Fintech and Banks Collaboration: Does it Influence Efficiency in the Banking Sector?

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Abstract

The efficiency of the banking sector in Sub-Saharan Africa is low compared to rest of the world and Fintech is taunted to alter this scenario. Efficient banks increase financial stability, intermediation and value to the shareholders. As Fintech innovations continue to alter the landscape in the banking sector, banks in Kenya are forming collaborations that are envisioned to shape the evolution of credit allocation and delivery of services. The study investigates the influence of Fintech on a bank's efficiency in credit allocation using the data envelopment model with input-orientation based on the intermediation dimension. Efficiency scores are decomposed as technical efficiency, pure technical efficiency and scale efficiency. Secondary data for the period 2009-2018 is extracted from thirteen banks sampled from the top fifteen banks in Kenya based on their market share. The banks are either locally owned or listed in Nairobi Securities Exchange, of which five have Fintech collaborations with a Pre-Fintech and Post Fintech period. Panel regression model tested the effect of financial ratios on technical efficiency of the banks. Fintech collaborating banks are more technically efficient based on models M1, M2 and M3 in Pre-Fintech. In Post Fintech, the Fintech banks are more efficient based on models M2, M3 and M4 but with decreasing returns to scale which is due to the banks being overly large, thus non-optimal in their operations. The positive effect on technical efficiency is observed from the ratios, liquidity, loan intensity, return on assets and cost of income. Cost of intermediation and credit risk had a negative effect on technical efficiency. Therefore, Fintech and banks collaborations did not significantly influence efficiency in the banking sector.

Keywords: Collaboration, efficiency, banks, Fintech, technical, and data envelopment analysis

1. Background of the Study

A symbiotic relationship is developing between the banks and the Fintech as strengths are offsetting one another's inherent weaknesses (Deloitte, 2018). The disruptive innovations, non-bank actors and mobile network providers (MNO) involved in the credit market are referred to as Fintech in this study. Fintech has the potential to accelerate and strengthen the gains made in financial development in Sub-Saharan Africa in the last two decades (IMF, 2019). Banks have embraced and will continue to embrace Fintech to operate a vertically integrated model and as a platform service provider. Fintech is going to power the banks by altering the way banks compete with each other and this has important implications for the banking landscape in credit provision (Accenture, 2016; Deloitte, 2018; World Bank, 2017). At the moment, Fintech accounts for 2% of the credit market (Financial Stability Board [FSB], 2019). Collaboration is more likely between Fintech and the financial service providers, as one Australian bank analyst postulated, "One Fintech will eventually gobble all others, then it will be gobbled up by a bank" (Deloitte, 2018).

Global Fintech investments have had an upward trend. In 2016, 2017 and 2018 the respective investments were USD 63.4 B, USD 50.8 B and USD 111.8 B with 1893 deals, 2165 deals and 2196 deals (KPMG, 2019). A compounded annual growth rate of 44% was realized in Fintech investments between 2013 and 2017 (Ernst & Young [EY], 2018). Artificial intelligence investment in Fintech between 2016 and 2022 is expected to have a growth rate of 63% (EY, 2018). Fintech investments in USA stand at US $ 29 billion, followed by China, then UK and India (Carmona et al., 2018). In 2017, 33% of digitally active consumers globally were using Fintech. The UK, Spain and Germany had 41%, 37% and 35% digitally active consumers respectively. Globally, 50% of users use Fintech for payments and transfers, 24% on insurance, 20% on savings/ investments and 10% on financial planning (Carmona et al., 2018).

The launch of Mpesa in 2007 has continued to provide lessons for banks on how to increase credit allocation in the economy, increase revenues and serve the customers more efficiently. There are approximately 34.8% of the adults using digital credit in Kenya by in the year 2017 (Gubbins and Totolo, 2018). In 2015, the Kenyan commercial banks with Fintech collaborations had 34.65M deposit accounts and 8.51M loan accounts when combined together. For the top three banks active in Fintech and mobile network operators partnerships, Commercial bank of Africa (with Mshwari), Equity (with Equitel) and Kenya Commercial bank (with KCB Mpesa) had the respective deposit accounts, 12.98M, 8.78M and 3.8M accounting for 73.8% of total deposit accounts. The respective loan accounts were 2.69M, 0.95M and 1.26M accounting of 57.6% of total loan accounts (Gubbins and Totolo, 2018). The Kenya Commercial Bank integrated report shows the influence of digital innovations in its operations. Between 2016 and 2017, the mobile loan disbursement increased from USD 0.141B to US 0.296B, cost to serve a customer decreased from USD 2.83 to USD 2.03, while mobile banking transactions increased from 53M to 89M (Kenya Commercial Bank, 2017). Equity bank digitalization and disruptive innovations shows an upward trend. In 2016 to 2017, Equitel users decreased from 65% to 54%, Eazzy Banking App usage increased from 1% to 20% while branch transactions decreased from 6% to 4% in the same period. (Equity Bank, 2017).

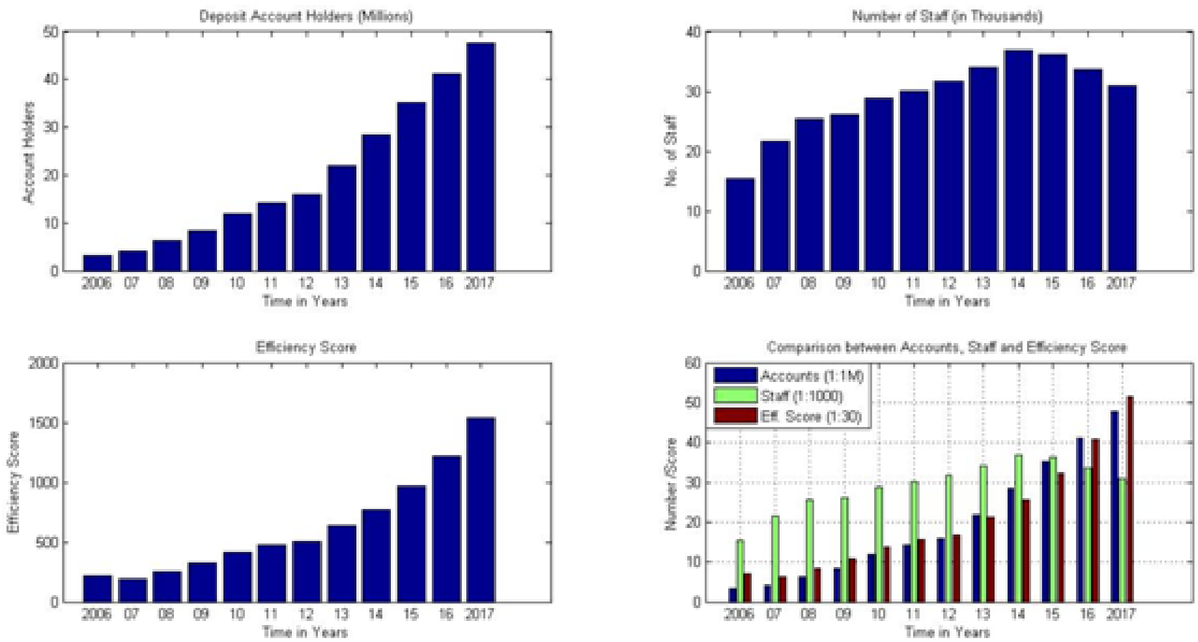

Figure 1: Growth of deposit account holders compared to the number of staff which influences the efficiency score in the banking sector.

