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Determinants of commercial banks' efficiency in Rwanda

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Abstract

This study investigates the drivers of cost efficiency of 10 Rwandan commercial banks for the 2012Q1-2021Q3 period, using the true fixed effects model, which makes it possible to integrate unobserved bank-specific heterogeneity in the inefficiency function at the mean level. This study is in line with the central bank's role of ensuring financial stability. The study builds on Gisanabagabo and Ngalawa (2017), the only study about the subject matter in Rwanda, to make the necessary adjustments: First, this study uses a larger sample with respect to time and number of commercial banks; Second, the study also uses a more flexible translog cost function, rather than a linear function and it models heterogeneity across banks as part of the inefficiency term rather than using individual dummy variables as this may lead to over-parameterization; Finally, the study deals with correlation among variables in both the inefficiency function and the cost function by implementing a single-step estimation procedure. Empirical estimations show that credit risk positively affects inefficiency while intermediation ratio, bank funding structure, and capital ratio negatively affect inefficiency, especially since 2018. The estimated efficiency score stands at 81.3 percent compared to 88.56 percent obtained by Gisanabagabo and Ngalawa (2017), and the differences are due to the employed methodologies and samples. The paper recommends that Rwandan commercial banks should strengthen existing measures to further mitigate credit risk, and increase intermediation, funding structures, and capitalization so as to deal with macro-financial shocks.

KeyWords: Stochastic Frontier, Cost Efficiency, Rwandan Commercial Banks, Panel.

JEL Classification Numbers: C23, C24, D21, G21, G28.

1. Introduction

Availability and efficient use of financial resources are one of longstanding economic development challenges. In a developing country like Rwanda, where the banking sector is dominant, banks can influence economic performance if they can efficiently perform their intermediation role (Levine, 1997). Efficient intermediation implies that commercial banks can efficiently mobilize savings and channel them to productive activities and thus impact economic growth and development. In addition, commercial banks need to be efficient so as to be able to cushion themselves from competitors and macro-financial shocks. Commercial banks are considered to be efficient if: (1) they can generate high profits; (2) they are well-capitalized and able to mitigate risks; and (3) they can offer good quality financial products to clients at favorable prices (Berger et al., 1993b). For a central bank that cares about financial sector stability and economic growth, the analysis of commercial banks' efficiency is a very important exercise as it can lead to recommendations that can inform policy geared towards improving efficiency.

As noted by Karangwa and Nyalihama (2018), Rwanda's financial sector has continued to grow following financial liberalization that started in 1995 and the putting in place of a more regulatory and supervisory framework conducive to financial sector development. Before 1995, there were 5 banks in Rwanda (Karangwa and Nyalihama, 2014). However, the number of banks increased from 8 in 1995 to 18 in 2017 (Karangwa and Nyalihama, 2018) and then to 16 as at the end March 2020 (Kigabo, 2021). As of end March 2021, the number of banks still stood at 16, including 11 commercial banks, 3 microfinance banks, 1 development bank, and 1 cooperative bank (NBR, 2022).

In its vision 2050, Rwanda aspires to attain an upper middle-income status by 2035 and a high-income status by 2050, with an annual GDP per capita of US$4,035 and US$12,476, respectively. This ambitious long-term development agenda will be achieved by recording high sustained economic growth, supported by a well-developed and efficient financial system. Despite the noticeable expansion of Rwanda's financial sector, especially in the post-1995 period, financial sector development is still impeded by some structural challenges. For example, the deposit-to-GDP ratio stood at 17.4 percent in 2017, private credit by deposit money banks to GDP ratio stood at 19.9 percent, while bank credit to bank deposits ratio stood at 114.1 percent during the same period. These numbers imply that the mobilization of savings by the banking system is still not enough to cover the demand for credit in the economy.

Like most of its East African peers, the table 1 indicates that by 2019, Rwanda still had high bank overhead costs to total assets ratio (6.5 percent) compared to 1.3 percent for a high-income country like Singapore with a highly developed financial system. The net interest margin, which is one of the measures of the efficiency of intermediation, stood at 9.3 percent in Rwanda compared to 1.9 percent in Singapore and 3.7 percent in South Africa, indicating that intermediation efficiency is still low in Rwanda.

The main cause of intermediation inefficiency in Rwanda has been reported to be credit risk (non-performing loans or loan loss provisions), overhead costs, loans' market concentration, the real economy (inflation or economic activities), and alternative financial investment opportunities, especially the treasury bills (Karangwa and Nyalihama, 2014; Kigabo et al., 2016; Karangwa and Nyalihama, 2018; Kigabo and Barebereho, 2007) noted that the lending rate is more rigid compared to the deposit rate. The volatility in the deposit rate was mainly driven by the fact that the deposit market is dominated by large depositors with negotiating power, the emergence of new competing investment opportunities like T-bills, and economic activities that affect the balance sheets of depositors. Conversely, the rigidity in the lending rate was influenced by operating costs, loans' market provisions, and loan loss provisions as a measure of credit risk.

While intermediation efficiency in Rwanda has been studied, the wider scope of banks' efficiency has not been adequately investigated. Intermediation efficiency is one aspect of bank efficiency as the latter may include either cost efficiency or profit efficiency, which are basically two sides of the same coin as per the duality theorem (i.e., there is a duality between cost minimization and profit maximization). The only study on Rwanda that examined cost efficiency was by Gisanabagabo and Ngalawa (2017). The study estimated a linear cost function and a linear function for the inefficiency term using annual data on seven (7) Rwandan commercial banks covering the period 2007-2013.

The Gisanabagabo and Ngalawa (2017) study was based on the intermediation approach, where operating income was used as the output, whereas operating cost was used as the input. They measure total costs as total interest paid on deposits and borrowed funds plus non-interest operating costs. The output (i.e., operating income) is divided into the total amount of interest income and total non-interest income. Other included variables are the price of capital normalized by the price of labor, the ratio of the price of funds to the price of labor, a time trend, and dummy variables capturing bank-specific characteristics. The price of capital is measured as the depreciation of both physical capital and intangibles, while the price of labor is the total bill for wages, salaries, and other fringe benefits. The price of funds is measured as the total amount spent as interest on deposits and borrowed funds. The bank-specific variables are management, foreign, and government. Foreign equals 1 if majority shareholders are foreign and 0 otherwise, government equals 1 if major government intervention occurred to prevent bank bankruptcy and 0 otherwise; management equals 1 if a bank had a minimum of 2 CEOs in the 2007-2013 period and 0 otherwise. These measures of bank heterogeneity are considered as the only explanatory variables in the linear inefficiency model.

