go as deep as revealing itself on the cyclical deviation. The central bank's supports for the existing scope of sustained increase in credit growth with no vulnerability risks is the microprudential and macroprudential tool kit.

The sustenance of a higher credit growth path relies on continued investment in a better functioning financial system that allows innovative and efficient resource allocation than it does on the ability to mobilise more savings. This finding, inferred from the interest rate spread being statistically insignificant in our empirical estimates, aligns with (Levine 2021). A key source of innovation stems from digital financial services that have a strong relationship with financial depth and ultimately economic growth (Misati, Osoro, Odongo and Abdul, 2024).

Rwanda's credit market ecosystem will of necessity take on board important nuances. The first is the ability of the banking industry, given the bank-led attribute of the system, to intermediate foreign savings. The economy's open capital account offers the necessary policy support. Second is the strategic imperative of complementing foreign savings that typically have a long tenor attribute with the capital market products, specifically corporate bond issuance. That will result in a hybrid financial system that blends the entrenched bank-based market with aspects of a market-based system that could be superior in aspects such as enabling long-tenor liabilities be matched with the much-needed long term assets (Osoro and Osano, 2014; İcke and İcke, 2019).

REFERENCES

Arcand, J.L., Berkes, E. & Panizza, U. (2015), “Too much finance?”. Journal of Economic Growth 20, 105–148.

Beck, T., Levine, R., and Loayza, N. (2000), "Finance and the sources of growth," Journal of Financial Economics, 58(1-2), 261–300.

Demirgüç-Kunt, A. and Levine, R. (2004), “Bank-Based and Market-Based Financial Systems: Cross-Country Comparisons” in Demirgüç-Kunt A. and Levine, R., eds, Financial Structure and Economic Growth: A Cross-Country Comparison of Banks, Markets and Development, MIT Press, Chapter 3.

Drehmann, M. and Yetman, J. (2018) “Why You Should Use the Hodrick-Prescott Filter – at Least to Generate Credit Gaps”, BIS Working Paper No. 744.

Easterly, W., Islam, R., and Stiglitz, J. (2000), "Shaken and Stirred, Explaining Growth Volatility," Annual Bank Conference on Development Economics. World Bank, Washington D.C.

Hamilton, J. D., (2018), “Why You Should Never Use the Hodrick-Prescott Filter,” The Review of Economics and Statistics (2018) 100 (5), 831–843.

İcke, B. T, and İcke, M.A. (2019). “Bank-Based Versus Market Based Financial System: Does it Really Matter?”, European Journal of Business and Management, 11 (9), 135 – 149.

Karekezi, J.C., Owolabi, S.A., Ogbebor, P.I., and Nduka, M.M. (2024), “Financial Development and Real Gross Domestic Product in Rwanda”, International Journal of Economics, Finance and Management Sciences, 12 (2), 101 - 112.

Kindleberger, C. P. (1978), Manias, Panics, and Crashes: A History of Financial Crises, Basic Books, New York.

King, R. G. and Levine, R. (1993), "Finance and growth: Schumpeter might be right," The Quarterly Journal of Economics 108(3), 717–37.

Levine, R. (2021). “Finance, Growth, and Inequality”, IMF Working Paper No. WP/21/164.

Levine, R. (2005), "Finance and growth: Theory and evidence," in Aghion, P. and Durlauf, S., eds, Handbook of Economic Growth, Vol. 1, chapter 12 Elsevier, 865–34.

Levine, R., Loayza, N. and Beck, T. (2000), "Financial intermediation and growth: Causality and causes," Journal of Monetary Economics, 46(1), 31–77.

Loayza, N., Ouazad A. and Rancière R. (2018), "Financial development, growth, and crisis: is there a trade-off?" in T Beck and R Levine (eds), Handbook of Finance and Development, Edward Elgar Publishing, chapter 10.

Mikebanyi, P. and Kigabo, T.R. (2021). “Financial Development and Economic Growth, The Case of Rwanda”, BNR Economic Review, 18, 85-119.

Minsky, H. P. (1974), "The modeling of financial instability: An introduction," in Modelling and Simulation, Vol. 5, Proceedings of the Fifth Annual Pittsburgh Conference, Instruments Society of America, 267–72.

Minsky, H. P. (1982). “The Financial-Instability Hypothesis: Capitalist Processes and the Behavior of the Economy” Hyman P. Minsky Archive. Paper 282. 36.

Minsky, H. P. (1986). “The Evolution of Financial Institutions and the Performance of the Economy”, Journal of Economic Issues, 20(2), 345 – 353.

Misati, R., Osoro, J., Odongo, M. and Abdul, F. (2024), "Does digital financial innovation enhance financial deepening and growth in Kenya?", International Journal of Emerging Markets, 19 (3), 679-705.

Moura, A. (2024). “Why You Should Never Use the Hodrick-Prescott Filter. A Comment on Hamilton (The Review of Economics and Statistics, 2018)”, Journal of Comments and Replications in Economics, 3, 1-17.

Newey, W. K., and West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703–708.

Osoro, J and Osano, E. (2014). “Bank-based versus market-based financial system: Does evidence justify the dichotomy in the context of Kenya? KBA Centre for Research on Financial Markets and Policy Working Paper Series, No. 10.

Rajan, R. G. (2005), "Has financial development made the world riskier?" Proceedings of the 2005 Jackson Hole Conference organized by the Kansas City Fed.

Rajan, R. G and Zingales, L. (1998), "Financial dependence and growth," American Economic Review 88(3), 559–86.

Reinhart, C M and Rogoff, K. S., (2013), "Banking crises: an equal opportunity menace", Journal of Banking and Finance 37(11), 4557–4573.

Schularick, M and A M Taylor (2012), "Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008", American Economic Review 102(2), 1029-61.

Sufi, A and Taylor, A. M., (2021), "Financial crises: A survey", NBER Working Paper No. 29155.

Wolf, M., (2009). "Why dealing with the huge debt overhang is so hard", Financial Times, 27th January 2009.

RBA/WPS/09-2025

Digital Finance and Credit Access Perspectives: A comparative analyses of Kenya and Rwanda

Samuel Tiriongo & Hillary Mulindi

Abstract

Access to credit is vital for economic development, yet it remains elusive for many in Kenya and Rwanda. The study aimed at ascertaining the effect of fintech usage on access to financial services as measured by loan approval and /or rejections in a comparative study of Kenya and Rwanda, drawing from the countries' significant strides in integrating fintech in their financial systems, as case studies for other frontier economies. Employing data from Rwanda's Finscope 2020 and Kenya's Finaccess 2024 surveys conducted in 2020 and 2024 respectively, the results reveal key similarities and differences in the dynamics of digital credit access and Fintech usage in Kenya and Rwanda. For Kenya, loan access is dependent significantly on fintech usage (by type), source of income, education status, urban being the region of residence and age of household head. However, loan rejection probabilities decline with an increase in education level, residence in urban areas and advancement in age of household head beyond 20 years. In this regard, policymakers could consider measures to enhance usage of fintech, support financially literacy programmes through the education system, to support a strong access to credit. For Rwanda, loan access probabilities appear to decline with fintech usage (at various degrees based on use cases), but increase with reliance on formal employment and individuals attaining secondary level of education. Loan rejection incidences seem to decline with reliance on self and formal employment (but increase with reliance on informal employment and support from others) as a source of income, attaining post-secondary education, urban dwelling and with age. In this regard, policymakers could consider addressing three key challenges to improve digital credit access: limited creditworthiness signals, mismatched financial products, and exclusion of informal sector participants. This requires expanding credit information infrastructure, aligning consumer protection policies with digital realities, and promoting differentiated FinTech products tailored to underserved groups.

Keywords: Fintech, credit access, financial inclusion

1.0 Introduction

Access to credit is increasingly recognized as a critical element for economic development, especially in emerging economies. Studies have shown that household's access to finance has a strong positive relationship with economic growth (Sahay et al., 2015). Moreover, the International Finance Corporation (IFC) estimates that 40 percent of formal micro, small, and medium enterprises (MSMEs) in developing countries face an annual financing gap totaling $5.2 trillion. No doubt, small and medium enterprises (SMEs) that represent about 90 percent of businesses and contribute over 50 percent to global employment and up to 40 percent of GDP in emerging economies, face substantial barriers when seeking essential credit (IFC, 2017).

In the context of Sub-Saharan Africa, where formal employment opportunities remain limited and informal sector participation is widespread, the role of accessible financial services becomes even more important, given that Africa is ranked among the lowest regions in terms of access to financial services. This urgency is underscored by the region's ranking among the lowest globally in terms of financial access. For example, only 23% of adults in Africa have an account with a formal financial institution, compared with 89% in high-income regions and 55% in East Asia & Pacific (IMF 2019). Lack of access to accounts with a formal financial institution excludes whole populations from the security and reliability provided by these institutions. However, the recent developments have seen digital financial services, fronting as financial technology (Fintech) emerging as a promising frontier in catalyzing access to credit.

Within the East African region, Kenya and Rwanda serve as prominent examples of how digital financial services can enhance financial inclusion and credit access. More specifically, the evolution of fintech in Kenya and Rwanda presents distinct but complementary narratives regarding the interaction between fintech and traditional banking institutions, particularly on digital payment infrastructure,

credit rating systems, and financial inclusion. In Kenya, for instance, fintech which was pioneered by mobile network operators (MNOs) like Safaricom through M-Pesa, has fundamentally reshaped the financial landscape by expanding financial inclusion and bridging the physical distance to financial services. The average distance to the nearest M-Pesa agent shrank from 9.2 kilometers to just 1.4 kilometers between 2007 and 2015, illustrating fintech's role in overcoming logistical barriers that traditionally hindered banking access (Suri & Jack, 2016). This disruption, while initially perceived as competitive, has evolved into a form of symbiosis where commercial banks integrate fintech solutions to manage micro-accounts and cost-effectively reach previously underserved customers (Ndung'u, 2022).

In contrast, Rwanda's fintech journey is still nascent, though similarly transformative. The Rwandan government actively promotes digital payments through platforms like MTN Mobile Money and Airtel Money, targeting rural populations where banking penetration remains limited (Yumvuhore, 2022). The National Bank of Rwanda (BNR) has implemented forward-looking policies, such as interoperability mandates and the Rwanda National Digital Payment System (R-NDPS), to foster financial inclusion while also addressing cybersecurity and consumer protection (National Bank of Rwanda, 2018; NISR, 2024). Despite these advancements, cultural preferences for cash and limited digital literacy continue to slow full adoption of digital financial services in Rwanda (World Bank, 2020).

A significant dimension of fintech's impact in both Kenya and Rwanda lies in its influence on credit access, particularly through the emergence of digital credit models that function similarly to neobanks. In Kenya, app-based digital lenders like Tala, Branch, and Saida offer short-term microloans through mobile platforms, eliminating the need for physical bank branches (Ndung'u & Oguso, 2021a). These platforms leverage alternative data sources, such as mobile transaction histories and social media activity, to assess creditworthiness, thereby circumventing traditional barriers like collateral requirements and irregular income flows that previously excluded many borrowers (Ndung'u & Oguso, 2021b; Gubbins & Totolo, 2018). Although initially unregulated, the Central Bank of Kenya (CBK) brought these lenders under its regulatory oversight through the 2021 Amendment of the CBK Act, enhancing transparency and consumer protection (Gwer et al., 2019).

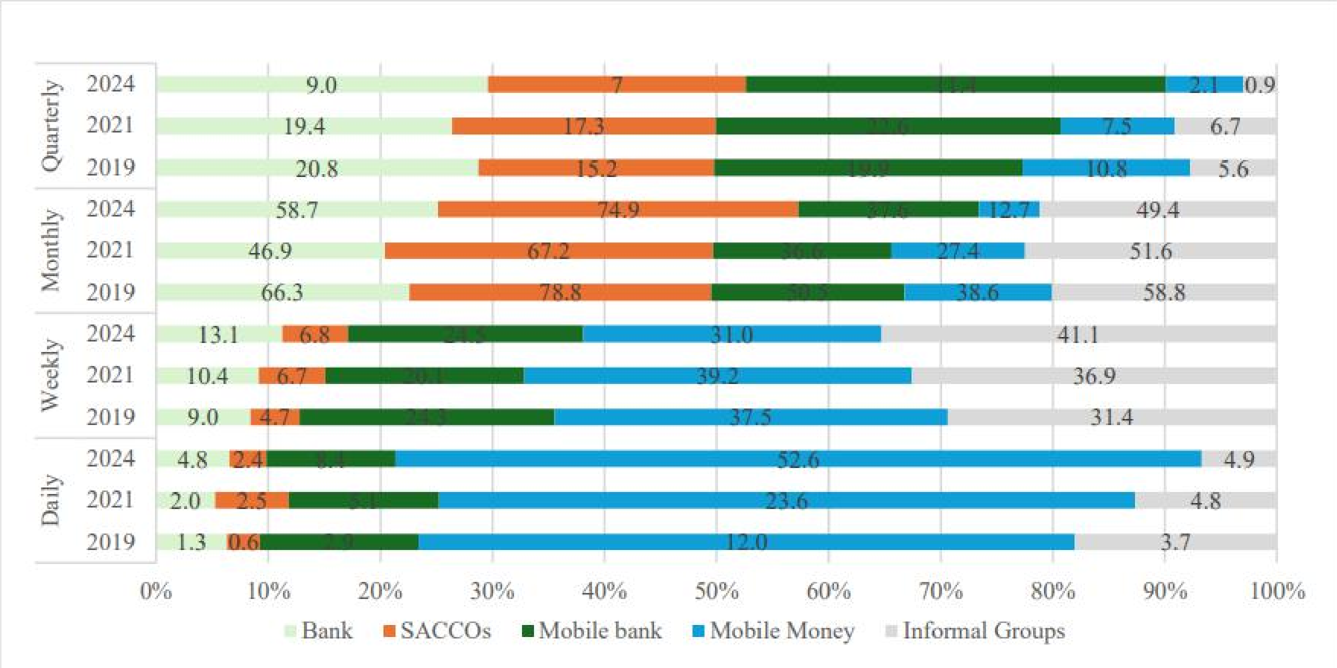
Conversely, Rwanda's regulatory approach leans towards automated supervision and data security through the BNR's electronic data warehouse, while also seeking to integrate fintechs via regulatory sandboxes (Dusengimana, 2016). Although Rwanda has yet to see a proliferation of fully digital neobank-style lenders, mobile credit products like MTN's MoKash are slowly bridging this gap by offering digital savings and credit options without traditional bank accounts (Mushinzimana et al., 2025).

Beyond expanding access, fintech has injected substantial competitive impetus into the banking sectors of both countries, compelling traditional institutions to innovate and restructure. In Kenya, the rapid rise of fintech initially threatened to erode banks' deposit bases; however, empirical evidence suggests that banks have successfully defended their positions through strategic partnerships, brand strength, and regulatory trust (Mashamba & Gani, 2023; Kubuga & Konjaang, 2016). Products like M-Shwari, a collaboration between Safaricom and Commercial Bank of Africa (Now NCBA), exemplify how banks have co-opted fintech innovations to retain market share while tapping into new customer segments (Najaf et al., 2021). Meanwhile, Rwanda's commercial banks, though still at a relatively early stage of digital transformation, have begun adopting digital tools to enhance service delivery and reach unbanked populations (Billas, 2017).

