FinTech and CO2 Emission: Evidence from (Top 7) Mobile Money Economies in Africa

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FinTech and CO2 Emission: Evidence from (Top 7) Mobile Money Economies in Africa

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Abstract

Financial technology has evolved from a mediation role into an established sub-market within the financial ecosystem, gaining a superior advantage over the traditional financial system. Therefore, to ascertain if this advantage extends to protecting our environment, this study estimates the relationship between financial technology and carbon emission from the top seven (7) mobile money economies in sub-Saharan Africa. A balanced panel dataset from 2009 to 2020 is employed and estimated with the FMOLS estimator after checking for cross-sectional dependence, unit-root, stationarity, and cointegration. Results from the estimation suggest a negatively significant relationship between financial technology and carbon emission in these countries. However, domestic credit to the private sector revealed a statistically insignificant relationship with carbon emission for the same period. Further, foreign direct investment reduces carbon emissions. However, gross domestic product and trade openness increases carbon emission in these countries. Therefore, it is recommended that financial technology developers in the sub-region should consider green financial products and services to ensure cleaner production and a better environment.

Keywords: Financial Technology, Carbon emission, Trade Openness, Foreign Direct Investment, Economic Growth, Mobile Money.

Introduction

Per the original definition of Financial Technology (FinTech), studies strongly link FinTech with the provision of affordable, accessible, and secure financial products and services without borders (Coffie et al., 2020; Lagna & Ravishankar, 2022). While this is justified, given the need to ensure financial inclusion in areas where traditional financial institutions fail, current studies extend the benefit of FinTech to include poverty reduction, employment creation, and economic growth (Demir et al., 2022; Saiedi et al., 2020). Consequently, this signifies the growth of the FinTech industry worldwide (Kang, 2018; Saiedi et al., 2020). Further, it places FinTech within the circle of production and economic growth factors. Therefore, carbon emission (C02), which is empirically tied to productive activities and economic growth (Munir & Ameer, 2020; Nguyen & Kakinaka, 2019), is an interesting phenomenon that could be influenced by FinTech. This is grounded in studies (Mukhtarov et al., 2020; Zhou et al., 2020) that affirm a significant positive relationship between financial development and C02.

The call for a rapid reduction in the emission of C02 worldwide to save the environment has witnessed the establishment of divergent environmental laws (Charfeddine & Kahia, 2019; Dehghan Shabani & Shahnazi, 2019; Zafar et al., 2019). Further, this has attracted several empirical studies attempting to find factors contributing to the emanation of C02 globally (Essandoh et al., 2020; Waheed et al., 2019; Yu et al., 2018). Critical factors like energy consumption, gross domestic product (GDP), foreign direct investment (FDI), innovation, and financial development are constantly modeled to influence C02 (Dehghan Shabani & Shahnazi, 2019; Essandoh et al., 2020). However, FinTech, which sits between technological innovation and financial development, is yet to receive the needed attention in this jigsaw puzzle. Consequently, this creates a research gap that requires immediate inquisition. This is because FinTech reduces transportation, increases financial accessibility, increases production, and is targeted at millennials who are interested in environmental sustainability (Memon et al., 2021; Lee, 2021). Thus, closing this gap would stimulate the development of optimal FinTech products/services focused on the environment.

Recent studies establish divergent associations between financial development and C02 emission (Mukhtarov et al., 2020; Musah et al., 2021; Zhou et al., 2020). While this is possible because of the contribution of finance to production and economic growth, the use of only "domestic credit to the private sector" as an explanatory variable ignores the role of FinTech in this relationship. Currently, FinTech is no longer just an intermediary service but an entire market (products and intermediaries) within the financial system (Du, 2018; Li & Huang, 2021; Saiedi et al., 2020) and thus, requires empirical attention. Therefore, this study seeks to reduce policy discrepancy by examining the nexus between FinTech and C02 using data from the top 7 mobile money economies in Africa. Specifically, the study seeks to answer the questions; what is the effect of FinTech on C02 emission in these countries (2009-2020), and what is the effect of domestic credit to the private sector on C02 emission in these countries (2009-2020). These countries and periods are selected based on the total infrastructural investment in FinTech from 2009 to 2020. Therefore, it is expected that FinTech would be captured in the financial development index for these periods. Consequently, running two separate models with domestic credit to the private sector and the financial development index (FinTech) would distinguish the effect of domestic credit to the private sector and FinTech on C02 emanation in these countries.

Using a first-generation econometric estimator (fully modified ordinary least squares-FMOLS) based on the cross-sectional dependence tests, the study confirms that; FinTech is significantly associated with C02 emanation in these countries for the period 2009-2020. Specifically, an increase in FinTech significantly reduces C02 emissions in the selected countries. This is consistent with the assertion that FinTech targets millennials who have a keen interest in environmental sustainability. On the other hand, credit to the domestic sector had a statistically insignificant relationship with C02 for the same period under consideration. Therefore, the outcome of the study, unlike other studies is significant to policymakers, industry practitioners, and researchers. To policymakers, the time is ripe to consider FinTech as a tool for C02 reduction. To industry practitioners, the development of FinTech products and services should be optimized to reduce transportation and the supply of funds for energy-efficient machinery and equipment. Finally, to researchers, this creates an avenue for the further exploration of FinTech and C02 emanation from different economies.

The remainder of the paper is organized as follows; the growth of Fintech, the discussion of literature, and the development of hypotheses. Next, the research methodology is presented, followed by the estimation of the research model. Finally, the discussion of findings, conclusion, limitations, and implications for future studies follows.

Literature Review

Over the past decade, FinTech has metamorphosed into a force in the financial system (Hendershott et al.,2021; Boot et al., 2021). Although this change was anticipated through the optimism of industry practitioners (Drasch et al., 2018; Gai et al., 2018), the onset of Covid-19 has propelled this transformation. Figure 1 summarizes the effect of FinTech on the financial system. Rationally, the supply of surplus funds moves through either an intermediary or a financial market to the deficit side of the equation. However, because of delays, inaccessibility, and cost, FinTech promises to first serve as an intermediary between the surplus and deficit side of the equation either directly or via the financial market or the intermediaries with the use of blockchain, the internet, and registries. Although, this has been the initial promise of FinTech, currently an entirely new market where different financial assets like cryptocurrencies and NFTs are available to both the surplus and deficit sides of the equation exist.

