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The Effect OfFinancial Technology Firms' Collaboration On The Technical Efficiency Of Commercial Banks In Kenya

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Abstract:
In 2019, the global Fintech market was worth $233.8 billion, representing a Compound Annual Growth Rate (CAGR) of 15.82 percent since 2010. The Fintech industry in Sub-Saharan Africa (SSA) consists of over 1,500 functional firms. Among the 1,500 firms, local players constitute 80 per cent, and international institutions cover the remaining 20 per cent. In Kenya, number of fintech firms increased by 28 percent between 2010 and 2020. Currently, the country has approximately 300 players in the fintech sector. The acceleration of fintech collaboration has come because commercial banks are working towards improving their efficiency. Kenyan commercial banks had an average bank's technical efficiency of 69 per cent against a benchmark of 100 per cent between 2001 and 2017. This indicates that during that period, the banks could have produced their output with 31 per cent less of their inputs. The status of efficiency among commercial banks indicates a worrying trend that requires the adoption of technology, reforms, and changes in the current business model to ensure the banking system attains efficiency. The research intends to determine the impact of fintech collaboration on the bank's technical efficiency of commercial banks in Kenya. The analysis used input variables such as operating costs, while the output variables were bank services, such as deposits and loans. The approach focuses on evaluating whether banks are efficient on the revenues and costs Also, the study determined the level to which fintech has collaborated with the Kenyan banks and identify the determinants of such collaborations. To achieve this, the research utilized secondary panel data from 2008 to 2021. Data was collected from statistical abstracts and published financial statements from the Central Bank of Kenya (CBK), commercial banks, and Kenya Bankers of Association (KBA). The study concentrated on all of Kenya's commercial banks in all three tiers. This allowed estimation in both larger and smaller financial institutions. The technical efficiency of the Kenyan banks was estimated by employing a two stage Data Envelopment Analysis (DEA) approach. The multiple regression models were performed on the outcome found in the first stage of the DEA model.

Key Word*:Fintech, Fintech collaboration, and Bank's technical efficiency.*

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I. Introduction

Fintech is the application of innovative technology and digital capabilities to improve business models and customer experience in financial services (Cook, 2017; Varga, 2017). As such, organizations can combine technology with advanced business models to transform the provision of services in the financial sector. Bates (2017) highlights that fintech has undergone through three major phases (Table no 1).

Table no 1: Major Phases of Global Fintech (1866 – Present).

Fintech 1866 -1967	Fintech 1967- 2008	Fintech 2008 - Present
• Trans-Atlantic cable laid off • Telegraph • Rapid exchange of monetary data between parties involved in financial transactions.	• Technological systems to facilitate the exchange of money electronically • Online banking and ATMs • Traditional financial firms embraced use of information technology to improve their product delivery	• New entrants embraced modern technology to offer non-intermediated financial services • Financial firms enter a new landscape of competitiveness

Source: Consumers International (2017)

In view of the growing demand in the sector, the global Fintech market was worth $53.8 billion in 2010 and grew to $276.4 billion in 2020, equivalent to a CAGR of 16.04 percent in the period (FT Partners, 2021).

Amid conventional financial players, 82 percent intend to strengthen collaboration with fintech firms in the next five years. Ernest & Young (2019) indicates that the number of Fintech in Africa and Kenya has grown at a CAGR of 24 and 28 percent respectively over the past 10 years. The number of fintech companies in Kenya account to 20% of fintech firms in SSA and is ranked third in SSA, after Nigeria and South Africa (Kiamba & Sotiriou, 2022). The growth in Kenya is due to the widespread use of mobile telephone and acceptance of modern technological innovations (Ndung'u, 2019).

The financial system in Kenya is divided into the banking and non-banking sectors. The banking division has commercial banks and Central Bank of Kenya. The non-banking financial sector consists of other financial institutions, pension funds, and insurance firms. Fintech collaborations include KCB M-Pesa for KCB, Equitel money for Equity Bank and M-Shwari for NCBA Bank. Fintech firms have led to a surge in non-branch transactions, where over 67 percent of transactions for commercial banks being conducted on mobile phones in 2020 (KBA, 2021).