The efficiency gains resulting from fintech innovations are profound, reducing operational costs, accelerating loan processing, and enhancing regulatory oversight through technologies like RegTech and SupTech. For instance, Rwanda's BNR employs automated supervision to monitor financial institutions in near-real time, improving compliance and risk management (National Bank of Rwanda & Access to Finance Rwanda, 2018).

More generally, mobile money services, online lending platforms, and alternative credit scoring mechanisms have become critical cogs in addressing financial exclusion, particularly among unbanked and underserved populations (Beck et al., 2016). For Kenya, for instance, the adoption of mobile money services surged in the last three years, from 23.6 percent in 2021 to 52.6 percent in 2024 (KNBS, 2024), reflecting its growing acceptance and use out of its convenience and accessibility. The increasing adoption of mobile money services enables households to manage income-consumption volatility (FSD Kenya, 2014). Moreover, this uptake has stretched into the intermediation space where technology is serving as a platform for savings mobilization and credit extension (FSD Kenya 2016), with the more recent development being the Kenyan government-backed financial inclusion facility/initiative, that is, the Hustler Fund, which has gained significant traction, with 28 percent of the population utilizing it, particularly in urban areas where higher-income individuals, both formally and informally employed, are more likely to borrow. Kenya has also witnessed a sharp rise in daily financial service usage, largely driven by mobile money. Daily mobile banking usage increased to 8.4 percent, while daily bank transactions rose to 4.8 percent. On a monthly scale, bank transactions grew from 46.9 percent to 58.7 percent, while SACCOs maintained strong engagement at 74.9 percent (Figure 1).

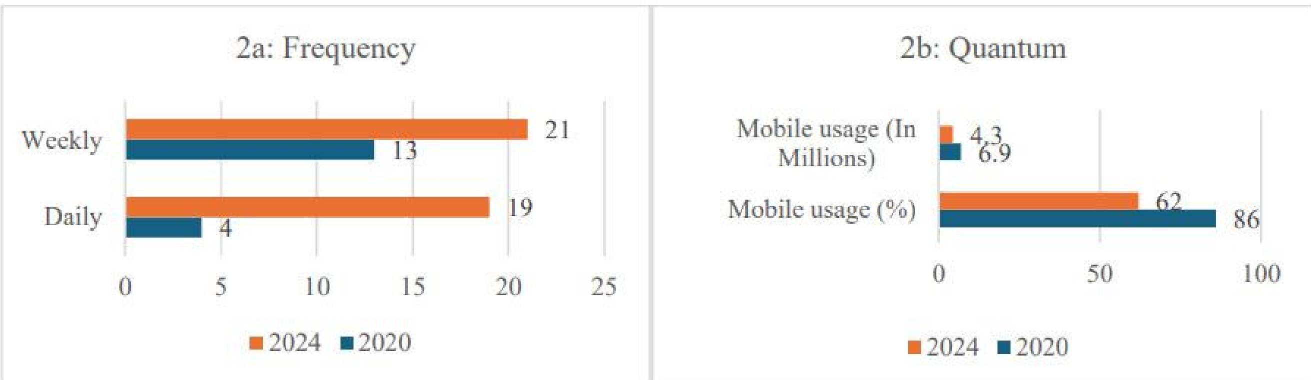
Figure 1: Frequency of mobile money usage, Kenya



Source: Finaccess survey 2024

Similarly, as depicted in Figure 2, mobile money ownership in Rwanda has grown significantly. The uptake of transactional accounts; including both bank and mobile wallet accounts; rose from 66 percent (4.7 million) in 2020 to 77 percent (6.2 million) in 2024. This growth is largely driven by the increased adoption of mobile wallets, which expanded from 60 percent (4.2 million) in 2020 to 77 percent (6.3 million) in 2024. The use of mobile money for financial transactions has also surged. Approximately 86 percent (6.9 million) of the population in Rwanda now own or have used mobile money, while the proportion of adults with registered mobile wallets in their names increased from 60 percent (4.3 million) in 2020 to 77 percent (5.8 million) in 2024. Since 2020, there has been a notable rise in mobile money usage on a daily and weekly basis. In 2024, daily usage reached 19 percent, up from 4 percent in 2020, while weekly usage grew to 21 percent from 13 percent over the same period. However, monthly usage has declined.

Figure 2: Mobile usage in Rwanda



Source: Finscope survey 2024

Despite these advancements, the available data shows that credit access in both Kenya and Rwanda remains a significant challenge. In Rwanda, while informal financial mechanisms continue to serve as important alternatives for many adults, their usage has declined from 78 percent (5.6 million) in 2020 to 72 percent (5.9 million) in 2024. In Kenya, reliance on informal-only financial services has increased, with access rising from 4.7 percent in 2021 to 5.2 percent in 2024. These trends highlight persistent gaps in the effectiveness of formal credit provision, leaving many individuals and small businesses dependent on informal lending sources, which are often costly. Given these challenges, the question, does fintech carry the silver lining to provide an anchor for long term sustainable growth in access and usage of formal financial credit. This study seeks to assess the extent to which usage of FinTech innovations influence credit access in Kenya and Rwanda. The cross-country study helps identify, if any, potential heterogeneity across countries; whether fintech impact is country-specific or carry's uniform effects in revolutionizing credit markets.

The remainder of the paper is structured as follows. Section 2 reviews existing literature, while section 3 presents the data, variables and methodology issues. Section 4 presents the results and discussions. Finally, section 5 concludes and highlights policy recommendations.

2.0 Review of Literature

Three financial theories directly underpin the role of Fintech in accelerating access to credit. The financial intermediation theory that advances the notion that financial institutions act as intermediaries, can reduce transaction costs and improve efficiency in financial markets (Diamond, 1984). FinTech enhances this process by leveraging digital platforms to connect borrowers and lenders more efficiently, thereby increasing credit accessibility and affordability (Philippon, 2016).

Alternatively, Stiglitz and Weiss (1981) argue that information asymmetry creates barriers to credit access, as traditional lenders may lack sufficient data to assess borrower risk. Here, fintech can address this challenge through big data analytics and alternative credit scoring models, which utilize transaction histories, mobile phone usage, and social media activity to assess creditworthiness (Bazarbash, 2019).

The Technology Adoption Model (TAM) explains how digital financial services are adopted based on perceived ease of use and usefulness (Davis, 1989). FinTech applications, such as mobile lending and digital wallets, provide user-friendly solutions that encourage financial inclusion and promote credit uptake (Venkatesh et al., 2003).

From an empirical standpoint, recent studies have demonstrated that FinTech has a profound contribution on increasing financial inclusion. Through mobile phones, users in remote or underserved regions can conduct financial transactions without visiting a bank. Services like M-Pesa in Kenya and Momo in Rwanda have become notable gateways to savings, loans, and insurance products. For example, Jack and Suri (2016) found that the adoption of M-Pesa in Kenya significantly improved access to financial services, particularly among low-income households, enhancing their ability to access credit and manage financial risks.

Koomson et al. (2021) examined FinTech adoption in sub-Saharan Africa and found a positive correlation between mobile money usage and formal credit uptake, particularly for women and rural populations. Fintech has also revolutionized credit scoring through the use of alternative data. Chen and Faz (2015) highlighted that the use of alternative data in credit scoring significantly reduced loan default rates and expanded credit access among first-time borrowers. Studies, such as the World Bank (2021), similarly emphasize the potential of alternative data sources in addressing inf ormation asymmetry between borrowers and lenders.

However, Fintech's transformative impact is not uniform across Africa. Gwer et al. (2023) in their analyses of the impact of digital lending platforms in East Africa found that while mobile-based credit solutions increased financial inclusion, it also triggered over-indebtedness of borrowers due to the embedded relatively high-interest rates.

A majority of studies while assessing the role of fintech have focused on access to financial services with limited views on role of usage. While both Kenya and Rwanda have taken strides in integrating Fintech into credit systems, there is still significant gaps and lack of evidence to demonstrate the specific role of fintech usage in access to financial services rather than just access via digital payments. This study attempts to fill this gap in literature.

2.1 Study Objectives

This study seeks to examine the specific effect of fintech usage in access to financial services in Rwanda and Kenya, drawing from the countries' significant strides in integrating fintech in their financial systems, as case studies for other frontier economies.

3.0 DATA, VARIABLES AND METHODOLOGY

3.1 Data

The paper utilizes data drawn from Rwanda's Finscope 2020 and Kenya's Finaccess 2024 surveys conducted in 2020 and 2024 respectively, by each country. In the 2020 Finscope survey, a total of 12,480 interviews were conducted. In comparison, 20,871 households were successfully surveyed in the 2024 Finaccess survey. Both surveys benefited from sampling frames aligned to global best practices since they were designed and mapped by the respective countries' official statistical authorities.

3.2 Econometric Model and Variable Description

The empirical equation estimated from the data is presented in Equation 1.

$$P(Credit\ access_i) = \frac{1}{1+exp^{(-y)}} \qquad \text{..........(1)}$$

where $(Credit\ access_i)$ is the probability of a customer being able to access credit.

$$y_{i,z} = \beta_0 + \beta_1 Fintech\ Usage_{i,z} + \beta_2 Income\ level_{i,z} + \beta_3 Education_{i,z} + \beta_4 Region_{i,z} + \beta_5 Age\ group_{i,z} + e_i \text{.....(2)}$$

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

The independent variables were grouped into several thematic categories, each generating multiple dummy variables for analysis. For FinTech usage, three types of transactions were considered with a view of capturing the extent to which individuals interact with digital financial services. These transactions were insurance-related transactions, utility payments, and business and financial transactions.

Regarding income-generating activities, five categories were created based on the respondent's primary source of income: formal sector employment, self-employment, financial support from other individuals, participation in the informal sector, and farming activities.

The education level of respondents was grouped into four categories: no formal education, primary education, secondary education, and post-secondary education. The region of residence was captured using two categories: urban and rural, reflecting the geographical disparities in access to financial services.

In terms of age group, respondents were classified into seven cohorts: 16–19, 20–24, 25–29, 30–38, 39–44, 45–49, and over 50 years and z reflect the individual country considered in the analysis and it is defined as:

$$z = \begin{cases} 1 = Kenya \\ 2 = \text{Rwanda} \end{cases}$$

3.3 Estimation Strategy

The study adopted multinomial logit model to examine the role of fintech usage on credit access. This modelling approach was considered on account of two reasons. First, a customer faces three possible credit access outcomes: applying and being approved, applying and being denied, or not applying at all. These outcomes reflect both the customer's decision-making and the strategic response of the digital credit provider.

Such behaviour is appropriately modelled using probabilistic discrete choice frameworks, particularly the multinomial logit model, which estimates the likelihood of selecting among multiple, mutually exclusive outcomes. Second, as a non-linear framework, the multinomial logit model is well-suited to isolate the effects of explanatory variables on categorical outcomes, even when the predictors are skewed or non-normally distributed. Moreover, Logistic regression is suitable for this situation in which the dependent variable is categorized (Hosmer et al., 2013).

4.0 RESULTS AND DISCUSSIONS

4.1 Descriptive Analysis

Descriptive statistics were conducted to provide to characterize survey data respondents' key demographic and socio-economic differences that help contextualize access to credit and digital financial service uptake. Kenya and Rwanda post some similarities in demographic distributions in terms of age with a substantial segment (26.16 percent) in Kenya aged over 50, while Rwanda has 28.89 percent in this age bracket. The bulk of both countries' populations falls within the 25 to 38 age range, typically associated with the prime working years (Figure 3).

However, there are few notable differences in terms of level of education (Figure 4), with nearly half of the Kenyan population (46.86 %) possessing at least secondary (intermediate level) education, compared to 27.66 percent in Rwanda. Notably, 20.14 percent of Rwandan respondents reported having no formal education, a figure significantly higher than Kenya's 14.47 percent.

Figure 3: Distribution of respondents age, Kenya and Rwanda

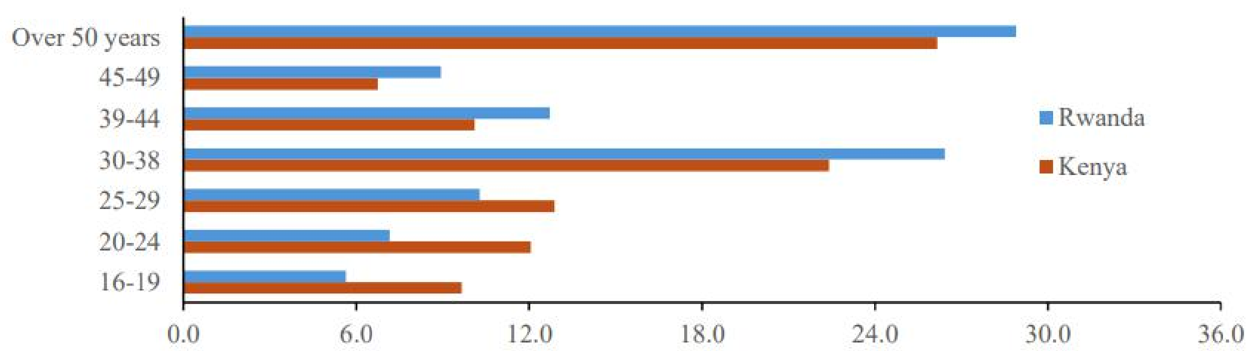
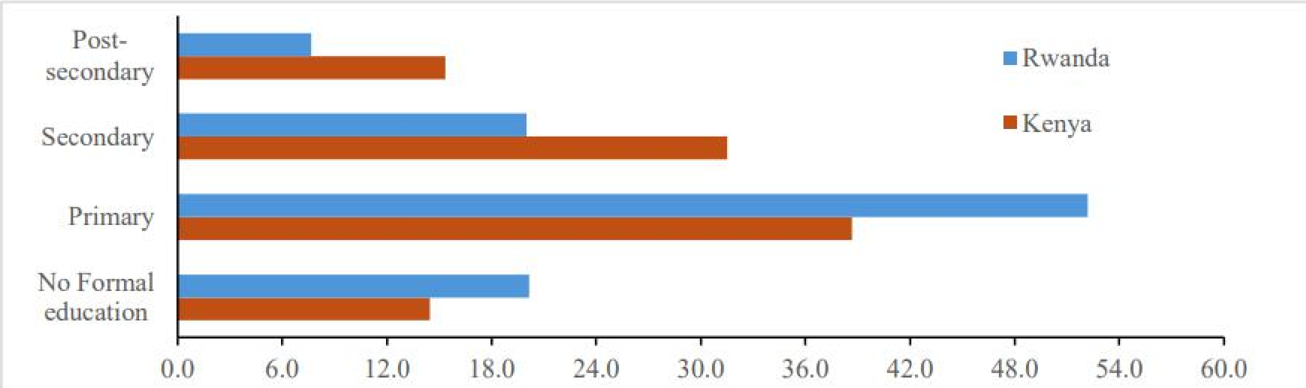
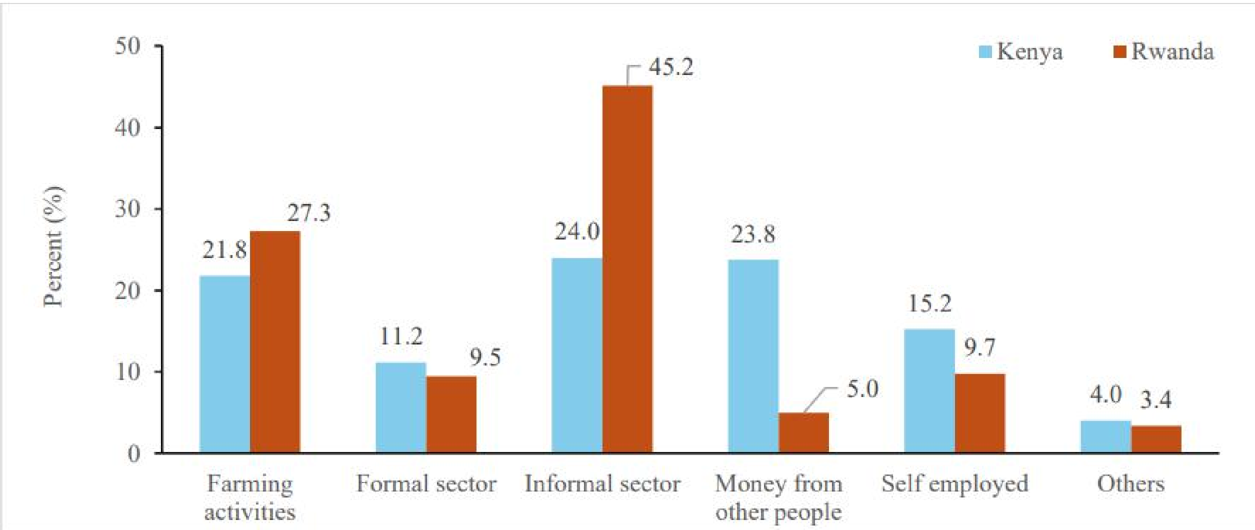


Figure 4: Distribution of respondents' education level, Kenya and Rwanda



There is evident country heterogeneity in households' engagements in income-generating activity. For Kenya, there is evident relatively more reliance on formal sector employment, individuals receiving support from others, and self-employment. For Rwanda, households rely more (than Kenyan households) on informal sector employment and farming activities (Figure 5). This, particularly variations in reliance on the informal employment) reveals evident differences in structural characteristics of the two economies' labor market dynamics. Variations in income sources and nature impact risk profiles of households with direct implications on their financial inclusion prospects (Honohan et al., 2009).