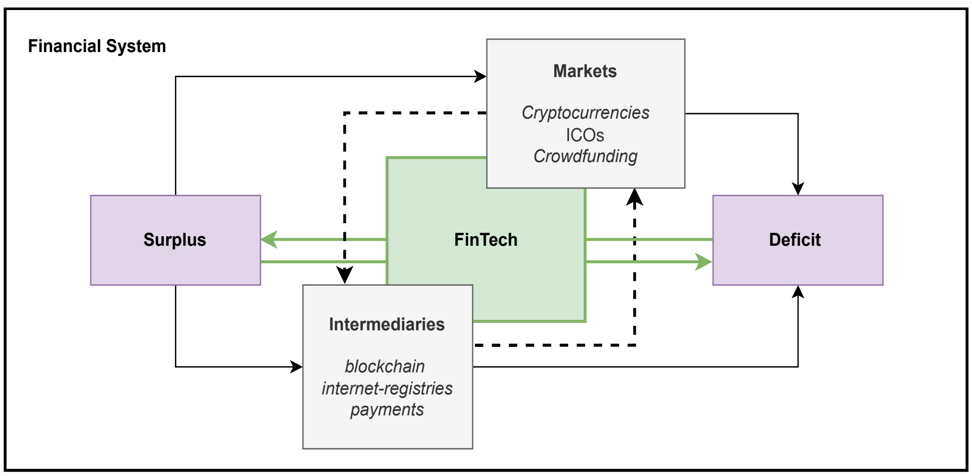

Figure 1. The State of the FinTech
Source: Authors' Construct

Financial technology (FinTech) has attracted attention from scholars recently, given the ongoing divergent opinions of research on the ability to maximize resource utilization through improved methods and processes to reduce carbon emission (CO2) globally. Some studies confirm a direct relationship between FinTech and CO2. According to Tao et al. (2022), FinTech has the potential to reduce greenhouse gas emissions in China. This suggests that the overall development of FinTech would minimize the emission of CO2. Croutzet and Dabbous (2021), using the fixed-effect estimator with Driscoll-Kraay standard errors, confirmed a positive association between FinTech development and renewable energy utilization in 21 OCED countries to indicate that FIN promotes the use of energy sources that are CO2 efficient. Elheddad et al. (2021) studied the effect of e-finance on CO2 in 29 OECD countries from 2007 to 2016 and found FIN to reduce CO2 in these countries to confirm the EKC hypothesis. However, some studies postulate that FIN would affect CO2 only through green financing. Per Puschmann et al. (2020), in a qualitative literature review, observe that the subject of FinTech green finance is still in its infancy. Therefore, although studies confirm positive associations between FinTech and CO2 emission, the optimal positive impact of FinTech on the environment would be attained when FinTech products and services become greener.

According to Yang et al. (2021), using data from 30 provinces and municipalities in China indicates that FinTech promotes green finance, which influences positive environmental health. Consequently, the study suggests a policy reform that can establish a bond between FinTech and green financing in China to reduce CO_2. In support of this assertion, Zhou et al. (2020) also found a positive association between FinTech, green finance, and green growth. However, there existed a regional heterogeneity in the outcome. This proves that in regions where FinTech is highly developed, there is a higher probability of improved green finance and green growth. Finally, the overall financial development is credited for the escalation in CO_2 emission by some studies; Musah et al. (2021), in the study of trade openness and CO_2 emission, introduced financial development as a control variable and found that financial development increases CO_2 in (D8) countries. Again, Yasin et al. (2021) found that financial development, urbanization, composition effect, and energy consumption worsen CO_2 emission. Mukhtarov et al. (2020) confirm that financial development and economic growth have a positive and significant impact on energy consumption. Nonetheless, According to Ma and Fu (2020), using the GMM found financial development worsens CO_2 emissions in developing countries than in developed countries. These suggest that financial development without FinTech or green finance consideration could be detrimental to the environment in the long run (Zhou et al., 2020). Figure 2 provides an overview of the expected relationships between the variables outlined in the study. Specifically, the study expects FinTech to reduce the emanation of CO_2. However, the study assumes that Domestic Credit to Private Sector (DCP) will escalate C02 emanation in these countries for the same period. Finally, foreign direct investment FDI is expected to have a negative relationship with carbon (C02) emanation, while the gross domestic product (GDP) and trade openness (TOP) are both expected to have positive relationships with C02 emanation in these countries.

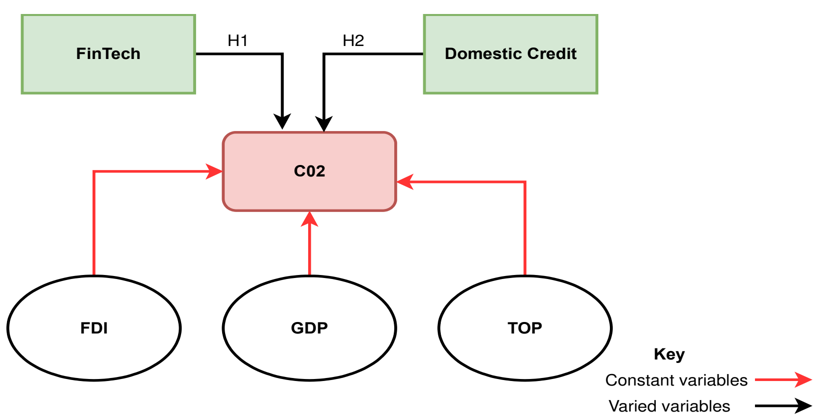

Figure: Conceptual Framework
Source: Authors' Construct

Research Methodology

Data sources and description

The study employs quantitative longitudinal data for the estimation of the model to provide answers to the research questions outlined. Consistent with existing studies (Coffie et al., 2020; Pan et al., 2020), this type of data is preferred because it captures the effect of time on the interactions between the variables employed in the study. Thus, this helps to estimate the relationship between financial technology and carbon emission from the selected top mobile money countries (Ghana, Kenya, Nigeria, Senegal, Uganda, and Tanzania). The countries included are ranked by the Groupe Speciale Mobile Association (GSMA, 2021)[1] as the top mobile money countries in Africa. GSMA ranks these countries based on the total investments made toward financial technology infrastructure. Although there are other countries with mobile money deployment, these seven selected top mobile money countries provide standardized outcomes to justify the generalization of policy recommendations. Table **1** summarizes details of the data employed for the study. Data is gathered from two (2) main sources; the World Development Index (WDI) and the International Monetary Fund FinAcess (IMF) on Carbon Emission (C02), Financial Technology (FinTech), Domestic Credit to Private Sector (DCP), Trade openness (TOP), Foreign Direct Investment (FDI), and Gross Domestic Product (GDP). Data on these variables are gathered from the years 2009 to 2020. This period is considered appropriate for the study because it captures both the emergence and growth stages of mobile money (FinTech) in sub-Saharan Africa. Therefore, given the outcome of existing studies (Musah et al., 2021; Mukhtarov et al., 2020; Zhou et al., 2021) suggesting the positive interaction between FinTech and carbon emission, results from the current study are better justified for the period selected.

