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

Davis Bundi Ntwiga[a]

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Abstract

This Efficient banks increase financial stability, intermediation and value to the shareholders. As Fintech innovations continue to alter the landscape in the banking sector in Kenya, the collaboration between Fintech and bank will continue to shape the evolution of credit allocation and delivery of services. This study investigates if Fintech and bank collaboration have a negative or positive influence on efficiency in the banking sector. The data envelopment analysis is applied with input-orientation based on four intermediation dimension models. Efficiency scores are decomposed into technical efficiency, pure technical efficiency and scale efficiency. Financial statement data from 2009-2018 for top 15 banks based on the market share of which 13 banks are either locally owned or Nairobi Securities Exchange-listed, with 2 foreign-owned banks excluded from the study. Among these two categories, 5 banks have Fintech collaborations. The study period is segmented into Pre-Fintech, 2009-2014 and Post Fintech, 2015-2018. Descriptive statistics summarize the data, Kruskall Wallis and Conover tests for the Post-Hoc with Panel regression model testing the effect of financial ratios on technical efficiency of banks for Pre-Post Fintech period. Fintech collaborating banks had superior management performance and higher efficiency scores in Pre-Fintech and Post Fintech compared to the NSE listed and locally owned banks based on model M4. Fintech collaboration significantly reduced the cost of intermediation, and increased the scale of operations, a decrease in returns to scale. Therefore, Fintech and banks collaborations had a positive effect on efficiency in the banking sector but it is not statistically significant.

Keywords: *Collaboration, Efficiency, Banks, Fintech, Technical, and Data Envelopment Analysis*

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1.0 Background of the Study

A symbiotic relationship is developing between the banks and the Fintech as their strengths are offsetting one another's inherent weaknesses (Deloitte, 2018). Banks in Kenya are leveraging on the digital space to grow their balance sheet.

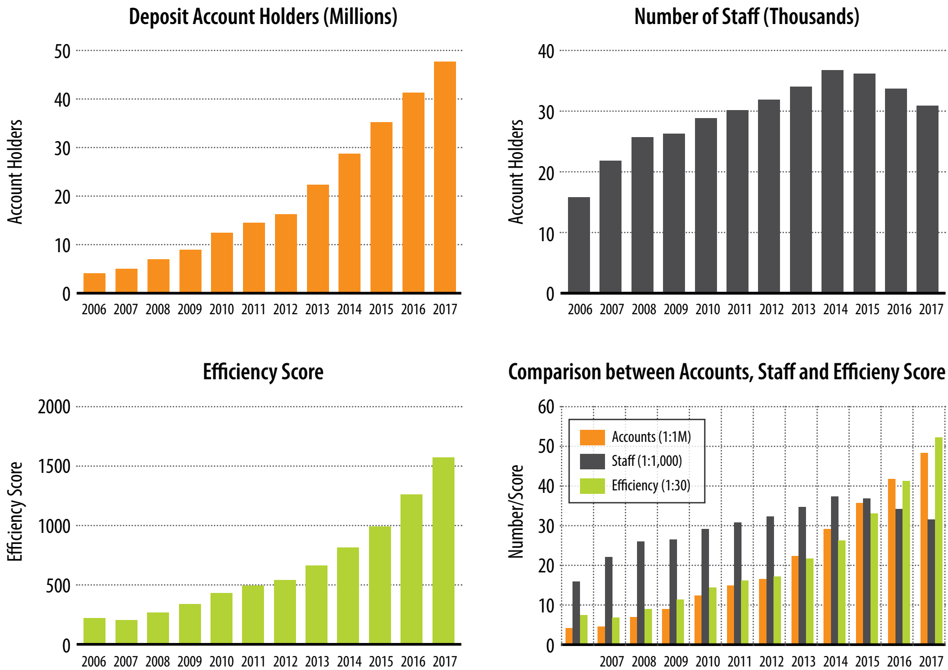
Some banks are setting up their own Fintech subsidiaries while others are forming partnerships with the established Fintech companies (Central Bank of Kenya [CBK], 2017). These partnerships and subsidiaries are referred to as collaborations. The disruptive innovations, non-bank actors and mobile network providers involved in the credit market are referred to as Fintech – the technology-enabled innovations in the financial services (Financial Stability Board [FSB], 2019). Banks operations are envisioned to change dramatically over the next decade due to technological advancements and changing consumer preferences. This is likely to redefine the business models on services and products offered as well as how interactions occur and user experience. The use of technology in the banking sector is not new, but the extent of Fintech growth in the past decade in many spheres of the economy including the financial sector has not gone unnoticed (Coetzee, 2018).