In figure 1, even with an increase in number of deposit account holders, the number of staff in the banking sector continued to decrease since 2015 (CBK, 2017). The likely explanation is that banks have adopted more technology to be able to cater for increase in accounts. This has had a positive effect on the efficiency score of the banking sector in Kenya. The choice of the Pre-Fintech and Post Fintech period for this study are guided by figure 1.

The efficiency of the banking sector fosters economic development through financial intermediation and optimal allocation of financial resources (Corbae and Levine, 2018). Banks play a crucial role in money supply by accepting deposits and lending money directly to their customers. An efficient banking sector increases credit allocation to the economy (Yilmaz and Gunes, 2015), withstand shocks and contribute to the stability of the financial sector (Lema, 2017). For a bank to be efficient, it should transform the expense inputs to more productive output as services and products. A bank is technically efficient if it produces a given set of outputs using the smallest possible amount of inputs (Abel and le Roux, 2016; Singh and Fida, 2015). Efficiency makes banks more resilient to shocks, promote economic growth, solve the problem of information asymmetry, mitigate economic fluctuations and promote economic growth (Novickyte and Drozdz, 2018).

The efficiency with which resources are deployed by banks is an important performance measurement. An efficient bank is expected to increase value to the shareholders through effective utilization of resources rather than through exploitation of market power (Abel and Bara, 2017). Adopting better technologies is one sure way to increase efficiency in the banking sector. Because of the ever changing banking landscape due to technological innovations, globalization and financial environment, the evaluation of performance and efficiency of the banking sector in any country is of paramount importance (Xu, 2011). For a competitive banking sector, it is only strong, profitable and efficient banks can reduce the probability of bankruptcy and provide a realistic return to the shareholders (Lema, 2017; Yilmaz and Gunes, 2015).

1.1 Problem Statement

Technological changes and collaborations and competition through Fintech are likely to influence bank's business models, alter the diversity in lending and bank efficiency (Corbae and Levine, 2018). Bank and Fintech collaborations can develop a convergence node between the previously separated market players to drive evolution (EY, 2018; Accenture, 2016) to alter market power and efficiency in the banking sector (FSB, 2019). Fintech in less developed financial markets fill the existing gap in provision of financial services (Carmona et al., 2018), and can reshape efficiency and improve delivery of services and access (World Bank, 2017). Financial industry efficiency in Sub-Saharan Africa is the lowest in the world and Fintech can alter the scenario (IMF, 2019). A need exists to increase a bank's operations to operate at most productive scale and reduce the poor utilization of inputs (Abel and Bara, 2017; Singh and Fida, 2015). In Kenya, since 2015, the bank's employees continue to decrease even with an increase in number of deposit accounts opened (CBK, 2017) and the possible reason is the intermediation process has received a boost from the Fintech and bank collaborations.

In Kenya, Fintech and bank collaborations started in 2011 and continue to be embraced. The study investigates if Fintech has had an influence on bank's technical efficiency. An analysis of the Kenyan banks technical efficiency is presented using DEA technique to estimate the influence of Fintech and bank collaboration and how they affect efficiency in the banking sector by optimizing inputs for a productive operating scale. Efficiency is decomposed into technical, pure technical and scale efficiencies. The DEA model employed input-orientation as banks have more control over inputs with the intermediation dimension. Input-orientation targets to reduce the input amounts as much as possible while keeping the present output levels.

1.2 Objective of the Study

Investigate the influence of Fintech and bank collaboration on the bank's efficiency in credit allocation by optimizing inputs for a productive operating scale.

1.3 Key Hypothesis

Ha: A bank's technical efficiency is increased by Fintech collaboration.

The study contributes to existing knowledge and policy by articulating the pace of changes and diffusion process in financial services innovations. The analysis on technical efficiency of the banks offers more insights to banks that are yet to collaborate with Fintech. As regulators and stakeholders consider the risks inherent from Fintech collaborations, they can ponder on the strengths of Fintech and make informed Fintech investment decisions. Kenya is a leader in mobile money services and the influence it has had on the economy can continue to encourage more Fintech and banks collaboration.

The rest of the paper is organized as follows. Section 2 is the review of relevant literature. Section 3 has the research methodology which comprises of the data source, empirical model, definition and measurement of variables and econometric approach. Section 4 presents the data analysis, findings and discussions for the technical efficiency in the banking sector, as overall technical efficiency, pure technical efficiency and scale efficiency. Section 5 has the conclusions and policy recommendations.

2 Relevant Literature Review

This section discusses the theoretical literature and empirical literature on bank's efficiency scores using the data envelopment analysis method. The section concludes with a summary of the findings and lessons from the empirical review.

2.1 Theoretical Literature

The efficient structure hypothesis (ESH) predicts that efficient firms come out ahead in competition and grow as a result. ESH observes that a bank's structure arises because of superior operating efficiency and a positive relationship between firm profit and market structure exists. This in turn leads to increase in market concentration (Molyneux and Forbes, 1995). The argument on ESH by Demsetz (1973) is that efficiency determines the structure of firms as more efficient firms can afford more market share and hence more market power. Efficiency precedes market power in the banking system as it lowers it operating costs and is better able to acquire more market share resulting in higher market power (Moyo, 2018).

Efficiency in the banking sector is multifaceted with studies taking different dimensions. A bank is technically efficient if it produces a given set of outputs using the smallest possible amount of inputs (Abel and Bara, 2017). In the Data envelopment analysis (DEA) model, the measure of efficiency can apply two types of orientation. The output-oriented models, which answer the question "By how much can output quantities be proportionally expanded without altering the input quantities used?" or the input-oriented models which answers the question "By how much can input quantities be proportionally reduced without changing the output quantities produced?" (Titko and Jureviciene, 2014).

The intermediation approach view banks as intermediaries who channel funds from surplus units to deficit units, collecting funds from depositors and converting them to loans. The production approach assumes that banks are considered as producer of deposits, loans and services by using resources and inputs like capital and labour, (Singh and Fida, 2015). The profitability approach assumes cost-related items such as personnel expenses, non-interest expenses as inputs and revenue-related items such as net interest income and non-interest income as outputs (Novickyte and Drozdz, 2018). The DEA model creates an efficient frontier and evaluates the efficiency of a decision unit. The model is designed to maximize the relative efficiency of each decision unit (Zimkova, 2015).

The assumptions of CRS and VRS are different. VRS means that equiproportionate increases in factor inputs yield a greater (or less) than equiproportionate increase in output. CRS assumption is taken to mean that equiproportionate increases in factor inputs yield an equiproportionate increase in output. The choice of the model specification as VRS or CRS has a significant effect on research results. In using VRS, the number of efficient banks will be larger than under CRS because the data space under the VRS curve is smaller than under the CRS curve (Titko and Jureviciene, 2014).