Table 1. Data source and description

Variables	Role	Description	Source
C02	Response Variable	Carbon Emission in Metric Tons	WDI (2020)
FinTech	Explanatory Variables	Financial Development Index	IMF FinAcess (2020)
DCP		Domestic Credit to Private Sector	WDI (2020)
TOP	Control Variables	Import + Export /GDP	WDI (2020)
FDI		FDI inflow percent of GDP	WDI (2020)
GDP		Gross Domestic Product 2015 constant	WDI (2020)

Note: Authors' Construct

Model Specification

The purpose of the study is to explore the relationship between CO2 emission and financial technology from seven (7) top mobile money economies in sub-Saharan Africa. To estimate this relationship, financial technology (FinTech) and Domestic Credit to the Private Sector (DCP) are employed as explanatory variables in two separate equations. Further, the study controls for Trade Openness (TOP), Foreign Direct Investment Inflow (FDI), and Gross Domestic Product (GDP) in both equations. However, the study has a keen interest in capturing the effect of time on this relationship. Thus, consistent with existing literature (Musah et al., 2021; Coffie et al., 2020), a panel time-series econometric model is employed for this purpose. Specifically, the model forms are derived as follows;

$$C02_{it} = f(\text{FinTech}_{it}, TOP_{it}, GDP_{it}, FDI_{it}) \tag{1a}$$

$$C02_{it} = f(DCP_{it}, TOP_{it}, GDP_{it}, FDI_{it}) \tag{1b}$$

[1] https://www.gsma.com/mobileeconomy/

Where, $C02_{it}$, FinTech_{it} , DCP_{it} , TOP_{it} , GDP_{it} and, FDI_{it} designates carbon emission, financial technology, domestic credit to the private sector, trade openness, gross domestic product, and foreign direct investment of country i in time t, correspondingly. Additionally, equations (1a) and (1b) are econometrically converted into a panel configuration as;

$$C02_{it} = \alpha_i + \beta_1 \text{FinTech}_{it}, \beta_2 TOP_{it}, \beta_3 GDP_{it}, \beta_4 FDI_{it} + \varphi_{it} \tag{2a}$$

$$C02_{it} = \alpha_i + \beta_1 DCP_{it}, \beta_2 TOP_{it}, \beta_3 GDP_{it}, \beta_4 FDI_{it} + \varphi_{it} \tag{2a}$$

Where, $\beta_1, \beta_2, \beta_3, \beta_4, and \beta_5$ in equation (2a) are coefficients of FinTech, TOP, GDP, and FDI correspondingly. In equation (2b), $\beta_1, \beta_2, \beta_3, \beta_4, and \beta_5$ represents coefficients of DCP, TOP, GDP, and FDI correspondingly. Again, for equations (2a) and (2b), α_i represents the time-invariant country-specific effects with φ_{it} representing the stochastic white noise error terms. Conversely, to ensure the robustness of the approximation by minimizing heteroscedasticity problems, we follow existing literature (Musah et al., 2021) to log-transform equations (2a) and (2b) as follows;

$$lnC02_{it} = \alpha_i + \beta_1 ln\text{FinTech}_{it} + lnTOP_{it} + \beta_3 lnGDP_{it} + \beta_4 lnFDI_{it} + \varphi_{it} \tag{3a}$$

$$lnC02_{it} = \alpha_i + \beta_1 lnDCP_{it} + \beta_2 lnTOP_{it} + \beta_3 lnGDP_{it} + \beta_4 lnFDI_{it} + \varphi_{it} \tag{3b}$$

Where, *lnC02, ln*FinTech*, lnDCP, lnTOP, lnGDP,* and *lnFDI* designate the log-transformations of the variables *CO2,* FinTech*, DCP, TOP, GDP,* and *FDI* respectively. The alteration supports the approximation and interpretation of the models as elasticities. Comparable to existing literature (Musah et al., 2021; Coffie et al., 2020), the current study projects, $\pm\beta_{1\text{-}4}$ for equations (3a) and (3b), correspondingly given dissimilar conditions. Explicitly, for equation (3a), β_1 is likely to be positive when FinTech promotes activities that increase carbon emissions. On the other hand, β_1 would be negative if FinTech encourages activities that lessen the emission of carbon in the selected countries (Tao et al., 2022; Croutzeta & Dabbousb, 2021; Elheddad et al., 2020). Per equation (3b), $\beta_1$would be positive if DCP boosts investment in high carbon emission activities (Musah et al., 2021); otherwise, β_1 would be negative. Following this, β_2 β_3, andβ_4 for equations (3a) and (3b) are all expected to be positive in the case where TOP, GDP, and FDI stimulates activities that increase carbon emission in these countries (Musah et al., 2021; Essandoh et al., 2020). On the other hand, β_2 β_3 and, β_4 for the equations would be negative to indicate that TOP, GDP, and FDI encourage investment in carbon-efficient machinery and equipment in these countries (Musah et al., 2021; Bokpin, 2017).

