UNIVERSITY OF EXETER | BUSINESS SCHOOL

Department of Economics Discussion Papers

ISSN 1473-3307

Financial technology and human development in Africa: The moderating impact of energy poverty

Rilwan Sakariyahu, Fatima Oyebola Etudaiye-Muhtar, Rodiat Lawal, and Olayinka Oyekola

Paper number 23/02

Financial technology and human development in Africa: The moderating impact of energy poverty

Rilwan Sakariyahu (Corresponding author)
Business School, Edinburgh Napier University, Edinburgh, UK.
Email: r.sakariyahu@napier.ac.uk

Fatima Oyebola Etudaiye-Muhtar
Ilorin Business School, University of Ilorin, Ilorin, Nigeria.
Email: etudaiye.mf@unilorin.edu.ng

Rodiat Lawal
School of Finance and Management, SOAS University of London, London, UK.
Email: 676091@soas.ac.uk

Olayinka Oyekola
Department of Economics, University of Exeter, Exeter, UK
Email: O.Oyekola@exeter.ac.uk

Abstract

Several studies in the academic literature have identified the critical role of financial technology (fintech) in improving socio-economic conditions of nations, measured by human development index (HDI). However, despite the efforts to increase HDI using fintech, the ranking of African countries on the index table remains low. Given that access to electricity is imperative for fintech, and fundamental to human development, we provide novel evidence by investigating the degree to which the prevailing energy poverty in Africa affects the success of fintech on human development on the continent. Employing a number of econometric techniques which include linear (OLS, Prais-Winsten), instrumental-variable (GMM) and non-linear (M-M Quantile) regression models, our empirical framework is robust to heteroscedasticity, endogeneity, and cross-sectional dependence among countries. Our results show that fintech has a significant positive impact on human development and the impact remains consistent irrespective of the estimation methods employed. However, when we split our sample based on regions and income classification proposed by the World Bank, our results show that the impact of fintech, when interacted with access to electricity, on human development is more pronounced in the upper-middle, high-income, Eastern, Central and Southern countries. The Western countries have not significantly benefitted from fintech adoption, perhaps because those countries fall in the low-income categories and have a high prevalence of energy challenge. In light of the current state of human development in Africa, our study advocates for more investment in energy infrastructure for the rapid realization of the gains of fintech.

Keywords: fintech, human development, energy poverty, access to electricity, sub-Saharan Africa

JEL classification: C22, O43, Q4, Q43, Q48, Q55

1. Introduction

Over the past few decades, the goal of raising human development has been integral to the design of domestic programs around the world, with human development index (HDI) being the prominent measure to assess nations' socio-economic status. HDI is a tool developed by the United Nations to supplement metrics on economic growth and development. It evaluates the wellbeing and quality of life of a country's populace, thus placing greater emphasis on the capabilities and functioning of residents rather than the country at large (Chakravarty, 2003; Yumashev et al., 2020). The significance of HDI is that it directs the attention of governments towards implementing policies that not only improve the economy but also enhance human welfare. Hence, it has two dimensions – social and economic. The social dimension of HDI measures the health of the people, life expectancy at birth, access to information and knowledge, while the economic dimension underscores living standards and average income of the population (Hickel, 2020). The index is constructed to range between 0 and 1; a score of at least 0.80 indicates that the country in question ranks high in both social and economic dimensions.

Considering the vast benefits associated with human development, the majority of countries have embraced the yardsticks of HDI with a massive drive towards improving their socio-economic conditions. Meanwhile, in Africa, despite the quest to increase HDI, the ranking of African countries on the index table remains low. Although countries in Africa have increased budgetary spending on the metrics of HDI, such as education, health, and Information and Communications Technology (ICT), the effects remain largely varied across countries. A recent study has shown that only a few countries in sub-Saharan Africa, such as Seychelles, Mauritius, Botswana, South Africa and Gabon, and a couple of North African countries, have witnessed an increase in HDI within the past decade (Sarkodie & Adams, 2020). The evidence in Figure 1, which displays the average HDI scores for sub-Saharan Africa and the world, over our sample period (2002-2020), confirms that human development is much lower in sub-Saharan African countries than the world average. In particular, the mean HDI score in sub-Saharan Africa in 2020, the final year of our study sample, was still below the mean HDI score for the world at the start of the study sample in 2002 (UNDP, 2022). The continuing low-level HDI ranking of African countries impedes the continent's overall development and prevents its citizens from harnessing their potentials. Africa thus provides a unique opportunity to learn more about the following question: What factors promote (or impede) human development? This study offers a novel and profound answer to this important question.