The DEA model estimates the efficiencies of the banks as Technical efficiency (TE), Pure Technical Efficiency (PTE) and Scale Efficiency (SE). A firm is TE if it produces a given set of outputs using the smallest possible amount of inputs, or TE is the ability of the bank to maximize outputs from a given set of inputs and is associated with managerial decisions. The PTE is a measure of technical efficiency which represents managerial flaw in handling resources used to run the bank that is the management performance (Singh and Fida, 2015). SE is the relationship between the level of output and the average cost hence it relates to the size of operation in the organization or scale of production, the optimal bank size (Abel and Bara, 2017; Singh and Fida, 2015). Pure technical efficiency means proportional reduction in input usage if inputs are not wasted and scale efficiency is the proportional reduction if the bank achieves constant returns to scale.

A bank can operate under constant return to scale, decreasing returns to scale and increasing return to scale. An organization is experiencing an increasing (decreasing) return to scale if the output increases (decreases) more than the inputs. For increasing return to scale, the organization faces the problem of undersize thus should increase its size. For the decreasing return to scale, the organization is overly large above the optimal size. The decreasing or increasing returns to scale signals an organization operating outside the optimal scale. A constant return to scale if the output changes proportionately with an increase or decrease in inputs, hence the organization is scale efficient (Abel and Bara, 2017).

2.2 Empirical Literature

Banks in Kenya exhibit monopolistic competition and are leveraging on the digital space to grow their balance sheet. Some banks are setting up their own Fintech subsidiaries while others forming partnerships with the established Fintech companies (Central Bank of Kenya [CBK], 2017). The effects of banks embracing technology indicates that in 2017, one employee was serving 1,222 customers compared to 1,544 customers in 2016 (CBK, 2017). In Kenya, M-Pesa has revolutionized the banking sector by increasing penetration and financial access. M-Pesa processes more transactions domestically daily than Western Union does globally reaching more than 70% of the country's adult population (Moyo, Nandwa, Odour and Simpasa, 2014). Banks have always adapted to regulatory, cultural and technological shifts, but the pace of change due to Fintech has accelerated the dramatically and quickly changed the bigger picture of banking (Microsoft, 2019). The banking systems efficiency increased with or without competition but the mean efficiency of the model with competition being higher than the model without competition (Akande, 2018).

Bank's capabilities and Fintech firms will promote symbiotic relationships in the future as continued technological innovation will propel this collaboration (Indigo Sky, 2018). A report by The Economist (2017) noted that banks do not hire for transformation, they are concerned with continuity. The collaborations with Fintech companies are to harness the skills and attitudes they do not have. Banks are neither the beginning nor the end of the value chain, so they need to act as trusted intermediary and focus on outcomes (Microsoft, 2019). As the marginal utility of data increases, more added-value in new services is likely to have greater implications for the market structure (FSB, 2019). The financial industry competition and efficiency in Sub-Saharan Africa can be altered by Fintech. Bank competition in the region is low compared to the rest of the world (IMF, 2019).

The DEA model has been applied extensively in estimating efficiency in the banking sector. The determinants of efficiency in the Ethiopian commercial banks over the period from 2011 to 2014 are examined by Lema (2017). Technical efficiency is estimated using DEA with input variables (deposit, operating expenses and interest expense) and output variables (loan, interest income and non-interest income). The status efficiency based on CRS and VRS assumptions have a little difference with an overall increase in the commercial banks efficiency. Banks found to be less efficient under VRS are also inefficient under CRS assumption but some banks are efficient under VRS and inefficient under CRS assumption.

Islamic and conventional banking efficiency analysis using DEA is presented by Yilmaz and Gunes (2015). Technical, pure technical and scale efficiencies are analyzed for the Turkish banking industry for the period 2007 to 2013. The study applied intermediation approach for the DEA model with input variables (deposits and fixed assets) and output variables (loans, income and investments). The findings noted that conventional banks pure technical inefficiencies dominate the scale inefficiencies as managers did not follow appropriate practices and in selecting incorrect input combinations. In Islamic banking, scale inefficiencies dominate pure technical efficiencies in Turkey with an average score of 89.2% in all the years under study.

A cross country banking sector analysis for Latvian and Lithuanian banks is the work of Titko and Jureviciene (2014). The study compared the DEA efficiency score and traditional bank performance ratios; and efficiency of larger banks compared with smaller banks. The input-oriented DEA model is applied under the assumption of VRS. The intermediation approach has input variables (deposits) and output variables (loans and investments). The production approach has input variables (interest expenses and staff costs) while output variables (deposits and loans). The findings are that there is no statistical significant correlation between efficiency scores and financial ratios while larger banks are more efficient than the smaller banks in the sample of study.

A study in China's banking sector efficiency is investigated using the technical efficiency, pure technical efficiency and scale efficiency. DEA is used to estimate banking efficiency scores where a comparison between other newly joint stock banks and state owned banks is conducted (Xu, 2011). Newly joint stock banks are more efficient than the state owned banks but the overall efficiency in the banking sector increased during the ten year period under study. The overall bank's efficiency in China is low and the government should create a better environment to facilitate the achievements gained so far in the sector.

The efficiency of Lithuanian banking sector and bank performance in a low interest rate environment is estimated with DEA (Novickyte and Drozdz, 2018). Efficiency scores are calculated with the variable returns to scale and the constant return to scale assumptions. Five models with different combinations of input and output variables are considered based on input-orientation with profitability, intermediation and production dimensions. The efficiency scores are presented as technical efficiency, pure technical efficiency and scale efficiency. The study findings showed that all banks in the study are technically efficient with an average score of 80% based on production dimension. On the profitability dimension, banks are able to manage the low interest rates environment with intermediation dimension showing efficient use of the available resources.

The efficiencies of commercial banks of Oman are investigated using technical, pure technical and scale efficiencies. The research takes two-step DEA procedure (Singh and Fida, 2015). In the first step, DEA measures technical efficiency scores and the second step used Tobit model, censored regression to investigate the determinants of technical efficiency. The log of capital adequacy, total assets, operating profit to total assets and loan to deposit ratio form the independent variables for the Tobit model and the technical efficiency scores form the dependent variable. The result showed that technical inefficiency in the Oman banking sector is due to both poor input utilization that is managerial inefficiency, and failure to operate at most productive scale size, that is scale inefficiency.

A study of Zimbabwean banks using DEA covered the period 2009-2015. The DEA input variables (capital, interest expense and non-interest expenses) and the output variables (total loans and non-interest income). A decomposition of technical efficiency into pure technical efficiency and scale efficiency is undertaken with a sample of eleven banks, six domestic and five foreign banks (Abel and Bara, 2017). The average score for pure technical and scale efficiencies is 96.6% and 85.6% respectively with a technical efficiency score of 82.9%. The managerial efficiency scores were higher than technical efficiency scores as majority of the banks were operating at the wrong scale of operations. The operations are under decreasing returns to scale, indicating an opportunity to increase operations to obtain optimum scale.

In summary, the literature review found that DEA estimates technical efficiency using the input variables (deposits, operating expenses, labor expenses and interest expenses) and output variables (loan, interest income, and operating profit and non-interest income). The intermediation, profitability and production dimensions are applied based on VRS, CRS or both CRS and VRS scales. The input-orientation is commonly used in the DEA. The banking sector efficiency is decomposed into technical efficiency, pure technical efficiency and scale efficiency. Banks with higher ratio of loans to deposits are more efficient which indicates managerial efficiency. Larger banks are more efficient than smaller banks while domestic banks are relatively efficiency compared to foreign banks. Poor input utilization is evidence of managerial inefficiency which is observed through technical inefficiency. For scale inefficiency, the bank has failed to operate at the most productive scale size. The efficiency of the financial industry in Sub-Saharan Africa is low compared to the rest of the world. Fintech can alter this trend by accelerating and shift the pace of change in competition and efficiency of the industry.