Statement of Problem

The first half of 2022 saw $124 million being invested in the fintech sector. This is a huge improvement compared to $75 million of the funding that was invested in 2018 (Fintech Global, 2022). Despite the growth in fintech, Kenya commercial banks have recorded an average bank's technical efficiency of 69 percent against the benchmark of 100 percent. This is an indication that during that period, the banks could have produced their output with 31 percent less of their inputs. Adoption of technology and reforms in the banking system is crucial in averting the worrying trend on inefficiency by banks.

Previous studies in Kenya on fintech collaboration such as Okodo (2019) and Ntwiga (2020) have sought to establish whether fintech collaboration had influenced the efficiency in the banking sector. Ntwiga (2020) found out that efficiency leads to bank stability, higher shareholders' value, and intermediation. However, Ntwiga (2020) paid attention to five major banks whereas the approximation of technical efficiencies among banks is improved when the decision units for the DEA are increased.

Therefore, the study aimed to determine the effect of fintech collaboration on technical efficiency of commercial banks in Kenya while using all the commercial banks in Kenya.

Conceptual Framework

The conceptual framework that links technical efficiency with fintech collaboration originates from the theoretical foundations of theory of financial intermediation and the technology acceptance model (TAM). The theory of financial intermediation stipulates that commercial banks are intermediaries that are tasked with the role of channeling funds from where they are in surplus to where they are needed through taking deposits and offering them to the borrowers as loans. Banks have over the years been offering intermediation services while fintech brings developed networks in which the bank can utilize to improve their approach of offering the services. The collaboration between fintech and the commercial banks provides an opportunity for the banks to carry out the intermediary services at affordable rates leading to a convenient and efficient approach.

Under the technology acceptance model, commercial banks are likely to accept and adopt new technology when they perceive the technology to be useful for them. Lai (2017) mentions that perceived usefulness may be in the form of efficiency, profitability, customer experience, increased revenue, reduction in costs and efficiency of the operations.

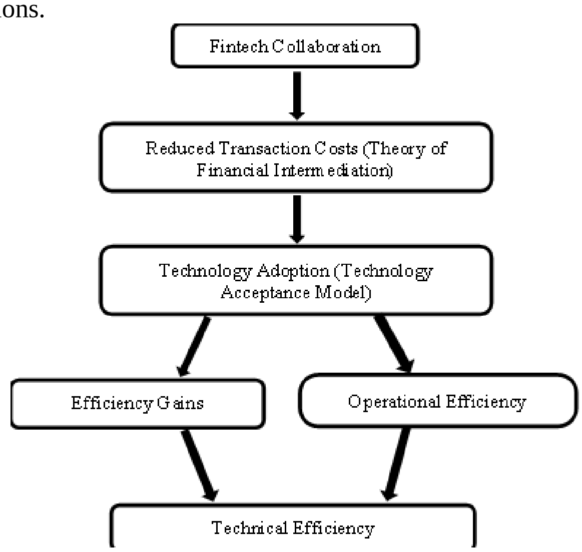

Figure no 1: Conceptual framework for fintech collaboration with technical efficiency.

Empirical Literature

Empirical studies conducted in the past such as Kiilu (2016), Guild (2017), Sy et al., (2019), Okodo (2019), Ky, Rugemintwari, & Sauviat (2019 and Ntwiga (2020) all brought forward mixed outcomes on the relations held by fintech collaboration on the working and efficiency of banks. Some of these studies advocate for fintech collaboration in that they positively attribute to improved operations of banks. Studies supporting fintech collaboration include but are not limited to Kiilu (2016), Guild (2017), Sy et al., (2019), Okodo (2019), and Ky, Rugemintwari, & Sauviat (2019). On the other hand, studies such as Ntwiga (2020) indicate that collaboration between fintech and banks did not significantly influence efficiency for the banks. Majority of these studies revolve around the causality affiliation between fintech collaboration and the proficiency of banks while the current study aimed to bring out the influence of fintech collaboration on bank's technical efficiency of Kenya's banks.