Burgeoning studies in the broader economics and finance literature have identified various factors that boost human development in both developed and emerging markets. Essentially, a strand of the literature emphasizes the critical role of fintech. Proponents of fintech argue that its efficient use can protect the most disadvantaged in the society (Owusu-Agyei et al., 2020). For instance, studies argue that through technological innovations, fintech enhances financial inclusion (Tekin, 2020), reduces transaction cost (Wang et al., 2019), provides access to faster and cheaper finance among the poor (Tekin, 2020), increases literacy rate through information sharing (Owusu-Agyei et al., 2020), creates job opportunities for citizens (Hussain et al., 2021) and reduces poverty and inequality (Ababio et al., 2021), all of which positively affect human development. On the contrary, critics of fintech argue that it can be a source of economic instability and political manipulations (Wei, 2018). Others opine that fintech is not eco-friendly, because of the enormous amount of energy needed to run and process computer software and hardware (Potter, 2020; Chen et al., 2021). Besides, studies show that fintech adoption could lead to transfer of financial crises and risks from developed nations to emerging ones (Cole & Obstfeld, 1991; Wei, 2018).

Notwithstanding, fintech development is rapidly expanding and has become increasingly integrated into the economic strategies of most nations. However, it is reckoned in the literature that the impact of fintech on human development largely depends on macroeconomic and institutional quality variables such as GDP, corruption, domestic savings, rule of law, transparency, and efficiency of the domestic financial system (Owusu-Agyei et al., 2020; Sarkodie & Adams, 2020). For example, countries are less likely to attract investments into their fintech ecosystem if they have poor corporate governance structures and frequent economic instability. More importantly, another aspect of examining the impact of fintech on human development, especially in Africa, is to consider the availability of electricity. The development and adoption of fintech is deemed to rely heavily on energy sources which are in acute shortage in several parts of Africa. Andersen & Dalgaard (2013) note that a significant proportion of sub-Saharan Africans do not have constant access to electricity, and the erratic supply has forced many African firms and households to pay a chunk of their incomes to provide their own electricity.

Electricity connects everything in the technological world, and to this end, fintech may not achieve the intended goal of improving HDI in Africa if there is persistent energy challenge. As a nation's population increases, so will its energy demand. The relationship between fintech and human development has received significant interest in the literature with conflicting outcomes (Daniela & Sally, 2017; Tekin, 2020; Owusu-Agyei et al., 2020; Ofosu-Mensah et al., 2021). However, to the best of our knowledge, research on how energy moderates the duo remains unaddressed in the literature. Given that a reliable electricity supply is at the heart of fintech, and human development, there is a compelling motivation to fill this research vacuum. This further underscores the fresh insights offered in this study by investigating the degree to which energy poverty moderates the success of fintech on human development in Africa.

To achieve this objective, we use a panel data sourced from the World Bank Database (World Development Indicators), comprising of 43 countries in sub-Saharan Africa spanning the period 2002-2020. Employing several econometric techniques, which include linear (OLS, Prais-Winsten), instrumental-variable (GMM) and non-linear (M-M Quantile) regression models, our empirical framework is robust to heteroscedasticity, endogeneity and cross-sectional dependence among countries. Our main findings are as follows. We provide novel evidence of the relationship between fintech and human development in Africa using access to electricity as a moderating factor. Our results show that fintech has a significant positive impact on human development. This significant positive impact remains consistent regardless of the estimation methods. Furthermore, we split our sample based on regions and income classification proposed by the World Bank. Our results show that the impact of fintech on HDI, when interacted with access to electricity, is more visible in the upper-middle and high-income countries. The low-income countries have not significantly benefitted from fintech adoption, perhaps because countries in the low-income category have a high prevalence of energy challenge. In addition, we find that the increasing effect of the interactive term on HDI are pronounced in Eastern, Central and Southern regions. It is, however, not surprising that an insignificant relationship is registered for the Western region. This is perhaps because most of the countries in the Western region fall in the lower-income category and face acute energy crisis. This confirms that fintech may not accomplish the goal of improving HDI in Africa if energy crisis persists. Lastly, we introduce quantile regressions as a robustness to cater for the fact that countries' HDI characteristics are not the same across a given distribution of fintech measures. We therefore examine whether the impact of fintech on HDI across the quantiles, changes over time with distribution. Our findings do not materially differ from the baseline results. Notably, our results reflect significant implications for key stakeholders such as governments, development agencies, and policy makers.