Model Estimation

To estimate the relationship between financial technology (FinTech) and carbon emission (CO2) in the selected countries. We follow a series of recognized econometric procedures that are rooted in existing literature (Acheampong, 2018; Essandoh et al., 2020; Zafar et al., 2019) to deliver robust outcomes. Consequently, first, we conduct a cross-sectional dependence test to understand the spatial nexus between the panel to rule out cross-sectional correlation errors, which customarily produces invalid statistical conclusions. To serve as a robustness check, the Breusch-Pagan LM test and the Pesaran scaled LM test are undertaken to validate the results. The Pesaran (Pesaran et al., 2004), cross-sectional reliance test per the established panel data model is expressed as;

$$y_{i,t} = \alpha_i + \beta_{i,t} x_{i,t} + \mu_{i,t} \tag{4}$$

where $i = 1,2, \dots N$ and $t = 1,2 \dots, T$, $\beta_{i,t}$ is a $K \times 1$ vector of parameters to be estimated, $x_{i,t}$ characterizes a $K \times 1$ vector of input variables, α_i conversely, designates the time-invariant individual nuisance estimates and, $\mu_{i,t}$ signifies the error terms anticipated to be both individually and identically dispersed. Therefore, the test of the null hypothesis and alternative hypothesis of no cross-sectional reliance is correspondingly stated as;

$$H_o: \rho_{ij} = \rho_{ji} = cor(\mu_{it}, \mu_{jt}) = 0 \; for \; j \neq i \tag{5a}$$

$$H_A: \rho_{ij} = \rho_{ji} = cor(\mu_{it}, \mu_{jt}) \neq 0 \; for \; some \;\; j \neq i \tag{5b}$$

Where, ρ_{ij} orρ_{ji} is the correlation coefficient derived from the error terms of the model and is specified by the relation;

$$\rho_{ij} = \rho_{ji} = \frac{\sum_{t=1}^{T} \mu_{it} \mu_{jt}}{(\sum_{t=1}^{T} \mu_{it}{}^2)^{1/2} (\sum_{t=1}^{T} \mu_{jt}{}^2)^{1/2}} \tag{6}$$

Accordingly, per the pairwise correlation coefficients, $\hat{\rho}_{ij}$ amongst the cross-sectional residuals, the cross-sectional dependence test statistic by Pesaran is given as;

$$CD_P = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \rightarrow N(0,1) \tag{7}$$

Further, the study engaged the Breusch and Pagan (Breusch & Pagan, 1980), LM tests by finding the sum of squared coefficients of correlation amongst the cross-sectional residuals with the ordinary least squares technique. The LM_{BP} the test statistic is given as;

$$LM_{BP} = T \sum_{i-1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{8}$$

Where$\hat{\rho}_{ij}$ refers to the sample estimate of cross-sectional association amongst residuals. N and T is the number of cross-sections and time dimensions correspondingly, and i denotes each individual variable. Per the null hypothesis of no cross-sectional associations, fixed N and $T \rightarrow \infty$, the CD_{LM1} is approximated to Chi-Square distribution with N(N-1)/2 degrees of freedom.

The Pesaran (Pesaran et al., 2004), cross-sectional dependency Lagrange Multiplier (CD_{LM}) test sums the squares of the correlation coefficient between cross-sectional residuals. The technique is suitable when $T > N$ or $N > T$, where N is the cross-sectional dimension and T is the time dimension of the panel, and is asymptotically standard and normally dispersed. Therefore, the test is derived by using the procedure:

$$CD_{LM} = \sqrt{\frac{1}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} T\hat{\rho}_{ij}\right) \tag{9}$$

Where $\hat{\rho}_{ij}$ is expressed as a sample estimate of the cross-sectional association between residuals. Thus, the null hypothesis of this test is just like the CD_P and LM_{BP}tests.

Second, we estimate the integration properties of the variables employed in the study to conclude whether they are stationary at level form, first-level integration, or second-level integration. Accordingly, this can be computed using the Levin, Lin and Chu (LL&C) t-test, Im, Pesaran and Shin (IPS) test, Augmented Dickey-Fuller-Fisher (ADF-Fisher) test, and Phillip-Perron Fisher (PP-Fisher). However, per the results depicted in table 5 on the outcome of the cross-sectional relationship tests, the first-generation panel unit root tests are deemed appropriate for the determination of the integration properties of this study. Consequently, we follow the following procedure;

$$\Delta y_{it} = \rho_i y_{it-1} + \delta_i X_{i,t} + \varepsilon_{i,t} \tag{10}$$

where $i = 1,2, \dots N$ for each country in the panel $t = 1,2 \dots, T$ designates the period under consideration, $X_{i,t}$ denotes the vector of exogenous variables of the model encompassing fixed effects or individual time trends, ρ_i symbolizes autoregressive coefficients, and $\varepsilon_{i,t}$ denotes the error terms of the stationary categorization. Specifically, y_{it} becomes weak in a stationary trend whenever $\rho_i < 1$, otherwise if $\rho_i = 1$, then y_{it} has a unit root. To eliminate issues of autocorrelation, Levin et *al.* (Im et al., 2003) proposes higher-order differential time-delay terms comparable to the ADF and it is stated as;

$$\Delta y_{it} = \rho_i y_{it-1} + \delta_i X_{i,t} + \sum_{j=1}^{\rho_i} \theta_{ij} \Delta y_{it-1} + \varepsilon_{i,t} \tag{11}$$

where ρ_i represents the number of lags in the regression and $\varepsilon_{i,t}$ is the error term. Again, Im et *al.* (Im et al., 2003) stipulated a t-bar statistic as the mean of the individual ADF statistic as;

$$\bar{t} = \frac{1}{N}\sum_{i=1}^{N} t_{\rho_i} \tag{12}$$

where t_{ρ_i} signifies the individual t-statistic to test the null hypothesis of no stationarity. Largely, the t-bar statistic is dispersed around the null hypothesis where critical values for given values of *N* and *T* are specified by Im et *al.* (Im et al., 2003). The LLC unit root test assumes $\rho_i = \rho$, to indicate that cross-sectional units are non-stationary while the Fisher-ADF test and the Fisher PP test allow ρ_i to vary across dissimilar cross-sections. To ensure robustness in serial correlation, the Fisher-PP test uses the Phillips-Perron individual unit root test for each cross-section. Therefore, the merged p-value from both tests is given as;

$$\rho = -2\sum_{i=1}^{N} In_{\rho i} \rightarrow X^2_{2N} \quad (13)$$

where ρ_i is the p-value obtained from the estimated individual unit root test for cross-section i, the test statistics ρ follows a X^2_{2N} distribution with 2N degree of freedom as Ti→∞ for all N. The null hypothesis of unit root for all *N* cross-sections is given as:

$$H_0: \alpha = 0, \text{ for all } i \; (i = 1, \ldots, N) \quad (14a)$$

On the other hand, the alternative hypothesis provides that some cross-sections have unit-roots. This is given as;

$$H_1: \begin{cases} \alpha \neq 0 \; for \; some \; i \\ \alpha < 0 \; for \; other \; i \end{cases} \quad (14b)$$

Where variables are stable, regression analysis is employed to understand their attributes. However, a co-integration test must be performed prior to the regression analysis. Conversely, where variables are found to be unstable the analysis should be abrogated.