Fintech has the potential to accelerate and strengthen the gains made in financial development in Sub-Saharan Africa (SSA) in the last two decades (IMF, 2019). Only 25 percent of people in SSA have a bank account, but many more have access to a mobile phone, creating a fertile ground for testing new payment systems and lending to consumers with little or no credit history (Vives, 2017). Fintech can improve management efficiency, service quality, core competitiveness, market share and scope of financial services, thus improving the overall efficiency (Hu et. al., 2019). Fintech is going to power the banks by altering the competitive dynamics and the credit provision landscape even though at the moment, Fintech accounts for 2 percent of the credit market (FSB, 2019; Accenture, 2016; Deloitte, 2018; World Bank, 2017). The new generation of business models based on Fintech and big data have the potential to disrupt banks and increase Fintech presence in the credit market (Vives, 2017). Algorithms based on big data have emerged from artificial intelligence, advanced computing power and mobile hardware and mobile storage through cloud. These new techniques could lower the financial intermediation costs as the screening costs for credit allocation are automated (Vives, 2017).

Although banks have the technology for their day to day operations, Fintech emergence cannot be ignored. Banks will have to adapt to be compatible with the technological solutions that Fintech offer (Coetzee, 2018). A major contribution of Fintech is the efficiency-enhancing role in overcoming information asymmetries in the banking sector (Vives, 2017). The efficiency of the banking sector fosters economic development through financial intermediation and the 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, withstand shocks and contribute to the stability of the financial sector (Lema, 2017; Yilmaz and Gunes, 2015). For a bank to be efficient, it should transform the inputs into 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 the exploitation of market power (Abel and Bara, 2017). A competitive banking sector is stable, profitable and efficient, and this reduces the probability of bankruptcy and provides a realistic return to the shareholders (Lema, 2017; Yilmaz and Gunes, 2015). The collaboration of banks and Fintech means that there is a large and potentially welfare-enhancing disruptive capability with benefits to the consumers and banks (Vives, 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 the number of deposit account holders, the number of staff in the banking sector had a peak in 2014 and a downward trend is observed from 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** with 2014 as the end of the Pre-Fintech and 2015 as the start of the Post Fintech period.

Fintech is likely to have covered the gap in the reduction of the number of employees as deposit accounts continue to increase. An analysis of the Kenyan banks' technical efficiency is presented using Data Envelopment Analysis (DEA) technique to estimate the influence of Fintech and bank collaboration and how they affect efficiency in the banking sector. The efficiency scores estimated from the DEA model is decomposed into technical, pure technical and scale efficiencies. The input-orientation and intermediation dimension of the DEA model is used as banks have more control over inputs. Input-orientation targets to reduce the input amounts as much as possible while keeping the present output levels.

1.1 Problem Statement

Technological changes, 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) and to alter market power and efficiency in the banking sector (FSB, 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 the number of deposit accounts opened (CBK, 2017). The top three banks active in Fintech had 57.6 percent of total loan accounts in the Kenyan banking sector (Gubbins and Totolo, 2018).

Disruptive innovations have the potential to improve management efficiency, the scope of financial services, consumer interactions and service quality. This study investigates to what extent Fintech and bank collaboration have had an influence on bank's efficiency. Is there evidence that Fintech and bank collaboration has had a positive or negative influence on efficiency in the banking sector? Also, the study contributes to the existing scanty research in this area.

1.2 Objective of the Study

To analyze the extent to which Fintech and bank collaboration have had an influence on the bank's efficiency in credit allocation.

1.3 Key Hypothesis

Ha: Fintech and banks collaboration had a positive influence on efficiency in credit allocation in the banking sector.

The study contributes to existing knowledge and policy by articulating the influence that Fintech and bank collaboration have had in enhancing efficiency in the banking sector. The analysis of 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 a review of relevant literature with theoretical and empirical reviews. 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 efficiency scores in the banking sector, as overall technical efficiency, pure technical efficiency and scale efficiency. Section 5 has the conclusions and policy recommendations.

2.0 Relevant Literature Review

This section discusses the theoretical literature on data envelopment analysis model. The empirical literature on Fintech and bank collaboration, bank's efficiency scores using the data envelopment analysis method and findings from previous studies. The section concludes with a summary of the key findings from the empirical literature.