Against this background, and in the light of the current state of human development in Africa, this study contributes to the academic literature on several fronts. First, we extend prior studies in the human development literature by demonstrating that an improvement in HDI is a *sine qua non* for the prosperity of the African continent. Research studies on human development (such as Ranis et al., 2006; Harttgen & Klasen, 2012; Sarkodie & Adams, 2020) argue that countries that place strong emphasis on HDI tend to witness rapid economic growth and development. The findings of our study further reinforce this position. Second, we contribute to the extant literature on fintech by demonstrating the significant role it plays in improving HDI and how energy poverty in the African region limits its impact. Despite the abundance of studies in the financial literature exploring the linkage between fintech and human development, less attention has been paid to the influence of energy supply. Our study therefore complements prior studies to advocate for more investment in energy infrastructure for the rapid realization of the gains of fintech. We opine that a significant improvement in access to constant electricity will motivate fintech usage among economic units and spur a positive impact on HDI. Third, by stratifying our sample into regions and income classification, we render more far-reaching insights into the peculiar plights of each region, rather than a composite evaluation. This approach offers valuable information for development institutions and other key stakeholders in providing unique solutions to the current HDI status of the African region. Finally, from a theoretical perspective, our results are consistent with the *internet growth and contestable market theory*, as well as *energy consumption-growth hypothesis*. These theories postulate that greater use of internet facilities, amid stable electricity, especially by disadvantaged units in an economy, propels an increase in standard of living and improves economic growth.

The remainder of this paper is structured as follows. In section 2, we give some background to our study by reviewing related studies in the literature that have considered fintech and human development and providing a brief overview of the relevant institutional developments in Africa. In section 3, we provide details of our data and methodology. Our empirical findings, significance, and policy implications are presented in section 4. Finally, the paper is concluded in section 5.

2. Background

The theoretical background of our study stems from the finance-growth literature that is focussed on how development in the financial sector enhances economic development. Ang (2008) argues that this is made possible through two main channels: total factor productivity (qualitative channel) and capital accumulation (quantitative channel). The total factor productivity channel comes into play when the financial system makes use of information technology to enhance the development of a country's industries by providing efficient credit facilities and such other innovative financial services as required by economic units. Likewise, Wachtel (2001) identifies the promotion of higher savings rates, through the provision of attractive and innovative products to encourage savings mobilization, as one of the channels through which financial development influences economic development of a country. These assertions suggest that technological innovations in financial services and products are necessary inputs that would positively influence the economic and social wellbeing of economic units. Financial technology may generally be defined as applying innovative technology to improve financial activities that would otherwise not be available to some economic units (Leong & Sung, 2018; Schueffel, 2016). With the adoption of fintech, it is expected that these units would have improved access to financial services, savings mobilization, and access to credit facilities that would impact positively on human capital development, health and education, which are all major components of human development (Demirgüç-Kunt et al., 2018; Matekenya et al., 2020). Human development, as espoused by Nussbaum (2000), includes a set of policy targets such as health, integrity, property rights and affiliation etc. that improve the living standards and well-being of individuals in an economy. Going further, the United Nations Development Program (UNDP) in 2018 refines the concept of human development to include improvement in health and education and political/institutional freedom. It is computed as the geometric average of three normalised indices encapsulating enjoying a long and healthy life, being knowledgeable, and possessing a decent standard of living, all of which are core policy targets for most national governments.

In line with the total factor productivity channel, some studies adopted the *internet growth and contestable market theory*, while drawing on the *unified theory of acceptance and use of technology* (UTAUT), to explain the ways through which use of technology influences financial access and ultimately improves the standard of living conditions of economic units as championed by the HDI (see, for instance, Asongu & Le Roux, 2017; Owusu-Agyei et al., 2020; Goel & Hsieh, 2002). The *internet growth and contestable market theory* outlines that internet usage mostly by disadvantaged units in an economy leads to increased financial access and greater competition due to lower transaction costs, reduction in both entry barriers and information asymmetry. In addition, the UTAUT provides plausible reasons that account for differences in internet adoption and use in different countries. These include the geographical setting and institutional quality of countries (Wang and Wang, 2010).