This paper addresses the identified research gaps in the Gisanabagabo and Ngalawa (2017) study. First, the study used fewer observations (i.e., annual data for 2007-2013), which we address by using 2012Q1-2021Q3 data for 10 (rather than 7) commercial banks.

Second, the use of a linear cost function has also been contested in the literature, where more data consistent functional forms, such as the Cobb-Douglas and Translog functions, are more preferred. A linear cost function assumes that the effect of each variable on total cost is the same over time. In this paper, we use a flexible translog function as in Gunes and Yildirim (2016) because it permits substitution effects among inputs and is claimed to be a relatively dependable approximation to reality (Battese and Coelli, 1995).

Third, the inclusion of dummy variables to capture bank-specific heterogeneity may lead to over-specification of the cost function, leading to underestimation of the inefficiencies. To overcome this, we allow the heterogeneity to be part of the inefficiency distribution and thus account for unobserved bank-specific heterogeneity at a mean level in cost efficiencies. We then specify a time-varying inefficiency function with a vector of time-variant variables hypothesized to influence bank efficiency (Greene and

Table 1: Financial structure and intermediation for selected economies

Country	Year	WBIG	LL-GDP	PC-GDP	BD-GDP	BC-BD	BO-TA	NIM	BC
Burundi	2017	LIC	23.4	14.6	18.5	79.0	4.3	9.6	91.9
Kenya	2017	LMIC	36.0	29.6	32.7	90.5	6.0	9.4	36.6
Rwanda	2017	LIC	19.5	19.9	17.4	114.1	6.5	9.3	58.2
Singapore	2017	LIC	127.6	125.0	118.6	105.4	1.3	1.9	89.3
South Africa	2017	UMIC	42.9	64.4	57.9	111.1	3.6	3.7	76.7
Tanzania	2017	LIC	20.9	13.2	16.7	79.2	7.2	9.4	48.9
Uganda	2017	LIC	16.6	13.4	17.4	77.4	6.7	10.3	54.2

WBIC: World Bank Income Group; LIC: Low-Income Country; LMIC: Lower-Middle Income Country; UMIC: Upper-Middle Income Country; LL-GDP: Liquid Liabilities to GDP (in percentage); PC-GDP: Private Credit to GDP (in percentage); BD-GDP: Bank Deposits to GDP (in percentage); BC-BD: Bank Credit to Bank Deposits (in percentage); BO-TA: Bank Overhead costs to Total Assets (in percent); NIM: Net Interest Margin (in percentage); BC: Bank Concentration (in percentage).

Source: Financial structure database of Beck et al., 2019, 18^{th} October 2019.

Segal, 2004). These time-variant drivers of inefficiency are usually balance sheet variables (Berger et al., 1993b). Fourth, since the sample of Rwandan commercial banks is not random, we estimate the flexible translog cost function assuming true fixed effects (Farsi et al., 2006). Fifth, this study is further supported by the fact that since 2013, there have been increased investments, especially in technology (e.g., software) and digital financial infrastructure, aimed at scaling up the operational efficiency of commercial banks. Thus, it is worth investigating whether this has affected the cost efficiency of banks.

Finally, unlike in the Gisanabagabo and Ngalawa (2017) study, we estimate the cost function and the inefficiency function simultaneously rather than following a two-step procedure, where the cost function is estimated first, inefficiency scores are derived and then used in the estimation of the inefficiency function (Kalirajan, 1981). The estimation of inefficiency using the two-step procedure is quite flawed, as noted by Coelli (1996). This is because the factors that are included in the inefficiency function are also included as some of the explanatory variables in the cost function, which makes the estimated inefficiencies not independently and identically distributed. The solution to this is the use of a single-step estimation procedure to control for correlation between variables included in the cost function and those included in the inefficiency function (Kumbhakar, 1996).

In the one-step procedure, the inefficiency effects are well-defined as a function of the bank-specific factors and combined directly into the maximum likelihood (ML) estimation. Our focus on commercial banks is based on the fact that they account for about 67 percent of the total assets for the entire financial sector (NBR, 2022; Kigabo, 2021), while 10 commercial banks for which data were existing for the 2012q1-2021q3 period are chosen. This study is built on the following research questions: (1) what is the degree of efficiency in Rwanda across the selected commercial banks and across time? (2) what are the driving factors for commercial banks' efficiency in Rwanda?

The remainder of this paper is structured as follows: Section 2 highlights the literature on bank efficiency. Section 3 gives the methodology employed in the empirical analysis. Section 4 discusses financial sector development in Rwanda and also presents the results from the empirical estimations. Lastly, Section 5 concludes the paper.

2. Literature review

For a developing country, the attainment of sustainable economic growth and development requires the contribution of a stable and efficient banking system (Gunes and Yildirim, 2016). A banking system that can efficiently mobilize resources and channel them to their most productive use is needed to promote economic growth (Freixas and Rochet, 2008). According to Cihák et al. (2012) , banks are likely to be more efficient if they can screen and identify firms with the most profitable investments and when they can monitor the use of funds and scrutinize the managerial performance of corporations that borrowed from them as this reduces wastage of resources and fraud by corporate insiders.

Generally, bank efficiency means the ability of a bank to produce maximum output using a minimum amount of inputs (Kablan, 2010). Studies on bank efficiency generally focused on the measurement of cost efficiency (Lelissa, 2014), profit efficiency (Isik and Hassan, 2002), or both profit and cost efficiency (Ncube, 2009).

In the aftermath of the 2008 global financial crisis, researchers and policymakers focused on unpacking the causes of financial fragility and the measures to ensure financial stability. Recently, attention has shifted to assessing bank efficiency amidst complexities brought about by financial innovations, cross-border operations, interconnectedness, and emerging regulations (Kiemo and Kamau, 2021).

Studies on bank efficiency across the world have generally focused on the measurement of inefficiency levels as well as ascertaining the main factors behind such inefficiencies so as to inform policy reforms. Both cost and profit efficiency levels have been reported to be lower in developing countries compared to developed countries. Bank efficiency is expected to improve, especially in the aftermath of reforms such as privatization and financial liberalization, foreign entry of new banks, mergers and acquisitions, as well as changes in macroeconomic and regulatory conditions (Tecles and Tabak, 2010).

Most of the studies on bank efficiency have been conducted for the case of developed countries (Berger and Humphrey, 1997), Asian countries (Maggie and Heffernan (2007); Aigner et al. (1977) and Latin America (Carvallo and Kasman, 2005), while few studies have covered African, particularly Sub-Saharan Africa (Miencha, 2015). The little interest in Sub-Saharan Africa has been due to the low level of financial development, a nascent banking sector, a limited number of market activities, and a lack of good quality data (Chen et al., 2009).