2.1 Theoretical Literature

The efficient structure hypothesis (ESH) predicts that efficient firms come out ahead in the 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 its 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 deemed efficient if it produces a given set of outputs with minimum amount of inputs (Abel and Bara, 2017).

In this study, the DEA technique is applied to estimate efficiency scores. The DEA is a non-parametric model and a mathematical programming technique that 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 technique 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).

In the 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 technical efficiency entails overall technical efficiency (TE) estimated by the constant return to scale (CRS), pure technical efficiency (PTE) estimated by the variable return to scale (VRS) and the Scale efficiency (SE) estimated by the ratio of TE and PTE (Yilmaz and Gunes, 2015).

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 TE which represents a 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). The PTE means proportional reduction in input usage if inputs are not wasted and scale efficiency is the proportional reduction in input if the bank achieves constant returns to scale.

A bank can operate under constant return to scale, decreasing returns to scale and increasing the 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).

The three main approaches or dimensions in the DEA model are intermediation, production and profitability that are defined based on the input and output variables of the model. 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 a 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 creates an efficient frontier and evaluates the efficiency of a decision unit and is designed to maximize the relative efficiency of each DMU (Zimkova, 2015).

2.2 Empirical Literature

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, and so they need to act as a 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).

2.2.1 Fintech and Efficiency Interactions

Global Fintech investments and deals have had an upward trend. In 2016, 2017 and 2018 the respective investments and deal count were USD 63.4 B, USD 50.8 B and USD 111.8 B with 1,893 deals, 2,165 deals and 2,196 deals (KPMG, 2019). A compounded annual growth rate of 44 percent 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 percent (EY, 2018). Fintech investments in the USA stand at US $ 29 billion, followed by China, then UK and India (Carmona et al., 2018). In 2017, 33 percent of digitally active consumers globally were using Fintech. The UK, Spain and Germany had 41 percent, 37 percent and 35 percent digitally active consumers respectively. Globally, 50 percent of users use Fintech for payments and transfers, 24 percent on insurance, 20 percent on savings/ investments and 10 percent on financial planning (Carmona et al., 2018).

In Kenya, 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 was approximately 34.8 percent of the adults using digital credit in Kenya in 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 percent of total deposit accounts. The respective loan accounts were 2.69M, 0.95M and 1.26M accounting of 57.6 percent 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 show an upward trend. In 2016 to 2017, Equitel users decreased from 65 percent to 54 percent, Eazzy Banking App usage increased from 1 percent to 20 percent while branch transactions decreased from 6 percent to 4 percent in the same period. (Equity Bank, 2017). As observed by Vives (2017), Fintech has the potential to lower the cost of intermediation by overcoming information asymmetries and developing a culture of efficient operational design.

An examination of if mobile money hinders or promotes bank performance found that the number of years banks have a partnership with MNO is strongly related to bank performance. The sample is split into small and large banks, with small banks involvement in mobile money being strongly associated with profitability and efficiency, but not with stability. Large banks perfectly mimicked the observations in the overall banking sector (Ky, Rugemintwari and Sauviat, 2019). Fintech has the potential to increase a bank's efficiency but has little effect on market structure (IMF, 2017).

Banking Sector Efficiency

The DEA model has been applied extensively in estimating efficiency in the banking sector. Lema (2017) examined efficiency in the Ethiopian commercial banks from 2011-2014. The efficiency based on CRS and VRS assumptions has a little difference with an overall increase in the commercial banks' efficiency. The TE, PTE and SE are analyzed for the Turkish banking industry for the period 2007 -2013 for Islamic and conventional banks (Yilmaz and Gunes, 2015). The study applied intermediation approach input variables (deposits and fixed assets) and output variables (loans, income and investments). The findings, conventional banks PT inefficiencies dominate the scale inefficiencies as managers did not follow appropriate practices and selected incorrect input combinations. In Islamic banking, scale inefficiencies dominate PT inefficiencies in Turkey with an average score of 89.2 percent in all the years under study.

A study by Titko and Jureviciene (2014) 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 findings are that there is no statistically significant correlation between efficiency scores and financial ratios while larger banks are more efficient than the smaller banks. China's banking sector efficiency is investigated using the TE, PTE and SE. A comparison is made between newly joint-stock banks and state-owned banks. (Xu, 2011). Newly joint-stock banks are more efficient than the state-owned banks, with the overall efficiency in the banking sector increasing but more is required from the government to enhance efficiency in the banking sector (Xu, 2011).