II. Material And Methods

Analytical Framework

This analysis employs a non-experimental panel study. This type of design is a systematic approach that makes use of empirical inquiry in situations where the researcher does not have any control of the explanatory variable (Lenis, 2017). Panel data leads to a more accurate conclusion of the parameters under study as it contains more degrees of freedom as compared to cross-sectional data. Also, panel data helps to minimize estimation biases that could arise from grouping data into a single time series; hence it helps to overcome the endogeneity problem.

Theoretical Framework and Model Specification

Efficiency is given by dividing the sum of the weighted sum of outputs with the weighted sum of inputs.

$$Efficiency = \frac{\text{Weighted sum of outputs}}{\text{Weighted sum of inputs}} \tag{3.1}$$

The weights of the ratio in equation 3.1 have been obtained from the restraint that related ratios for each decision-making unit (DMU) was equal or less than one. Quotient of the weighted sum of outputs to the weighted sum of inputs for every DMU was maximized using a linear multiple programming model as shown below:

$$Max\ (hc), hc = \textstyle\sum_{r=1}^{s} u_r\, y_{rc} \div \sum_{i=1}^{m} v_i X_{ic} \tag{3.2}$$

$$Subject\ to: \sum_{r=1}^{s} u_r\ y_{rj} \div \sum_{i=1}^{m} v_i\, X_{ij} \quad \leq 1 ? j = 1;\ u_r, v_i \geq \epsilon$$

$$r = 1, \dots, s; i = 1, \dots, m\ and\ j = 1, \dots, n$$

Where hc = relative efficiency of decision-making unit or bank, c = decision making unit or bank, y_{rj} = output's r quantity from bank j, X_{ij} = input's i quantity to bank j, u_r = weight selected for output r, v_i = weight selected for input i, n = number of banks, m = number of inputs, and s = number of outputs.

Representative solution for (v, u) based on Charnes – Cooper transformation is as follows:

$$\textstyle\sum_{i=1}^{m} v_i X_{ic} = 1 \tag{3.3}$$

The efficiency score hc is equated to one, resulting to the linear programming model as shown below:

$$Max\ (hc), hc = \textstyle\sum_{r=1}^{s} u_r\, y_{rc} \tag{3.4}$$

$$Subjected\ to \begin{cases} \displaystyle\sum_{i=1}^{m} v_i X_{ic} = 1 \\ \displaystyle\sum_{r=1}^{s} u_r\ y_{rj} - \sum_{i=1}^{m} v_i\, X_{ij} \quad \leq 0 \\ u_r, v_i \geq 0 \quad i = 1, \dots, m\ \ j = 1, \dots, n \end{cases}$$

The model is applied for each bank under study and looks towards the grouping of inputs and outputs (u_r, v_i) that yields to the highest amount of efficiency (hc).

The empirical model used a two stage DEA model to determine how fintech collaboration has affected the bank's technical efficiency of Kenya's commercial banks. The first stage involved measuring and ranking commercial banks based on their efficiency and performance. The second stage makes use of the multiple regression model to identify the determining factors of bank's technical efficiency of Kenyan banks.

The outcome of the weighted efficiency scores was plugged into the computation of the bank's technical efficiency scores through the efficiency maximizing problem shown below:

$$Max\ hc = \frac{uy_j}{vx_j} \tag{3.5}$$

$$Subject\ to: 1 > \frac{uy_1}{vx_1}, \qquad 1 > \frac{uy_2}{vx_2}, \qquad 1 > \frac{uy_3}{vx_3},\ \ u, v > 0$$

Where c = decision making unit or bank, y_j = number of outputs from bank j, X_j = number of inputs to bank j, u = weight chosen for outputs, v = chosen weight for inputs.