Figure 5: Distribution of respondents' income generating activities, Kenya and Rwanda



The use of Fintech to accomplish financial transactions remains limited in both countries. In particular, 93.1 percent and 71.1 percent of respondents in Kenya and Rwanda reported that they do not use FinTech to complete financial transactions (Figure 6a). It is no surprise, as fintech solutions, despite their convenience, are often associated with higher transaction costs. Among those who use digital financial services, utility payments were the most frequently cited reason for use, indicating a narrow and primarily bill-focused engagement with digital platforms (Figure 6b). The low adoption of diverse FinTech services underscores the untapped potential of digital finance in both countries, and justify the need to explore its role in financial access.

Figure 6a: Distribution of respondents' use of Fintech on Financial transactions

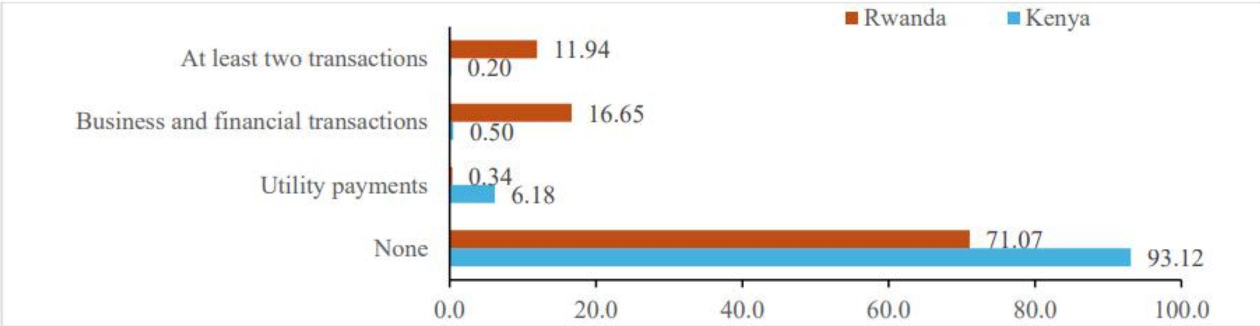
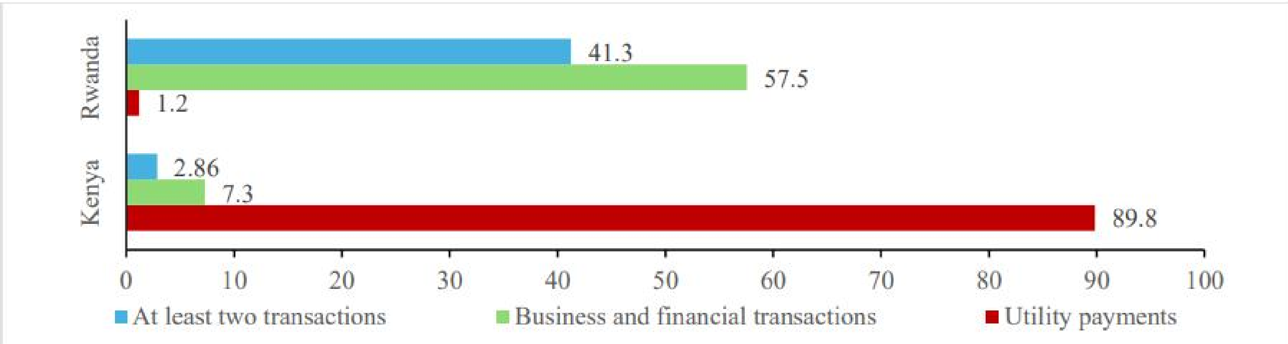


Figure 6b: Disaggregation of respondents' preferred transactions when using F intech solutions



In terms of credit access patterns, there is a significant divergence between Kenya and Rwanda. In Kenya, 7.4 percent of respondents had credit approved while 12.6 percent had their applications rejected. Urban dwellers in Kenya were more likely to be approved (12.65 percent) compared to rural residents (5.42 percent), and credit approval -though at a low level - peaked among individuals aged 25 to 38 years. Formal sector employees had the highest approval rates at 37.86 percent (See Table 1 and Table 2).

Table 1: Credit access pattern by Use of fintech and income generating activities in Percentage, Kenya

Use of Fintech on Financial Transaction					Income generating activity					
Credit Access	None	Utility payments	Business and financial transactions	At least two transactions	Farming activities	formal sector	informal sector	Money from other people	Self employed	Others
Applied and approved	7.42	14.42	19.05	31.71	7.95	37.86	0.00	0.00	13.07	0.00
Applied and rejected	12.55	14.42	12.38	14.63	10.87	14.86	16.91	8.35	15.21	7.05
No credit applied	80.02	71.17	68.57	53.65	81.19	47.28	83.09	91.65	71.72	92.95

Table 2: Credit access pattern by age group and region in Percentage, Kenya

Age group								Region	
Credit Access	16-19	20-24	25-29	30-38	39-44	45-49	Over 50 years	Rural	Urban
Applied and approved	0.45	5.13	13.10	12.72	8.77	8.81	4.89	5.42	12.65
Applied and rejected	3.72	17.93	19.76	15.76	14.41	12.93	6.69	11.04	15.69
No credit applied	95.84	76.94	67.14	71.52	76.81	78.27	88.43	83.53	71.66

Rwanda, by contrast, exhibits low credit approvals (1.78% of respondents) as many of the loan applications were rejected (79.04%) particularly across income types, age groups and education levels (See Table 3 and Table 4). Additionally, informal workers notably receive minimal credit, potentially as lenders shy away from lending to individuals with irregular income flows.

Table 3: Credit access pattern by Use of fintech and income generating activities in Percentage, Rwanda

Use of Fintech on Financial Transaction					Income generating activity					
Credit Access	None	Utility payments	Business and financial transactions	At least two transactions	Farming activities	formal sector	informal sector	Money from other people	Self employed	Others
Applied and approved	1.78	11.63	8.66	4.83	2.61	7.62	2.89	1.77	4.45	8.33
Applied and rejected	79.04	76.74	86.48	92.55	83.57	87.13	78.83	78.14	89.29	58.33
No credit applied	19.18	11.63	4.86	2.62	13.82	5.25	18.28	20.10	6.26	33.33

Table 4: Credit access pattern by age group and region in Percentage, Rwanda

	Age group							Region	
Credit Access	16-19	20-24	25-29	30-38	39-44	45-49	Over 50 years	Rural	Urban
Applied and approved	2.98	5.04	4.91	3.94	4.10	2.15	1.86	2.21	4.55
Applied and rejected	74.43	81.17	82.76	83.13	82.91	83.66	81.06	79.25	84.78
No credit applied	22.59	13.79	12.32	12.92	12.99	14.18	17.08	18.55	10.67

4.2 Multinomial Logit Model

Table 5 presents the multinomial logistic regression estimated, giving a deeper insight into the factors influencing digital credit access in Kenya and Rwanda. In Kenya, Fintech usage is positively associated with credit approval as a measure of access. More importantly, respondents engaging in business and financial transactions via digital platforms exhibit a significantly higher probability of obtaining a credit approval relative to those using it for insurance related transactions.

Rwanda, however, presents a contrasting scenario. FinTech usage does not significantly improve credit access for those using it for utility payments and business and financial transactions compared to those using it for insurance related transactions. In fact, when credit access denial is assessed, fintech usage increases the probability of a rejection of a loan application. The question is, does fintech usage in Rwanda create a burden for borrowers to demonstrate their credit worthiness for conventional loans? The discrepancy between the two countries could be considered as a pointer to the different use cases for digital financial services and other idiosyncrasies in the potential of usage of digital financial services influencing approvals for loans. Moreover, it is also important to acknowledge differences in the loan approval criteria applied in the two countries and time-inconsistency in the data (four-year gap in datasets) which may partly account for the observed differences.

Income source emerges as a strong predictor of credit approvals in Rwanda. Individuals drawing incomes from formal sector employment are more likely to obtain of their credit application than those from farming activities. However, those that depend on support from others are significantly less likely to obtain approval of their loans than those depending on framing activities; indicating over-reliance by lending institutions on formal income and own-generated income as a key determinant of loan access.

Additional dynamics are also observed in the role of income source on the probability of a loan application being rejected. Relative to income from farming activities, income from formal and selfemployment enhances an individual’s chances that their loan application would not be rejected. However, individuals whose incomes come from others and informal sector face a higher probability of their loan being rejected. These dynamics are not significant in Kenya.

While education level, particularly secondary education, is important in significantly and positively influencing credit approval in Rwanda (but not in Kenya), households in urban areas in Kenya enjoy better loan approvals than their counterparts in rural areas; perhaps confirming the hypothesis that urban dwelling predisposes individuals to better connectivity and other supportive infrastructure that increases one's propensity to make more formidable applications for loans. In contrast, there is no significant difference in region in the access to credit from an approval standpoint in Rwanda. However, urban dwellers in Rwanda enjoy less probabilities of a loan application being rejected than their counterparts in rural areas. This is, also the case in Kenya.

Another differentiating factor is the role of age of household head in influencing access to finance across the two countries. Notably, being aged between 30 and 44 years old in Kenya (prime working age with high productivity and investment acumen), increase one's probability of obtaining approval on a loan application. This is, however, not the case in Rwanda as there is no significant difference across age in access to finance. However, age plays a critical role in influencing loan rejection probabilities. The probability of loan rejection seems to decline with age beyond 20 years but thereafter diminish at over 50 years for Kenya (and not for Rwanda).

Table 4: Credit access pattern by age group and region in Percentage, Rwanda

	Y=1 (Applied for credit and got Approved)				Y=2 ((1), Applied for credit and got rejected)			
	Kenya		Rwanda		Kenya		Rwanda	
		Marginal Effects		Marginal Effects		Marginal Effects		Marginal Effects
Usage of Fintech (reference category are insurance related transactions)								
None	1.429	0.044	-0.510*	-0.125	0.658	-0.030	1.790***	0.142
	(0.899)		(0.152)		(0.892)		(0.169)	
Utility payments	0.630	0.045	1.219**	-0.160	0.337	-0.011	1.486**	0.093
	(0.915)		(0.504)		(0.901)		(0.513)	
Business and financial transactions	2.634*	0.054	0.781***	-0.058	0.520	-0.022	0.499**	0.019
	(1.437)		(0.147)		(1.048)		(0.195)	
Income generating activity(reference category are farming activities)								
Self employed	-0.667	0.028	-0.115	0.025	-0.343	0.416	-0.240*	-0.023
	(2706.96)		(0.1878)		(2706.96)		(0.134)	
Money from other people	-45.581	-0.005	-0.680**	-0.053	-24.063	0.891	0.544***	0.069
	(2621.69)		(0.333)		(1742.05)		(0.118)	
Informal sector	-45.537	0.037	0.058	-0.039	-23.662	0.849	0.330***	0.038
	(2640.98)		(0.138)		(1742.05)		(0.062)	
Formal sector	-21.159	0.012	0.427**	0.018	-21.04	0.080	-0.367**	-0.035
	(1742.06)		(0.173)		(1742.05)		(0.149)	
Education (reference category is no education)								
Primary	-0.166	0.067	0.160	0.044	0.906***	-0.031	-0.364***	-0.048
	3201.19)		(0.205)		(0.133)		(0.066)	
Secondary	0.251	0.099	0.680**	0.079	1.198)***	-0.048	-0.904***	-0.104
	(3170.11)		(0.214)		(0.135)		(0.097)	
Post secondary	23.178	0.120	1.877	-0.256	1.538***	-0.072	1.152*	0.146
	(2768.16)		(1.090)		(0.143)		(0.636)	
Region (reference category is rural area)								
Urban	0.185**	0.008	0.313	0.0256	0.127***	-0.007	-0.307***	-0.036
	(0.134)		(0.118)		(0.060)		(0.058)	
Age group (reference category is below 20)								
20.24	0.909	0.100	0.277	0.059	1.629***	-0.068	-0.474**	-0.070
	(0.812)		(0.276)		(0.143)		(0.140)	
25-29	1.317	0.120	0.280	0.082	1.789***	-0.080	-0.670***	-0.094
	(0.803)		(0.265)		(0.147)		(0.132)	
30-38	1.771**	0.100	0.147	0.095	1.783***	-0.080	-0.746***	-0.102
	(0.801)		(0.249)		(0.144)		(0.114)	
39-44	(2.261***	0.093	0.142	0.091	1.794***	-0.082	-0.705***	-0.098
	(0.829)		(0.265)		(0.160)		(0.127)	
45-49	1.604	0.077	-0.436	0.100	1.560***	-0.065	-0.658***	-0.091
	(0.833)		(0.310)		(0.178)		(0.134)	
Over 50 years	-0.096	0.018	-0.296	0.108	0.046	0.002	-0.757***	-0.103
	(0.808)		(0.266)		(0.168)		(0.114)	
Constant	-1.598		3.775***		18.839		-2.247***	
	(3270.64)		(0.344)		(1742.055)		(0.211)	
Observations	20,871		12,066					
LR chi2 (52)	33863.63		1183,25					
Prob >chi2	0.0000		0.0000					
Pseudo R2	0.6839		0.0877					

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

CONCLUSION AND POLICY RECOMMENDATION

The study aimed at ascertaining the effect of fintech usage on access to financial services as measured by loan approval and /or rejections in a comparative study of Kenya and Rwanda, drawing from the countries' significant strides in integrating fintech in their financial systems, as case studies for other frontier economies.