The efficiency of the Lithuanian banking sector and bank performance in a low-interest-rate environment is estimated with DEA. Five models based on input-orientation with profitability, intermediation and production dimensions. All banks in the study are TE with an average score of 80 percent based on production dimension. On the profitability dimension, banks are able to manage the low-interest rates environment, and the intermediation dimension showing efficient use of the available resources (Novickyte and Drozdz, 2018). The Oman commercial bank efficiencies are investigated with two-step DEA procedure. In the first step, DEA measures TE scores, and the second step, the Tobit model, censored regression to investigate the determinants of TE. Technical inefficiency in the Oman banking sector is due to both poor input utilization, the managerial inefficiency, and failure to operate at most productive scale size, the scale inefficiency (Singh and Fida, 2015). A DEA analysis of Zimbabwean banks for the period 2009-2015 with a sample of 11 banks, 6 domestic and 5 foreign banks had an average score of 96.6 percent, 85.6 percent and 82.9 percent for the PTE, SE and TE respectively. The managerial efficiency scores were higher than TE scores as majority of the banks were operating at the wrong scale of operations, the decreasing returns to scale (Abel and Bara, 2017).

In summary, the DEA model is applied to estimate efficiency scores. The intermediation, profitability and production dimensions are applied based on VRS, CRS or both CRS and VRS scales with the input-orientation. Banks with a higher ratio of loans to deposits are more efficient, an indication of managerial efficiency. Larger banks are more efficient than smaller banks while domestic banks are relatively efficient compared to foreign banks. Poor input utilization is evidence of managerial inefficiency which is observed through technical inefficiency. For scale inefficiency, the banks had failed to operate at the most productive scale size. Fintech overcomes information asymmetries and reduces cost of intermediation.

This study extends the work from previous studies on efficiency in the banking sector. The key contribution is to estimate if Fintech and bank collaboration had a positive or negative influence on the efficiency of banks in Kenya. This is achieved by comparing the Pre-Fintech (before the collaborations) and Post Fintech (after the collaborations); to test which of the two periods had higher efficiency scores among the banks in the sample.

3.0 Methodology

This study aimed at examining the positive or negative influence Fintech and bank collaboration had on technical efficiency in credit allocation through optimization of inputs by banks using the DEA model. This section presents a discussion on the data source, definition and measurement of variables, methods of analysis and the econometric approach.

3.1 Data Source

The analysis employed financial statement data for a period of 10 years (2009-2018) from the top 15 banks in Kenya based on their market share (CBK, 2018). The 15 banks are selected because the required banks with Fintech collaboration are in that sample. Among the 15 banks, 13 banks are either locally owned or are listed at the Nairobi Securities Exchange (NSE). The 5 banks with Fintech collaboration are locally owned or listed at the NSE or are both locally owned and NSE listed. Therefore, from 15 banks, we have 13 banks based on shareholding information as locally owned or NSE listed and 2 banks as foreign-owned which are excluded from the sample. The 13 banks form the two groups while the third group, Fintech collaborating banks are extracted from the two groups. A bank can be locally owned, NSE listed and/or Fintech collaborating. This is an overlap but well depicted in **Table 1**.

The 10 year period is segmented into the Pre-Fintech (2009-2014) and Post Fintech (2015-2018), the Fintech collaborating period. The purpose to analyze and compare the two periods with the aim of finding out if the Post Fintech period had an increase in efficiency as compared to the Pre-Fintech period. Did the banks' efficiency increase in the Post Fintech as compared to the Pre-Fintech period?

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				

Y –Yes, banks belong to the sample

Table 1 highlights the 13 banks that are either locally owned or NSE listed of which the 5 banks with Fintech collaboration are its subset. Group G1, the locally owned banks, Group G2, the NSE listed banks and Group G3, the Fintech collaboration banks. We observe that there is an overlap because a bank can be locally owned, NSE listed and has Fintech collaboration. In **Table 1**, the symbol Yes (Y) indicates where the bank belongs and shows the Pre-Fintech and Post Fintech period.

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 influence Fintech collaboration had on efficiency by comparing the analysis of Pre-Fintech and Post Fintech period using Panel regression analysis. This is to test which variables have had an influence on 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 with the input and output variables - deposits, interest income, loans and interest expenses.