For the case of Central and Eastern Europe, Kasman and Yildirim (2006) investigated cost and profit efficiency for the eight countries that had become new members of the European Union. Their study used data covering 190 banks for the period 1995-2002. They used country-specific variables so as to account for the differences in macroeconomic and financial conditions among these countries. Based on the estimations from the Fourier flexible cost and profit functions, their findings indicate that foreign banks are generally more efficient compared to domestic banks. They also indicate that the banking systems in these countries are cost/profit inefficient: on average, cost efficiency stood at 0.2 while profit efficiency stood at 0.36, and that efficiency levels are not improving over time. Also, cost and profit efficiency scores vary across countries and across different size groups.

Berger and Humphrey (1997) surveyed 130 frontier efficiency studies for 21 countries. Though these studies use different methodologies and cover different institutional types and data, the general conclusion is that there is a prevalence of inefficiency in financial institutions across the world. On average, 20 percent of the increase in costs is due to inefficiency, which dominates scale and scope economies. Hasan et al. (2009) estimated a translog cost frontier using data for 152 countries and found that mean efficiency for the banking sector ranged between 28 percent and 91 percent.

A study by Kiyota (2009) covering 29 Sub-Saharan (SSA) countries during the 2000-2007 period concluded that there was a relative increase in cost inefficiency, standing between 1.05 percent and 1.06 percent for the countries included in the sample. Their findings are based on the estimation of a translog cost function. Kablan (2010) found that Sub-Saharan banks are cost-efficient but argues that efficiency levels could be further improved via better functioning judicial and legal systems as well as the increased access to information on borrowers to help curb the problem of high non-performing loans, highlighted as a major impediment to efficiency in SSA.

A study by Kablan (2007) on West African Monetary Union (WAMU) member countries covering the period 1993-1996 concluded that the banking sector was generally cost-efficient, with an average efficiency score of 67 percent. Their findings are based on estimations from a translog cost function.

At the country level, most studies found that the banking institutions were cost-efficient. For the case of Ethiopia, Data Envelopment Analysis (DEA) estimations using data covering the 2008-2012 period indicate that the average efficiency of the banking sector stood at 86.7 percent, meaning that only 12.3 percent of resources were wasted. Estimations from a translog cost function covering data for 8 South African commercial banks indicated an improvement in cost efficiency over time, from 40.4 percent in 2000 to 66.2 percent in 2005 (Ncube, 2009). Hasan et al. (2009) concluded that the mean efficiency of the banking sector stood at more than 90 percent in Micronesia, Ethiopia, and Honduras.

Some studies justify high-cost efficiency scores with policy reforms such as privatization and financial liberalization/financial sector reforms. These were generally carried out on a group of emerging countries (Fries and Taci, 2005) as well as on a single-country basis (Hauner and Peiris, 2005). These reforms were often put in place as a response to certain macro-financial shocks. For example, in response to the banking crisis of the 1980s, monetary authorities adopted strict regulatory measures to ensure financial stability by setting up a single supervisory body for WAEMU countries and for Central African countries, respectively. In other SSA countries, the role of supervision was entrusted to central banks (Kablan, 2010).

In line with the above, Hauner and Peiris (2005) used the DEA method to estimate efficiency scores for Ugandan commercial banks covering the period 1999-2004 and concluded that cost efficiency stood at an average of 92.6 percent, supported by the privatization of the largest commercial bank (i.e., Uganda Commerical Bank) that led to increased competition. However, findings regarding the effect of policy reforms on the cost efficiency of banks are quite mixed. For example, financial liberalization helped to increase cost efficiency in Taiwan (Chen, 2001) but led to reduced/weak cost efficiency in Croatia Kraft et al. (2006) and Korea (Hao et al., 2001).

In the case of East Africa, Podpiera and Cihak (2005) concluded that banks were generally inefficient in Kenya, Tanzania, and Uganda despite the banking reforms carried out in those countries and the entry of foreign banks. Other studies link efficiency levels with macro-financial shocks. For example, due to the global financial crisis, inefficiency increased from 8.56 percent to 13 percent for Tanzanian banks. (Aikaeli, 2006) findings were based on the estimation of a translog cost frontier using data for Tanzania for the 1998-2004 period. However, DEA results showed that commercial banks were technically efficient, with efficiency scores standing at 96.1 percent under the Constant Returns to Scale (CRS) assumption and at 97.5 percent under the Variable Returns to Scale (VRS) assumption. For Kenya, Kamau (2011) found that commercial banks' efficiency scores were low, owing to the global financial crisis. These mixed findings are partly due to differences in methodology, that is, parametric (stochastic frontiers) versus non-parametric (Data Envelopment Analysis).

The studies that associate efficiency levels and the age of the bank (i.e., old versus new) include Kraft et al. (2006), who argued that old banks are more likely to be efficient compared to new ones.

Their argument is that the old banks have gained business experience, have better managerial efficiency, and thus operate closer to the efficiency frontier. Studies that analyze the effect of bank ownership structure on bank efficiency are quite varied in terms of empirical findings and scope.

With respect to scope, some studies focus on assessing efficiency levels for publicly versus privately owned banks, while others focus on domestic versus foreign banks. For the case of Kenya, the average efficiency score for public banks was relatively higher compared to private banks, though the difference is not all that big. Hasan and Marton (2003) concluded that banks with foreign ownership were more efficient compared to those with domestic ownership, and this could be related to the fact that foreign banks tend to import modern technologies, such as the computerization of bank processes and use of Automated Teller Machines, from their home countries (Kablan, 2010). Conversely, domestic banks were found to be efficient compared to foreign banks for the case of Malaysia (Tahir et al., 2010). For the case of Ghana, Buchs and Mathisen (2005) found that foreign banks were more efficient in generating revenue (interest, commissions, and fees).

The entry of foreign banks can be beneficial if they own a big share of banking system assets and import innovative intermediation methods. Some studies have argued that foreign bank penetration is higher in Anglophone countries than in Francophone African countries and that in the former, banks tend to be efficient owing to better management and technology (Kirkpatrick et al., 2008). Increased entry of foreign banks was also found to reduce inefficiency in the case of 11 transition economies (Bonin et al., 2005). A combination of entry of foreign banks and privatization was found to positively affect efficiency in 22 developing countries (Boubakri et al., 2005).