This study is an extension of previous studies, but with the value addition of considering the influence of Fintech on banking sector efficiency in Kenya by optimizing inputs for a productive operating scale. The study applied DEA technique and considered four models with different combinations of input and output variables, based on intermediation dimension. The input-orientation for the VRS and CRS are used to investigate if Fintech and bank collaborations are influencing efficiency in the Kenyan banking sector.

3.0 Methodology

This study aimed at examining the influence of Fintech on technical efficiency in credit allocation through optimization of inputs by banks with Fintech collaboration using the DEA model. The following section presents a discussion on the empirical model, definition and measurement of variables, econometric approach and sources of data.

3.1 Data Source

The objective is to investigate the influence of Fintech and bank collaboration on the technical efficiency in the banking sector. The analysis employed financial statement data for a period of 10 years, 2009-2018, using a sample of 13 banks segmented into four groups based on shareholding information (Locally owned and NSE listed) and Fintech collaboration. The 11 banks are selected on the criteria in table 1 and should be among the top 15 banks according to market share. The secondary data on input variables (deposits, interest expenses, loans) and output variables (interest income, loans and deposits). A combination using 4 models based on intermediation dimension is applied to the input and output variables.

Table 1: Sample size based on shareholding information and Fintech collaboration

SN	Banks	Locally owned	NSE listing	Fintech	Pre-Fintech	Post-Fintech
	Groups	G1	G2	G2		
1	Barclays Bank of Kenya		Y			
2	Co-operative Bank	Y	Y	MCo-op	2009-2014	2015-2018
3	Commercial bank of Africa	Y		M-Shwari	2009-2012	2013-2018
4	Diamond Trust Bank		Y			
5	Equity Bank	Y	Y	Equitel	2009-2014	2015-2018
6	Family Bank	Y		Pesa-Pap	2009-2012	2013-2018
7	I & M Bank	Y				
8	Kenya Commercial Bank		Y	KCB Mpesa	2009-2014	2015-2018
9	NIC Bank	Y	Y			
10	National Bank		Y			
11	Stanbic Bank		Y			
12	Standard Chartered Bank		Y			
13	Prime Bank	Y				
Number in each sample		7	9	5		
Y –Yes, banks belongs to the sample						

Table 1 highlights the top 13 banks in Kenya based on the market share. The summaries are for the two samples based on the shareholding information. There are seven banks that are locally owned (Group G1) and nine banks are listed in the Nairobi Securities Exchange (Group G2). The third sample has five banks (Group G3) with Fintech collaborations and the period of Pre-Fintech and Post Fintech is highlighted. Among the top 15 banks, the study excludes Citibank and Bank of Baroda.

3.2 Variables definition and measurements

Table 2 presents the list of variables in the DEA model using the intermediation dimension, with the respective definition and measurements. Table 3 has the variables for testing the significance of Fintech collaboration influence on efficiency using regression analysis. This is to test what influences efficiency among the banks under study.

Table 2: The variables in the DEA model

SN	Variable	Variable name	Measurement
1	D	Deposit	The sum of demand, saving and time deposit.
2	IE	Interest expenses	The sum of payment on saving, fixed deposits and demand deposits
3	L	Total loans	This includes real estate, consumer, commercial and industrial loans.
4	II	Interest income	The sum of interest on loans, advances and interest on treasury bills.

Table 2 presents the secondary data variables for the DEA model using the four models are deposits, loans, and interest income and interest expenses.

Table 3: Financial ratios for the panel regression analysis

SN	Variable	Variable name	Measurement
1	CR	Credit risk	Ratio of non-performing loans to total loans – high ratio implies lower efficiency due to loan portfolio deteriorating
2	LR	Liquidity ratio	Ratio of loans to deposits – low ratio signals high operating efficiency
3	LI	Loan intensity	Ratio of loans to assets – high ratio increases risk
4	CI	Bank's cost of intermediation	Ratio of net interest income over average total assets – high cost implies credit rationing
5	CIR	Cost income ratio	Ratio of cost to income – a measure of efficiency in profitability, the higher the ratio, the lower the efficiency
6	ROA	Return on assets	Measures the profitability of the bank. It is related to optimal use of resources and the expectation is a positive relationship between profitability and efficiency measures.

Table 3 presents the secondary data from the financial statements with four ratios, credit risk, liquidity risk, loan intensity and bank's cost of intermediation and the bank size which is the log of total assets. The variables examine the determinants of the efficiency score among the banks in the study.

3.3 Methods of analysis

The R software and Microsoft Excel analyzed the data. The study adopts descriptive statistics to summarize the DEA input and output variables for each bank. The panel regression model is regressed against the financial ratios in table 3 for both the Pre-Fintech and Post Fintech periods for each of the three groups. The DEA model estimated the technical efficiency of the banks based on intermediation dimension with a combination of input and output variables.

3.3.1 Data Envelopment Analysis

The data envelopment analysis (DEA), a non-parametric model and a mathematical programming technique measures the efficiency of a decision making unit (DMU) relative to other similar DMU. The DEA model calculates the efficiency of each DMU using the actual observed values for the inputs and outputs of each DMU (Thu Vu and Turnell, 2010). The CCR model is the basic DEA model introduced by Charnes, Cooper and Rhodes (1978) and has constant return to scale (CRS) assumes no significant relationship between the scale of operations and efficiency while delivering the overall technical efficiency. The CRS assumption holds when all DMUs are operating at an optimal scale. A modification of CRS by Banker, Charnes and Cooper (1984) became the BCC model which accommodates variable returns to scale (VRS) (Repkova, 2015).

The efficiency score is estimated as the ratio of weighted outputs to weighted inputs for each variable of every DMU in order to maximize its efficiency score (Charnes, Cooper and Rhodes, 1978). Weights are determined by solving the following linear programming problem:

$$Max\ h_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \quad Subject\ to: \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1;$$

$$u_{r,} \quad v_i \geq 0; \quad r = 1, \dots, s; \quad i = 1, \dots, m; \quad j = 1, \dots, n.$$

The efficiency rate for each DMU of the reference set of DMU's is evaluated relative to other set members (Charnes, Cooper and Rhodes, 1978). The maximal efficiency score is equal to 1, and the lower values indicate relative inefficiency of analyzed objects. The technical efficiency entails overall technical efficiency (TE) estimated by the constant return to scale (CRS) DEA, pure technical efficiency (PTE) estimated by the variable return to scale (VRS) DEA and the Scale efficiency (SE) estimated by the ratio of TE and PTE (Yilmaz and Gunes, 2015). The analysis considered the input-oriented DEA model for each VRS and CRS; with the intermediation dimension.

Table 4: DEA input and output variables for the intermediation dimension

Model	**Input variable**	**Output variable**
M1	Deposits	Loans
M2	Interest expenses	Interest income
M3	Interest expenses	Deposits
M4	Loans	Interest income

Table 4 highlights the intermediation dimension and the four models with the respective input and output variables. The DEA variables estimate the technical, pure technical and scale efficiency of the banks with Fintech collaboration.