Table 3: Financial ratios for the panel regression analysis

SN	Variable	Variable name	Measurement
1	CR	Credit risk	The ratio of non-performing loans to total loans – high ratio implies lower efficiency due to loan portfolio deteriorating
2	LR	Liquidity ratio	The ratio of loans to deposits – low ratio signals high operating efficiency
3	LI	Loan intensity	The ratio of loans to assets – high ratio increases risk
4	CI	Bank's cost of intermediation	The ratio of net interest income over average total assets – high cost implies credit rationing
5	CIR	Cost income ratio	The 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 six ratios, credit risk, liquidity risk, loan intensity, bank's cost of intermediation, Cost to income and return on 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 DEA model estimates the efficiency scores for the three groups of banks in the Pre-Fintech and Post Fintech period. Descriptive statistics summarized the efficiency scores data estimated by the DEA model.

3.2.1 Data Envelopment Analysis

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:

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.

Table 4 highlights the intermediation dimension and the four models with the respective input and output variables. The DEA variables estimate the technical (CRS), pure technical (VRS) and scale efficiency (ratio of CRS and VRS) of the banks with Fintech collaboration. The input-orientation approach is used as banks have more control over their inputs.

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

$$u_r,\ v_{i\geq 0};\quad r=1,\ldots,s;\quad i=1,\ldots,m;\quad j=1,\ldots,n.$$

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

3.3.2 Kruskall Wallis and Conover Tests

Among the four models in **Table 4**, two models are selected based on the high-efficiency scores for further treatment with Kruskall Wallis and the Conover-Iman test (Post Hoc) non-parametric tests. The Kruskall-Wallis test is a nonparametric test that is used to determine if there are statistically significant differences between two or more groups of an independent variable on a continuous or ordinal variable. Conover test is a Post Hoc test ideal when the Kruskall Wallis test is rejected. Conover preserves the ranks that the Kruskall-Wallis uses, and uses a pooled variance estimate to construct Post-Hoc t-test statistics. The three groups G1, G2 and G3 are compared in the Pre-Fintech and Post-Fintech periods.

3.3.3 Panel Regression Model

The panel regression is based on fixed effects as this caters (controls) for individual variations that may impact or bias the predictor or outcome variables. The equation for the fixed effects model becomes:

$$Y_{it} = \beta_1 X_{it} + \alpha_i + u_{it}$$

Where:

Y_{it} : Dependent variable where i=bank and t=time

X_{it} : Independent variable where i=bank and t=time

β_1 : Coefficient of the first independent variable

u_{it} : The error term

α_i : Unknown intercept for each bank (i=1,2,...n)

The panel regression model is applied to one model among the two models which have most of the financial ratios being statistically significant as tested with Kruskall Wallis and Conover tests. Two-panel tests based on this one model are performed for the Pre-Fintech and Post Fintech period. The Panel regression dependent variable is the efficiency scores and the independent variables are the selected six financial ratios, in **Table 3**. This is to expound more on what contributes to the efficiency scores among the banks. All three groups of banks are tested for the Pre-Fintech and Post Fintech periods for comparison purposes.

3.4 Econometric Approach

The DEA does not require the specification of the underlying technology in the analysis and continues to gain popularity in the 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.

3.4.1 Fintech Collaboration

The Fintech collaborations in the banking sector are incorporated in this study by considering the Pre-Fintech and Post-Fintech Periods. Did the introduction of Fintech during the Post Fintech period show a marked increase in efficiency among the banks as compared to the Pre-Fintech period? The consideration of the three groups of banks is to compare if the Fintech collaborating banks are significantly different in terms of efficiency scores compared to the NSE listed and locally owned banks.

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 model M1 is using the intermediation dimension with input variable (Deposits) and output variable (Loans) as depicted in **Table 5**.

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

Efficiency	Statistic	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
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

Efficiency	Statistic	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
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 banks in group G1 had increasing returns to scale for nine years with a decrease in the year 2016. 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 percent - 17.1 percent), NSE listed (3.2 percent - 16.8 percent) and locally owned (1.2 percent - 17.1 percent). Therefore, the three groups of banks did not exhibit a difference in their efficiency or inefficiency scores based on SE.

The inefficiencies due to managerial decisions (PTE) were; Fintech banks (8 percent to 12.1 percent), locally-owned banks (11.1 percent to 16.5 percent) and NSE listed banks (3.3 percent - 10 percent). 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 is due to both the scale of operations and managerial decisions.

Table 6: Summary of groups in Pre-Post Fintech for 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 and TE for the NSE listed banks increased while 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 the output variable (Interest income).