While studies on measurement and drivers of efficiency have been extensively studied for individual African countries and sub-regions, Gisanabagabo and Ngalawa (2017) did the only study on Rwanda. Using data for seven (7) Rwandan commercial banks for the 2007-2013 period, the stochastic frontier estimations showed that average efficiency stood at 88.56 percent but varied across banks with respect to bank ownership (foreign versus domestic) and management as measured by the tenure of the banks' executive officers (CEOs). Foreign ownership increased efficiency while the short tenure of CEOs increased inefficiency. The paper argues that foreign ownership is linked to the importation of new technologies and better management practices. In this study, we build on the Gisanabagabo and Ngalawa (2017) paper and make certain modifications to address the research gaps mentioned in the introduction section.

3. Methodology

The empirical literature has focused on the estimation of efficiency scores as well as on the determination of the drivers of efficiency (De Abreu and Ceglia, 2018). Both the Data Envelopment Analysis (DEA) and Stochastic Frontier Approach (SFA) have been used to measure the degree of efficiency of firms, particularly of financial institutions such as banks. Being a parametric method, the SFA is more advantageous compared to the DEA (i.e., a non-parametric method).

The main challenge highlighted in most of the studies is the estimation of the efficiency frontier, which is defined by the efficiency levels of the best-performing firms in the sample. For the case of commercial banks, there is generally no sufficient information regarding their production and cost-management technologies. Thus, researchers rely on accounting data from the banks' financial statements regarding costs, inputs, outputs, revenues, and profits to impute efficiency levels and to define the efficiency frontier. Both parametric[1] and non-parametric[2] approaches have been used to measure efficiency levels and to estimate the efficiency frontier. The Non-parametric approaches put relatively less emphasis on the specification of the best practice frontier. Being

[1] These are mainly: (1) The Stochastic Frontier Approach (SFA); (2) The Distribution Free Approach (DFA); and, (3) The Thick Frontier Approach (TFA).

[2] These are: (1) Data Envelopment Analysis (DEA); and, (2) Free Disposal Hull (FDH).

mathematical programming tools, they assume that there are no random errors. In reality, however, there are likely to be random errors due to, for example, measurement errors that can lead to biased estimation of efficiency levels. Conversely, the parametric approach imposes a functional form (and the associated behavioral assumptions) that pre-defines the shape of the frontier. The main drawback of the parametric approach is that misspecification of the functional form leads to biased estimation of the efficiency frontier and efficiency scores of the firms in the sample. There is generally no consensus regarding which of the two approaches is better in terms of yielding efficiency scores that are close to reality (Berger et al., 1993a).

There is consensus that the SFA has advantages over the DEA. First, the SFA enables the decomposition of the error term into a random and inefficient term, with the former capturing measurement error and exogeneous shocks. Second, the SFA results are not greatly contaminated by outliers. The SFA estimates the frontier, which is the possible maximum output given a set of inputs. The best performing banks are on the frontier, while the relatively inefficient ones are below the frontier. The frontier and bank-level efficiency scores are determined from estimations of a given objective function, which are generally production, cost, and profit functions. The objective function can be linear, Cobb-Douglas, Constant Elasticity of Substitution (CES), Fourier transformation, and translogarithmic, among others. Third, the SFA enables the identification of variables that significantly affect efficiency.

Even though "…the choice between the various parametric models and estimation procedures is based primarily on ease of use and/or the apparent reasonableness of underlying assumptions, rather than on any strong theoretical foundation" (Berger and Humphrey, 1997, p. 37), the SFA is generally more advantageous compared to the other parametric approaches, namely, the Distribution Free Approach (DFA) and the Thick Frontier Approach (TFA). The main weaknesses of the DFA are that: (1) it assumes that the inefficiency of a particular firm/bank is stable over time. This is unrealistic since inefficiency levels can vary over time due, for example, to deterioration in bank management; (2) it does not impose a distribution assumption[3] of the inefficiency term. In fact, the inefficiency term can follow any distribution as long as estimated inefficiencies are positive, and (3) the mean of the random error converges to zero over time[4]. The TFA is often criticized based on the fact that: (1) it does not impose a distribution assumption on both the random error and the inefficiency term; (2) it does not provide exact point estimates of efficiency for individual firms as it is mainly designed to help in estimating the general level of overall efficiency.

The DEA is simply a mathematical programming tool in which several input-output combinations are used to generate efficiency scores for each firm. The most efficient firm (s) define the envelope surface, and the efficiency scores for other firms are computed relative to this envelope surface. In this paper, we estimate the cost function, and this choice is based on the fact that the specification of the cost function enables us to include multiple outputs in measuring efficiency (Kablan, 2010).

In our study, we use the SFA to estimate a translogarithmic cost function for 10 Rwandan commercial banks whose data are available on a quarterly basis for the period 2012Q1-2021Q3. The translog function is flexible as it takes into account complementarities between explanatory variables and also imposes no restrictions on the functional form (Kablan, 2010).

Empirical evidence shows that the translog function is a fair representation of actual data and is also more flexible since it enables substitution among inputs (Battese and Coelli, 1995). We define the cost function in its generic form along the lines of Aigner et al. (1977) and Meeusen and Van Den Broeck (1977) as follows:

$$C_{it} = C\left(y_{it}, w_{it}, \beta\right) exp\left(u_{it}\right) exp\left(v_{it}\right) \dots\dots\dots\dots\dots.(1)$$

Where "i" denoted bank, with i=1,…., 10. Likewise, "t" denoted time, with t=2012Q1,…, 2021Q3. y_{it} stands for output of bank "i" at a time "t," and as noted above, this can be more than one output; w_{it} is a vector of input prices for bank "i" at time "t"; β is a vector of parameters; u_{it} is the non-negative error term representing bank-level inefficiency; v_{it} is the random error term, capturing measurement errors and exogenous shocks, assumed to be i.i.d N(0, δ_v^2). For this model to hold, u_{it} is assumed to be independently distributed of v_{it}.

As already mentioned, a translogarithmic version of equation (1) will be estimated. Aside from the functional form, we need to provide theoretical backing for the modelling of the inefficiency term (u_{it}). Another issue that needs to be settled out is the choice of outputs, inputs, and the vector of input prices. For the case of commercial banks, the outputs and inputs are quite hard to define.

However, three approaches have been used to address this issue, namely, the intermediation approach (Chortareas et al., 2016), the value-added approach (Berger et al., 1987), and the user-cost approach (Hancock, 1985). The three approaches provide guidelines on classifying balance sheet items as either outputs or inputs.