Utilizing data from Rwanda's Finscope 2020 and Kenya's Finaccess 2024 surveys conducted in 2020 and 2024 respectively, the results reveal key similarities and differences in the dynamics of digital credit access and Fintech usage in Kenya and Rwanda.

For Kenya, loan access is dependent significantly on fintech usage (by type), source of income, education status, urban being the region of residence and age of household head. However, loan rejection probabilities decline with an increase in education level, residence in urban areas and advancement in age of household head beyond 20 years. In this regard, policymakers could consider measures to enhance usage of fintech, support financially literacy programmes through the education system, to support a strong access to credit.

For Rwanda, loan access probabilities appear to decline with fintech usage (at various degrees based on use cases), but increase with reliance on formal employment and individuals attaining secondary level of education. Loan rejection incidences seem to decline with reliance on self and formal employment (but increase with reliance on informal employment and support from others) as a source of income, attaining post-secondary education , urban dwelling and with age. In this regard, it is essential to catalyse digital credit access. First, Rwanda should expand and integrate its credit information infrastructure. The observed link between FinTech usage and lower credit access points to limited lender confidence, likely stemming from inadequate borrower data and/ or issues with the credit bureaus coring models. Strengthening credit reference bureaus (CRBs) to have more robust models and incorporate non-traditional data, such as utility payments and mobile money transactions, can help build more accurate borrower profiles.

Second, aligning consumer protection policies with digital credit realities is crucial. High rejection rates often stem from opaque eligibility criteria and poorly designed products. Introducing mandatory feedback on loan denials can help users understand and improve their credit standing. Enforcing strong disclosure standards and grievance mechanisms will also build trust. Additionally, establishing a publicly accessible "Total Cost of Credit" website, modelled on those in Kenya and South Africa, will enhance transparency and comparability across lenders.

Finally, Rwanda needs to promote differentiated FinTech products tailored to underserved groups. Since access improves with formal employment and education, yet most Rwandans rely on informal incomes, lenders should develop tiered or group-based loan offerings suited to informal workers. Expandin access to youth-oriented and micro-loans will also help reduce exclusion for demographics currently facing high rejection rates.

REFERENCES

Access Finance Rwanda (2024). Finscope Report (2024). Kigali, Rwanda

Bazarbash, M. (2019). FinTech in Financial Inclusion: Machine Learning Applications in Assessing Credit Risk. International Monetary Fund.

Beck, T., Chen, T., Lin, C., & Song, F. (2016). Financial innovation: The bright and the dark sides. Journal of Banking & Finance, 72, 28-51.

Central Bank of Kenya (2023). Annual Supervision Report. Nairobi: Nairobi.

Chen, G. C., & Faz De Los Santos, P. X. (2015). The potential of digital data: far can it advance financial inclusion? (No. 95202, pp. 1-4). The World Bank.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 319–340.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. Review of Economic Studies, 51(3), 393–414.

Dusengimana, J. D. (2016). Financial services and customers' welfare in Rwanda:(case of BPR Muhima branch) (Doctoral dissertation, University of Rwanda).

FSD Kenya (2014). Kenya financial Diaries: Shilingi kwa shilingi – the financial lives of the poor. Nairobi

FSD Kenya (2016). The Growth of M-Shwari in Kenya – A Market Development Story: Going Digital and Getting to Scale with Banking Services. Nairobi.

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

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

Honohan, Patrick & Beck, Thorsten & Demirguc-Kunt, Asli. (2009). Access to Financial Services: Measurement, Impact, and Policies. World Bank Research Observer. 24. 119-145. 10.1093/wbro/lkn008.

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied logistic regression (3rd ed.). New York, NY: Wiley.

International Finance Corporation (2017). SME Financing gap assessment of the shortfalls and opportunities in financing micro, small and medium enterprises in emerging markets. Washington, D.C.

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

Kenya National Bureau of Statistics (2024). Finaccess Report (2024). Nairobi

Kiarie, K., & Munene, R. (2024). Effect of digital credit on the financial performance of commercial banks in Kenya. International Academic Journal of Economics and Finance, 4(1), 368-386.

Koomson, I., Martey, E., & Etwire, P. M. (2023). Mobile money and entrepreneurship in East Africa: The mediating roles of digital savings and access to digital credit. Information Technology & People, 36(3), 996-1019.

Kubuga, K. K., & Konjaang, J. K. (2016). Mobile money – a potential threat to banks? International Journal of Computer Applications, 975, 8887.

Mashamba, T., & Gani, S. (2023). Fintech, bank funding, and economic growth in Sub-Saharan Africa. Cogent Economics & Finance, 11(1), 2225916. https://doi.org/10.1080/23322039.2023.2225916

Mushinzimana, L., Faisal, A., Teressia, A. (2025). Strategy For Evaluating the Strengths, Weaknesses, Opportunities, And Threats of The Business Community in Rwanda in Adopting Digital Transformation to Increase Financial Benefits. Indiana Journal of Economics and Business Management, 5(1), 64–96.

Najaf, K., Mostafiz, M. I., & Najaf, R. (2021). Fintech firms and banks sustainability: Why cybersecurity risk matters? International Journal of Financial Engineering, 8(2), 2150019.

National Bank of Rwanda (2024). Financial Stability Report. Kigali: NBR.

National Bank of Rwanda and Access to Finance Rwanda. (2018). Business Plan for the Rwanda National Digital Payment System. NBR. Available at https://bit.ly/3nwiCu1

National Bank of Rwanda. (2018). Rwanda payment system strategy towards a cashless Rwanda 2018-2024. Available at https://bit.ly/3iscu2E

Ndung'u, N. (2022). Fintech in Sub-Saharan Africa. WIDER Working Paper, No. 2022/101. Helsinki: The United Nations University World Institute for Development Economics Research (UNUWIDER). https://doi.org/10.35188/UNU-WIDER/2022/235-5

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

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

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

NISR. (2024). Rwanda Finscope Report 2024 (Tech. Rep.).

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

Sahay et al. (2015). Rethinking Financial Deepening: Stability and Growth in Emerging Markets. IMF Staff Discussion Note 15/08, International Monetary Fund, Washington.

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

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

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.

World Bank (2021). Fintech and the Future of Finance in Africa. Washington, DC: World Bank Group.

World Bank. (2020). Rwanda Economic Update: Accelerating Digital Transformation in Rwanda. http://documents.worldbank.org/curated/en/912581580156139783/pdf/Rwanda-EconomicUpdate-Accelerating-Digital-Transformation-in-Rwanda.pdf

Yumvuhore, C. (2022). Mobile money services and financial Inclusion in rural area of Rwanda. A casestudy of Nyamasheke District (Doctoral dissertation, University of Rwanda).

RBA/WPS/10-2025

The effect of competition between banks and fintechs on profitability in Rwanda's Banking Sector

Ronald Ochen, Faith Atiti and Linda Josephine

Abstract

In this paper, we analyse the impact of fintech on the performance of the banking sector in Rwanda using annual panel data from 2018 to 2023, which includes eight commercial banks and two microfinance banks. Employing a Two-Way Fixed-Effects linear regression model, our findings from the balanced panel analysis indicate that fintech has a positive and statistically significant relationship with the return on assets of banks. This suggests that the integration of fintech solutions—such as mobile banking, electronic banking, mobile money, and point-of-sale systems—into bank operations significantly enhances their revenue generating capabilities, ultimately improving their financial performance. This relationship emphasises the potential impact of fintech on traditional financial performance metrics and highlights the importance of embracing technological advancements in the financial sector. Moreover, results from the case study approach reveal persistent gaps in Rwanda's regulatory framework that hinder comprehensive bank-fintech integration and collaboration. These include the lack of dedicated digital credit regulation, open banking still in the draft stage, sluggishness of innovation rollout from the sandbox, fragmented data-sharing standards, missing consumer protection specifics for partnerships, absence of tiered capital requirements to support start-ups, and limited clarity on cloud outsourcing and cross-border data. Based on these results, we recommend that commercial banks and microfinance institutions enhance their use of online platforms and cutting-edge financial technology that integrates mobile money, e-wallets, and e-commerce payments. We also suggest that the National Bank of Rwanda expedite the closure of the gaps in the regulatory frameworks and strengthen interregulator collaboration to foster development in the financial sector. The findings of this study contribute significantly to the ongoing global discourse on the disruptive effects of fintech in the traditional banking sector.

Keywords: Fintechs, Banks, Profitability, Two-way Fixed Effects Model, Rwanda

1. Introduction

The rapid rise of financial technology (fintech) has revolutionised the global financial services landscape, changing the competitive interplay between conventional banks and fintech companies and will continue to reshape the future of the financial services industry. Traditionally viewed as the cornerstone of financial services, banks now face competition from fintech companies that provide efficient, cost-effective, and tailored solutions, including peerto-peer lending and mobile payments, among others. In response, banks are reassessing their strategies, investing in digital upgrades and exploring partnerships that enhance their technological capabilities. Deloitte (2018) argued that fintech has transformative potential for banks and can foster a symbiotic relationship, balancing each other's weaknesses.

Studies indicate that fintechs can positively and negatively impact commercial banks' performance, depending on competition and banking innovations. This rivalry has led to major market shifts affecting efficiency, customer choice, innovation, and earnings. Degryse et al. (2020) found that in Singapore, increased fintech competition led to better asset utilisation and profitability as banks adapted their models. Conversely, Sami et al. (2023) noted a negative effect on profitability due to decreased interest income and rising operational costs. In China, Zhao et al. (2022) reported that fintech development harmed bank profitability and asset quality but improved management efficiency. In the UK, Apostolos & Goran (2023) observed that fintech proliferation positively influenced profitability by boosting net interest margin and yields on assets. In Kenya, Ntwiga (2020) found that fintech collaborating banks had superior management performance and higher efficiency and that fintech collaborations had significantly reduced intermediation costs and decreased the returns to scale, although findings were not statistically significant.

In Rwanda, the financial sector has experienced significant advancements due to government support and private-sector innovation. The government has fostered a well-regulated market, stimulating competition between fintechs and traditional banks. While traditional banks still dominate the credit market, nearly 100 fintech companies are emerging, offering innovative and accessible credit options. Moreover, since the COVID-19 pandemic, the number of financially included adults has risen to 96% of the adult population, up from 72% in 2016. Digital financial inclusion has also surged from 30% in 2016 to 73% in 2024 (Finscope Survey, 2024). This serves as an impetus to investigate the effects of financial technology on the performance of banks and to examine the role of the regulatory environment in bolstering the adoption and integration of financial technology.

This paper makes three important contributions to the existing literature. First, by using data from both commercial banks and microfinance institutions, it captures the effects of fintechs on the profitability of the entire banking sector. Second, it explores both the internal impact of banks adopting financial technology and its subsequent effects on bank profitability. This adds to the ongoing discussions about how financial technologies are transforming the banking industry. Third, this study sheds light on an under-researched topic within the context of a developing country like Rwanda, where fintech is rapidly emerging.

The main objective of this study is to investigate the influence of fintech on the performance of Rwanda's banking sector. Specifically, we examine the adoption and integration of financial technologies like Mobile Money, Mobile Banking, Point of Sale and Internet Banking on the profitability of commercial and microfinance banks in Rwanda. The central question of the study focuses on how competition acts as a mediating factor between banks and fintechs, driving fintech adoption and reshaping market dynamics in Rwanda. In other words, we aim to determine whether the uptake of fintechs has increased or decreased banks' profits.

Additionally, we examine how the regulatory environment has fostered collaboration between fintechs and banks. To investigate this relationship, we utilize a case study approach, drawing insights from other sub-Saharan African countries and in the East African region to identify lessons that Rwanda could learn from their experiences.

To address this central question, we employ a Two-Way Fixed Effects (FE) model, utilising a strongly balanced panel of annual data from 2018 to 2023. This data is sourced from the National Bank of Rwanda and the audited financial statements of the banks. It allows us to empirically test the relationships between fintechs and the profitability of banks. The rest of the paper is structured as follows: Section 3 provides the literature review, both theoretical and empirical. Section 4 presents the methodology, including the empirical model and strategy and data sources. Section 5 presents the empirical results and analysis. Section 6 concludes the paper.

3. Literature Review

3.1. Theoretical Literature

Competition and Innovation

The theory was proposed by Christensen (1997) and explains that new small entrants into an industry can easily challenge established players if they join with unique resources that can shake the market. The theory points out that small organisations with disruptive innovations, especially those targeting underserved market segments, can create stable solutions and, over time, displace the existing service providers, transforming market structures and competitive dynamics.

Disruptive Innovation Theory

This theory illustrates how simpler and newer technologies or business models can challenge established sectors by providing more accessible and affordable options. Fintech, an emerging field that utilises technology for innovative financial solutions, is closely aligned with this concept. Fintech firms focus on underserved markets, offering user-friendly, cost-effective services that confront traditional financial institutions (Solanki and Sujee, 2022). By tackling problems such as high fees and outdated technology, they attract a wider range of customers, especially those overlooked by conventional banks. The connection between Fintech and Disruptive Innovation Theory becomes apparent through its representation of disruptive models. Startups pinpoint and cater to previously neglected or underserved segments with customised, technology-driven solutions that are more affordable and accessible. Gradually, these innovations present a significant competitive threat to established financial entities. Fintech's implementation of technology to develop new financial products disrupts the traditional financial environment, forcing incumbents to adapt or risk losing their market presence. The relationship between Fintech and Disruptive Innovation Theory highlights how innovation meets unfulfilled customer needs, gradually displacing established players. As Fintech continues to develop, its influence on the financial sector intensifies, emphasising the ongoing significance of Disruptive Innovation Theory in contemporary business scenarios (Ibidunni et al., 2022).

Porter's Theory of Competitive Advantage

According to Nayak et al. (2023), Companies in the financial technology (Fintech) sector align their strategies with Porter's theory by focusing on differentiation through innovative, customer-focused financial products and seeking cost leadership through efficient operations. They hone in on niche markets, developing new customer segments while providing competitive pricing and challenging traditional financial institutions hampered by outdated systems. By implementing strategies that align with Porter's concepts, fintech companies disrupt the financial industry, effectively competing and carving out a distinctive advantage. This strategic alignment reflects Porter's lasting impact, influencing competition andtransforming the financial sector within the ever-evolving landscape of Fintech.

Dynamic Capability Theory

Introduced by Shuen et al. (1997), the theory emphasises a firm's ability to adapt, integrate and reconfigure internal and external resources and capabilities in a rapidly changing environment. The theory suggests that banks can indeed maintain a competitive edge by adapting their models, integrating, building and reconfiguring internal resources to include Fintech innovations. For banks, the theory emphasises the importance of adaptability in a dynamic environment by leveraging Fintech advancements for innovation and efficiency.

