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Technical Efficiency in the Kenyan Banking Sector: Influence of Fintech and Banks Collaboration

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Abstract Efficient banks increase financial stability, intermediation and value to the shareholders. As Fintech innovations continue to alter the financial landscape in Kenya, banks will leverage on Fintech to enhance efficiency. This study investigates if Fintech and bank collaboration has an influence on efficiency in the banking sector. A two step data envelopment analysis is applied with input-orientation based on three intermediation dimension models. Efficiency scores are decomposed into technical, pure technical and scale efficiencies. Financial statement data from 2009-2018 for five banks with Fintech collaborations form the analysis. The study period is segmented into Pre-Fintech, 2009-2014 and Post Fintech, 2015-2018. Descriptive statistics summarize the data with Panel regression model testing the selected financial variables influence on efficiency of banks in the Pre-Post Fintech period. In the ten year period, technical inefficiency based on the three models for the Pre-Post Fintech period is failure to operate at the most productive scale, poor input utilization and managerial inefficiencies. For the Panel regression, loan intensity in model M1, return on asset in model M2, and cost of intermediation in model M3 had a significant and positive influence on technical efficiency. Fintech and banks collaboration has had a positive influence on efficiency in the Kenyan banking sector.

Keywords: *collaboration, efficiency, banks, Fintech, technical, and data envelopment analysis*

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1. Background of the Study

Banks in Kenya are leveraging on the digital space to grow their balance sheet in the credit market. Some banks are setting up their own Fintech subsidiaries while others are forming partnerships with the established Fintech companies [1]. A symbiotic relationship is developing between the banks and the Fintech as their strengths are offsetting one another's inherent weaknesses [2]. These partnerships and subsidiaries are referred to as collaborations. The disruptive innovations, non-bank actors and mobile network operators (MNO) involved in the credit market are referred to as Fintech – the technology enabled innovations in the financial services [3]. 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. 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 [4].

Fintech has the potential to accelerate and strengthen the gains made in financial development in Sub-Saharan Africa (SSA) in the last two decades [5]. 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 [6,7]. Fintech can improve management efficiency, service quality, core competitiveness, market share and scope of financial services [8]. Fintech is going to power the banks by altering the competition dynamics and the credit provision landscape even though at the moment, Fintech accounts for 2 percent of the credit market [2,3,9,10]. 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. Algorithms based on big data have emerged from artificial intelligence, advanced computing power, mobile hardware and mobile storage through cloud. These can lower the financial intermediation costs as the screening for credit allocation is automated [6].

Fintech emergence cannot be ignored and banks will have to adapt to be compatible with the technological solutions that Fintech offer [4]. A major contribution of Fintech is the efficiency-enhancing role in overcoming information asymmetries in the banking sector [6,11]. The efficiency of the banking sector fosters economic development through financial intermediation and optimal allocation of financial resources [12]. 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 [13,14]. A bank is technically efficient if it produces a given set of outputs using the smallest possible amount of inputs [15,16]. Efficiency makes banks more resilient to shocks, promote economic growth, solve the problem of information asymmetry and mitigate economic fluctuations [17].

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 [18]. A competitive banking sector is stable, profitable and efficient, and this reduces the probability of bankruptcy [13,14]. 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 [6].

In this paper, we analyze Fintech and bank collaboration in the Kenyan banking sector and its influence on their technical efficiency. Kenya is a leader in mobile money services and the impact it has had on the economy can continue to encourage more Fintech and banks collaboration. 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 are decomposed into technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE). 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. There is scanty research on influence of Fintech and bank collaboration on bank's technical efficiency and this paper covers that gap. Thus, we investigate to what extent Fintech and bank collaboration has had an influence on bank's efficiency.

The rest of the paper is organized as follows. Section 2 has the literature review based on 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 study summary and conclusions.

2. Literature Review

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, increasing the market concentration [19]. The argument on ESH by [20] is that efficiency determines the structure of firms as more efficient firms can afford more market share and 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 [21]. 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 [18].