[3]Assuming a distribution assumption is useful for inference and hypothesis testing.

[4] This may not apply to all firms due to heterogeneity issues.

The intermediation approach assumes that banks transform collected deposits and other purchased inputs (such as physical and financial capital) into different categories of bank assets, such as loans and investment in securities.

To perform the intermediation role, the bank incurs costs such as interest paid on borrowed funds and operating expenses. Under this approach, deposits, liabilities, labor, and capital are regarded as inputs, while assets such as loans are regarded as outputs.

The user-cost approach classifies outputs and inputs based on the criterion of the contribution of a financial product to the bank's net income. A financial asset is considered as an input if its financial performance exceeds the opportunity cost of funds. Liability becomes an asset when its financial cost is below the opportunity cost (Hancock, 1985). The value-added approach classifies the banks' balance sheet items (i.e., assets and liabilities) as either outputs or inputs based on their contribution to value-added or because they are associated with the consumption of real resources (Berger et al., 1987).

Since deposits constitute elements on which the customers bear opportunity cost and since they play a role in the creation of value-added for the bank, they are considered as both outputs and inputs as per user-cost and value-added approaches, just like deposits, loans also contribute to the creation of the bank's value-added and are thus also considered as outputs.

In view of the above, we will follow the intermediation approach as in Gunes and Yildirim (2016), whereby the total cost of the bank is defined as the sum of interest and non-interest expenses. Since loans and government securities have the biggest share in total bank assets, we shall use them as the only two outputs. This is premised on the fact that the main activities of banks in Sub-Saharan are: taking deposits, giving out loans, and investing in securities (Kablan, 2010). The importance of loans and securities is also evidenced by their respective big share in total assets (see figure 1).

Just like in other Sub-Saharan African countries, banks in Rwanda have adopted a strategy that gives deposits a large share in the output combinations they offer, given the lower intermediation ratio, suggesting that banks face challenges regarding the transformation of deposits into credit to the private sector (Kablan, 2010).

Regarding input prices, we include the price for labor and physical capital as the first input price. The second input price is the price for loanable funds. The table below precisely defines the variables included in the translog stochastic cost frontier estimation (ignore time-index (t) and bank index (i)).

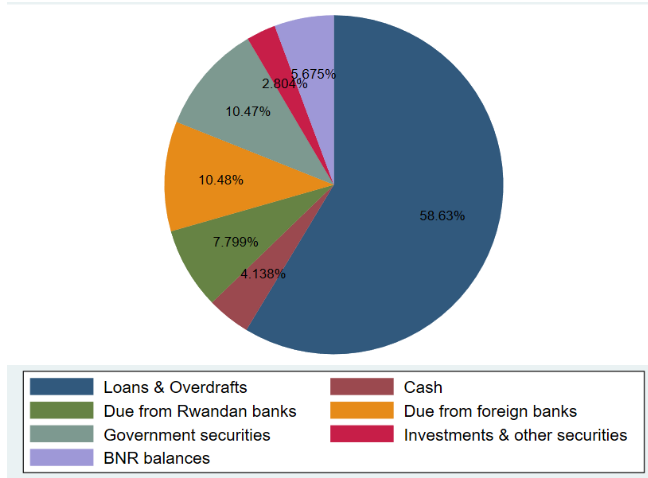

Figure 1: Average share in total assets (net), in percent

As noted in the introduction, conditioning bank inefficiency on a set of dummy variables to capture bank-specific characteristics is not a good idea as it may lead to over-specification of the cost function and underestimation of inefficiency levels, a problem that is solved by using the modified true fixed effects model (Greene, 2004).

The original true fixed effects model treats time-invariant bank-specific heterogeneity and time-varying inefficiency separately by integrating dummy variables, such as for management quality, ownership structure, and the degree of government intervention into the cost function. The same dummy variables are again used in the time-varying inefficiency function. This is the approach used by Gisanabagabo and Ngalawa (2017), which yields a biased estimation of inefficiency, worsened by the two-step estimation procedure since some of the explanatory variables in the cost function are similar and thus correlated with those in the inefficiency model. The best way is to exclude time-invariant fixed effects from the cost function and include them only in the inefficiency function, which is the basis of the modified true fixed effects model.

Consequently, we follow the modified true fixed effects model (Greene, 2004; Gunes and Yildirim, 2016), where heterogeneity is embedded in the inefficiency distribution. The inefficiency distribution is defined by mean cost inefficiency (μ_{it}) and the variance of inefficiency (δ_u^2):

$$\left(N\left(\mu_{it}, \delta_u^2\right)\right| \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

This way, unobserved time-invariant bank-specific heterogeneity (ξ_i) can be accounted for by defining an equation for mean cost inefficiency:

$$\mu_{it} = \xi_i + \eta' z_{it} \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Table 2: Variable(s) definition(s)

Variable	Description
Inc	Natural log of the ratio of cost_tot to w_2, due to normalization.
cost_tot	Total expenses, containing: Interest expense-deposits; Other interest expenses; Provisions for bad debts; Salaries, wages and staff costs; Premises, depreciation and transport; and, Other expenses.
lny_1	Natural log of output 1: Loans and overdrafts (net).
lny_2	Natural log of output 2: Government securities.
Lnw	Natural log of the ratio of w_1 to w_2, due to normalization.
w_1	expense_nonint/assets_tot ; used as a proxy for the price of labor and capital.
expense_nonint	Total non-interest expenses composed of Provisions for bad debts; Salaries wages and staff costs; Premises, depreciation and transport; and, Other expenses.
assets_tot	Total assets (net).
Lnassets	Natural log of assets_tot.
w_2	expense_int/assets_tot ; used as a proxy for the price of loanable funds.
expense_int	Total interest expenses composed of Interest expense-deposits; and, Other interest expenses.
Intermediation ratio	Ratio of total net loans to total deposits.
Bank funding structure	Ratio of total deposits to total liabilities.
Liquidity ratio	Ratio of liquid assets to total net assets.
Credit risk	Natural log of Non-Performing Loans (NPLs).

In equation (2) u_{it} stands for the inefficiency term, while in equation (3), η denotes parameters to be estimated. Mean cost inefficiency is conditioned on the time-variant z_{it} correlates, extracted from the banks' balance sheets. These are[5]: lnassets (-), used to control for the impact of scale bias on inefficiency; intermediation ratio (-); bank funding structure (-); capital ratio (-); and finally, credit risk (+). As mentioned before, "i" denotes bank, with i=1,...., 10. Likewise, "t" denotes time, with t=2012Q1,..., 2021Q3.