3.3.2 Econometric approach

The efficiency of a bank can be estimated using a parametric, the stochastic frontier analysis (SFA) model or a non parametric approach, the data envelopment analysis (DEA) model. The DEA does not require the specification of the underlying technology in the analysis and continues to gain popularity in analysis of efficiency in the banking sector (Lema, 2017). DEA model provides a wide range of opportunities for studies in the area of performance measurement (Titko and Jureviciene, 2014). Data envelopment analysis (DEA) is less data demanding thus useful for small data samples (Singh and Fida, 2015). According to Novickyte and Drozdz (2018), DMUs should be at least three times larger than the total number of inputs plus outputs used in the model.

4.0 Results and discussions

This section has the results and discussions based on the data analysis and findings from the DEA model and the desktop reviews. The results for each of the four models M1, M2, M3 and M4 are presented based on the DEA input-orientation.

4.1 Model M1

The intermediation dimension using the Model M1 with input variable (Deposits) and output variable (Loans).

Table 5: Descriptive statistics for the efficiency scores based on Model M1

Efficiency	Statistic	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Locally owned banks – G1											
TE	Mean	0.757	0.795	0.864	0.830	0.802	0.839	0.874	0.706	0.825	0.799
	SD	0.207	0.161	0.164	0.168	0.189	0.151	0.152	0.172	0.151	0.127
PTE	Mean	0.835	0.876	0.889	0.856	0.840	0.872	0.884	0.854	0.861	0.871
	SD	0.226	0.184	0.172	0.168	0.188	0.159	0.153	0.184	0.158	0.129
SE	Mean	0.910	0.914	0.974	0.969	0.953	0.964	0.988	0.829	0.959	0.917
	SD	0.090	0.090	0.035	0.033	0.057	0.051	0.019	0.098	0.028	0.044
RTS		I	I	I	I	I	I	I	D	I	I
NSE Listed banks – G2											
TE	Mean	0.797	0.755	0.928	0.805	0.856	0.891	0.910	0.841	0.864	0.841
	SD	0.123	0.309	0.092	0.119	0.107	0.082	0.100	0.109	0.129	0.143
PTE	Mean	0.921	0.922	0.967	0.933	0.917	0.935	0.942	0.900	0.905	0.916
	SD	0.119	0.107	0.048	0.092	0.089	0.075	0.097	0.117	0.124	0.111
SE	Mean	0.872	0.832	0.961	0.869	0.939	0.955	0.968	0.938	0.959	0.921
	SD	0.126	0.332	0.093	0.137	0.118	0.075	0.068	0.071	0.092	0.125
RTS		D	D	D	D	I	I	I	I	I	I
Fintech Collaborations – G3											
TE	Mean	0.809	0.858	0.900	0.859	0.812	0.869	0.878	0.719	0.844	0.837
	SD	0.117	0.111	0.131	0.167	0.160	0.132	0.130	0.190	0.167	0.142
PTE	Mean	0.900	0.908	0.920	0.889	0.879	0.910	0.905	0.866	0.882	0.882
	SD	0.141	0.109	0.136	0.176	0.180	0.141	0.142	0.181	0.170	0.140
SE	Mean	0.906	0.947	0.979	0.967	0.928	0.957	0.972	0.829	0.957	0.948
	SD	0.099	0.078	0.023	0.037	0.072	0.049	0.032	0.102	0.025	0.030
RTS		D	I	I	I	I	I	I	D	I	I

I – increasing; D – Decreasing; and RTS – Returns to scale

In table 5, the five banks in group G1 had increasing returns to scale for nine years with a decrease in the year 2017. For group G2, from 2009 to 2012, the return to scale was decreasing and increased from 2013 to 2018. Banks with Fintech collaboration had a decrease in returns to scale in 2009 and 2016 while the rest of the years had an increase in returns to scale. The Scale efficiency for the ten year period varied based on the banks grouping. The Fintech collaborating banks SE ranges between 82.9 percent and 97.9 percent; NSE listed banks had SE between 83.2 percent and 96.8 percent while locally owned had SE of between 82.9 percent and 98.8 percent. Therefore, the scale of operations inefficiencies were Fintech banks (2.1% - 17.1%), NSE listed (3.2% - 16.8%) and locally owned (1.2% - 17.1%).

The inefficiencies due to managerial decisions (PTE) differ as per group. Fintech banks (8% to 12.1%), locally owned banks (11.1% to 16.5%) and NSE listed banks (3.3% - 10%). The NSE listed banks had lower managerial inefficiencies as compared to Fintech banks and locally owned banks. Therefore, the main source of technical inefficiencies in the intermediation process among the three groups of banks as a result of both the scale of operations and managerial decisions.

Table 6: Summary of groups per period in Model M1

	Pre-Fintech			Post-Fintech		
	Mean	SD	CV	Mean	SD	CV
Locally owned banks						
TE	0.814	0.167	20.505	0.801	0.156	19.464
PTE	0.861	0.174	20.165	0.868	0.149	17.124
SE	0.947	0.065	6.876	0.924	0.081	8.770
RTS	Increasing			Increasing		
NSE listed banks						
TE	0.839	0.163	19.399	0.864	0.120	13.836
PTE	0.932	0.088	9.477	0.916	0.109	11.915
SE	0.905	0.169	18.678	0.946	0.090	9.510
RTS	Decreasing			Increasing		
Fintech collaborators						
TE	0.851	0.130	15.237	0.820	0.158	19.325
PTE	0.901	0.136	15.147	0.884	0.147	16.616
SE	0.947	0.064	6.779	0.926	0.078	8.462
RTS	Increasing			Increasing		

In table 6, Fintech collaborating banks TE, PTE and SE decreased between the Pre and Post Fintech periods but the returns to scale (RTS) is increasing in the two time periods. The SE for the NSE listed banks increased while TE and PTE decreased during Pre-Post Fintech period with a decrease and increase in returns to scale respectively. The locally owned banks TE and SE decreased while PTE increased in the two time periods, with increasing returns to scale. An increase in returns to scale indicated an opportunity to increase in size to achieve an optimal scale of operations while a decrease indicated operations beyond the optimal size. On average, the locally owned banks and Fintech collaborating banks technical inefficiencies in utilizing the deposits and to issue loans is as a result of managerial inefficiencies for Pre and Post Fintech. The NSE listed banks technical efficiencies in Pre-Fintech is due to the scale of operations and the Post Fintech is as a result of managerial decisions.

4.2 Model M2

Model M2 applied the intermediation dimension using the input variable (Interest expenses) and output variable (Interest income).