Thirdly, we assessed the co-integration properties of the data to understand the long-term structural association between the variables chosen for the study. Consequently, first-generation tests: the Pedroni test (Pedroni, 2007) and the Kao test (Kao, 1999) are preferred. They are useful in this study because they consider cross-sectional independence with individual effects. Accordingly, the Pedroni panel co-integration test is based on the expression provided in Eq. (15);

$$y_{it} = \alpha_i + \delta_i t + \beta_{1i}x_{1i,t} + \beta_{2i}x_{2i,t} + \cdots + \beta_{mi}x_{mi,t} + \varepsilon_{it} \quad (15)$$

where α_i and β_{ij} are the intercepts and slope coefficients which vary across cross-sections, $t = 1, \ldots, T$, $i = 1, \ldots, N$, $m = 1, \ldots, M$, x and y are anticipated to be integrated of the same order level (I(1)). Thus, the null hypothesis of no co-integration of the Pedroni panel co-integration test is given as;

$$\varepsilon_{it} = \rho_i \varepsilon_{it-1} + \mu_{it} \quad (16)$$

The alternative hypothesis incorporates the homogeneous hypothesis ($H_A: \rho_i = \rho < 1$) for all individual series for the within dimension test, the heterogeneous alternative ($H_A: \rho_i < 1$), and for all individual series for between dimension test. After providing evidence of the existence of co-integration amongst the variables employed in the study, the next step is to determine the model estimator.

Finally, we estimate the long-run relationships by employing an estimator to examine the effects of the various explanatory variables on the corresponding response variables. In the presence of cross-sectional associations, the Augmented Mean Group (AMG) estimator is preferred. Conversely, in the absence of cross-sectional affiliations, the Fully Modified Ordinary Least Square (FMOLS) estimator is a better estimator. Consequently, we employed the FMOLS for this study because this estimator provides robust estimates when there is cross-sectional independence and eliminates spurious regressions which is a popular issue when using the ordinary least squares (OLS). Again, the FMOLS handles any potential endogeneity issues in the regressors because of the existence of long-run affiliations between the variables. Further, the FMOLS estimator yields asymptotically unbiased estimates and produces nuisance parameter-free standard normal distribution (Pedroni, 2001). Following these reasons, our model from Equations (3a) and (3b) would be estimated per the equations specified below:

$$ln\ F\mathrm{FinTech}_{\mathrm{it}}|lnTOP_{\mathrm{it}}|lnGDP_{\mathrm{it}} + lnFDI_{\mathrm{it}} = \alpha_i + \beta_i lnC02_{it} + \sum_{k=-K_i}^{K_i} \gamma_{ik} \Delta lnC02_{it-k} + \varphi_{it} \tag{17a}$$

$$ln\ DCP_{\mathrm{it}}|lnTOP_{\mathrm{it}}|lnGDP_{\mathrm{it}} + lnFDI_{\mathrm{it}} = \alpha_i + \beta_i lnC02_{it} + \sum_{k=-K_i}^{K_i} \gamma_{ik} \Delta lnC02_{it-k} + \varphi_{it} \tag{17b}$$

for $i = 1,2, \ldots, N$ and $t = 1,2, \ldots, T$. where $ln\mathrm{FinTech}_{it}$,$lnDCP_{it}$,$lnTOP_{it}$,$lnGDP_{it}$, $lnFDI_{it}$, and $lnC02_{it}$ denotes the natural logarithm of financial technology, domestic credit to the private sector, trade openness, gross domestic product, foreign direct investment, and carbon emission whilst Z_{it} is a vector characterizing the natural logarithm of the control variables TOP_{it}, GDP_{it}, FDI_{it}, and Z_{it} are cointegrated with slopes β_i, δ_i, θ_i' which varies homogenously across i.

Let $\xi_{it} = (\mu_{it}, \Delta\mathrm{FinTech}_{it}, \Delta CRD_{it},\ \Delta Z_{it})$ be a stationary vector incorporating the estimated residuals. Furthermore, let$\Omega_{it} = lim_{T\to\infty} E\left[T^{-1}(\sum_{t=1}^{T} \xi_{it}) \sum_{t=1}^{T} \xi_{it}{}'\right]$ be the long-run covariance for the vector process which is converted into $\Omega_i = \Omega_i^0 + \Gamma_i + \Gamma_i'$ where Ω_i^0 is the cotemporaneous covariance and Γ_i is a weighted sum of autocovariance. Thus, per the established connections, the FMOLS estimators for β_i is stated as;

$$\hat{\beta}^*{}_{NT} - \beta = \left(\sum_{i=1}^{N} \hat{L}_{22i}^{-2} \sum_{t=1}^{T} \left(lnC02_{it} - \overline{lnC02}_i\right)^2\right)^{-1} \sum_{i=1}^{N} \hat{L}_{11i}^{-1} \hat{L}_{22i}^{-1} \left(\sum_{t=1}^{T} \left(lnc02_{it} - \overline{lnC02}_i\right)\mu_{it}{}^* - T\hat{\gamma}_i\right) \tag{18}$$

Heteroskedasticity and Serial Correlation Tests

After the estimation of the long-run associations amongst the variables, there is the need to establish the validity of the model by checking heteroskedasticity and serial correlation in the model. According to Gujarati and Porter (2009), the presence of heteroskedasticity or serial correlation inhibits the OLS estimators from being the *Best Linear Unbiased Estimators (BLUE)*. This makes the estimator inefficient, leading to imprecise predictions. Therefore, to eliminate this problem, the Breusch and Pagan (Breusch & Pagan, 1979) test for heteroskedasticity and the Wooldridge (Wooldridge, 2015) test for serial correlation are employed accordingly.