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 were approximately 34.8 percent of the adults using digital credit in Kenya in 2017 [22]. In 2015, the top three banks active in Fintech and MNO partnerships are, Commercial bank of Africa (with Mshwari), Equity bank (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 [22].

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 [23]. Equity bank digitalization and disruptive innovations shows 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 [24]. As observed by [6], 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 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 [25]. Fintech has the potential to increase a bank's efficiency but has little effect on market structure [26].

Technological changes, collaborations and competition through Fintech are likely to influence bank's business models, alter the diversity in lending and bank efficiency [12]. Bank and Fintech collaborations can develop a convergence node between the previously separated market players to drive evolution [9,27], to alter market power and efficiency in the banking sector [3]. A need exists to increase a bank's operations to operate at most productive scale and reduce the poor utilization of inputs [16,18]. In Kenya, since 2015, the bank's employees continue to decrease even with an increase in number of deposit accounts opened [1,22].

The DEA model has been applied extensively in estimating efficiency in the banking sector. A study by [13] examined efficiency in the Ethiopian commercial banks from 2011-2014. The efficiency based on constant return to scale (CRS) and variable return to scale (VRS) assumptions have 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 [14]. 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 [28] 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 statistical 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 [29]. A comparison is made between newly joint stock banks and state owned banks. Newly joint stock banks are more efficient than the state owned banks, with an increase in the overall efficiency in the banking sector [29].

The efficiency of Lithuanian banking sector and bank performance in a low interest rate environment is estimated with DEA. Five models are considered 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 [17]. 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 poor input utilization, the managerial inefficiency, and failure to operate at most productive scale size, the scale inefficiency [16]. 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 (PTE) were higher than scale of operations (SE) scores as majority of the banks were operating at the wrong scale of operations, the decreasing returns to scale [18].

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 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 efficiency 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 in the credit market.

3. Methodology

This section highlights the data source, data analysis methods, the Data Envelopment Analysis (DEA) technique, definition and measurement of variables and econometric approach.

The analysis employed financial statement data for a period of ten years (2009-2018) from five banks in Kenya with Fintech collaborations. The 10 year period is segmented into the Pre-Fintech (2009-2014), before Fintech collaboration, and Post Fintech (2015-2018), the Fintech collaborating period. The Fintech collaborations in the banking sector are incorporated in this study by considering the Pre-Fintech and Post-Fintech Periods. Did the banks efficiency significantly increase in the Post Fintech as compared to the Pre-Fintech period? The five banks in the study sample are Kenya Commercial bank (KCB-Mpesa), Co-operative bank (MCo-op), Commercial bank of Africa (M-Shwari), Equity bank (Equitel) and Family bank (Pesa-Pap)

3.1. Data Envelopment Analysis

In this study, 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 [30]. The CCR model is the basic DEA technique introduced by [31] and has the CRS, which assumes no significant relationship between the scale of operations and efficiency while delivering the overall TE. A modification of CRS by [32] became the BCC model which accommodates the VRS [33].

The TE entails overall TE estimated by the CRS, while PTE is estimated by the VRS and the SE is estimated by the ratio of TE and PTE [14]. 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 managerial flaw in handling resources used to run the bank that is the management performance [16]. 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 [16,18]. 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 (decreasing) returns to scale, the bank faces the problem of undersize (overly large), thus operating below (above) the optimal size. A constant return to scale is observed if the output changes proportionately with an increase or decrease in inputs, hence the organization is scale efficient [18].

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 producer of deposits, loans and services by using resources and inputs like capital and labour [16]. 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 [17]. 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 [34]. 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. Weights are determined by solving the following linear programming problem:

$$Maxh_{o=}\frac{\sum_{r=1}^{s}u_r y_{ro}}{\sum_{i=1}^{m}v_i x_{io}} \, Subject\ to: \frac{\sum_{r=1}^{s}u_r y_{rj}}{\sum_{i=1}^{m}v_i x_{ij}} \le 1;$$

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

The maximal efficiency score is equal to 1, and the lower values indicate relative inefficiency of analyzed objects [31].