However, we need to define a probability distribution for the inefficiency term. With a half-normal distribution, most banks tend to be clustered around full efficiency, unlike when a truncated normal distribution is assumed (Greene, 1990). Thus, we assume that the inefficiency term follows a truncated normal distribution with a heterogenous mean across banks. The efficiency score for an individual bank is computed as the ratio of the cost of the most cost-efficient bank (i.e., one with zero or least costs) to the cost of the bank in the equation. To ensure that cost efficiency lies within the boundary of 1 and 0, the generic form of the cost efficiency function can be stated as:

$$CE_{it} = exp\left(-u_{it}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

From the foregoing theoretical background, we define our empirical translogarithmic cost function as follows:

$$lnC_{it} = \beta_0 + lny_{1it} + lny_{2it} + lnw_{it} + 0.5*(lny_{1it}*lny_{2it}) + 0.5*(lny_{1it}*lnw_{it}) + 0.5*(lny_{2it}*lnw_{it}) + 0.5*lny_{1it}^2 + 0.5*lny_{2it}^2 + 0.5*lnw_{it}^2 + \varepsilon_{it} \ldots\ldots(5)$$

Where ε_{it} is the composite error term, decomposed into the random errors (v_{it}) and the inefficiency term (u_i) as follows:

$$\mu_{it} = \xi_i + \eta' z_{it} \ldots\ldots\ldots\ldots(6)$$

As noted above, we assume a modified true effects model based on assumptions embedded in equation (2) and equation (3) above. The true fixed effects model is more valid for this study, given that we do not randomly select the sample of banks from a large pool but rather pick commercial banks operating in Rwanda. Data on bank-specific variables are obtained from the quarterly balance sheets of 10 out of 11 licensed commercial banks over the 2012Q1-2021Q3 period. One bank is not considered due to the insufficient data coverage within the sample period. To accommodate for the dynamic nature of bank efficiency, we estimate a time-varying decay true effects model.

To estimate the translogarithmic cost function, we assume symmetry regarding the square terms and cross-products, respectively. This implies starting with 0.5 as the coefficient on cross-products and square terms. We also normalize total costs and price for labor and capital (w_1) by the price for loanable funds (w_2) to ensure linear homogeneity of the cost function. In addition, we impose regularity conditions by including capital ratio among the z_{it} correlates in the mean cost inefficiency equation.

[5] Expected signs are put in parentheses, showing whether the variable increases (+) or reduces (-) inefficiency. Justifications are given in Gunes and Yildirim (2016).

The assumptions of linear homogeneity, regularity conditions, and symmetry ensure that the cost function is monotonically increasing in input prices and outputs and concave in input prices, which is consistent with economic theory.

The parameters of the translog cost function (equation 5) and the of the inefficiency model (equation 3) must be estimated simultaneously, in a single-step procedure as noted in Greene and Segal (2004) , to correct for biases that may result from the potential correlation between variables included in the cost function and those included in the inefficiency function. We use the maximum likelihood method in the estimation, where the likelihood function is formed using the following parameterizations:

$$\lambda = \frac{\sigma_v}{\sigma_u} \quad (7)$$

$$\sigma = \sqrt{\sigma_u^2 + \sigma_v^2} \quad (8)$$

To carry out the estimations, we use the "sfpanel" command and make use of the true fixed effects options as documented in the Stata journal (Belotti et al., 2013). In addition, we derive variables of the translog function using the automated Stata module by Du (2017). Single-step maximum likelihood estimation of the cost function and inefficiency model gives the bank-specific intercepts (denoted as alpha in Stata). A joint significance of these coefficients can then be tested for the validity/presence of fixed effects.

4. Financial sector development in Rwanda and drivers of commercial banks' efficiency

This section begins by summarizing the financial sector developments that have affected intermediation efficiency over the years. We then proceed to give empirical estimations for the stochastic cost frontier, separated into two parts: estimation results for the cost function and the estimation results for the inefficiency function. We then present some graphics showing efficiency and inefficiency levels across banks and across time. Thereafter, we give conclusions and policy recommendations.

4.1. Summary of financial sector developments in Rwanda

As noted in the introduction, Rwanda's financial sector has progressively become more liberalized since 1995. A preliminary assessment by the IMF (2011) in 2011 indicated that financial liberalization had led to the increased entry of new banks and thus to competition, resulting into intermediation efficiency as measured by declining net interest margins and/or interest rate spreads (Karangwa and Nyalihama, 2014). The improvement in the regulatory framework, in line with the Basel principles, was one of the reasons for the continued deregulation of the financial sector.

The financial sector has also been expanding over time. Prior to 1995, there were only 12 financial institutions, composed of 5 banking institutions and 7 non-banking institutions. By the end of December 2020, Rwanda's financial sector grew to 504 institutions, composed of 16 commercial banks, 14 insurance companies, 1 public pension fund, 12 private pension funds, 457 Micro Finance Institutions (MFIs), and 4 Non-Deposit Taking Financial Institutions (NDFIs). However, the banking sector remains the dominant financial sector component in Rwanda, with 67 percent share in total assets (Kigabo, 2021).

As noted in table 1, intermediation efficiency is still low in Rwanda compared to countries like Singapore and South Africa with more developed financial systems. For example, by 2017, the net interest margin, which is one of the measures of the efficiency of intermediation, stood at 9.3 percent in Rwanda compared to 1.9 percent in Singapore and 3.7 percent in South Africa.

The interest rate spread remains high due to high and rigid lending rates, among other factors. Commercial banks largely rely on deposits from the social security fund and other financial corporations (i.e., insurance companies, MFIs, and SACCOs), with an average share in total deposits of 45.4 percent between 2015 and 2019. This means that banks compete to attract large depositors by offering them favorable remuneration on their deposits, which increases the cost of funds and contributes to high lending rates (Kigabo, 2021). In addition to the high cost of funds, Rwanda, just like most of its East African peers, still has high bank overhead costs to total assets ratio (6.5 percent) compared to 1.3 percent for a high-income country like Singapore with a highly developed financial system as noted in table 1.

In view of the above and in line with empirical evidence, factors like cost of funds, credit risk, overhead costs among others, have been highlighted as drivers of the observed high interest rate spread in Rwanda (Kigabo et al., 2016; Karangwa and Nyalihama, 2018). The main activity of commercial banks in Rwanda is lending, given that the average share of loans and overdrafts (gross) in total assets (net) stood at around 58.6 percent between 200Qq1 and 2021Q3 while the share has been generally above 50 percent, ranging between 48.8 and 67.2 percent.