Results

Descriptive Statistics

Following the estimation procedure employed for the conduct of this study, the first result is reported on the descriptive statistics of the study data. Table 2. Summarizes the results of the statistics. The mean values for the series show that GDP has the highest value compared to TOP, DCP, FDI, CO2, and FinTech respectively. Further, looking at the values for the standard deviation, GDP again shows the highest value of 9.196 to explain that the data points are not scattered around the mean value of 14.929. Except for FDI with a standard deviation of 1.504, FinTech, TOP, DCP, and CO2 all show values less than 1.000 to indicate that the values are closer to the mean values of 0.311, 0.278, 0.346, and 0.574 respectively. On the skewness of the distribution, C02, TOP, and FDI are negatively skewed while FinTech, DCP, and GDP are positively skewed respectively. Again, the kurtosis values show that only FDI has a leptokurtic shape. All the other variables (C02, GDP, DCP, FinTech, and TOP) have a platykurtic shape. The Jarque-Bera test shows that all the variables are not normally distributed. Per the correlation matrix in table **2**, an increase in C02 emissions in these countries are positively and significantly related to FinTech, DCP, TOP, and GDP. This suggests that as C02 increases, these variables also increased. On the other hand, the statistics show that C02 emissions in these countries are negatively associated with FDI to show that FDI growth reduces C02 emissions. Finally, the VIF and tolerance test results justified the absence of multi-collinearity amid the explanatory series.

Table 2 Summary Statistics

Descriptive Statistics

Variables	Mean	Std.Dev	Skewness	Kurtosis	Jarque-Bera	Probability
lnCO2	-1.112	0.574	-0.585	2.065	7.847	0.019
lnFinTech	-2.026	0.311	0.328	1.806	6.498	0.038
lnDCP	2.830	0.346	0.743	2.249	9.705	0.007
lnTOP	5.552	0.278	-0.012	2.321	1.613	0.046
lnGDP	14.929	9.196	0.301	1.116	13.695	0.001
lnFDI	0.344	1.504	-1.355	4.108	30.006	0.001

Correlational Matrix and Multicollinearity test

Variable	lnCO2	lnFinTech	lnDCP	lnTOP	lnGDP	lnFDI
lnCO2	1.000					
lnFinTech	0.547	1.000				
	0.000***					
lnDCP	0.303	0.111	1.000			
	0.005**	0.041*				
lnTOP	0.091	0.312	-0.229	1.000		
	0.408	0.003**	0.003**			
lnGDP	0.499	0.766	0.124	0.338	1.000	

	0.000***	0.000***	0.047*	0.001**		1.000
lnFDI	-0.116	-0.372	-0.037	0.301	0.137	
	0.034*	0.000***	0.021*	0.005**	0.042*	

Note: *** and ** represents statistical significance at 1% and 5% respectively.

Next, Table 3 summarizes the results of the principal components analysis for the study variables. Accordingly, FinTech and GDP are loaded under component 1^{k} while DCP, TOP, and FDI are all loaded under component 2^{p}. Consequently, the results suggest that the covariates are all significant and able to justify the emission of C02 in these countries. This is based on the loadings of the principal components analysis (PCA) results.

Table 3. Principal Components Analysis

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.477	0.417	0.246	3.882
Comp2	1.059	0.545	0.176	4.942
Comp3	0.514	0.040	0.085	5.456
Comp4	0.474	0.405	0.079	5.931
Comp5	0.068	---	0.011	6.000
Principal Components (Eigenvectors)				
Variables	Comp1	Comp2		
lnFinTech	0.589^{k}	-0.072		
lnDCP	0.163	-0506^{p}		
lnTOP	0.251	0.625^{p}		
lnGDP	0.561^{k}	0.183		
lnFDI	-0.091	0.585^{p}		

Note: k and p imply significant loadings under component 1 and component 2, respectively

Cross-sectional dependence tests results

Before the empirical analysis, cross-sectional reliance tests as mentioned in the earlier section were performed on the panel data employed. The results are based on three distinctive tests of cross-sectional dependence which include the Breusch and Pagan LM test, Pesaran scaled LM and Pesaran CD tests are there reported in Table 4. As shown in the table, outcomes from the aforementioned CD tests employed all failed in rejecting the null hypothesis of cross-sectional independence at a 10% level of significance. Meaning, that cross-sectional residual reliance across country groups cannot be considered. With the failure to reject the null hypothesis of cross-sectional independence, the study adopts first-generation panel unit root tests which include Levin, Lin, and Chu (LL&C) t-test, Im, Pesaran, and Shin (IPS) test, Augmented Dickey-Fuller Fisher (ADF-Fisher) and Phillips-Perron Fisher (PP-Fisher) to examine the integration properties of employed variables.

Table 4. Cross-sectional dependence and heterogeneity tests results

Equation	Tests	Statistic	Prob
Model 1	Breusch-Pagan LM	22.870	0.350
	Pesaran Scaled LM	0.288	0.772
	Pesaran CD	-0.559	0.575
Model 2	Breusch-Pagan LM	12.395	0.928
	Pesaran Scaled LM	-1.327	0.184
	Pesaran CD	-0.801	0.423

Note: *** and ** represents statistical significance at 1% and 5% respectively.

Unit root and cointegration tests results

Before conducting the panel cointegration test to examine the existence of long-run affiliations amid variables employed for the study, we investigate the integration properties of these variables. The panel unit root tests commonly used as reported in Table 5 are Levin, Lin, and Chu (LL&C) t-test, Im, Pesaran, and Shin (IPS) test, Augmented Dickey-Fuller Fisher (ADF-Fisher), and Phillips-Perron Fisher (PP-Fisher). The results disclose the variables to be analyzed are not stationary at their level forms but rather become stationary when differenced in the first order. Thus the variables employed within the study are integrated in the same order (I(1)).

Table 5. Unit root and cointegration tests results

Variables	CADF		CIPS		Decision
	I(0)	I(1)	I(0)	I(1)	Stationary
lnCO2	13.434 (0.492)	26.340 (0.023*)	-0.227 (0.409)	-1.966 (0.024*)	Stationary
lnFinTech	18.874 (0.169)	33.796 (0.002**)	-0.622 (0.266)	-2.899 (0.001**)	Stationary
lnDCP	20.753 (0.108)	27.533 (0.000***)	-0.606 (0.271)	-1.373 (0.005**)	Stationary
lnTOP	25.705 (0.091)	29.454 (0.020*)	-1.875 (0.070)	-1.951 (0.025*)	Stationary
lnGDP	12.673 (0.552)	28.433 (0.012**)	-0.265 (0.395)	-1.880 (0.030**)	Stationary
lnFDI	15.839 (0.323)	38.851 (0.000***)	0.327 (0.628)	-3.418 (0.000***)	Stationary

Note: *** and ** represents statistical significance at 1% and 5% respectively.