3.2. Empirical Literature

Reviewed empirical studies elicit mixed conclusions on the impact of Fintechs on banking performance. Many studies have been conducted on the impact of Fintech on the performance of Chinese commercial banks. For instance, Tong and Wang (2024) and Shu and Hong (2023) present significant findings regarding the impact of financial technology (Fintech) on the performance of traditional banks. Both studies concluded that integrating Fintech solutions greatly enhances operational efficiency, customer engagement, and profitability for banks. The research highlights those innovations, such as digital payment systems, online lending platforms, and advanced data analytics, that create a more streamlined banking experience, ultimately benefiting both banks and their customers.

Liu and Kwan (2021) also present evidence that increased fintech investment is positively associated with bank profitability, as measured by ROA and ROE, as well as operational efficiency, in Asia. Similarly, Khalaf et al. (2023) found that adoption of financial solutions improved efficiency and productivity and reduced operational costs for banks in the Middle East and North Africa (MENA) region, although the degree of significance varied depending on size, mobile and internet banking usage. Vlora and Blake (2024) showed that fintech adoption impacts profitability based on focus, where investments in operational efficiency negatively affect ROA, while fintech adoption targeting business opportunities, credit cost reduction and customer understanding improves ROA and NIM. Riama and Chanda (2020) in their comparative analysis of banks using fintech solutions and those that do not, concluded that banks using fintech solutions had better customer satisfaction rates, lower operational costs and higher profitability.

Thuong et al. (2024) show that the diversity of bank-fintech cooperation tended to enhance banks' risk-adjusted returns of Vietnamese banks. In Nigeria, Renu et al. (2021) also found a significant and positive impact of Fintech adoption on bank ROA and ROE. Across the findings, authors reiterate the need for continuous and strategic adjustments and adaptability of the business models of banks to the evolving digital financial technology. Hussain et al. (2023) revealed a positive and significant relationship between fintech adoption and the financial performance of banks. Kharrat et al. (2023) provides micro-level evidence on how fintech innovations can enhance performance, profitability, stability, and efficiency in both Islamic and conventional banking sectors in the Middle East and North Africa (MENA).

While the majority of studies indicate positive impacts of fintech on banking performance, some have been inconclusive or produced mixed findings, highlighting some complexities between fintech and the conventional banks' relationship. This may be a result of different nuances, including varying contexts, regulatory landscape or methodologies deployed. Omarini (2021) showed that the impact of fintech on banks in Europe was not uniform; Some bank performance improved due to partnerships and innovations while others encountered profit erosion. Similarly, Vagara (2017) noted that some banks experienced pressure on net interest margins due to fintech competition while others enhanced their performance through digital collaboration. Harmadi et al. (2022) concluded that fintech adoption did not affect the performance and risk of conventional banks in Indonesia.

Ozil (2017) in his review of several banks in Africa found effects of fintech on banks to be ambiguous, on one hand enhancing profitability and inclusion and on the other, eroding bank's traditional fee income and demand for credit. Meanwhile, controlling for bank size, capitalisation, ownership and financial sector developments Khan et al. (2024) found a nonlinear relationship between fintech and bank efficiency. Initially fintech hamper bank efficiency but continued adoption beyond a certain point enhances it, exhibiting a U-Shaped relationship, with a slower initial decline and a quicker transition to the better efficiency phase. Similarly, Song et al. (2023) revealed a dual effect of fintech on bank profitability; they found that in the early stages of Fintech development, there was a negative correlation with commercial banks' profitability. But as Fintech continues to evolve, technology spillover contributes to improved profitability for commercial banks. Shuli et al. (2022) concluded that fintech has a U-shaped impact on banks' profitability, reducing the profitability of banks in the short term but gradually improving in the middle and later stages. Onchenge (2023) concluded that large banks were more sensitive to changes in fintech development compared to small and medium-sized banks.

A few findings have however diverged from the mostly positive and sometimes non-linear nexus between fintech and banks. Mansour (2024) found that Fintech development is significantly and negatively related to bank performance, i.e., Fintech development significantly weakens bank performance. Berisha and Rayfield (2025) concluded that the overall adoption of fintech negatively impacted returns on assets in Kosovo; specific areas such as mobile banking and digital lending demonstrate positive effects. Hussein (2023) found that cyber and operational risks for adopting fintech have a negative impact on bank performance, although some of the risks could be mitigated by outsourcing. All said, we believe the fintech impact may vary across business segments. Therefore, an approach to the analysis that looks at the segments or areas of focus, including retail, corporate, MSMEs and investment, may have more nuanced findings, and therefore, an area we recommend for further analyses.

4. Methodology

4.1. Conceptual framework

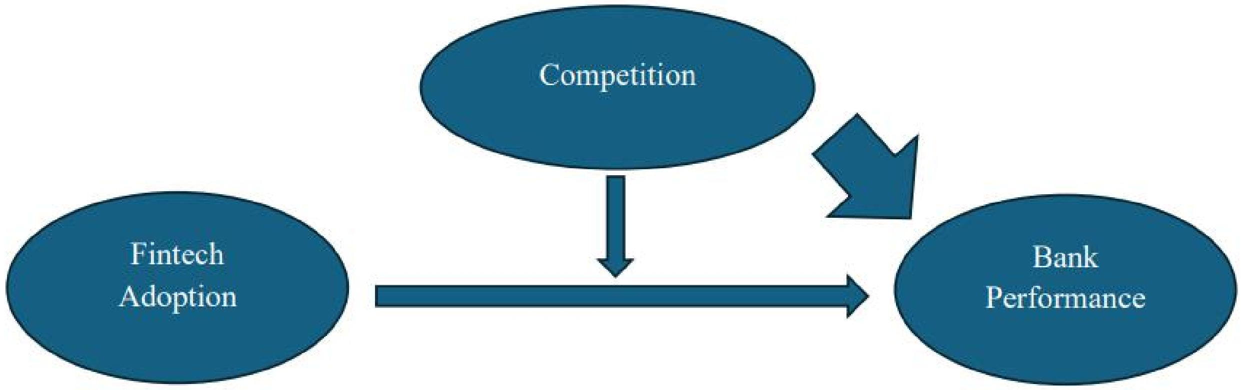
The framework co-opted in Figure 1 demonstrates the direct effect of adopting and integrating financial technologies on bank performance, as well as its indirect influence through heightened competitiveness, which serves as a mediating factor.

The incorporation of financial technologies allows banks to optimise their processes, improve service delivery, and access previously underserved markets, ultimately leading to enhancedfinancial results. For example, studies by Omarini (2017) discovered that the digital transformation in banking, propelled by fintech solutions, results in greater operational efficiency and increased customer satisfaction, both of which are vital performance indicators. Gomber et al. (2017) state that fintech innovations enable banks to distinguish their services and react more quickly to market fluctuations, thereby bolstering their competitive stance. Likewise, Vives (2019) asserts that banks utilising fintech benefit from reduced costs and improved responsiveness to customer wants.

Relatedly, competition mediates the relationship between fintech adoption and bank performance. For example, Allen and Santomero (2001) pointed out that banks functioning in competitive settings or with a significant level of internal competition exhibit better risk management, innovation, and customer retention, all contributing to improved financial results. Riaz et al. (2023) assert that the relationship between fintech adoption and bank performance is significantly influenced by competitiveness. Hussain et al. (2023) found that competitiveness had a significant mediation impact on the increase in fintech adoption and, consequently, on the financial performance of banks.

These findings support the theoretical framework in which fintech adoption influences bank performance in both direct and indirect ways by enhancing competitiveness. This dual pathway emphasises the necessity of not only investing in fintech solutions but also integrating themwith broader competitive strategies to fully capitalise on their advantages.

Figure 1: Conceptual framework of the study



Source: Riaz et al. 2023

4.2. Empirical Model and Strategy

To investigate the influence that internal adoption of financial technologies by banks have on the performance of their performance. To do this, we employ a Two-Way FE model as deployed by scholars (Song, 2023; Shu and Hong, 2023; Mansour, 2024; Tong and Yang, 2025) in similar studies. The panel linear regression model is illustrated as follows:

$$ROA_{it} = \beta_0 + \beta_1 FI_{it} + \beta_2 CIR_{it} + \beta_3 LAR_{it} + \beta_4 GDP_{it} + \alpha_i + \gamma_{it} + \epsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

As shown in equation 1 above, β_o is the intercept of the model, β_1 1 is the coefficient of the core explanatory variable, $\beta_2,\ldots,\beta_4$ are coefficients of both the bank-specific and macro control variables, α_i represents the fixed effects for the units, in this case, the banks, γ_{it} denotes the fixed effects for the period for time t and ϵ_{it} is the disturbance term of the model.

We choose to utilize a Two-Way Fixed Effects model instead of a random effects model due to the significant advantages that align with the specific nuances of our study. Firstly, it integrates both temporal and unit-specific components, addressing unobserved heterogeneity that is unique to each unit and period. Additionally, it accounts for latent confounding factors and facilitates the estimation of treatment effects even in the presence of time-invariant and unit-invariant variables (Imai and Kim, 2020). Secondly, fixed effects models control for the likelihood of omitted variable bias stemming from unobserved factors that remain constant over time but differ across entities (Green, 2018). Thirdly, unlike random effects models, which operate under the assumption that individual-specific effects are not correlated with the independent variables, fixed effects models acknowledge that such effects may indeed be correlated (Wooldridge, 2010). Lastly, consistent with the scope of our study, fixed effects models are especially appropriate for research involving a limited number of groups or clusters. In these scenarios, random effects models might yield unreliable estimates, while fixed effects models are still capable of producing consistent results (Clark and Linzer, 2015).

Additionally, the study's empirical strategy consists of five main steps. First, we describe the data to understand its characteristics. Next, we conduct a pairwise correlation test at a 5% significance level to establish the relationships between the variables. The second step involves conducting the cointegration test of the variables to determine whether there exists a long-run and stable relationship among the variables used in the model. In the third step, we estimate a Two-Way FE empirical model with robust standard errors to address possible heteroskedasticity in the residuals. We then perform the Hausman specification test to decide between the Fixed Effects (FE) and Random Effects (RE) models. To do this, we estimated the Two-Way FE model with robust standard errors. Following that, we run both the fixed effects model and the random effects model, conducting the Hausman test to determine which model is more appropriate. The results indicate that the probability value (p-value) of the Chi-Square is significant at the 5% (0.05) level of significance, confirming that we reject the null hypothesis that the model is random effects and conclude that the model to be used in the study is a FE model (see Table 1 below).

Table 1: Hausman (1978) specification test

	Coef
Chi-square test value	29.363
P-value	0.0000

We then estimate the chosen Two-Way FE model with robust standard errors as seen in Table 7. After that, we conduct a Variance Inflation Factor (VIF) test to check for multicollinearity in the regression results. The results indicate a mean VIF value of less than 5, which suggests an absence of significant multicollinearity among the independent variables in the estimated model. This low level of collinearity enhances the reliability of the model's coefficient estimates, ensuring that the impact of each predictor remains distinct and interpretable. Such findings reinforce the model's suitability for accurately assessing the relationships among the variables in question.

Table 2: Variance Inflation Factor

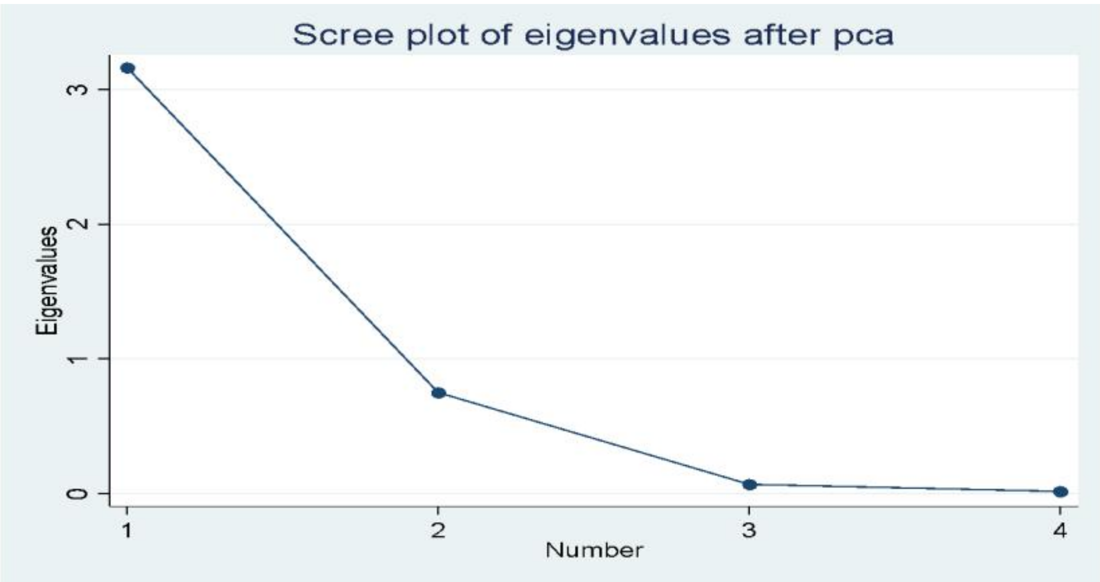
	VIF	1/VIF
Ibank 1 2	3.795	0.263
Ibank 1 3	3.469	0.288
LAR	3.375	0.296
Ibank 1 5	3.336	0.3
CIR	3.331	0.3
Ibank 1 4	3.314	0.302
Ibank 1 6	2.815	0.355
Ibank 1 7	2.665	0.375
Ibank 1 8	2.433	0.411
Ibank 1 9	2.023	0.494
Ibank 1 10	2.008	0.498
F1	1.971	0.507
Iyears 2021	1.713	0.584
Iyears 2019	1.577	0.634
Iyears 2022	1.573	0.636
GDP	1.547	0.647
Mean VIF	2.559	

Separately, we constructed the Fintech Index using a Principal Components Analysis (PCA) model, incorporating variables such as Mobile Banking, Internet/Electronic Banking, Mobile Payments, and POS Merchant services. These variables have been identified in several studies (Cornerstone Reports, 2019; Lien et al., 2020; Dwivedi et al., 2021; PwC Global, 2022; Berisha and Rayfield, 2025) as key indicators of banks' adoption of financial technology. Additionally, Khera et al. (2021) computed a similar Fintech Index using proxy variables for digital financial inclusion, including electronic/internet banking, mobile banking, mobile money, and paymentcards (POS).

To develop our index, we initially performed a Principal Component Analysis (PCA) using the specified variables that capture the various dimensions of the fintech ecosystem. By analyzing the eigenvalues derived from this PCA model, we identified which variables exhibited the highest coefficients, indicating their significant contribution to the overall variance. Following this analysis, we generated a post-estimation scree plot of the eigenvalues, as represented in Figure 1, which visually illustrates the proportion of variance explained by each principal component. This step is crucial for determining the optimal number of components to retain in the model. Figure 2 shows that the curve begins flattening from Principal Component 2 since it completely flattens out at Principal Component 3.

After establishing the key components, we predicted the scores for the PCA models based on the selected variables. Subsequently, we proceeded to estimate the Fintech Index by applying weighted values derived from the two PCA models. This approach allows us to quantify the impact of each principal component systematically, ensuring that our index accurately reflects the multifaceted nature of fintech development.

Figure 2: Scree plot for computed Fintech index



Source: Authors construction using data from the National Bank of Rwanda

4.3. Data and Variables

The study employs a data set of annual bank-level information, encompassing detailed financial statements and key performance indicators for both commercial banks and microfinance institutions. This dataset covers a significant period from 2018 to 2023, allowing for in-depth longitudinal analysis (refer to Table 3 for elaborate information). In addition, the graphical representation of the outcome variable is illustrated in Figure A3, which highlights notable trends and patterns over the specified years. This reinforces the growing impact of Fintech innovations on traditional and microfinance banking performance.