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

Efficiency	Statistic	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
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

Efficiency	Statistic	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
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 return to scale 20 percent of the time, NSE listed had 60 percent and Fintech collaborating banks with 20 percent. In this study period, Fintech collaborators managerial inefficiencies range from 13.4 percent to 21 percent and scale inefficiencies of between 3.7 percent and 20.8 percent. In the category of NSE listed banks, managerial inefficiencies lie between 13.6 percent and 31.6 percent, the scale inefficiencies of between 11.1 percent and 55 percent. Banks that are locally owned had scale inefficiencies of between 0.4 percent and 28.6 percent with managerial inefficiencies of between 20.6 percent and 45.1 percent. On average, Fintech banks are operating on appropriate scale as compared to NSE listed and locally owned banks.

Table 8: Summary of groups per period in Model M2

Efficiency	Pre-Fintech			Post Fintech		
	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 return 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 three groups of banks had the highest variability in TE as compared to PTE and SE in the Pre-Fintech and Post-Fintech periods.

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	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Locally Owned banks											
TE	Mean	0.599	0.582	0.730	0.723	0.694	0.602	0.606	0.537	0.604	0.600
	SD	0.282	0.251	0.224	0.192	0.214	0.207	0.185	0.227	0.193	0.190
PTE	Mean	0.673	0.730	0.774	0.833	0.768	0.752	0.846	0.813	0.763	0.727
	SD	0.316	0.288	0.247	0.194	0.243	0.236	0.197	0.184	0.178	0.192
SE	Mean	0.895	0.798	0.955	0.869	0.910	0.809	0.730	0.690	0.803	0.835
	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											
TE	Mean	0.709	0.570	0.475	0.438	0.500	0.353	0.647	0.704	0.762	0.718
	SD	0.288	0.243	0.248	0.233	0.211	0.262	0.223	0.202	0.225	0.203
PTE	Mean	0.940	0.828	0.698	0.719	0.726	0.864	0.925	0.819	0.784	0.748
	SD	0.097	0.183	0.241	0.213	0.209	0.156	0.123	0.205	0.230	0.224
SE	Mean	0.749	0.689	0.683	0.621	0.695	0.419	0.699	0.863	0.972	0.965
	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											
TE	Mean	0.824	0.768	0.759	0.865	0.850	0.729	0.708	0.653	0.754	0.721
	SD	0.190	0.156	0.160	0.120	0.115	0.160	0.190	0.278	0.228	0.197
PTE	Mean	0.856	0.876	0.819	0.962	0.929	0.870	0.860	0.852	0.868	0.854
	SD	0.190	0.131	0.183	0.058	0.102	0.183	0.195	0.203	0.180	0.200
SE	Mean	0.960	0.873	0.934	0.902	0.914	0.851	0.835	0.785	0.879	0.858
	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 9**, Fintech collaborators and NSE listed banks had decreasing returns to scale 60 percent of the time during the period 2009-2018 and locally owned having decreasing returns to scale 20 percent of the time. The scale efficiency for Fintech collaborators range from 78.5 percent to 96.0 percent, NSE listed from 41.9 percent to 94.0 percent and locally owned banks from 69.0 percent to 95.5 percent. The PTE of Fintech collaborators range from 85.2 percent to 96.2 percent, NSE listed banks from 69.8 percent to 94.0 percent and locally owned banks from 67.3 percent to 84.6 percent. Therefore, based on interest expenses and deposits, the Fintech collaborating banks have better management decisions and ability to select the optimal operating scale.

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 percent compared to NSE listed with 64.2 percent and locally owned with 87.3 percent for the Pre-Fintech period. For the Post Fintech, NSE listed had the highest SE of 87.5 percent, Fintech banks with 83.9 percent and locally owned with 76.5 percent. 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 technical inefficiency scores of 34.5 percent in Pre-Fintech and 41.3 percent in Post Fintech; with NSE listed banks having 49.2 percent technical inefficiency in Pre Fintech versus 29.2 percent in Post Fintech. The Fintech collaborators had 20.1 percent technical inefficiency in Pre-Fintech and 29.1 percent 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

Efficiency	Statistic	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
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 percent of the time during the period 2009-2018 with NSE listed banks having 50 percent chance of increasing returns to scale and locally owned banks had 80 percent. Technical efficiencies in the Fintech collaborating banks, NSE listed banks and locally owned banks changes annually from the scale of operations to managerial decisions. The scale inefficiencies for Fintech banks range from 1.5 percent to 12.5 percent; NSE listed from 4.2 percent to 78.8 percent and locally owned banks from 0.9 percent to 13.9 percent. The pure technical inefficiencies for locally owned banks range from 0.9 percent to 13.9 percent; NSE listed banks from 5.2 percent to 61.8 percent and Fintech banks from 1.1 percent to 9.2 percent. Therefore, Fintech collaborating banks have a superior operating scale and management decisions in allocating loans to consumers. This contribution is likely based on Fintech collaborations influence.