Per the results of the panel unit root tests, cointegration statistics from the Pedroni cointegration test are estimated to examine the long-run connection between the variables proposed in models 1 and 2. The outcome of the tests is reported in Table 6. The outcomes of Model 1 and Model 2 are statistically significant. consequently, rejecting the null hypothesis of no co-integration. In conclusion, the Pedroni panel cointegration test results suggest the variables are cointegrated in the two models proposed for the study.

Table 6. Cointegration tests

	Alternative hypothesis	Within-dimension		Weighted Statistic		Between-dimension	
		Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Model 1	Panel v-Statistic	-1.125	0.861	-1.930	0.973		
	Panel rho-Statistic	2.521	0.992	2.453	0.992		
	Panel PP-Statistic	-1.708	0.042	-3.259	0.000		
	Panel ADF-Statistic	-1.453	0.048	-1.802	0.035		
	Group rho-Statistic					3.833	0.999
	Group PP-Statistic					-3.014	0.001
	Group ADF-Statistic					-1.600	0.054
	Alternative hypothesis	Within-dimension		Weighted Statistic		Between-dimension	
		Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Model 2	Panel v-Statistic	-1.436	0.924	-2.167	0.984		
	Panel rho-Statistic	2.431	0.992	2.123	0.983		
	Panel PP-Statistic	-0.421	0.336	-2.423	0.007		
	Panel ADF-Statistic	-1.136	0.127	-1.357	0.045		
	Group rho-Statistic					3.674	0.999
	Group PP-Statistic					-2.257	0.009
	Group ADF-Statistic					-1.214	0.003

Note: *** and ** represents statistical significance at 1% and 5% respectively.

Panel models

The study employs two distinct models to examine the role of FinTech in reducing carbon emissions in the top 7 mobile money economies in sub-Saharan Africa. Accordingly, table **7.** summarizes the results from the two models. Per model 1, where FinTech is employed as the explanatory variable with TOP, GDP, and FDI as control variables, the study shows a negative significant relationship between C02 emission and FinTech with -0.329^{**} to suggest that a unit increase in FinTech in these countries reduces carbon emission -0.329%. Further, TOP and GDP show a positive significant relationship with CO2 to reveal that a 1% increase in TOP and GDP increases C02 in these countries by 0.444 and 0.545 respectively. On the other hand, FDI had a significant negative relationship with C02 in these countries to show that as FDI increases by 1% percent, C02 reduces by -0.020%. Per model 2, where DCP is employed as the explanatory variable with TOP, GDP, and FDI as control variables, the study reveals a statistically insignificant relationship between DCP and C02 emission for the period under consideration in these top mobile money economies in sub-Sahara Africa. However, just like reported in model 1, the control variables TOP, GDP, and FDI all show statistically significant relationships with C02 emissions in these countries. Specifically, a 1% increase in TOP and GDP increases C02 emissions by 0.381 and 0.471 respectively. Again, FDI shows a negative relationship to indicate that a unit increase in FDI reduces carbon emission by -0.027%. For robustness, the R-square and the adjusted R-square values for models 1 and 2 are indicative that both models perform better than a zero model.

Table 7. FMOLS

	Variables	Coef.	Std.Error	t-Stats	Prob.	R-Square	Adj. R Square
Model 1	lnFinTech	-0.329	0.131	-2.513	0.014^{**}		
	lnTOP	0.444	0.067	6.622	0.000^{***}		
	lnGDP	0.545	0.096	5.634	0.000^{***}	72.496	79.760
	lnFDI	-0.020	0.012	-1.587	0.030^{*}		
Model 2	lnDCP	0.108	0.073	1.466	0.147		
	lnTOP	0.381	0.071	5.353	0.000^{***}		
	lnGDP	0.471	0.098	4.869	0.000^{***}	65.215	73.054
	lnFDI	-0.027	0.014	-1.862	0.045^{*}		

Note: *** and ** represents statistical significance at 1% and 5% respectively.

Discussion of Results

To estimate the connection between FinTech and Carbon emission in the top 7 mobile money economies in sub-Sahara Africa from 2009 to 2020, we employ two models with financial technology (FinTech) and Domestic Credit to the Private Sector (DCP) as the explanatory variables. This is to help compare results for studies using DCP and this current study opting for FinTech. First, we test for the cross-sectional dependence of the residual terms. Accordingly, the results accepted the null hypothesis of no correlations in the error terms and thus shocks are not transferred from one country to the other (Musah et al.,2021). Next, we examined the integration order of the series and found that using the CIPS and CADF, all the series become stationary at the first-level difference. This suggests long-run cointegration affiliation for the series. Before estimating the final models, the panel cointegration test performed confirmed the long-run relationship between the variables. This permits the estimation of a Fully Modified Ordinary Least Square (FMOLS) to examine the nexuses between the variables.

Financial Technology (FinTech) shows a negative significant relationship with C02 emission in the 7 countries while DCP showed a statistically insignificant relationship with C02. This suggests that FinTech reduces C02 emissions in these economies by -0.329%. This result is consistent with existing studies on the nexus between FinTech, green finance, and C02 emission. On the other hand, unlike the study of Musah et al (2021) finding a positive significant relationship between DCP and C02, this study reveals statistically insignificant outcomes for the period under study. This suggests that the ability of FinTech to penetrate rural areas undesired by traditional financial institutions is creating an opportunity for less carbon and energy consumption activities. For example, most rural folks are no longer going to migrate or travel from point A to point B to access financial services (Asongu, 2018; Bukari & Koomson, 2020; Mawejje & Lakuma, 2019). Consequently, this study suggests the optimal design of future FinTech products and services to focus on less carbon-emitting investment activities. Similar to the emergence of green finance activities in developed countries (Ren et al., 2020; Saeed Meo & Karim, 2022), the growing Fintech landscape of Africa should be developed to harness the power of technology and finance toward the funding of environmentally sustainable projects. Further, mobile money service providers and governments in these countries should prioritize the mass diffusion and continual usage of mobile money services to reduce carbon emissions through migration (Gumba, 2018; Ligon et al., 2019). Therefore, the introduction of a mobile money tax which threatens mass usage and continual usage of mobile money and financial technology products should be reviewed accordingly (Coffie et al.,2022).