Table 3: Summary of the variables used in the study

Variable type	Variable	Variable symbol	Unit of measurement	Literature	Source
Outcome variables	Return on Assets	ROA	Percentages	Berisha (2025); Tong and Yang (2024); Song (2023); Li (2023), etc	Bank's audited financial statements
Core explanatory variable	Fintech Index	FI	Index	Conerstone reports, (2019); Lien et al., (2020); Dwivedi et al., (2021); Pwc Global, (2022)	Authors
	GDP Growth	GDP	Percentages	Shu and Hong (2023); Tong and Yang (2024); Song (2023), etc.	National Bank of Rwanda
Control variables	Loan to Asset Ratio	LAR	Percentages	Berisha (2025); Tong and Yang (2024); Song (2023); Li (2023), etc.	Bank's audited financial statements
	Loan-to-Deposit Ratio	LDR	Percentages	Berisha (2025); Tong and Yang (2024); Song (2023); Li (2023), etc.	Bank's audited financial statements
	Cost to Income Ratio	CIR	Percentages	Berisha (2025); Tong and Yang (2024); Song (2023); Li (2023), etc.	Bank's audited financial statements

Source: Author's construction

5. Empirical Results and Analysis

Table 4 presents an overview of the characteristics of the variables under study within the banking sector in Rwanda from 2018 to 2023. Notably, the average returns on assets for banks in this period stood at 7%, reflecting a steady performance in generating profits relative to their assets. At the same time, the cost-to-income ratio averaged around 69.6%, indicating that banks spent approximately 69.6 cents for every Rwanda Franc earned, a figure that highlights the operational efficiency and cost management strategies employed during this time frame. In terms of lending practices, the loans-to-assets ratio averaged 45%, suggesting that nearly half of the total assets held by banks were allocated to loans, which is a critical measure of banks' engagement in credit activities. The loans-to-deposit ratio averaged 70%, suggesting that banks are effectively leveraging deposits to extend credit, although this also raises questions about liquidity management and risk exposure. Additionally, the economic backdrop in Rwanda has been characterised by robust growth, as evidenced by an average economic growth rate of approximately 7% over the same period, which likely contributed to the increased demand for banking services. Mobile banking, an essential aspect of financial technology, experienced significant growth with an average increase of 13%, indicating a shift towards digital solutions that enhance customer accessibility and convenience. However, it is particularly noteworthy that the average mean of the Fintech index is recorded at 1.85, and the standard deviation is 1.33, respectively. These data points underscore the emerging landscape of financial technology innovations within Rwanda's banking sector, revealing a high degree of uptake and variability in the adoption and impact of Fintech solutions.

Table 4: Descriptive Statistics

Variable	Obs	Mean	Std. Dev	Min	Max
ROA	60	7.009	4.428	1.082	21.062
FI	60	1.857	1.333	-1.956	1.479
CIR	60	69.562	37.912	19.4	195.253
LAR	60	45.305	17.218	1.815	91.548
GDP	60	6.983	4.776	-3.4	10.9
LNMB	60	13.046	1.697	10.883	15.433
LDR	60	70.003	30.438	24.941	177.893

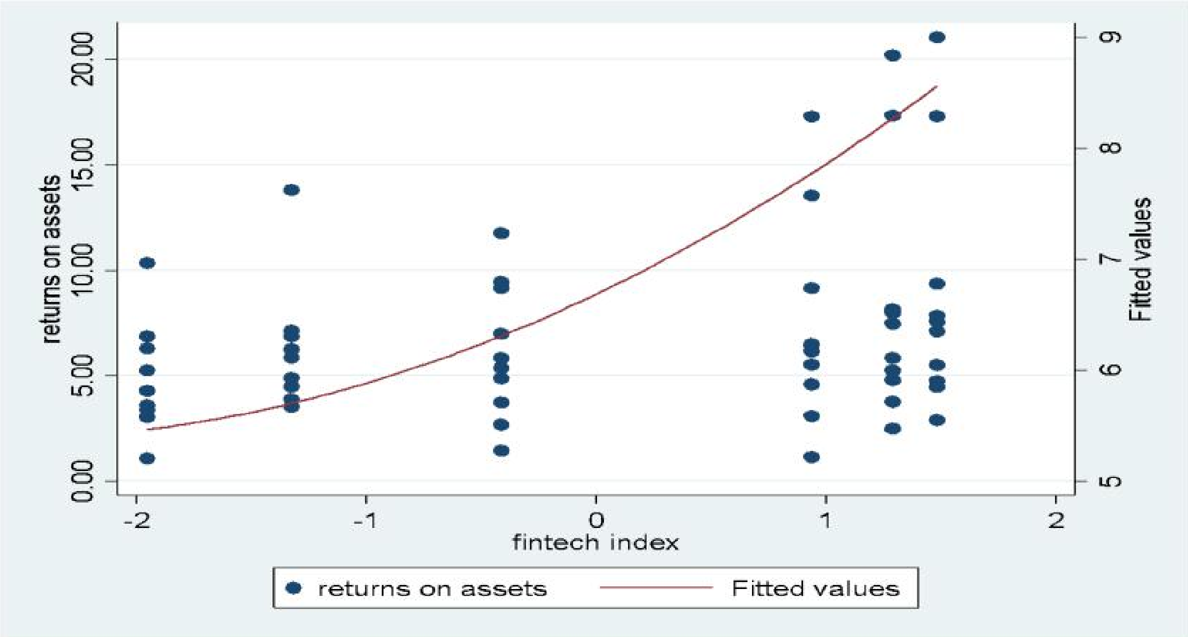
Table 5 illustrates the interconnectedness of the variables analysed in this study. The data reveals a benign, positive, and statistically significant correlation among the variables, confirmed at a 10% level of significance, except for economic growth, denoted as GDP. This suggests that as one variable increases, the others tend to increase as well, highlighting a noteworthy synergy among them. Furthermore, the off-diagonal elements in the correlation matrix are all equal to one, indicating a perfect linear relationship between each pair of variables, which underscores the strength and consistency of their interactions.

Table 5: Pairwise Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) ROA	1.000						
(2) FI	0.278*	1.000					
(3) CIR	0.286*	-0.223	1.000				
(4) LAR	0.487*	-0.072	0.213	1.000			
(5) GDP	0.075	0.132	-0.150	-0.017	1.000		
(6) LNMB	0.282*	0.954*	-0.217	-0.089	0.071	1.000	
(7) LDR	0.464*	-0.112	0.075	0.761*	0.001	-0.094	1.000

Furthermore, Figure 3 presents a robust positive correlation between returns on assets and the Fintech index, indicating a strong relationship between financial technology adoption and the profitability of these banking entities.

Figure 3: Positive correlation between Returns on Assets and Fintech Index



Source: Authors construction using data from the National Bank of Rwanda

Based on the results presented in Table 6, we reject the null hypothesis, which posits that there is no cointegration among the variables at a significance level of 5%. This conclusion is supported by the p-values derived from the modified Dickey-Fuller test, the standard DickeyFuller test, and the unadjusted Dickey-Fuller test statistics. The strong statistical evidence suggests that the variables in the model are indeed cointegrated, indicating a long-run equilibrium relationship among them. This finding implies that, despite any short-term fluctuations, the variables will move together over time, affirming the stability and reliability of the relationships identified in the model.

Table 6: Kao test for cointegration

Ho: No cointegration Ha: All panels are cointegrated	Number of panels = 10 Avg. number of periods = 3.9	
Cointegrating vector: Same		
Panel means: Included	Kernel: Bartlett	
Time trend: Not included	Lags: 1.80 (Newey-West)	
AR parameter: Same	Augmented lags: 1	
	Statistic	P-value
Modified Dickey-Fuller t	1.7562	0.0395
Dickey-Fuller t	2.8898	0.0019
Unadjusted Dickey-Fuller t	-6.2997	0.0000

The analysis presented in Table 7 highlights critical insights regarding the impact of financial technologies (Fintech) on the profitability of banks, specifically their returns on assets. The core explanatory variable, identified as the Fintech index, exhibits a positive and significant correlation with the ROA of both commercial banks and microfinance institutions. The results show that holding other factors constant, bank integration of financial technologies contributes approximately 96% of the bank's returns on assets. This suggests that integrating Fintech solutions—such as mobile banking, electronic banking, mobile money, and point-of-sale merchants—into their business models significantly enhances the banks' revenue-generating capabilities, ultimately leading to improved financial performance. These findings align with previous research conducted by Kharrat (2023), Song et al. (2023), Li et al. (2023), Riaz et al. (2023) and Tong and Yant (2024), which also established a positive and significant link between Fintech adoption and enhanced bank profitability.

Additionally, our results reveal a robust positive relationship between the loans-to-assets ratio and returns on assets. In this regard, a percentage increase in the bank's loan-to-assets ratio leads to an increase in the bank's returns on assets by approximately 10%, holding other factors constant. These findings align with Berisha and Rayfield (2025). They indicate that as banks increase their lending relative to their total assets, they experience a corresponding increase in profitability. It emphasises the importance of efficient asset utilisation in driving financial growth within banking institutions.

Conversely, the analysis shows that the cost-to-income ratio—a critical measure of operational efficiency, representing the costs incurred in generating income- has a negative and significant effect on returns on assets. The percentage change in the cost-to-income ratio leads to a decrease in the bank's returns on assets by approximately 3%, holding other factors constant. The findings align with similar studies like Renu (2021), Tong and Yang (2025), Shu and Hong (2023), Song et al. (2023), Berisha and Rayfield (2025), among others. This relationship suggests that as the cost-to-income ratio increases, the efficiency of asset utilisation declines, ultimately leading to lower profitability.

In other words, a higher percentage of income is being consumed by costs, resulting in diminished returns generated from the assets employed by the company. Aside from the banks' internal processes, this could be attributed to the inflationary pressures experienced in the country. The finding highlights the importance of managing operational costs effectively to enhance profitability and optimise asset performance. Therefore, justifying banks' need to manage costs to reduce operational costs per unit of income to observe a substantial uptick in their returns on assets reinforces the notion that operational efficiency through Fintech adoption could reduce the costs for banks.

On the macroeconomics front, the GDP control variable shows a positive but not significant sign on the effect on return on assets. In other words, despite the insignificance, a percentage change in the GDP results in an increase in the bank's returns on assets by about 5%, holding other factors constant. Our findings, however, differ from those of studies like Shu and Hong (2023); Tong and Yang (2024); Song (2023), who found mixed results. This implies that as Rwanda’s economy has grown, the banking sector has seen more activity but since it's not significant, there might be other confounding macro factors that impact the banks performance.

Table 7: Two-Way FE main model of the study

ROA	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
FI	0.964	0.328	2.93	0.005	0.301	1.628	**
CIR	-0.025	0.013	-1.85	0.071	-0.051	0.002	*
LAR	0.098	0.037	2.66	0.011	0.024	0.172	**
GDP	0.054	0.0660	0.81	0.422	0.090	0.187	
Banks: base AB Bank	0	.	.	.	.	.	
Access Bank	-11.152	2.669	-4.18	0	-16.538	-5.766	***
BOA Rwanda	-9.095	2.678	-3.40	0.002	-14.499	-3.69	***
Bank of Kigali	-10.418	2.59	-4.02	0	-15.645	-5.192	***
Ecobank	-7.563	2.576	-2.94	0.005	-12.761	-2.364	***
Equity Bank	-9.741	2.421	-4.02	0	-14.626	-4.856	***
Guarantee Trust Bank	-6.93	2.343	-2.96	0.005	-11.659	-2.201	***
I&M Bank	-10.514	2.374	-4.43	0	-15.305	-5.722	***
NCBA Bank	-8.572	2.199	-3.90	0	-13.01	-4.134	***
Urwego Bank	-1.614	2.279	-0.71	0.483	-6.214	2.986	
2018 base year	0			.	.	.	
2019	-12.76	30.983	-0.41	0.683	-75.286	49.766	
2020	178.585	417.052	0.43	0.671	-663.061	1020.231	
2021	-41.243	93.448	-0.44	0.661	-229.829	147.342	
Constant	-111.7	295.276	-0.39	0.7	-710.59	481.191	
Mean dependent var	6.952	SD dependent var			4.444		
R-squared	0.808	Number of obs			59		
F-test	12.205	prob >F			0.000		
Akaike crit. (AIC)	278.935	Bayesian crit. (BIT)			314.253		

*** p<.01, ** p<.05, * p<.1

5.1. Robustness Checks

Like similar studies (Song et al., 2023; Li et al., 2023; Tong and Yang, 2024) have done, to take a broad view of the applicability of our findings, we swap the core outcome variables and the dependent variables in the Two-Way FE model. In Table 7, we substitute the Fintech index with the natural logarithm of mobile banking to determine if we achieve a similar result. The findings reveal a similar positive and significant coefficient for the outcome variable. Moreover, this finding is consistent with those of Berisha and Rayfield (2025). Additionally, after adjusting the control variables by replacing the loan-to-asset ratio with the loan-to-deposit ratio, we observe consistent results in the coefficient, aligned with those seen in the primary Two-Way FE model. We also performed a normality test on the model's residuals using the multivariate normality test. The Doornik-Hansen test statistic indicates that the residuals are normally distributed around the mean, as evidenced by the p-value, which exceeds the 5% significance level (Table 8). Furthermore, the historical data presented in Figure A2 supports this conclusion.