Table 1 highlights the intermediation dimension and the three 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.

3.2. Variables Definition and Measurements

In this section, the three models in Table 1 and the variables in Table 2 estimates the TE, SE and PTE for the step one DEA model. In the second step DEA, using the Panel regression model, the efficiency scores in step one are regressed with the variables in Table 3 [16].

Table 2 presents the variables for the step one DEA model using the intermediation dimension with the input and output variables - deposits, interest income, loans and interest expenses.

Table 3 presents the seven variables from the financial statements, credit risk, liquidity risk, loan intensity, bank's cost of intermediation, Cost to income, return on assets and bank size. The variables test the influence of Fintech and bank collaboration by comparing the panel regression model in the Pre-Fintech and Post Fintech period for step two DEA. The efficiency scores are the dependent variables and the seven measurements are the independent variables for the model.

Table 1. DEA Input and Output Variables for the Intermediation Dimension

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

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 3. Financial Variables 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.
7	BS	Bank size	Natural logarithm of the value of the bank's total assets

3.4. Methods of Analysis

The R software and Microsoft Excel analyzed the data. The DEA model estimates the efficiency scores for the five Fintech collaborating banks based on the three models in Table 1 in the Pre-Fintech and Post Fintech period. Descriptive statistics summarized the efficiency scores data estimated by the DEA model.

3.4.1. 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:

$$Y_{it} = \beta_i X_{it} + \alpha_{i+U_{it}}$$

Where:
Y_{it}: Dependent variable where i=bank and t=time
X_{it}: Independent variable where i=bank and t=time
β_i: Coefficient of the independent variables (i=1,2,…n)
u_{it}: The error term
α_i: Unknown intercept for each bank (i=1,2,…n)

The panel regression is performed for each of the three models for the Pre-Fintech and Post Fintech period. The Panel regression dependent variable is the efficiency scores and the independent variables are the selected seven financial variables, in Table 3. This is to expound more on which among the variables contributes to the efficiency scores among the Fintech collaborating banks in the Pre-Fintech and Post-Fintech period.

3.5. Econometric Approach

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 [13]. DEA model provides a wide range of opportunities for studies in the area of performance measurement [28], and is less data demanding thus useful for small data samples [16].

4. Results and Discussions

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

4.1. Descriptive Statistics

This section highlights the summary statistics for the TE, PTE and SE based on the mean, standard deviation and the return to scale.

Table 4. Descriptive Statistics for the Efficiency Scores based on Model M1, M2 and M3

Efficiency	Statistic	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Model M1											
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
Model M2											
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
Model M3											
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

I – increasing; D - decreasing; RTS - Returns to scale

Table 5. Models Summary based on Efficiency Scores Descriptive Statistics

Efficiency Score	Pre-Fintech			Post-Fintech			Percent (%)
	Mean	SD	CV	Mean	SD	CV	
				Model M1			
TE	0.851	0.13	15.237	0.820	0.158	19.325	-3.643
PTE	0.901	0.136	15.147	0.884	0.147	16.616	-1.887
SE	0.947	0.064	6.779	0.926	0.078	8.462	-2.218
RTS	Increasing			Increasing			
				Model M2			
TE	0.799	0.148	18.476	0.709	0.211	29.708	-11.264
PTE	0.885	0.144	16.297	0.859	0.179	20.828	-2.938
SE	0.906	0.094	10.414	0.839	0.201	23.966	-7.395
RTS	Increasing			Decreasing			
				Model M3			
TE	0.893	0.084	9.446	0.895	0.096	10.712	0.224
PTE	0.944	0.083	8.75	0.974	0.047	4.78	3.178
SE	0.947	0.058	6.114	0.920	0.096	10.469	-2.851
RTS	Increasing			Decreasing			