Table 7: Descriptive statistics for the efficiency scores based on Model M2

Efficiency	Statistic	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Locally Owned banks											
TE	Mean	0.547	0.526	0.578	0.556	0.603	0.522	0.549	0.551	0.606	0.603
	SD	0.325	0.290	0.263	0.230	0.282	0.246	0.215	0.221	0.203	0.215
PTE	Mean	0.549	0.586	0.607	0.665	0.615	0.648	0.758	0.794	0.779	0.745
	SD	0.326	0.308	0.276	0.236	0.282	0.252	0.235	0.208	0.217	0.241
SE	Mean	0.996	0.895	0.952	0.832	0.975	0.803	0.746	0.714	0.785	0.816
	SD	0.002	0.059	0.043	0.134	0.034	0.169	0.214	0.240	0.147	0.130
RTS		I	I	I	I	I	I	D	D	I	I
NSE Listed Banks											
TE	Mean	0.614	0.479	0.396	0.455	0.506	0.345	0.639	0.671	0.670	0.696
	SD	0.268	0.249	0.252	0.238	0.230	0.270	0.241	0.198	0.210	0.187
PTE	Mean	0.755	0.752	0.684	0.759	0.766	0.766	0.864	0.818	0.761	0.808
	SD	0.209	0.213	0.257	0.229	0.225	0.228	0.175	0.201	0.229	0.206
SE	Mean	0.791	0.623	0.590	0.605	0.665	0.450	0.739	0.827	0.889	0.868
	SD	0.213	0.222	0.267	0.237	0.222	0.286	0.209	0.149	0.121	0.113
RTS		I	D	D	D	D	D	D	I	I	I
Fintech Collaborating banks											
TE	Mean	0.741	0.729	0.775	0.705	0.773	0.646	0.632	0.650	0.751	0.703
	SD	0.276	0.249	0.260	0.202	0.249	0.245	0.239	0.254	0.251	0.210
PTE	Mean	0.790	0.803	0.805	0.841	0.815	0.796	0.805	0.826	0.850	0.866
	SD	0.299	0.258	0.268	0.220	0.272	0.288	0.270	0.241	0.220	0.222
SE	Mean	0.950	0.905	0.963	0.847	0.956	0.826	0.799	0.792	0.885	0.820
	SD	0.102	0.055	0.049	0.144	0.071	0.165	0.191	0.212	0.178	0.151
RTS		I	I	I	I	I	I	D	I	I	D
I – Increasing; D- decreasing; and RTS – Returns to scale											

In table 7, during the ten year period, locally owned banks had a decreasing returns to scale 20% of the time, NSE listed had 60% and Fintech collaborating banks with 20%. In this study period, Fintech collaborators managerial inefficiencies range from 15% to 21% and scale inefficiencies of between 5% and 20.8%. In the category of NSE listed banks, managerial inefficiencies lie between 13.6% and 31.6%, the scale inefficiencies of between 11.0% and 55%. Banks that are locally owned had scale inefficiencies of between 0.4% and 28.6% with managerial inefficiencies of between 20.6% and 45.1%.

Table 8: Summary of groups per period in Model M2

	Pre-Fintech			Post Fintech		
Efficiency	Mean	SD	CV	Mean	SD	CV
Locally Owned banks						
TE	0.555	0.259	46.618	0.578	0.203	35.181
PTE	0.612	0.267	43.607	0.769	0.214	27.783
SE	0.909	0.114	12.577	0.765	0.182	23.759
RTS	Increasing			Decreasing		
NSE listed banks						
TE	0.466	0.254	54.612	0.669	0.202	30.179
PTE	0.747	0.218	29.219	0.813	0.198	24.383
SE	0.621	0.253	40.697	0.831	0.157	18.921
RTS	Decreasing			Increasing		
Fintech collaborating banks						
TE	0.728	0.230	31.551	0.684	0.225	32.829
PTE	0.808	0.245	30.331	0.837	0.221	26.381
SE	0.908	0.112	12.336	0.824	0.173	21.029
RTS	Increasing			Decreasing		

In table 8, locally owned and Fintech collaborating banks had a decreasing returns to scale in the Post Fintech period with NSE listed banks experiencing decreasing returns to scale in Pre-Fintech period. Fintech collaborating banks and locally owned banks had increasing returns to scale in the Pre-Fintech period and NSE listed banks in Post Fintech. Locally owned banks and Fintech collaborators technical inefficiencies are as a result of managerial decisions in Pre-Fintech time and scale operating inefficiencies in Post Fintech. The NSE listed banks technical inefficiencies are due to scale inefficiencies in Pre-Fintech and managerial decisions in the Post Fintech. The variability in technical efficiency of locally owned banks (CV=46.618%), NSE listed banks (54.612%) and Fintech collaborators (31.551%).

4.3 Model M3

Model M3 is based on the intermediation dimension using the input variable (Interest expense) and output variable (Deposits).

Table 9: Descriptive statistics for the efficiency scores based on Model M3

Efficiency	Statistic	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Locally Owned banks											
	Mean	0.599	0.582	0.730	0.723	0.694	0.602	0.606	0.537	0.604	0.600
TE	SD	0.282	0.251	0.224	0.192	0.214	0.207	0.185	0.227	0.193	0.190
	Mean	0.673	0.730	0.774	0.833	0.768	0.752	0.846	0.813	0.763	0.727
PTE	SD	0.316	0.288	0.247	0.194	0.243	0.236	0.197	0.184	0.178	0.192
	Mean	0.895	0.798	0.955	0.869	0.910	0.809	0.730	0.690	0.803	0.835
SE	SD	0.070	0.102	0.102	0.109	0.068	0.144	0.180	0.278	0.193	0.165
RTS		I	I	I	I	I	I	D	D	I	I
NSE listed banks											
	Mean	0.709	0.570	0.475	0.438	0.500	0.353	0.647	0.704	0.762	0.718
TE	SD	0.288	0.243	0.248	0.233	0.211	0.262	0.223	0.202	0.225	0.203
	Mean	0.940	0.828	0.698	0.719	0.726	0.864	0.925	0.819	0.784	0.748
PTE	SD	0.097	0.183	0.241	0.213	0.209	0.156	0.123	0.205	0.230	0.224
	Mean	0.749	0.689	0.683	0.621	0.695	0.419	0.699	0.863	0.972	0.965
SE	SD	0.287	0.252	0.248	0.263	0.215	0.290	0.205	0.121	0.042	0.048
RTS		I	D	D	D	D	D	D	I	I	I
Fintech Collaborating banks											
	Mean	0.824	0.768	0.759	0.865	0.850	0.729	0.708	0.653	0.754	0.721
TE	SD	0.190	0.156	0.160	0.120	0.115	0.160	0.190	0.278	0.228	0.197
	Mean	0.856	0.876	0.819	0.962	0.929	0.870	0.860	0.852	0.868	0.854
PTE	SD	0.190	0.131	0.183	0.058	0.102	0.183	0.195	0.203	0.180	0.200
	Mean	0.960	0.873	0.934	0.902	0.914	0.851	0.835	0.785	0.879	0.858
SE	SD	0.022	0.071	0.094	0.130	0.049	0.145	0.168	0.285	0.211	0.179
RTS		I	D	I	D	D	D	D	D	I	I
I – increasing; D - decreasing; RTS - Returns to scale											

In table 10, Fintech collaborators and NSE listed banks had decreasing returns to scale 60% of the time during the period 2009-2018, and locally owned having decreasing returns to scale 20% of the time. The scale efficiency for Fintech collaborators range from 78.5% to 96.0%, NSE listed from 41.9% to 94.0% and locally owned banks from 69.0% to 95.5%. The pure technical efficiency of Fintech collaborators range from 85.2% to 96.2%, NSE listed banks from 69.8% to 94.0% and locally owned banks from 67.3% to 84.6%. Therefore, based on interest expenses and deposits, the Fintech collaborating banks are more Scale and pure technical efficient.