The activities relating to fintech include, but are not limited to, mobile banking, mobile payments and blockchain technology. The moderating role of energy in fintech adoption is viewed from the supply side of access to electricity and communication facilities (Yermack, 2018) such that access to reliable and constant electricity to power the mobile tools would encourage the adoption and use of fintech. For our study, we make use of mobile cellular subscriptions as our fintech variable and include access to electricity as one of the reasons that may explain the cross-country differences in adoption. Further buttressing the *internet growth and contestable market theory* is the growth in recent studies that examined the use of fintech in developing countries to enhance financial inclusion and improve access to financial services in disadvantaged, or unbanked locations (Chhorn, 2021; Chinoda & Mashamba, 2021; Demirgüç-Kunt et al., 2018; Emara, 2022; Tekin, 2020). Based on the preceding theoretical discussions, we hypothesize that fintech adoption enriches human development with access to electricity playing a moderating role in the relationship in sub-Saharan African countries.

Empirical literature on the relationship between fintech and human development has produced mixed results. Several studies argue that fintech adoption in developing countries contribute to improvement in human development index through social welfarism. For instance, Apiors and Suzuki (2018) find that users of mobile money in Ghana have more savings, more investments in education and small businesses, resulting in a better way of life. Wieser et al. (2019) similarly document that in Uganda, mobile money transfer technology improved the welfare and financial position of money transfer recipients and the overall rural economy. Chhorn (2021), in a cross-country study of eight Southeast Asian countries for the period 1990 to 2017, report that fintech adoption (mobile money) positively affected HDI, irrespective of the economic, political, and institutional environment of the country. Also, Ofosu-Mensah et al. (2021), in a study of 20 frontier market economies, demonstrate that promoting financial inclusion through fintech adoption goes a long way in improving human development in the group of countries under investigation and recommended a holistic approach to implementing development policies that would enhance HDI. Other studies, such as Gomber et al. (2017), Jones (2018), and Lyons et al. (2020), analogously confirm the positive effects of financial technology adoption on the welfare and standard of living of economic units.

Despite the positive effect of fintech adoption, several studies show its weak effect with the argument that fintech adoption also depends on some factors such as institutional quality and rate of technology adoption, as well as the spill-over effect of fintech on other sectors of the economy. In a comparative study between Kenya and Jamaica, Minto-Coy & McNaughton (2016) argue that, in Kenya, the institutional framework is an important determinant influencing the level of adoption and success of innovation in financial technology usage through constant innovations and being up to date with changes in regulatory policies. This was, however, not the case for Jamaica, where the more developed regulatory environment, together with path dependency, obstructed the introduction and progress of mobile banking, a form of fintech (see also Johnson, 2016; Mbiti & Weil, 2015). Their findings strengthened the important role played by institutions in fintech adoption and its overall effect on a country's socio-economic status, proxied by HDI. Supporting this assertion, Asongu & Nwachukwu (2016) opine that governance and institutions play a principal role in the relationship between mobile money and inclusive human development in sub-Saharan Africa. Regarding other factors impacting the fintech-HDI nexus, Yermack (2018) notes that some of the significant barriers to fintech adoption in developing countries are electricity supply, communication infrastructures in place, and the political system in place. This connotes a supply-side problem such that residing in a country with a more reliable supply of electricity, devoid of frequent outages, would encourage the use of fintech services, thus implying the existence of a moderating effect of electricity in fintech adoption-HDI relationship.

3. Data and methodology

3.1. Data description

To evaluate the relationship between financial technology and human development, we construct our dataset as a panel of 43 countries in sub-Saharan Africa. The countries included in our sample are shown in the appendix and data is sourced from the World Development Indicators (WDI) of the World Bank's database. The time span for this study covers from 2002 to 2020. Our choice of this period is for two reasons. First, the availability of data; all the country-level variables adopted in the empirical equation are only available for these years, as at the time of writing. Second, we focus on this period due to the significance of the era; our timeframe falls within the United Nations Millennium Development Goals (MDG) era, where several countries galvanized unprecedented efforts to meet 8 different goals, of which, part of the strategy to achieving these goals was human development. More so, within this timeframe, fintech witnessed significant growth in its dynamics, as more countries continued to adopt fintech tools to increase their HDI statistics.

The dependent variable in our model is the yearly value of Human Development Index (HDI) for each sub-Saharan African country. The index is computed by the World Bank, with values ranging from 0 to 1 and covers both social and economic dimensions of each country. A country with a score of at least 0.80 is designated as a high human development country (see World Development Indicators database for further information on the characteristics of the variable). Prior studies that have used this index include Sarkodie & Adams (2020) and Matekenya et al. (2021).