To be able to give out credit, the main source of funds for commercial banks in Rwanda is deposits, explaining why deposits have a large share in total liabilities. Though the share of deposits in total liabilities has been declining

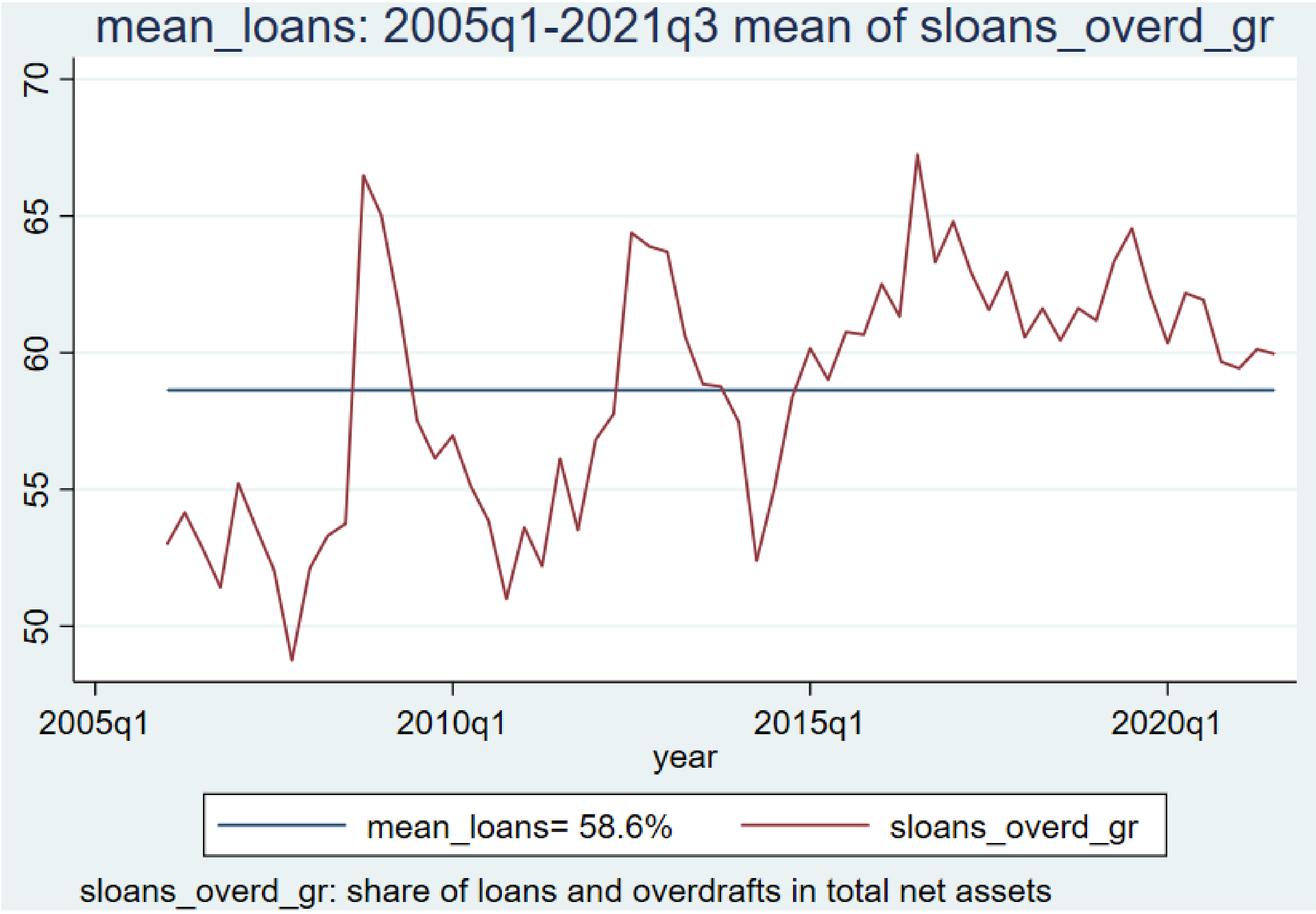

Figure 2: The share of loans in total assets (percent)

in recent periods, it is still high, standing at 83.3 percent and ranging between 73.7 percent and 90.5 percent for the 10 commercial banks during the 2006Q1-2021Q3. However, most of these deposits are short-term, leading to mismatches between long-term investment needs and short-term deposits.

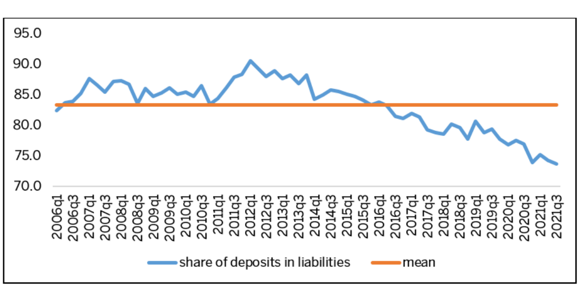

Figure 3: Share (percent) of deposits in total liabilities

In addition to the deposit market power in favor of the social security fund and other financial corporations, the loans market became concentrated since 2018, indicating the increase in loans market power for some banks (Kigabo, 2021). With such power, dominant banks can influence the setting of price (i.e., lending rate) or apply a market segmentation strategy by (1) applying lower lending rates to big borrowers relative to small ones; (2) concentrating their activities in urban areas with relatively high economic activities; and,(3) lending to less risky sectors of the economy (Kablan, 2010; Kigabo, 2021).

4.2. ***Empirical results***

As explained in Gunes and Yildirim (2016), the main focus is on the interpretation of the determinants of inefficiency for commercial banks in Rwanda. Apriori, the intermediation ratio, bank funding structure, capital ratio, and bank size are expected to negatively affect inefficiency, while credit risk is expected to positively affect inefficiency. Empirical results show that the intermediation ratio has a significant (at 1 percent) negative effect on commercial banks' inefficiency in Rwanda, given that banks with a high capacity to collect deposits and convert them into loans are considered more efficient.