Several diagnostic tests have been carried out to validate the panel data. The Hausman test was carried out with the aim of choosing between fixed effects or random effects. The null hypothesis has fixed effects as the preferred model while the alternative hypothesis has random effects. Also, heteroscedasticity test has been performed. The heteroscedasticity test embraced GLS approach with the null hypothesis being homoscedasticity.

The study used Stata for data processing and analysis. A descriptive statistic was conducted on quantitative data. The descriptive statistics contained measures of tendencies such as average mean and measures of dispersion such as standard deviation. Inferential statistics entailed regression, correlation, and analysis of variance to identify the variability between the variables. Bank's technical efficiency is obtained from both prior-fintech and post fintech durations and a comparison was conducted between the two periods to determine whether fintech collaboration has affected the bank's technical efficiency of Kenyan banks.

III. Results And Discussions

Descriptive Statistics

Descriptive statistics are important for this study as they present the essential characteristics of the data, such as the mean, standard deviation and the number of observations.

Table 2 shows that the mean value of the bank's technical efficiency (te) is 80.94 (standard deviation of 8.65). Since the standard deviation is less than 10, the data points are considered as being closely distributed around the actual mean and have no outlier. ROA refers to Return on Assets (ROA), LLP_TL refers to Total Loan Loss Provision to Total Loans, LN_DEP refers to natural log of total Deposits, LN_TA refers to Total Loans to Total Assets.

Table no 2: Shows Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Te	64	80.9375	8.653607	66	95
Roa	64	15.73688	15.9525	6.23	26.09
Roe	64	5.804855	5.920857	5.46	24.99
llp_tl	64	4.25187	1.108283	2.5	5.97
ln_dep	64	4.229531	1.001444	2.51	5.98
lns_ta	64	4.56625	1.228629	2.54	7
ln_ta	64	4.789063	1.139397	2.61	7.98

Diagnostic Tests

Table no 3: Kolmogorov-Smirnov Test

One-sample Kolmogorov-Smirnov test against theoretical distribution roa + roe + llp_tl + ln_dep + lns_ta + ln_ta			
Smaller group	D	P-value	Corrected
te:	-31.4131	0.000	0.000
Cumulative:	-68.9212	0.000	0.000
Combined K-S:	68.9212	0.000	0.000
Note: ties exist in dataset; there are 25 unique values out of 64 observations			

Table no 4: Breusch-Pagan Test

Breusch-Pagan / Cook-Weisberg test for heteroscedasticity	
Ho: Constant variance	
Variables: fitted values of te	
chi2(1)	= 0.08
Prob > chi2	= 0.7800

Table no 4 presents the fact that the data that was collected for Fintech in Banking was normally distributed since the p - value is 0.000 ($p < 0.05$). It demonstrates that the data for this research on the relationship between Fintech in Banking and Technical Efficiency did not suffer from any heteroskedasticity problems (Sig=.780, $p > 0.05$).

Table no 5: Hausmann Test for Fixed Effects vs Random Effects Tests

Source	SS	Df	MS		Number of obs =	64
					F(6,57) =	3.97
Model	1390.618	6	231.7697		Prob > F =	0.0022
Residual	3327.132	57	58.37073		R-squared =	0.2948

					Adj R-squared =	0.2205
Total	4717.75	63	74.88492		Root MSE =	7.6401
Te	Coef.	Std. Err.	T	P>|t|	[95% Conf. Interval]	
Roa	0.571848	0.1658935	3.45	0.001	0.2396517	0.9040438
Roe	0.058155	0.1810419	0.32	0.749	-0.3043753	0.4206851
llp_tl	1.027702	0.9628836	1.07	0.29	-0.900439	2.955843
ln_dep	-0.02578	1.002889	-0.03	0.98	-2.034031	1.98247
lns_ta	2.259512	0.8155528	2.77	0.008	0.626396	3.892629
ln_ta	0.504308	0.9204476	0.55	0.586	-1.338857	2.347472
_cons	54.0174	7.729655	6.99	0	38.53904	69.49577

The overall p-value is 0.000 (<0.05), hence the null hypothesis of the random effect model being consistent is rejected. We conclude the fixed effect model is more consistent and worth selecting.