Our set of explanatory variables contains indexes for fintech and institutional quality, and indicators to capture the macroeconomic environment of a country, with access to electricity acting as moderating factor. Following empirical postulations in the literature, we build a fintech index based on the following measures: individuals using the internet (% of population), fixed broadband subscriptions (per 100 people), mobile money penetration and mobile cellular subscriptions (per 100 people). We believe these proxies have a positive impact on HDI because an increase in their provision and usage can improve financial literacy and raise socio-economic conditions of citizens. Moreover, studies (such as Choi & Yi, 2009; Wang & Wang, 2010; Asongu & Roux, 2017; Owusu-Agyei et al., 2020) have used these variables and report significant effects on both human and economic development.

The next independent variable is the institutional quality index which is constructed based on the following 6 measures: control of corruption, government effectiveness, political stability and absence of violence, rule of law, voice and accountability and regulatory quality (Wang & Wang, 2010; Sarkodie & Adams, 2020). Since we assume that the sampled countries are likely to be deeply integrated, it is plausible to expect the institutional index variable to help control the impact of such integration on the HDI at country level. For example, countries in the Southern African region are notable for their strong institutional qualities compared to those in other parts of Africa, and these countries, on average, have higher HDI. Thus, an effort to capture such cross-country variations is warranted.

The macroeconomic indicators included are also driven by empirical arguments. They include: GDP per capita, a proxy used to measure the size of the economy and we expect it to relate positively with HDI (Asongu & Le Roux, 2017); inflation, a variable used to measure the purchasing power of the economy and we anticipate its increase will reduce HDI (Emara, 2022); population growth, a measure used to reflect a country's human capital and capture the increase (or decrease) in the number of people accessing a country's resources (Emara, 2022); and trade openness, which is used to measure a country's economic and trade freedom (Chinoda & Mashamba, 2021).

Lastly, we utilise access to electricity as the moderating variable. We define access to electricity as a condition of energy poverty which is characterized by intermittent supply of electricity to households and firms (Sarkodie & Adams, 2020; Banerjee et al., 2021). We collect this data from WDI's database of the World Bank. We further collect data on power generation as an alternative measure of energy poverty. Our main estimations only include access to electricity as a moderating variable. For conciseness, we do not report the output containing the alternative measure – power generation – because the sign and size of its coefficients are comparable to those of access to electricity. We report the descriptive statistics, correlation matrix, and variance inflation factor in tables 1, 2, and 3, respectively. Also, trend in access to electricity and power generation for our sampled countries are shown in Figures 2 and 3.

Please insert tables 1, 2 and 3 here

3.2. Model specification and estimation methods

We now turn our attention to the empirical models employed in this paper. Essentially, we use linear, instrumental-variable, and non-linear regression models to explain the impact of the explanatory variables on HDI. With regards to the linear models, first, we build a simple ordinary least squares (OLS) model, followed by a random-effect model, a choice informed by the output of the Hausman test. Next, we adopt a Prais–Winsten regression model to cater for heteroscedasticity inherent in the data. For the instrumental-variable model, we adopt Generalized Method of Moments (GMM) with a view to accounting for endogeneity. Lastly, we use the Method of Moments Quantile Regression (MM-QR) model as a non-linear approach to check for robustness. Details of the model specification are shown in the next sub-sections.

3.2.1. OLS and random vs fixed effects: Hausman test

We begin our empirical estimation with a pooled OLS regression defined as follows:

$$Y_{it} = \alpha_0 + \beta_1 X_{it} + \varepsilon_{it} \qquad (1)$$

where Y_{it} is the HDI for each sampled country each year, α_0 is the intercept, β_1 is the slope of the equation, X_{it} is a vector of predictors, and ε_{it} is the error term. However, given the nature of panel data, the OLS model may not account for random disturbances. Hence, we fit a random panel model of the following form:

$$Y_{it} = \alpha + \beta' X_{it} + \nu_i + \varepsilon_{it} \qquad (2)$$

where X_{it} refers to a K x 1 vector of strictly exogenous regressors (fintech index, institutional quality index, macroeconomic indicators, and access to electricity), and ν_i and ε_{it} are the disturbances and error term, respectively. In the above equations, subscripts i and t denote country and year, respectively.