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		

Efficiency	Pre-Fintech			Post Fintech		
	Mean	SD	CV	Mean	SD	CV
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 percent, Fintech banks with 10.7 percent and locally owned banks with 12.7 percent. 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 the 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

Groups		Pre-Fintech (Mean)				Post-Fintech (Mean)			
	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 in Post Fintech period. 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. As observed by Abel and Bara (2017), banks need to operate at the most productive scale and reduce the poor utilization of inputs. Technical inefficiency is due to both poor utilization of resources and failure to operate at most productive scale size (Singh and Fida, 2015).

In Post Fintech, the Fintech banks had technical inefficiencies for models M1, M2, M3 and M4 (18.0 percent, 31.6 percent, 29.1 percent and 10.5 percent) compared to NSE listed (13.6 percent, 32.1 percent, 29.2 percent and 15.6 percent), and locally owned (19.9 percent, 42.2 percent, 41.3 percent and 14.0 percent) 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 percent, 27.2 percent, 20.1 percent and 10.7 percent), NSE listed banks (16.1 percent, 53.4 percent, 49.2 percent and 27.0 percent) while locally owned banks (18.6 percent, 44.5 percent, 34.5 percent and 12.7 percent) respectively.

The three groups of banks had the lowest technical inefficiencies in models M1 and M4. Thus, models M2 and M3 are dropped and further analysis is based on models M1 and M4.

4.6 Further Analysis for Models M1 and M4

Model M1 and M4 are further tested based on the Kruskall Wallis test and post hoc test, the Conover-Iman test. The tests single out the variations in the statistical significance of TE, PTE and SE among the three groups of banks.

Table 14: Kruskall Wallis and Conover tests for Model M1

		TE		PTE		SE	
		Mean Diff.	p-value	Mean Diff.	p-value	Mean Diff.	p-value
Pre-Fintech							
Kruskall-Wallis		8.187	0.0167**	11.073	0.004**	10.327	0.0057**
Conover-Iman Test	Fintech-NSE	2.822	0.0064***	-2.711	0.008**	4.46	0.0002***
	Fintech-Local	-0.7055	0.2457	-5.293	0.000***	3.81	0.0009***
	NSE-Local	-3.527	0.0015**	-2.582	0.0104**	-0.649	0.2632
Post Fintech							
Kruskall-Wallis		7.269	0.0264**	7.84	0.02**	2.00	0.368
Conover-Iman Test	Fintech-NSE	1.371	0.102	-1.2204	0.172	0.981	0.1762
	Fintech-Local	-2.741	0.011**	-4.5	0.001***	1.373	0.102
	NSE-Local	-4.112	0.001***	-3.5	0.0034***	0.392	0.352

*p<0.1; **p<0.05; and ***p<0.01

Fintech – Fintech banks; Local – Locally owned banks; NSE – NSE listed banks

In **Table 14**, the Kruskall Wallis test for the three groups of banks is statistically significant for the Pre Fintech and Post Fintech periods based on TE and PTE. In the SE Post Fintech, the three banks scale efficiency is not significant. Fintech banks had higher scale efficiency scores in Pre and Post Fintech against the NSE listed banks and local banks but lowest in the Pre-Fintech for the PTE. Locally-owned banks had higher efficiency scores against NSE listed banks for TE and PTE for the Pre and Post Fintech periods. Therefore, based on model M1, Fintech and bank collaboration increased managerial inefficiency in Post Fintech period. Statistical significance is observed in the TE and PTE for the Pre-Fintech and Post-Fintech period. Scale efficiency is significant in the Pre-Fintech period only.