Table 8: Normality test of the residuals of the Two-Way FE model

Test for multivariate normality		
Doornik-Hansen	chi2(2) = 4.396	Prob>chi2 = 0.1110

Table 9: Two-Way FE model (switching core outcome variable – Mobile Banking)

ROA	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
FI	0.726	0.247	2.93	0.005	0.227	1.225	**
CIR	-0.025	0.013	-1.85	0.071	-0.051	0.002	*
LAR	0.098	0.037	2.66	0.011	0.024	0.172	**
GDP	0.029	0.069	0.43	0.671	-0.110	0.169	
Banks: base AB Bank	0	.	.	.	.	.	
Access Bank	-11.152	2.669	-4.18	0	-16.538	-5.766	***
BOA Rwanda	-9.095	2.678	-3.40	0.002	-14.499	-3.69	***
Bank of Kigali	-10.418	2.59	-4.02	0	-15.645	-5.192	***
Ecobank	-7.563	2.576	-2.94	0.005	-12.761	-2.364	***
Equity Bank	-9.741	2.421	-4.02	0	-14.626	-4.856	***
Guarantee Trust Bank	-6.93	2.343	-2.96	0.005	-11.659	-2.201	***
I&M Bank	-10.514	2.374	-4.43	0	-15.305	-5.722	***
NCBA Bank	-8.572	2.199	-3.90	0	-13.01	-4.134	***
Urwego Bank	-1.614	2.279	-0.71	0.483	-6.214	2.986	
2018 base year	0			.	.	.	
2019	-2.019	14.465	-0.14	0.89	-31.21	27.172	
2020	38.453	200.58	0.19	0.849	-366.334	443.24	
2021	-8.333	42.634	-0.20	0.846	-94.373	77.706	
Constant	-28.79	162.42	-0.18	0.86	-356.566	298.986	
Mean dependent var	6.952	SD dependent var			4.444		
R-squared	0.808	Number of obs			59		
F-test	12.206	prob >F			0.000		
Akaike crit. (AIC)	278.935	Bayesian crit. (BIT)			314.253		

*** p<.01, ** p<.05, * p<.1

Table 10: Two-Way FE model (switching control variable – Loan to Deposit Ratio)

ROA	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
FI	0.943	0.338	2.79	0.008	0.260	1.625	**
CIR	-0.017	0.017	-1.01	0.317	-0.050	0.017	
LAR	0.047	0.023	2.10	0.042	0.009	0.093	**
GDP	0.045	0.073	0.62	0.539	0.102	0.191	
Banks: base AB Bank	0	.	.	.	.	.	
Access Bank	-10.421	3.527	-2.95	0.005	-17.539	-3.7302	***
BOA Rwanda	-9.096	3.128	-2.91	0.006	-15.408	-2.784	***
Bank of Kigali	-9.278	2.782	-3.34	0.002	-14.891	-3.664	***
Ecobank	-7.188	3.316	-2.17	0.036	-13.88	-0.496	**
Equity Bank	-8.689	2.891	-3.01	0.004	-14.533	-2.863	***
Guarantee Trust Bank	-6.763	2.957	-2.29	0.027	-12.731	-0.795	**
I&M Bank	-9.941	2.778	-3.58	0.001	-15.548	-4.334	***
NCBA Bank	-7.433	2.542	-2.92	0.006	-12.562	-2.304	***
Urwego Bank	-0.581	2.629	-0.22	0.826	-5.887	4.724	
2018 base year	0	.		.	.	.	
2019	-8.728	38.831	-0.22	0.823	-87.092	69.636	
2020	123.392	523.036	0.24	0.815	-932.137	1178.921	
2021	-28.419	117.144	-0.24	0.809	-264.825	201.987	
Constant	-75.699	369.734	-0.20	0.839	-821.822	670.484	
Mean dependent var	6.952	SD dependent var			4.444		
R-squared	0.781	Number of obs			59		
F-test	19.990	prob >F			0.000		
Akaike crit. (AIC)	286.713	Bayesian crit. (BIT)			322.031		

*** p<.01, ** p<.05, * p<.1

6. Case studies on bank-fintech anecdotes and regulatory frameworks that Rwanda could borrow lessons.

The fintech landscape in sub-Saharan Africa, is driven by mobile-first solutions, is fuelling competition between banks and fintechs, sparking innovation to address traditional banking gaps. In South Africa, competition between fintechs and banks has fostered a unique model of collaborative innovation rather than aggressive disruption.

Established banks such as Standard Bank and First National Bank (FNB) have adopted agile digital strategies to compete with fintechs by offering mobile-first banking solutions, enhancing user experience through artificial intelligence and advanced data analytics (Motloung, 2023). Meanwhile, digital-only banks like TymeBank and fintech payment platforms such as Yoco have gained significant market share by targeting underserved SMES with simplified, low-cost financial services. Rather than resisting fintech growth, South African regulators have embraced innovation through initiatives like the Intergovernmental Fintech Working Group and regulatory sandboxes. This collaborative atmosphere has allowed both banks and Fintechs to thrive while maintaining financial system stability and encouraging financial inclusion. As a result, innovation driven by this competitive-collaborative relationship has significantly reshaped South Africa's financial services landscape.

Nigeria's fintech sector has taken a more disruptive path, challenging traditional banks by offering faster, more accessible financial services, particularly in lending and payments. Fintechs such as FairMoney, Carbon, and Paystack have transformed how individuals and SMES access credit and process transactions, often bypassing the rigorous documentation and collateral demands of traditional banks (Hashem, 2022). This disruption has pushed Nigerian banks to innovate rapidly by launching digital arms and investing in mobile technology to retain customers. Moreover, the Central Bank of Nigeria has responded with a supportive regulatory framework that includes digital banking licenses, aiming to balance innovation with financial stability. The competition has expanded access to finance, especially for Nigeria's youthful, tech-savvy population, and helped integrate informal economic participants into the formal financial system. Consequently, fintech-led innovation, spurred by competition, is reshaping Nigeria's financial ecosystem by democratizing access to essential financial services.

In Tanzania, competition between banks and fintechs is largely centred around mobile money services, with telecom operators playing a dominant role in financial innovation. Platforms like Tigo Pesa, Airtel Money, and Vodacom's M-Pesa have introduced credit and savings services, enabling users to perform financial transactions using basic mobile phones (Ngassa & Kimaro, 2023). These innovations have effectively bypassed the limitations of traditional banking, such as the need for branch networks and formal identification. In response, commercial banks have partnered with mobile operators or developed mobile banking apps to stay competitive. The Bank of Tanzania has supported these efforts through policy frameworks that encourage interoperability and consumer protection. This competition has driven innovation, expanded financial inclusion to rural and underserved communities, and encouraged banks to simplify and digitise their services. As a result, the Tanzanian financial landscape has become more dynamic and inclusive, largely due to fintech-led transformation.

Kenya is widely recognised as a global leader in mobile financial innovation, primarily due to the success of M-Pesa and its integration with microcredit products like M-Shwari and KCB M-Pesa. These fintech solutions have redefined access to finance by enabling users to save and borrow money using their mobile phones, without requiring a bank account (Mwangi, 2024). Omondi (2017) found a positive and statistically significant relationship between access to Mshwari and access to credit in Kenya (Kiambu County). Further, while research on the direct impact of fintech on financial stability is limited, the growth in NCBA digital banking division earnings, underscores the positive impact of fintech on bank profitability. In 2024, despite a decline in earnings from NCBA's key digital products, MShwari & Fuliza (an overdraft facility on MPesa wallet), digital division revenues still increased by 74% to $57Mn in 2024. With 60Mn customers across the group, NCBA disbursed over $70Bn in digital loans in 2024.

The success of Mshwari has triggered quick adaptation by traditional banks, which are digitising rapidly, offering mobile apps, USSD-based services, and partnering with telecoms and fintech to deliver mobile banking to individuals and the large population of MSMEs. As competition intensifies, fintechs continue to innovate by targeting niche markets such as agribusiness, the gig economy, and youth entrepreneurs. The Central Bank of Kenya has played a key role in guiding this evolution by providing a conducive regulatory environment. Consequently, the rivalry between banks and fintechs has not only enhanced service efficiency but also accelerated financial inclusion, making Kenya a model for fintech-driven development in Sub-Saharan Africa.

Table 11 provides a comprehensive overview of the significant regulatory gaps that hinder the widespread adoption of financial technologies. These challenges are analyzed in the context of various regulatory frameworks, including the National Payments System, the National Financial Inclusion Strategy, and pertinent policies such as Data Protection regulations. By examining the inconsistencies and limitations within these frameworks, the table highlights key areas where regulatory adjustments are needed to foster innovation, enhance user trust, and ensure a more inclusive financial ecosystem.

Table 11: Regulatory gaps slowing deeper bank-fintech collaboration in Rwanda

No	Gaps	What Kenya and/or Uganda have done	Status in Rwanda
1	No dedicated digital regulation	Kenya's DCP Regulations 2022 license, cap fees, govern debt collection; Uganda subjects lenders to its Micro-Finance of NPS regimes.	Digital lenders are simply licensed as NDFSPs. Absense of tailored conduct rules makes banks wary of partnering on joing micro-lending products and exposes consumers to opaque pricing
2	Open-banking still only a draft	Kenya's CBK API consultation is already shaping bank tech road-maps; several banks run production APIs	BNR's draft directive (Dec 2024) sets a vision but gives no go-live dates or technical standards, so banks lack legal certainty to expose data or payments APIs to fintechs
3	Sandbox track record is thin	Kenya's sandbox (since 2019) has graduated multiple solutions, Uganda's accepted its second cohort in 2024	Rwanda's sandbox opened in 2022, but only the first cohort is still in "proof-of-concept". Limited precedents slow regulatory comfort with new partnership models (e.g,. Banking-as-a-Service).
4	Fragmented API/ data-sharing standards	Kenya's draft rules prescribe ISO 20022 and OAuth 2.0; Uganda is leveraging its Digital ID (NIRA) for e-kyc pilots.	The draft directive leaves API specs to later "technical notices," and there is no live national e-KYC gateway, forcing banks and fintechs to agree bilateral interfaces.
5	Consumer-protection specifics are missing for partnerships	Kenya's DCP rules plus Data-Protection COmmissioner guidance (feb 2024) set clear accountability splits.	Rwanda's Privacy Law is high-level; no sector guidelines yet on joint controllers/processors or on dispute resolution accross a bank-fintech value chain.
6	Capital & fit-and-proper requirements not tiered for start-ups	Kenya introduced "reg-lite" tiers (eg, PSP-Class C); Uganda allows "small PSP" licenses with lowercapital.	PSP category I license (RWF 200m minimum capital) can be prohibitive for early-stage fintechs, narrowing the pool of innovator banks that can partner with.
7	Limited clarity on cloud outsourcing & cross-border data	Both CBK & BoU issued could-outsourcing circulars in 2023.	BNR still applies the generic BCM (Business Continuity Management) regulation (2018) and ad-hoc approval. This uncertainty discourages joint SaaS deployments or regional data-lake projects.

Source: Authors compilation

CONCLUSION

The paper uses annual panel data from 2018 to 2023, involving 8 commercial banks and 2 microfinance banks in Rwanda, to examine the impact of Fintechs on the performance of the banking sector in Rwanda through a Two-Way Fixed-Effects linear regression model. The findings from the balanced panel analysis reveal that financial technology companies (Fintechs) exhibit a positive and statistically significant correlation with returns on assets. This implies that the integration of Fintech solutions such as mobile banking, electronic banking, mobile money and point of sale merchants into their business models significantly enhances the banks' revenue-generating capabilities, ultimately leading to improved financial performance.

In this regard, we recommend that both commercial banks and microfinance institutions significantly enhance their use of online platforms and cutting-edge financial technology (fintech) to devise innovative products and services that recognise the critical role of data in reshaping banking offerings. By leveraging advanced fintech solutions—such as artificial intelligence, machine learning, and blockchain technologies—these institutions can create customised financial products that cater to the unique needs of diverse customer segments.

This approach enables banks to improve their market responsiveness, allowing them to adapt quickly to emerging trends and customer demands. Additionally, by investing in technologydriven initiatives, financial institutions can optimise the use of their existing resources, reduce operational costs, and eliminate traditional geographic limitations to serve clients more effectively through digital channels.

In addition, banks, taking on this strategy, will not only foster digital transformation but also enhance overall profitability by driving customer engagement and retention. Furthermore, it will bolster the competitiveness of banks and microfinance institutions in an increasingly crowded market landscape as they position themselves as forward-thinking leaders in financial services. Ultimately, this proactive embrace of technological advancements will lay the groundwork for future growth and sustainability in their operations.

The Central Bank of Rwanda should adopt a less restrictive, proactive, co-creative and balanced approach in regulations to support fintechs' integration and collaboration with traditional banks. In other words, fast-track the gaps observed in the regulatory frameworks to enhance a collaborative environment for banks and fintech.

Strengthen interagency MOUs for both regulators and policymakers, like the National Bank of Rwanda, the Rwanda Utilities Regulatory Authority, the Rwanda Capital Markets Authority, and the Competition Authority, to provide single-window guidance and faster no-objection letters for partnerships.

Separately, the study's analysis encountered limitations with the data; we were constrained to consider some commercial and microfinance banks in the sample. Rwanda's banking sector seems to have experienced mergers and acquisitions of several banks; thus, the financial statements produced are more recent, restricting our sample for the study.

REFERENCES

Allen, F., & Santomero, A. M. (2001). What do financial intermediaries do? Journal of Banking & Finance, 25(2), 271-294. https://doi.org/10.1016/S0378-4266(99)00129-6

Apostolos & Goran (2023) "The impact of FinTech firms on bank performance: evidence from the UK"

Berisha, V., and Rayfield, B. (2025). Impact of internal Fintech on bank profitability. Investment Management and Financial Innovations, Volume 22, Issue 1, 2025. http://dx.doi.org/10.21511/imfi.22(1).2025.29

Clark, T. S., & Linzer, D. A. (2015). Should I Use Fixed or Random Effects? Political Science Research and Methods, 3(2), 399–408. https://doi.org/10.1017/psrm.2014.32

Christensen, C. M. (1997). Disruptive technologies: Catching the wave. The Journal of Product Innovation Management, 1(13), 75-76.

Cornerstone Reports (2019). Fintech adoption in the United States: the opportunity for banks and credit unions. Retrieved from https://www.crnrstone.com/hubfs/19-0130_Q2_Fintech-Adoption-inthe-US.pdf

Damilola, A. O. (2022). Fintech and Financial Inclusion in West Africa: Nigeria's SMES Market. International Journal of Multidisciplinary and Current Educational Research, 4, 210-2018.

Degryse et al. (2020) "The Effect of Fintech on Commercial Bank Performance: Evidence from EU"

Deloitte 2018, "Closing the gap in fintech collaboration | Overcoming obstacles to a symbiotic relationship"

Dixit, A., & Nalebuff, B. (1991). Thinking Strategically: The Competitive Edge in Business, Politics, and Everyday Life. W. W. Norton & Company.

Dong, Y., Meng, C., Firth, M. and Hou, W. (2014), "Ownership structure and risk-taking: comparative evidence from private and state-controlled banks in China"

Dwivedi, P., Alabdooli, J. I., & Dwivedi, R. (2021). Role of Fintech Adoption for Competitiveness and Performance of the Bank: A Study of Banking Industry in UAE. Journal of Global Business and Competitiveness, 16(2). https://doi.org/10.1007/s42943-021-00033-9

Finscope Survey, (2024). Rwanda Finscope Report. Available via: https://afr.rw/downloads/rwandafinscope-2024-report/

Gao, J. (2022). Comparison of fintech development between China and the United States. International Journal of Innovative Science and Research Technology (IJISRT), 6563524, 1272-6.

Green. W.H. (2018). Econometric Analysis (8th ed.). Pearson Education Limited London.

Giglio, F. (2021). Fintech: A literature review. European Research Studies Journal, 24(2B), 600-627.

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2017). On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. Journal of Management Information Systems, 35(1), 220–265. https://doi.org/10.1080/07421222.2018.1440766

Harmadi, Wisnu, Irwan & Atmaji (2022) "The Effect of Fintech on Conventional Bank Performance and Bank Risk"

Hashem, A. (2023). The impact of blockchain technology on financial services: mediating role of big data analytics. Journal of Logistics, Informatics and Service Science, 10(2), 91-107.

Hashem, I. (2022). Digital Credit and Financial Inclusion in Nigeria: A Fintech Revolution. African Journal of Financial Technology, 8(2), 115–132.