The capital ratio also has a significant (at 1 percent) negative effect on inefficiency, implying that the higher the capital ratio, the lower the inefficiency. This is because

Table 3: Single-step estimation results for the stochastic frontier cost function

Cost function		**Inefficiency function**	
lny_1	1.27	Intermediation ratio	-7.62***
	(1.41)		(-5.38)
lny_2	-0.21	Bank funding structure	-6.10*
	(-0.45)		(-1.82)
lnw	2.53**	Capital ratio	-34.14***
	(2.16)		(-3.30)
0.5*($lny_1 * lny_2$)	-0.06	Credit risk = ln(NPLs)	0.51*
	(-0.88)		(1.73)
		Bank size =ln(total assets)	0.66
			(1.24)
		σ_v _constant	-3.91***
0.5*($lny_1 * lnw$)	-0.25*	E(σ_u)	0.498
	(-1.91)		
0.5*($lny_2 * lnw$)	0.08		
	(0.90)		
0.5*lny_1^2	0.00		
	(0.08)	σ_v	0.142***
0.5*lny_2^2	0.05**		
	(1.98)		
0.5*lnw^2	0.01		
	(0.08)		

z statistics are in parentheses. **Source:** Own estimations. **Significance levels:*** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note that we considered that our sample of 10 commercial banks is not random. To formally test for this, we use a joint significance test for the following null hypothesis:
The Ho is actually a test for the presence of fixed effects. The chi-square statistic is 31.97 with a p-value of 0.000, which leads us to reject the Ho and conclude that the time-invariant bank-specific effects are statistically significant, thus justifying the use of the fixed-effects model.

a particular bank is well-capitalized either due to good quality management or efficient risk mitigation measures, all of which help cut inefficiencies.

Contrary to expectation, the log of total assets has a positive sign. However, it is statistically insignificant, implying that bank size does not explain differences in inefficiencies. As expected, credit risk, measured by the log of Non-Performing Loans (NPLs), has a positive marginally significant (at 10 percent) effect on commercial banks' inefficiency in Rwanda since banks with poor credit risk management measures tend to face operational challenges. The bank funding structure, which measures the coverage of liabilities by deposits, has a negative significant effect on inefficiency since a bank that can meet its obligations (i.e., liabilities) using mobilized savings is much more likely to increase its efficiency levels.

In line with the above empirical results, the estimated average efficiency score for the 10 Rwandan commercial banks included in the sample is 81.3 percent, compared to 88.56 percent obtained by Gisanabagabo and Ngalawa (2016). Differences could be a result of the use of different number of banks, time-period, functional form of the cost function, and the estimation technique. However, the efficiency scores vary across banks[6], time, and bank ownership.

Regarding bank ownership, it is clear that domestically-owned banks are more efficient than foreign-owned banks. The average inefficiency score for domestically-owned banks is estimated at 20.2 percent, compared to 18.8 percent for foreign-owned banks.

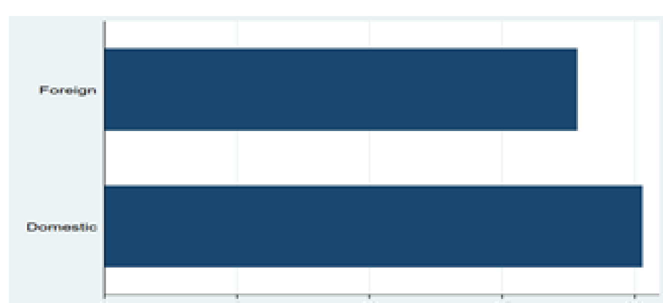

Figure 4: Inefficiency scores by bank ownership

The domestically-owned banks are Bank of Kigali, Banque Populaire du Rwanda, and Cogebanque, while foreign banks are Access Bank, Bank of Africa (BOA),

[6] Due to the sensitivity of the data, we do not report effiency levels by bank.

ECOBANK, Equity Bank, GT Bank, I and M, as well as the Kenya Commercial Bank (KCB). Obviously, the domestic banks have a large share in both the loans and deposit markets and have been on the market for quite long compared to foreign banks.

The period 2018-2022 was generally characterized by the increase in efficiency levels for the 10 Rwandan commercial banks due to the decline in credit risk, increase in the intermediation ratio, increase in the bank funding structure, and the increase in the capital ratio (figure 5).

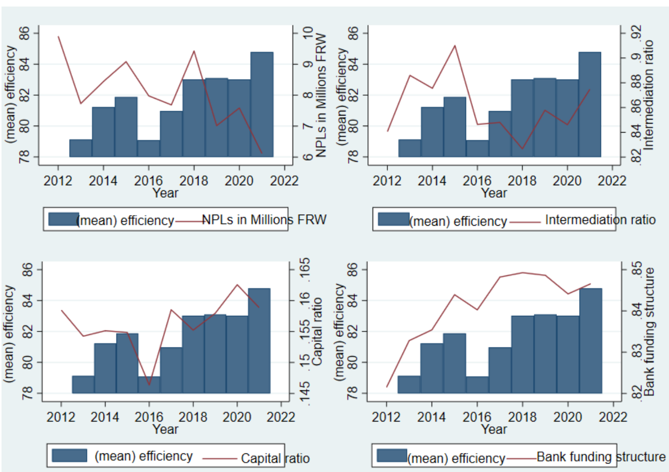

Figure 5: Efficiency levels by time

Given these developments in the Rwandan commercial banking industry, an updated study to complement Gisanabagabo and Ngalawa (2016)'s findings is highly important.

5. Conclusion and policy recommendation

This study builds on the Gisanabagabo and Ngalawa (2016) empirical analysis of the drivers of cost efficiency for the Rwandan commercial banks. The study employs a translog cost function and estimates a true fixed effects model using a single-estimation approach to be able to integrate unobserved bank heterogeneity in the inefficiency function at the mean level and thus control for the potential correlation between drivers of inefficiency and some of the explanatory variables in the cost function.

In line with increased financial sector reforms, empirical estimations (Table 3) and figure 5 show that, especially since 2018, intermediation ratio, bank funding structure, and capital ratio positively affect the efficiency levels of the ten Rwandan commercial banks included in the sample, whereas NPLs have a significant negative effect on efficiency levels.

Bank size does not seem to influence differences in efficiency scores across time and across banks. The choice for the true fixed effects is based on the fact that our sample is not randomly selected from a large pool of commercial banks. This is further validated by the test for the validity of the fixed-effects model.

Empirical findings also show that domestically-owned banks are more efficient than foreign-owned banks. This could be attributed to the fact the former has operated in Rwanda for quite some time and, therefore, could have established operational mechanisms to mitigate risks and manage costs. On average, the efficiency score is estimated at 81.3 percent compared to 88.56 percent obtained by Gisanabagabo and Ngalawa (2016), and the cited gaps could be a source of discrepancy.

As a policy recommendation, Rwandan commercial banks can generally record further reductions in inefficiencies if they put in place or strengthen existing measures to mitigate credit risk, increase intermediation, and increase their funding structures and capitalization, as these can help to deal with macro-financial shocks.

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