Table 15: Kruskall Wallis and Conover tests for Model M4

		TE		PTE		SE	
		Mean Diff.	p-value	Mean Diff.	p-value	Mean Diff.	p-value
Pre-Fintech							
Kruskall-Wallis		7.823	0.02**	7.684	0.02**	6.222	0.04**
Conover-Iman Test	Fintech-NSE	1.244	0.116	1.441	0.085	0.638	0.267
	Fintech-Local	3.530	0.002***	3.500	0.002***	2.807	0.007***
	NSE-Local	2.282	0.019**	2.058	0.029**	2.169	0.023**
Post Fintech							
Kruskall-Wallis		2.346	0.31	7.423	0.02**	0.269	0.87
Conover-Iman Test	Fintech-NSE	1.000	0.461	0.311	0.381	0.09	0.465
	Fintech-Local	1.400	0.098	3.889	0.002***	0.449	0.332
	NSE-Local	1.300	0.113	3.577	0.003***	0.359	0.364

*p<0.1; **p<0.05; and ***p<0.01

Fintech – Fintech banks; Local – Locally owned banks; NSE – NSE listed banks

In **Table 15**, Fintech banks had superior TE and PTE scores against the locally owned banks in the Pre- and Post Fintech periods. The NSE listed banks had superior efficiency scores against locally owned banks for the TE, PTE and SE in both the Pre and Post Fintech periods. Therefore, based on model M4, Fintech collaborating banks performed better against the locally owned and NSE listed banks in the TE, PTE and SE. The NSE listed banks performed better against locally owned banks in the Pre- and Post Fintech periods in the TE, PTE and SE. The managerial performance of the banks is statistically significant in Pre-Fintech and Post Fintech. The handling of resources and scale of production by Fintech collaborating banks is superior to that of the NSE listed and locally owned banks in the two time periods.

4.7 The Regression Model Results

The analysis of the four models shows that model M1 and M4 have the highest technical efficiencies among the three groups of banks. However, model M4 has more decreasing returns to scale in Post Fintech as compared to model M1 in the same period. This section considers model M1 to estimate the determinants of the efficiency scores based on the bank's credit risk, liquidity risk, loan intensity, cost of intermediation, cost to income and return on assets.

Table 16: 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 intermediation	0.642	-14.057**	4.367	2.683	-4.316*	-3.833*	-0.969**	-1.98*
	(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 Income	-0.168	-0.0071	-0.159	-1.433**	0.72*	-0.152	0.1037*	0.167
	(0.36)	(0.63)	(0.756)	(0.17)	(0.274)	(0.301)	(0.042)	(0.105)
Return on Assets	-2.492	4.26	-3.675	2.336	3.143	0.161	0.613	1.601
	(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***

*p<0.1; **p<0.05; and ***p<0.01

Table 16 presents the panel regression analysis for the technical efficiency scores against the financial ratios. The 13 banks combined show that the cost of intermediation, which is significant, has a negative effect on TE in the banking sector in the Post Fintech period. Loan intensity and liquidity are statistically 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 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 the 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. A reduction in cost of intermediation increased TE for the Fintech banks.

The Fintech collaborating banks had the highest positive influence on TE based on liquidity risk and return on assets, and lowest influence based on the 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. Thus, Fintech collaboration significantly reduced the bank's cost of intermediation. Vives (2017) noted that Fintech lowers information asymmetry and cost of intermediation.

5.0 Conclusions

The performance of the bank grouping depends on the model selected, based on the input and output variables. Fintech banks had better handling of loans, as input to receive the interest income, as output with increased efficiency as compared to other banks.

Locally-owned banks had superior efficiency scores in utilizing deposits to issue loans. The Fintech collaborations enhance management performance, increase the scale of operations in the banking sector and reduce the cost of intermediation. A general observation is that banks in the study sample are operating outside the optimal scale, as either decreasing or increasing returns to scale. Liquidity ratio, loan intensity, return on assets and cost of income has a positive influence on technical efficiency with cost of intermediation and credit risk has a negative effect on technical efficiency. As observed, banks with Fintech collaboration do not seem to significantly outperform those without Fintech in terms of efficiency scores, thus all banks, irrespective of if they have Fintech collaboration or not should continuously review their operations to remain competitive and efficient. Therefore, Fintech and banks collaborations had an influence on the bank and banking sector efficiency but the findings are not statistically significant.

Further research can analyze the individual bank technical efficiency to single out those operating in increasing or decreasing returns to scale. This could offer more insights on managerial flaws in handling resources and what is the optimal scale of production.

5.1 Policy Recommendation

Banks need to continuously review the scale of operations to optimize their size and increase efficiency with or without Fintech collaborations. Optimization should be both from the managerial decisions and scale of operations to increase technical efficiency.

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