Per models 1 and 2, Trade openness (TOP) and carbon emission (C02) in these countries show a positive significant relationship. This is consistent with existing studies to indicate that as these countries open up to trade activities such as the importation of goods, there is a high likelihood that C02 would escalate when the nature or type of goods imported are not energy efficient. Consequently, while this study affirms the significance of FinTech in reducing C02 emissions in these countries, the government must institute policies to curb carbon emissions through trade. The recent introduction of import restrictions on more than ten years old cars in some African countries like Uganda and Ghana can become a tool for eliminating high carbon-emitting vehicles. Similar policies could be directed towards boosting the development of FinTech. Again, governments in these countries should provide tax incentives for the importation of low energy consumption and low carbon-emitting machinery and equipment. Finally, similar to the incentives provided by developing countries (Acheampong, 2018; Gholipour et al., 2022) to innovators who target low carbon-emitting innovations, these countries should adopt such incentives.

The economic development activities of these countries per both models revealed a positive connection with carbon emission. Similar to other studies (Ozturk, 2017; Zafar et al., 2019), the development of every country through productive activities involves the use of energy and the emission of carbon (Munir & Ameer, 2020; Tran, 2022). However, economic development can be achieved with proactive steps toward the reduction of carbon and energy usage (Nawaz et al., 2021; Zhu et al., 2016). For example, several countries consider the use of diesel vehicles a thing of the past because of the need to reduce carbon emissions (Musah et al., 2021; Ji-feng et al., 2019; Ren et al., 2020; Yao et al., 2019). Therefore, moving towards a cashless economy that promotes the uptake of various digital financial services should be encouraged. Similarly, most countries favor electric vehicles better than gasoline (Ji-feng et al., 2019; Ren et al., 2020; Sarkodie & Strezov, 2018). Thus, it is possible to push the digital finance agenda in Africa. Although countries in the sub-region are far from making these types of decisions, several avenues could be harnessed to reduce the use of energy and the emission of carbon. For example, banks should provide cheaper funding for equipment and machinery that can increase production yet reduce carbon emissions.

Further, the importation of equipment that is excessively old and with higher carbon emission rate should be prohibited by the government or should have higher taxes to minimize the importation of such equipment. Again, alternative transportation modes like bicycles and the sub-way should be encouraged in these countries to reduce the number of vehicles on the road. Finally, the designers of houses and apartments in Africa should consider designs that provide optimal ventilation to prevent the use of air-conditioners that consumes more energy. Finally, foreign direct investment (FDI) is negatively associated with carbon emission (C02) in these countries for the period under study. This outcome is consistent with existing studies (Musah et al., 2021; Awunyo-Vitor & Sackey, 2018; Bokpin, 2017)) to signify that FDI inflow reduces carbon emission. This indicates that the policies of these countries concerning FDI are environmentally friendly and encourage lower emissions of C02. Therefore, current policies and future policies aimed at attracting FDI should not only be to increase economic development but must also be to protect the environment. Further, similar policies governing the operations of FDI's in these countries should be extended to guide the operations of local businesses to encourage investment in environmentally sustainable machinery and equipment.

Conclusion and Policy Recommendation

The study employs FMOLS in the estimation of the relationship between FinTech and C02 emission in the top 7 mobile money economies in sub-Sahara Africa. The study followed robust econometric steps to arrive at the study outcome by estimating cross-sectional dependence, unit root, cointegration, and the FMOLS to answer two key questions (1) what is the effect of FinTech on C02 emission in these countries (2009-2020, and (2) what is the effect of financial development on C02 in these countries?

Financial Technology (FinTech) reduces C02 emissions in these countries. However, for the same period, Domestic Credit to the Private Sector (DCP) shows a statistically insignificant relationship with C02 emissions in the same countries. We can explain this result because FinTech especially mobile money usage reduces the movement of individuals from one place to the other in search of financial services thereby reducing the use of C02 through transportation and migration. Domestic credit to the private sector is insignificant because providing funding through the traditional financial system is unlikely to reduce migration and the emission of carbon through transportation. Therefore, the study recommends the encouragement of mass FinTech diffusion and continual usage in sub-Saharan Africa. Further, the future design of FinTech products and services should target environmentally friendly financing. Lastly, governments in these countries can reconsider the taxation of FinTech services to minimize the risk of losing FinTech customers.

Trade openness is confirmed to increase C02 emissions in the selected countries aligned to other previous studies. This can be explained by the fact that the openness to trade opens the flood gate to the importation of goods that, if not regulated, lead to the acquisition of cheaper options with high energy usage and carbon emission characteristics. This suggests that although FinTech is capable of reducing carbon emissions in these countries, the more open these economies in terms of trade with other countries the higher the likelihood of increased carbon emission. Therefore, these countries must introduce strategic steps to curtail carbon emissions from trade-related activities. Specific standards limiting or prohibiting the importation of environmentally unfriendly goods should be introduced or further strengthened to reduce carbon emissions through trade activities.

GDP growth increases carbon emissions in the selected countries. This is because of the productive activities engaged in by these countries which use processes, equipment, and machinery that has the potential of emitting carbon. Further, the increased consumption pattern of citizens which comes with the growth in GDP in these countries concerning some specific goods and services contributes to the increased carbon emission. Consequently, although economic development is desirable to improve the social standards of the citizens of these countries, there should be a deliberate strategy to minimize economic-related carbon emissions. Further, FinTech innovations should be employed as a green financing tool to encourage lending to environmentally concerned businesses.

FDI inflow reduces the emission of carbon in these countries. This could be because of the policies instituted by these countries to attract investors willing to follow the environmental policies of the countries. Again, this could be because of the technology transfer from developing countries into these countries. Consequently, the FDI inflow policies of these countries should be commended for considering the environment. However, this is the time for FDI recipient countries to institute similar policies for local businesses/investors to promote greater environmental protection through minimal energy usage and carbon emission.

Limitations and further study

The study provides insight into a partially ignored phenomenon that has the potential to speed up the cashless economy agenda as well as environmentally sustainable living. However, being the earlier studies looking into this issue, there are a few limitations that future studies could look into. First, although, the study focuses on the top 7 economies in Africa, future studies could expand the scope to estimate the effect of FinTech on CO2. Again, future studies can employ second-generation econometric estimations to authenticate this outcome. Finally, future studies can employ other measures of Fintech from other databases to determine the existence of the association identified between CO2 and FinTech in this study.

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