In Table 4, Model M1 had decreasing returns to scale in the year 2009 and 2016 with eight years having increasing returns to scale. Model M2 (M3) has four (three) years increasing returns to scale and six (seven) years decreasing returns to scale. The scale efficiencies ranges in the three models are M1 (82.9% - 97.9%), M2 (78.5% - 96.0%) and M3 (87.5% - 98.5%). Model M3 had higher mean scale efficiencies for the ten year period among the five banks. The Pure technical efficiency scores are model M1 (86.6%-92.0%), M2 (81.9% - 96.2%) and M3 (90.8% - 98.9%). Model M3 had higher mean scale efficiencies. For the technical efficiency, the mean technical efficiencies are model M1 (71.9% - 90.0%), M2 (65.3% - 86.5%) and M3 (86.3% - 95.4%). Overall, model M3 had a better performance in terms of efficiency scores for the ten year period among the five Fintech collaborating banks.

The scale inefficiency due to the scale of operations are model M1 (2.1% - 17.1%), M2 (4.0%-21.5%) and M3 (1.5% - 12.5%). The inefficiency due to managerial decisions or PT inefficiency are model M1 (8.0%-13.4%), M2 (3.8%-18.1%) and M3 (1.1% - 9.2%).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. Therefore, the five banks exhibited poor utilization of inputs, managerial inefficiencies and not operating at an optimal scale.

In Table 5, the three models had an increasing return to scale in the Pre-Fintech period. There is decreasing returns to scale in Post-Fintech period for models M2 and M3 and increasing returns to scale for model M1. The comparison between Pre-and-Post Fintech period for model M3 shows an increase in the TE (0.22%) and PTE (3.18%) and a decrease in SE (-2.85%). Models M1 and M2 have the respective decrease in TE (-3.64% and -11.26%), PTE (-1.89% and -2.94%) and SE (-2.22% and -7.395%). The scale of operations contributed to technical inefficiencies. The five banks operated on a non-optimal scale of opearations.

The scale of operations and managerial decisions inefficiencies for the three models in the Pre-Fintech period are M1 (5.3% and 9.9%), M2 (9.4% and 20.1%) and M3 (5.3% and 10.7%) respectively. Model M2 (input as interest expenses and output ad deposits) is the most inefficient in the Pre-Fintech period for scale of operations and managerial decision making. For the Post-Fintech period, the scale of operations and managerial decisions inefficiencies for the models are M1 (7.4% and 18.0%), M2 (16.1% and 10.5%) and M3 (8.0% and 10.5%) respectively. Model M1 has the highest managerial decision making inefficiencies while M2 highly inefficient in the scale of operations.

In model M1, M2 and M3 in the Pre-Fintech period, poor input utilization is due to managerial inefficiency. For Post-Fintech, model M2 and M3 technical inefficiency is due to lack of operating at the most productive scale, while model M1, is due to managerial inefficiency [17].

4.2. Panel Regression Model

This section consider model M1, M2 and M3 to estimate the determinants of the efficiency scores regressed against the bank's credit risk (CR), liquidity risk (LR), loan intensity (LI), cost of intermediation (CI), cost to income (CIR), return on assets (ROA) and bank size (BS).

Table 6 presents the panel regression analysis for the TE scores against the selected variables. In model M1, liquidity ratio has a significant positive influence on TE in the Pre-Fintech and loan intensity is statistically significant in positively influencing TE in Post Fintech period. In Pre- Fintech, credit risk, cost of intermediation and bank size have a positive influence on TE while loan intensity, ROA and cost income ratio had a negative influence on TE. The introduction of Fintech increased the ROA, cost of intermediation, loan intensity and cost income ratio to positively influence TE.