Table 10: Summary of groups per period in Model M3

Efficiency	Pre-Fintech			Post Fintech		
	Mean	SD	CV	Mean	SD	CV
Locally Owned banks						
TE	0.655	0.225	34.335	0.587	0.190	32.435
PTE	0.755	0.246	32.526	0.787	0.183	23.262
SE	0.873	0.111	12.734	0.765	0.205	26.851
RTS	Increasing			Decreasing		
NSE Listed banks						
TE	0.508	0.262	51.625	0.708	0.208	29.422
PTE	0.796	0.201	25.216	0.819	0.203	24.729
SE	0.642	0.270	42.047	0.875	0.162	18.545
RTS	Decreasing			Increasing		
Fintech Collaborating Banks						
TE	0.799	0.148	18.476	0.709	0.211	29.708
PTE	0.885	0.144	16.297	0.859	0.179	20.828
SE	0.906	0.094	10.414	0.839	0.201	23.966
RTS	Increasing			Decreasing		

In table 10, Fintech collaborating banks had the highest SE of 90.6% compared to NSE listed with 64.2% and locally owned with 87.3% for the Pre-Fintech period. For the Post Fintech, NSE listed had the highest SE of 87.5%, Fintech banks with 83.9% and locally owned with 76.5%. For the Fintech banks, the variability in efficiency scores increased in Post Fintech as compared to Pre-Fintech. The NSE listed banks had higher variability in efficiency scores in the Pre-Fintech than Post Fintech period. The locally owned banks had inefficiency scores of 34.5% in Pre-Fintech and 41.3% in Post Fintech; with NSE listed banks having 49.2% technical inefficiency in Pre Fintech versus 29.2% in Post Fintech. The Fintech collaborators had 20.1% technical inefficiency in Pre-Fintech and 29.1% in Post Fintech.

4.4 Model M4

The intermediation dimension using Model M4 has the input variable (Loans) and output variable (Interest income).

Table 11: Descriptive statistics for the efficiency scores based on Model M4

Efficiency	Statistic	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Locally Owned banks											
TE	Mean	0.874	0.851	0.876	0.860	0.909	0.866	0.942	0.876	0.855	0.768
	SD	0.113	0.129	0.119	0.124	0.107	0.098	0.064	0.074	0.073	0.117
PTE	Mean	0.916	0.852	0.884	0.890	0.916	0.927	0.961	0.921	0.931	0.891
	SD	0.115	0.129	0.124	0.119	0.108	0.103	0.070	0.078	0.071	0.104
SE	Mean	0.955	0.998	0.991	0.965	0.992	0.934	0.981	0.952	0.919	0.861
	SD	0.057	0.001	0.016	0.024	0.004	0.034	0.023	0.030	0.052	0.068
RTS		I	I	I	I	I	I	I	I	D	D
NSE listed banks											
TE	Mean	0.549	0.112	0.675	0.709	0.849	0.888	0.871	0.892	0.831	0.780
	SD	0.177	0.333	0.155	0.147	0.097	0.077	0.081	0.075	0.079	0.131
PTE	Mean	0.733	0.382	0.808	0.825	0.902	0.948	0.940	0.934	0.930	0.922
	SD	0.196	0.468	0.199	0.166	0.112	0.066	0.086	0.068	0.077	0.099
SE	Mean	0.768	0.212	0.850	0.864	0.942	0.937	0.929	0.958	0.897	0.853
	SD	0.190	0.328	0.129	0.085	0.035	0.040	0.059	0.076	0.096	0.152
RTS		I	D	I	I	I	D	D	I	D	D
Fintech collaborating banks											
TE	Mean	0.877	0.877	0.878	0.888	0.954	0.887	0.935	0.863	0.927	0.855
	SD	0.080	0.116	0.097	0.078	0.050	0.089	0.053	0.107	0.060	0.139
PTE	Mean	0.954	0.908	0.926	0.950	0.969	0.959	0.978	0.948	0.989	0.979
	SD	0.064	0.126	0.103	0.068	0.053	0.091	0.038	0.072	0.016	0.047
SE	Mean	0.920	0.968	0.951	0.935	0.985	0.925	0.957	0.913	0.938	0.875
	SD	0.057	0.068	0.079	0.062	0.018	0.047	0.052	0.109	0.065	0.144
RTS		D	I	I	D	I	D	D	D	D	D

In table 11, Fintech collaborating banks had increasing returns 30% of the time during the period 2009-2018 with NSE listed banks having 50% chance of increasing returns to scale and locally owned banks had 80%. Technical efficiencies in the Fintech collaborating banks, NSE listed banks and locally owned banks changes annually from the scale of operations to managerial inefficiencies. The scale inefficiencies for Fintech banks range from 1.5% to 12.5%; NSE listed from 4.2% to 78.8% and locally owned banks from 0.9% to 13.9%. The pure technical inefficiencies for locally owned banks range from 0.9% to 13.9%; NSE listed banks from 5.2% to 61.8% and Fintech banks from 1.1% to 9.2%. Therefore, Fintech collaborating banks had far superior SE and PTE in allocating loans to consumers.

Table 12: Summary of groups per period in Model M4

Efficiency	Pre-Fintech			Post Fintech		
	Mean	SD	CV	Mean	SD	CV
Locally owned banks						
TE	0.873	0.110	12.576	0.860	0.102	11.823
PTE	0.898	0.112	12.507	0.926	0.081	8.781
SE	0.973	0.036	3.731	0.928	0.063	6.786
RTS	Increasing			Increasing		
NSE Listed banks						
TE	0.630	0.313	49.732	0.844	0.100	11.847
PTE	0.766	0.294	38.363	0.932	0.080	8.565
SE	0.762	0.301	39.535	0.909	0.105	11.584
RTS	Decreasing			Decreasing		
Fintech collaborating banks						
TE	0.893	0.084	9.446	0.895	0.096	10.712
PTE	0.944	0.083	8.750	0.974	0.047	4.780
SE	0.947	0.058	6.114	0.920	0.096	10.469
RTS	Increasing			Decreasing		

In table 12, the locally owned banks had increasing returns to scale in the Pre and Post Fintech period with NSE listed banks having decreasing returns to scale in the two time periods. The Fintech banks had decreasing returns to scale in Post Fintech and increasing returns to scale in Pre-Fintech period. NSE listed banks in the Pre-Fintech are technically inefficient with a score of 37.0%, Fintech banks with 10.7% and locally owned banks with 12.7%. The variability in the efficiency scores for NSE listed banks increased in Pre Fintech as compared to post Fintech. Managerial inefficiencies are the key contributor of technical inefficiency among the locally owned banks, with scale inefficiency for the NSE listed banks. For Fintech banks, technical inefficiencies are due to scale of operations post Fintech and managerial decisions Pre-Fintech period.

4.5 Summary of the four models

This section summarizes the intermediation approach with the four models analyzed based on the Pre-Fintech, Post Fintech and the three groups of banks, locally owned, NSE listed and the Fintech collaborators.