Hussain, A., Mia, Md S., Ahmed, F. (2023). A moderated mediation analysis on Fintech adoption, social influence, competitiveness and financial performance of commercial banks in Pakistan. Banks and Bank Systems, Volume 18, Issue 4, 2023. http://dx.doi.org/10.21511/bbs.18(4).2023.19

Hussein (2023) "The Relationship between the risks of adopting Fintech in banks and their impact on performance"

Hussein A. A, & M.A. Lokhande Ibidunni, A. S., Ufua, D. E., & Opute, A. P. (2022). Linking disruptiveninnovation to sustainable entrepreneurship within the context of small and medium firms: A focus on Nigeria. African Journal of Science, Technology, Innovation and Development, 14(6), 1591- 1607. https://doi.org/10.1080/20421338.2021.1975355

Imai, K., and Kim S. (2020). On the use of Two-way fixed effects regression models for causal inference with panel data. Political Analysis (2020). DOI: 10.1017/pan.2020.33

Khalaf & Omari (2020). The Impact of Fintech on the Efficiency of Conventional Banks"

Khalaf, Awad, Ahmed & Robert (2023) The Role of Fintech in Determining the Performance of Banks: The Case of Middle East & North Africa (MENA) Region

Khan, Kutan & Qureshi (2024) "Fintech Integration: Driving efficiency in Banking Institutions across the developing nations"

Kharrat, H., Trichilli Y., and Boujelbène, M. (2023). Relationship between Fintech index and bank's performance: a comparative study between Islamic and conventional banks in the MENA region. journal of Islamic Accounting and Business Research. DOI: 10.1108/JIABR-03-2022-0081

Khera, P., Y Ng, S., Ogawa, S., and Sahay, R. (2021). Measuring Digital Financial in Emerging and Developing Economies: A New Index. Retrieved from: https://www.elibrary.imf.org/view/journals/001/2021/090/article-A001-en.xml

Li, L., Gao, W., and Gu, W. (2023). Fintech, bank concentration and commercial bank profitability: Evidence from Chinese urban commercial banks. Financial Research Letters volume 57, November 2023, 104234. https://doi.org/10.1016/j.frl.2023.104234

Lien, N. T. K., Doan, T.-T. T., & Bui, T. N. (2020). Fintech and Banking: Evidence from Vietnam. The

Journal of Asian Finance, Economics and Business, 7(9). https:// doi.org/10.13106/jafeb.2020.vol7. no9.419

Liu & Kwan (2021) "Fintech & Bank Performance: Evidence from Emerging Economies

Mansour, N. (2024). The Impact of Fintech Development on Commercial Banks' Profitability. Journal of Organizational and End User Computing. Volume 36, Issue 1, January- December 2024. https://orcid .org/ 0000 -0001 -7690 -7096

Mashamba, T., & Gani, S. (2023). Fintech, bank funding, and economic growth in Sub-Saharan Africa. Cogent Economics & Finance, 11(1), 2225916.

Ministry of ICT and Innovation, Rwanda. (2023). Rwanda's Digital Financial Inclusion Strategy.

Mohammad et al. (2024) "The impact of FINTECH on banking performance: Evidence from Middle Eastern countries"

Morgenstern, O. (1976). The collaboration between Oskar Morgenstern and John von Neumann on the theory of games. Journal of Economic Literature, 14(3), 805-816.

Motloung, P. (2023). Fintech Collaboration and Regulation in South Africa's Banking Industry. South African Journal of Economics and Finance, 17(3), 89–104.

Mwangi, J. (2024). M-Pesa and the Transformation of Financial Services in Kenya. East African Business Journal, 13(1), 78–94.

Mwangi, J. K. (2024). The Role of Digital Payment Systems in Financial Inclusion: A Study of Mobile Banking Adoption in Kenya. Journal of Ecotrends and Management, 1(1), 10-23.

Narain, R., & Harris, J. (2020). The Impact of Open Banking on Financial Services: New Models and Consumer Benefits. Journal of Logistics, Informatics and Service Science, 1(8), 20-31.

Nash, J. F. (1950). Equilibrium points in n-person games. Proceedings of the National Academy of Sciences, 36(1), 48–49.

National Bank of Rwanda. (2023). Financial Stability Report.

Nayak, B., Bhattacharyya, S. S., & Krishnamoorthy, B. (2023). Integrating the dialectic perspectives of resource-based view and industrial organization theory for competitive advantage–a review and research agenda. Journal of Business & Industrial Marketing, 38(3), 656-679. https://doi.org/10.1108/JBIM-06-2021-0306

Ngassa, C., & Kimaro, E. (2023). Mobile Financial Services and Financial Inclusion in Tanzania. Journal of African Digital Finance, 10(4), 207–225.

Nguyen, T.T.H. (2021). "Measuring financial inclusion: a composite FI index for the developing countries", Journal of Economics and Development, Vol. 23 No. 1, pp. 77-99. https://doi.org/10.1108/JED-03-2020-0027

Ntwiga (2020) "The Effects of Fintechs on Bank Market Power and Risk-Taking Behaviour in Kenya" KBA Centre for Financial Markets and Policy Working Paper Series 44, Kenya Bankers Association. Available via: https://www.econstor.eu/handle/10419/249545

Omarini (2022) "The Changing Landscape of Retail Banking and the Future of Digital Banking"

Omarini, A. E. (2017). The digital transformation in banking and the role of Fintechs in the new financial intermediation scenario. International Journal of Finance, Economics and Trade, 1(1), 1–6. https://dx.doi.org/10.2139/ssrn.4862876

Osborne, M. J., & Rubinstein, A. (1994). A Course in Game Theory. MIT Press.

Ozil (2017) "Impact of digital Finance on financial inclusion and stability"

PwC Global. (2022). Global Fintech Report 2019. Retrieved from https://www.pwc.com/gx/en/industries/financial-services/assets/pwc-globalFintechreport2019.pdf

Renu, S., Garima, M., Vipin, J. (2021) "Fintech effect: Measuring impact of Fintech adoption on banks' profitability in Nigeria"

Riaz, N., Riaz, A., Tariq, R., and Muhammad, T. (2023). The Nexus Between Fintech Adoption and Bank Performance: A role of Competitiveness. Pakistan Journal of Humanities and Social Sciences, Volume 11, Number 04, 2023, Pages 3981–3993. DOI: 10.52131/pjhss.2023.1104.0668

Rodgers Onchenge (2023) "The Effect of FinTech Development on Bank Risk-taking: Evidence from Kenya"

Sami, B.N, Bertrand, C., Selim, E., Drilona, E., (2023) "Is FinTech Eating the Bank's Lunch?"

Shu, Z., and Hong, D. (2023). Fintech and Commercial Bank Profitability: Evidence from China. Journal of Industry and Engineering Management. (ISSN: 2959-0612) Vol. 1 No. 1, 2023. https://doi.org/10.62517/jiem.202303108

Shuli, L., Yangran, D., and Yong L. (2023) "How Do Fintechs Impact Banks' Profitability? —An Empirical Study Based on Banks in China"

Solanki, R., & Sujee, L. S. (2022). Fintech: A Disruptive Innovation of the 21st Century, or Is It? Global Business and Management Research, 14(2s), 76-87.

Song, X., Yu, H., and He, Z. (2023). Heterogeneous Impact of Fintech on the Profitability of Commercial Banks: Competition and Spillovers. Journal of Risk and Financial Management. 16: 471. https://doi.org/10.3390/jrfm16110471

Tarawneh & Arouri (2021) "Fintech Adoption and Financial Performance: Insights from EU Banks

Tong, X., and Yang, W. (2025). Empirical analysis of the impact of financial technology on the profitability of listed banks. International Review of Economics and Finance. 98 (2025) 103788. https://doi.org/10.1016/j.iref.2024.103788

Tu Le, Thanh Ngo, Dat T. Nguyen, Thuong T.M. Do (2024) - Fintech and banking: Friends or foes? Evidence from bank–fintech cooperation

Vives, X. (2019). Digital disruption in banking. Annual Review of Financial Economics, 11, 243–272. https://dx.doi.org/10.1146/annurev-financial-100719-120854

Vlora & Blake (2024) "Impact of Internal Fintech on Bank Profitability"

Von Neumann, J., & Morgenstern, O. (1944). Theory of Games and Economic Behaviour. Princeton University Press.

Wooldridge, J.M. (2010). Econometric Analysis of Cross Section and Panel Data (2nd ed.). MIT Press.

Zhao, Li, Yu, Chen, Lee (2022) "Riding the FinTech innovation wave: FinTech, patents and bank performance"

Zohar, A. (2019). The Role of Peer-to-Peer Lending in Financial Market Transformation: Opportunities and Challenges. Journal of Ecotrends and Management 3(1), 22-40.

APENDIX

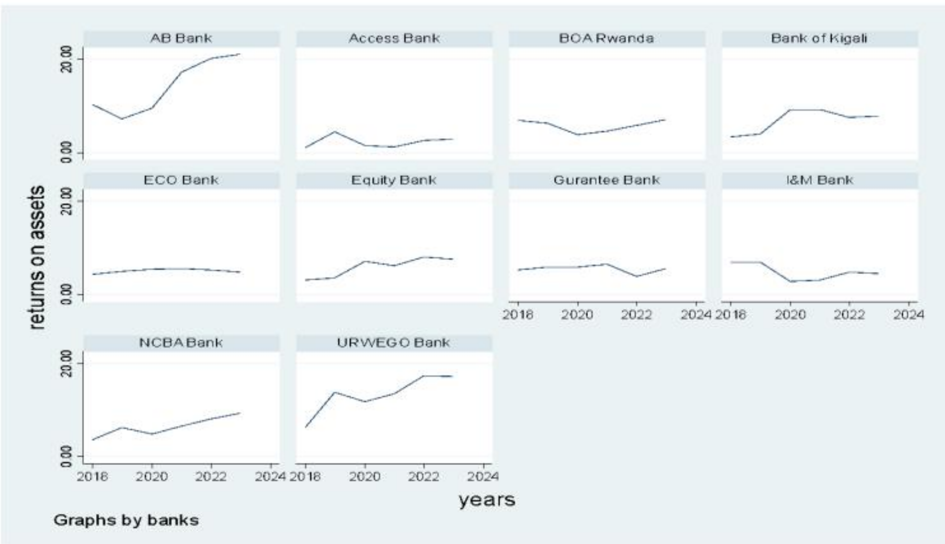
Table A1: List of Banks used in the analysis

Tiers	Bank name
Commercial banks	Access Bank
	Bank of Africa (BOA)
	Bank of Kigali
	EcoBank
	Equity Bank
	Guarantee Trust Bank
	I&M Bank
	NCBA Bank
Microfinance banks	AB Bank
	Urwego Bank

Table A2: Summary of variables used to compute the Fintech Index

Variable	Unit	Source
Mobile Banking	Value (Rwanda Francs Millions)	National Bank of Rwanda
Electronic Banking	Value (Rwanda Francs Millions)	National Bank of Rwanda
Mobile Money	Value (Rwanda Francs Millions)	National Bank of Rwanda
POS Merchant	Value (Rwanda Francs Millions)	National Bank of Rwanda

Figure A1: Graphical exposition of returns on assets by banks



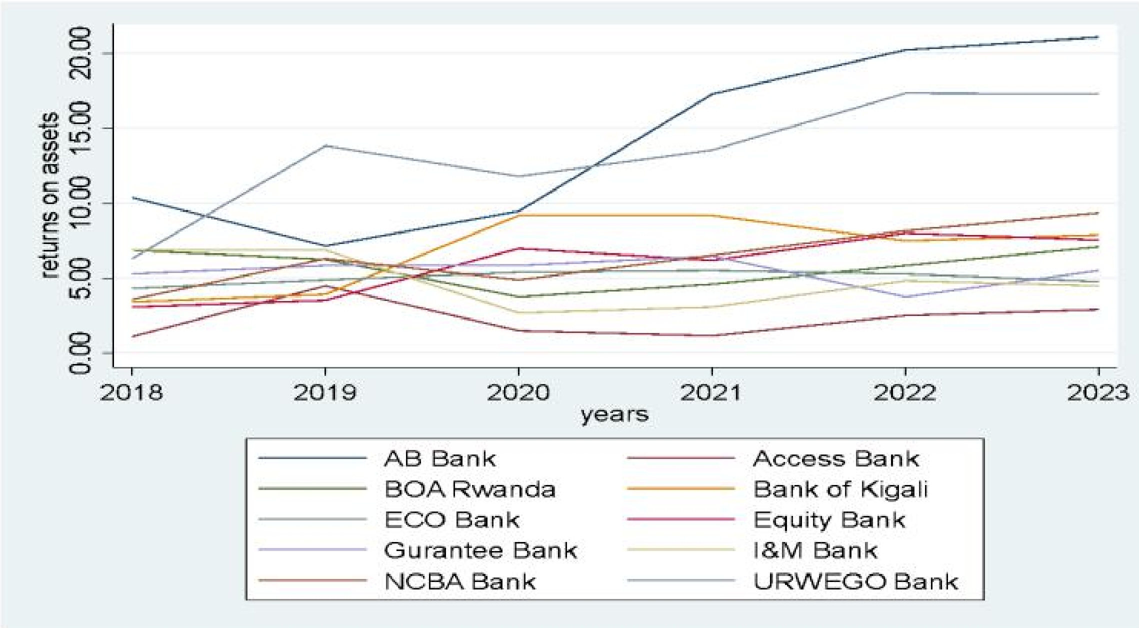
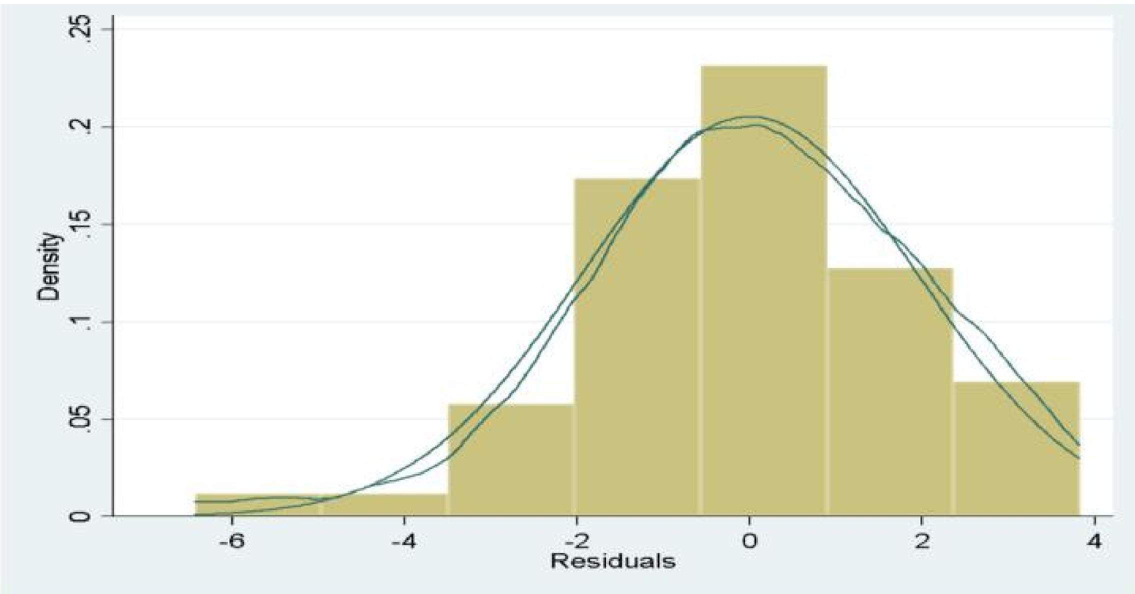


Figure A2: Graphical exposition of returns on assets by banks



Working Paper No. WP02-25

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July, 2025