Table no 6: Multi-collinearity

Variable	VIF	1/VIF
llp_tl	1.23	0.813590
Roe	1.19	0.838907
ln_ta	1.19	0.842377
ln_dep	1.09	0.918535
lns_ta	1.08	0.922803
Roa	1.04	0.960343
Mean VIF	1.14	

The result on multi-collinearity in table 6 shows that the study data between Fintech in Banking and Technical Efficiency did not suffer from any multicollinearity symptoms (Tolerance = 0.640; VIF = 1.14).

ANOVA for Technical Efficiency

Table no 7: ANOVA

One-way Analysis of Variance for te: TE					
				Number of obs =	64
				R-squared =	0.9056
Source	SS	df	MS	F	Prob > F
Between ln_ta	4272.5833	56	76.29613	1.2	0.4359
Within ln_ta	445.16667	7	63.59524		
Total	4717.75	63	74.88492		
	Intraclass	Asy.			
	correlation	S.E.		[95% Conf. Interval]	
	0.15133	0.43749		0	1.00881
Estimated SD of ln_ta effect		3.367538			
Estimated SD within ln_ta		7.974662			
Est. reliability of a ln_ta mean		0.16647			
(evaluated at n=1.12)					
Estimated SD of lns_ta effect		6.456649			
Estimated SD within lns_ta		5.770615			
Est. reliability of a lns_ta mean		0.57563			
(evaluated at n=1.08)					
Estimated SD of ln_dep effect		.			
Estimated SD within ln_dep		13.14154			
Est. reliability of a ln_dep mean		0.00000*			
(evaluated at n=1.08)					
Estimated SD of llp_tl effect		6.852357			
Estimated SD within llp_tl		5.291503			
Est. reliability of a llp_tl mean		0.63361			
(evaluated at n=1.03)					

From table no 7 above, the key finding was that Fintech variable (ROA) and (ROE) in Banking were significant to the Technical Efficiency of banks. Hence, there was a statistically significant and positive linear relationship between Fintech in Banking and Technical Efficiency since the p - value is 0.000 (< 0.05) at the 95% confidence level. The regression model was therefore confirmed to be fit for the research.

Multiple Variable OLS Regression

Table no 8 below sought to establish the causal-effect relationship and nature of the actual effect of Fintech in the banking sector and the technical efficiency when the alpha value is 0.05 or 5% (at the 95% level of confidence).

Table no 8: Multiple Variable OLS Regression

Source	SS	Df	MS		Number of obs =	64
					F(6,57) =	3.97
Model	1390.618	6	231.7697		Prob > F=	0.0022
Residual	3327.132	57	58.37073		R-squared=	0.2948
					Adj R-squared =	0.2205
Total	4717.75	63	74.88492		Root MSE=	7.6401
Te	Coef.	Std. Err.	T	P>|t|	[95% Conf. Interval]	
Roa	0.571848	0.165894	3.45	0.001	0.239652	0.904044
Roe	0.058155	0.181042	0.32	0.749	-0.30438	0.420685
llp_tl	1.027702	0.962884	1.07	0.29	-0.90044	2.955843
ln_dep	-0.02578	1.002889	-0.03	0.98	-2.03403	1.98247
lns_ta	2.259512	0.815553	2.77	0.008	0.626396	3.892629
ln_ta	0.504308	0.920448	0.55	0.586	-1.33886	2.347472
_cons	54.0174	7.729655	6.99	0	38.53904	69.49577

ROA and LNS_TA have positive coefficients (0.571 and 2.259 respectively), which is an indicator that ROA and ratio of Total Loans to Total Assets have a positive impact on the bank's technical efficiency. Their p -values are 0.001 and 0.008 (less than alpha of 0.05 at the 95% confidence level). The p-values indicate that the coefficients are statistically significant and that it is justifiable to reject the null hypothesis concerning the Return on Assets and ratio of Total Loans to Total Assets.