Table 13: Groups and models summary based on efficiency scores

		Pre-Fintech (Mean)				Post Fintech (Mean)			
Groups	Model	TE	PTE	SE	RTS	TE	PTE	SE	RTS
Locally owned banks	M1	0.814	0.861	0.947	I	0.801	0.868	0.924	I
	M2	0.555	0.612	0.909	I	0.578	0.769	0.765	D
	M3	0.655	0.755	0.873	I	0.587	0.787	0.765	D
	M4	0.873	0.898	0.973	I	0.860	0.926	0.928	I
NSE Listed banks	M1	0.839	0.932	0.905	D	0.864	0.916	0.946	I
	M2	0.466	0.747	0.621	D	0.669	0.813	0.831	I
	M3	0.508	0.796	0.642	D	0.708	0.819	0.875	I
	M4	0.630	0.766	0.762	D	0.844	0.932	0.909	D
Fintech Collaborating banks	M1	0.851	0.901	0.947	I	0.820	0.884	0.926	I
	M2	0.728	0.808	0.908	I	0.684	0.837	0.824	D
	M3	0.799	0.885	0.906	I	0.709	0.859	0.839	D
	M4	0.893	0.944	0.947	I	0.895	0.974	0.920	D
I – increasing; D- decreasing; RTS – returns to scale									

In table 13, for the Pre-Fintech period based on the four models, NSE listed and locally owned banks operated on decreasing returns to scale and Fintech collaborators on increasing returns to scale. In Post Fintech period, the locally owned banks operated on increasing returns to scale for model M1 and M4, with decreasing returns to scale for model M2 and M3. The NSE listed banks had increasing returns to scale for models M1, M2 and M3, with decreasing returns to scale for model M4. The Fintech collaborators in Post Fintech had increasing returns to scale for model M1 and decreasing returns to scale for models M2, M3 and M4.

Fintech banks had the lowest technical inefficiencies for models M2, M3 and M4 (31.6%, 29.1% and 10.5%) compared to NSE listed (32.1%, 29.2% and 15.6%), and locally owned (42.2%, 41.3% and 14.0%) respectively. Thus, Fintech collaborating banks are better able to utilize loans to interest income, interest expenses to deposits and interest expenses to interest income. Fintech collaborating banks in the Pre-Fintech had the lowest technical inefficiencies for the four models M1, M2, M3 and M4 (14.9%, 27.2%, 20.1% and 10.7%), NSE listed banks (16.1%, 53.4%, 49.2% and 27.0%) while locally owned banks (18.6%, 44.5%, 34.5% and 12.7%) respectively.

4.6 The Regression Model Results

The analysis of the four models shows that model M1 had the highest technical efficiencies among the three groups of banks. This section consider model M1 to estimate the determinants of these efficiency scores based on the bank’s credit risk, liquidity risk, loan intensity, cost of intermediation, cost to income and return on assets.

Table 14: Panel regression model estimation results for model M1

	Fintech Banks		Locally Owned		NSE Listed		Banks Combined	
Variable	PeF	PoF	PeF	PoF	Pef	PoF	PeF	PoF
Credit risk	-0.25	0.054	-2.57	3.327**	-0.0031	0.752	-0.00042	-0.113
	(0.72)	(1.36)	2.858	(0.366)	(0.002)	(0.34)	(0.0005)	(0.126)
Cost of	0.642	-14.057**	4.367	2.683	-4.316*	-3.833*	-0.969**	-1.98*
intermediation	(1.89)	(4.05)	3.09	(1.083)	(1.935)	(1.433)	(0.354)	(0.832)
Liquidity risk	0.382	1.271	0.106	0.942*	0.652***	0.875***	1.039***	0.937***
	(0.42)	(0.62)	0.371	(0.244)	(0.145)	(0.147)	(0.024)	(0.051)
Loan intensity	0.402	0.244	-0.085	-2.073*	0.409*	0.365	0.089*	0.213*
	(0.55)	(1.23)	0.729	(0.47)	(0.187)	(0.163)	(0.034)	(0.089)
Cost to	-0.168	-0.0071	-0.159	-1.433**	0.72*	-0.152	0.1037*	0.167
income	(0.36)	(0.63)	0.756	(0.17)	(0.274)	(0.301)	(0.042)	(0.105)
Return on	-2.492	4.26	-3.675	2.336	3.143	0.161	0.613	1.601
assets	(3.16)	(5.36)	3.283	(1.41)	(1.576)	(2.149)	(0.346)	(0.804)
R^2	0.404	0.696	0.319	0.974	0.952	0.924	0.987	0.933
F Statistic	2.15	3.44*	0.70	18.38*	6.56	18.23***	769.38***	76.35***

Table 14 presents the panel regression analysis for the technical efficiency scores and financial ratios. The thirteen banks combined show that credit risk and cost of intermediation, which is significant have a negative effect on TE in the banking sector in the Post Fintech period. Return on assets and cost to income have a positive effect on TE with loan intensity and liquidity being significant in positively influencing TE in the banking sector in the Post Fintech. Lema (2017) found that liquidity and return on assets have a positive influence on TE with credit risk having a negative influence on TE.

The overall model for the three groups of banks is significant in the Post Fintech period. The credit risk, liquidity risk, loan intensity and return on assets have a positive effect on TE of Fintech collaborators in the Post Fintech period with cost of intermediation which is statistically significant and cost to income having a negative effect on TE. In the locally owned banks category during the Post Fintech, credit risk, cost of intermediation, liquidity risk and return on assets have a positive effect on TE with loan intensity and cost to income, both statistically significant in negatively influencing TE. The NSE listed banks return on assets, credit risk, loan intensity and liquidity risk, which is significant have a positive effect on TE. The negative influences of TE for the NSE listed banks are cost to income and cost of intermediation, which is statistically significant.

The Fintech collaborating banks had the highest positive influence on TE based on liquidity risk and return on assets, and lowest influence based on cost of intermediation. The Fintech banks had higher lending compared to deposits in Post Fintech but all the banks combined had higher lending compared to deposits in Pre-Fintech period. Therefore, a bank's cost of intermediation has a profound influence on the TE of a bank but for Fintech banks, the influence is negative on TE.

5.0 Conclusions

Fintech collaborating banks are more technically efficiency based on models M1, M2 and M3 during the Pre-Fintech period. In the Post Fintech period, Fintech collaborators are more technically efficient in models M2, M3 and M4 but have decreasing returns to scale. NSE banks had higher technical efficiency in model M1 in the Post-Fintech period. Banks in the study sample are operating outside the optimal scale, as either decreasing or increasing returns to scale. Individual bank analysis on their technical efficiency can remedy this anomaly to increase efficiency as banks operating in decreasing returns to scale have more input and less output while those in increasing returns to scale have more output with less input, which is an ideal situation but with opportunities to expand their scale of operations. Liquidity ratio, loan intensity, return on assets and cost of income has a positive influence on TE with cost of intermediation and credit risk has a negative effect on TE. Therefore, Fintech and banks collaborations did not have a significant influence on the efficiency in the banking sector.

5.1 Policy Recommendations

a) Recommend that banks should continuously review and rescale their scope of operations to optimize the scale of operations to levels that guarantee both pure technical and scale efficiency.
b) A regulatory framework and collaborations are necessary to develop a mature financial ecosystem between banks and Fintech entrench a win-win relationship.

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