Table 6. Panel Regression Summary for Models M1, M2 and M3 in Pre and Post Fintech

	Model M1 Pre-Fintech				Model M2 Pre Fintech				Model M3 Pre Fintech			
	Estimate	Std. Error	t-value	Pr(>|t|)	Estimate	Std. Error	t-value	Pr(>|t|)	Estimate	Std. Error	t-value	Pr(>|t|)
CR	0.580	0.386	1.502	0.150	-0.941	1.566	-0.601	0.555	-0.532	0.482	-1.102	0.285
CI	0.660	1.057	0.625	0.540	7.600	4.282	1.775	0.093	1.947	1.319	1.476	0.157
LR	0.979	0.217	4.502	0.0003*	-1.116	0.881	-1.268	0.221	0.155	0.271	0.572	0.575
LI	-0.044	0.311	-0.141	0.889	-0.727	1.261	-0.577	0.571	-0.612	0.388	-1.576	0.132
CIR	-0.086	0.158	-0.546	0.592	0.924	0.640	1.443	0.166	0.419	0.197	2.123	0.048**
ROA	-0.04	1.162	-0.034	0.973	5.087	4.709	1.080	0.294	1.916	1.451	1.321	0.203
BS	0.004	0.015	0.265	0.794	0.065	0.059	1.094	0.288	-0.035	0.018	-1.908	0.072
R^2	0.961				0.536				0.856			
	Model M1 Post Fintech				Model M2 Post Fintech				Model M3 Post Fintech			
CR	-1.164	1.485	-0.784	0.456	3.078	2.245	1.371	0.208	-2.092	2.118	-0.988	0.352
CI	1.427	3.320	0.430	0.679	1.537	5.019	0.306	0.767	11.518	4.736	2.432	0.041**
LR	-0.368	0.475	-0.775	0.461	-1.224	0.718	-1.705	0.127	-0.831	0.678	-1.226	0.255
LI	2.013	0.522	3.857	0.005*	1.212	0.789	1.536	0.163	-0.410	0.745	-0.55	0.597
CIR	0.514	0.452	1.138	0.288	1.139	0.683	1.667	0.134	-0.086	0.645	-0.133	0.897
ROA	2.489	3.428	0.726	0.489	18.881	5.183	3.643	0.007*	-6.259	4.891	-1.280	0.236
BS	-0.086	0.057	-1.513	0.169	-0.072	0.086	-0.836	0.428	-0.070	0.081	-0.864	0.413
R^2	0.946				0.928				0.700			

For the model M2, introduction of Fintech increased ROA significantly from 5.087 to 18.881. The cost income ratio increased from 0.924 to 1.139, loan intensity from -0.727 to 1.212 and credit risk from -0.941 to 3.078 in influencing TE. In model M3, for the Pre-Fintech period, cost of intermediation, ROA, cost to income and liquidity ratio have a positive influence on TE with credit risk, loan intensity and bank size having a negative influence on TE. The Post Fintech, the cost of intermediation significantly influenced TE with other variables negatively influencing TE. A study by [13] observed that liquidity and ROA have a positive influence on TE with credit risk having a negative influence. In this study, liquidity and ROA influence on TE depends on the choice of the input and output variables for the three models under investigation. The R^2 indicates a strong correlation between TE and the selected financial variables in the three models for the Pre-Post Fintech period.

5. Conclusions

The technical efficiency of the banks depends on the model selected, determined by the input and output variables. The efficiencies decreased for models M1, M2 and M3 between the Pre-Post Fintech with a marginal increase in scale efficiency in model M3. The selection of input and output variables combination has a profound effect in estimating the efficiency of the banks. In the ten year period, among the three models, the Fintech collaborating banks were either operating in decreasing returns to scale or increasing returns to scale. Technical inefficiency based on the three models for the Pre-Post Fintech period is due to failure to operate at the most productive scale, managerial inefficiency and poor input utilization. Fintech is good for taking deposits and lending as model M1 has increasing returns to scale in the Pre and Post Fintech periods. Models M2 and M3 had increasing returns to scale in the Pre Fintech and decreasing returns to scale in the Post Fintech period. In Post Fintech, model M1 had a significant increase in loan intensity; model M2 significantly increased ROA and model M3, the cost of intermediation increased significantly in influencing TE. Thus Fintech and banks collaborations had a positive influence on bank's technical efficiency for deposits versus loans and interest expenses versus deposits models.

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 the optimal scale of production.

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