ROE, LLP_TL and LNTA have a positive coefficient hence ROE, ratio of Total Loan Loss Provision to Total Loans, natural log of Total Assets has a positive impact on the bank's technical efficiency. Their p-value are greater than 0.05 at the 95% confidence level. The p-values indicate that the coefficients are not statistically significant and that we cannot reject the null hypothesis concerning the Return on Equity, ratio of Total LoanLoss Provision to Total Loans, and natural log of Total Assets.

The negative coefficient for LNDEP is an indicator that the natural log of total Deposits has a negative impact on the bank's technical efficiency. The p-value is greater than 0.05 at the 95% confidence level, hence the coefficient is not statistically significant and that it is not justifiable to reject the null hypothesis concerning the natural log of total Deposits.

Correlation

The objective of the correlation analysis is to use the correlation coefficients to determine the strength or the significance of the correlation between the bank's technical efficiency and the independent variables.

Table no 9: Correlation Analysis

(obs=64)							
	Te	Roa	Roe	llp_tl	ln_dep	lns_ta	ln_ta
Te	1						
Roa	0.3997	1					
Roe	0.1321	0.1309	1				
llp_tl	0.1114	-0.0244	-0.2512	1			
ln_dep	0.0009	-0.1566	-0.1123	0.1628	1		
lns_ta	0.3387	0.0228	0.2029	-0.0619	0.1236	1	
ln_ta	0.1491	-0.0188	0.1426	0.2929	0.1269	0.1444	1

None of the independent variables had a significant correlation with the bank's technical efficiency. All the variables had a weak positive correlation with the bank's technical efficiency.

Panel Data Analysis

The result of panel data analysis is shown below, having the natural log of Total Assets as the panel variable. The bank size is measured by the total assets of the banks.

Table no 10: Panel Regression (Mixed effect)

panel variable: ln_ta (unbalanced)						
.xtreg te roa roe llp_tl ln_dep lns_ta, re						

Random-effects GLS regression					Number of obs=	64
Group variable: ln_ta					Number of groups=	57
R-sq: within = 0.4462					Obs per group: min=	1
between = 0.2831					avg =	1.1
overall = 0.2860					max =	3
Random effects u_i ~ Gaussian					Wald chi2(5) =	26.34
corr(u_i, X) = 0 (assumed)		Prob > chi2 =	0.0001			
Te	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Roa	0.541828	0.1557583	3.48	0.001	0.2365471	0.847108
Roe	0.140774	0.1778097	0.79	0.429	-0.2077266	0.489275
llp_tl	1.257453	0.9045219	1.39	0.164	-0.5153773	3.030284
ln_dep	0.535264	0.9696561	0.55	0.581	-1.365227	2.435755
lns_ta	2.250193	0.7747997	2.9	0.004	0.731614	3.768773
_cons	52.08551	7.266461	7.17	0	37.843	66.32751
sigma_u	5.852271					
sigma_e	4.946052					
Rho	.58333526 (fraction of variance due to u_i)					

All the variables are random terms. P-values for ROA and LNS_TA are less than the alpha value of 0.05. Hence, there is sufficient evidence to believe that the different ROA and LNS_TA values contribute significantly to the variation in the technical efficiency of Banks. ROE, LLP_TL, LNDEP data have a p-values that are greater than the alpha value of 0.05. Therefore, there is no sufficient evidence to believe that the different ROE, LLP_TL and LNDEP values contribute significantly to the variation in the technical efficiency of Banks.

IV. Conclusion And Implications

The findings corroborate the hypothesis that fintech significantly boosts their commercial banking economic sufficiency, processes, and revenues by reducing cost and increasing technical efficiency. With the emerging Fintech, institutions have a lot of ways to improve their profits. Among them, banks may increase their real-time access to products and services, execute targeted promotional campaigns based on consumer habits, and monetize the significance of customer insights. From 2010 to 2014 (pre-fintech phase), the research found that the volume of transactions made via mobile banking surged considerably. During the post fintech (2015 to 2021), banks implementing fintech facilities have significantly expanded their consumer reach, leading to better financial results and improved technical efficiency.

Based on the findings, commercial banks in Kenya should keep on investing on fintech innovations as the study has proven that such innovations are beneficial to the banks. However, regulations should also be increased by the regulating bodies to safeguard the savings and the investments of all the customers.

The main areas that the study focused on were fintech collaboration and technical efficiency of commercial banks. It would be beneficial for future studies to explore the impact of financial innovations on the profitability of different financial institutions beyond just commercial lenders. This would allow for a more comprehensive comparison of the results. A study could also explore the difficulties that organizations encounter when adopting technological innovations in finance.

References

[1]. Bates, R. (2017). Banking On The Future: An Exploration Of Fintech And The Consumer Interest. A Report ForConsumers International.

[2]. Cook, T. (2018). Why Fintech Matters: Reflecting On FSD Kenya's Work – Financial Sector Deepening Kenya. Retrieved 4 August 2023, From Https://Fsdkenya.Org/Blog/Why-Fintech-Matters-Reflecting-On-Fsd-Kenyas-Work/

[3]. Ernest &Young. (2019). Fintechs In Sub-Saharan Africa: An Overview Of Market Developments And Investment Opportunities. Hollandfintech.Com.

[4]. Fintech Global. (2022). Kenyan Fintech Investment Continues To Grow In H1 2022. Retrieved 15 October 2022, From Https://Member.Fintech.Global/2022/09/06/Kenyan-Fintech-Investment-Continues-To-Grow-In-H1-2022/

[5]. Guild, J. (2017). Fintech And TheFuture Of Finance. Asian Journal OfPublic Affairs, 17-20.

[6]. Kenya Bankers Association. (2019). State Of TheBanking Industry Report. Retrieved 17 January 2023, From Https://Www.Kba.Co.Ke/Downloads/Stateofbankingreport200618(Web).Pdf

[7]. Kiamba, E., &Sotiriou, A. (2022). Can Kenya's Fintech Boom Address TheMSE Finance Gap? Retrieved 15 October 2022, From Https://Www.Cgap.Org/Blog/Can-Kenyas-Fintech-Boom-Address-Mse-Finance-Gap

[8]. Kiilu, N. (2016). Effect Of Fintech Firms OnTechnical Efficiency Of The Banking Sector In Kenya (Doctoral Dissertation, University Of Nairobi).

[9]. Ky, S., Rugemintwari, C., &Sauviat, A. (2019). Is Fintech Good For Bank Performance? The Case Of Mobile Money In The East African Community. The Case OfMobile Money In The East African Community (June 5, 2019).

[10]. Lai, P. C. (2017). The Literature Review Of Technology Adoption Models And Theories For The Novelty Technology. JISTEM-Journal OfInformation Systems And Technology Management, 14(1), 21-38.

[11]. Lenis, D. (2017). Estimating Causal Effects With Non-Experimental Data (Doctoral Dissertation, Johns Hopkins University).

[12]. Mclaughlin, S. (2021). 2020 Annual Fintech Almanac. Ftpartners.Com. Retrieved 24 April 2021, From Https://Www.Ftpartners.Com/Fintech-Research/Almanac.

[13]. Ndung'u, N. (2019). Digital Technology AndState Capacity In Kenya. Washington, DC.

[14]. Ntwiga, D. B. (2020). Bank's Technical Efficiency In The Kenyan Banking Sector: Influence Of Fintech And Banks Collaboration. Journal Of Finance AndEconomics, 8(1), 13-20.

[15]. Okodo, J. O. (2019). Fintech Collaboration AndPerformance Of Commercial Banks In Kenya (Doctoral Dissertation, University Of Nairobi).

[16]. Sy, M. A. N., Maino, M. R., Massara, M. A., Saiz, H. P., &Sharma, P. (2019). Fintech In Sub-Saharan African Countries: A Game Changer? International Monetary Fund.

[17]. Varga, D. (2017). Fintech, The New Era Of Financial Services. Vezetéstudomịny-Budapest Management Review, 48(11), 22-32.