3.2.1.1. Why random-effect model?

The choice of random effect model is sequel to a series of specification tests. Generally, fixed-effect model is suitable when certain conditions are present. First, when the number of units (firm or country) in a panel data is relatively higher than the time span, using fixed-effect model will result in misspecification and the variance of the estimated parameters will be unnecessarily high due to significant loss of degree of freedom (Thomas et al., 2014). Second, fixed effect model is usually applied to observations that are specific to a firm or country. Considering the structure of our data (small T and large N), the random-effect model is most appropriate, and this is further buttressed with the outcome of Hausman test which suggests no evidence to reject the null hypothesis (see appendix).

3.2.2. Test for cross-sectional dependence among sampled countries

A common assumption in panel data models is that the cross-sections exhibit an independent error term. However, according to Driscoll & Kray (1998), cross-sectional dependence might occur due to unobserved common shocks. In such circumstances, the estimated parameters may be inconsistent. Generally, cross-sectional dependence is common when the time span (T) is greater than the units (N). Our data, however, defies this condition, as the unit (N) is larger than the timespan (T). Nevertheless, we employ Pesaran (2004) parametric testing procedure for cross-sectional dependence and the results (shown in the appendix) confirm no evidence of cross-sectional dependence.

3.2.3. *Accounting for serial correlation and heteroscedasticity (Prais–Winsten model)*

Another standard assumption in panel data is that the model residuals must be void of serial correlation and heteroscedasticity. This is because the results of a linear panel model data with serial correlation tend to be inefficient and produce biased standard errors (Thomas et al., 2014). Hence, validating these assumptions is imperative. We use the Wooldridge (2002) approach to test for serial correlation and our results suggest the presence of first-order serial correlation in the residuals. Also, we use the Wald test to check for heteroscedasticity in the model and the results indicate its presence. Consequently, there is need to run a regression model to adjust the standard errors.

Given the presence of autocorrelation and heteroscedasticity in our residuals, we follow the approach suggested by Prais–Winsten (1954) and run a regression method that transforms the residuals as *first-order AR* pattern and systematically corrects the standard errors, as shown below:

$$\varepsilon_{it} = \alpha\varepsilon_{it-1} + \beta_{it} \qquad (3)$$

where α depicts the autocorrelation parameter and β represents the independent identically distributed parameter.

3.2.4. Accounting for endogeneity (Instrumental variable (IV) model)

A major concern in the use of panel data model is the presence of endogeneity which often leads to biased and inefficient estimates. We suspect endogeneity in some of the control variables, particularly the macroeconomic indicators. For instance, higher GDP per capita may increase HDI and vice versa while higher inflation may also have bi-directional causality with HDI. To correct for endogeneity problems and possible issues of non-normal distribution, we employ an instrumental variable method - Generalized Method of Moments (GMM)- to estimate the model. Unlike the static panel, the GMM estimator, as proposed by Arellano and Bond (1991), contains the lag of the dependent variable which eliminates individual effects while accounting for momentum and inertia. The model is specified as follows:

$$Y_{it} = \alpha + Y_{it-1} + \beta' X_{it} + \delta_i + \mu_t + u_{it} \qquad (4)$$

where Y_{it} refers to HDI of country i. Y_{it-1} is the lagged value of HDI, X_{it} denotes the vector of regressors, and δ_i, μ_t and u_{it} refer to country dummies, time effect, and the error term, respectively.

3.2.5. Accounting for non-linearity (MM-quantile regression)

Lastly, there may be concerns that some of the observed variations in the estimates of HDI may reflect the fact that country-characteristics are not the same across a given distribution of fintech. To examine this issue, we use quantile regression developed by Koenker (1978) which estimates the effect of regressors on the dependent variable at different points of the dependent variable's conditional distribution. We introduce quantile regressions, first, as a robust technique to cater for our estimations given that the standard assumption of normality of the error term might have been violated. Also, to get information about points in the distribution of the dependent variable other than the conditional mean (Baur, 2013). The estimating equation is specified below:

$$Q_{HDI_{it}}(\tau_j / X_{it}) = (\sigma_i + \gamma_{iq}(\tau)) + X'\beta(\tau_i) + \emptyset_i(\tau_j) + U_t(\tau_j), \tau_j \epsilon (0,1) \quad (5)$$

where $Q_{HDI_{it}}(\tau_j / X_{it})$ is the quantile of HDI conditioned on X_{it}, implying that the HDI variable is conditioned on the location of independent variables, X_{it} . Essentially, quantile estimates are conditioned on the coefficients' location, scale, magnitude, and sign (Machado & Silva, 2019). We therefore determine the total impact of the regressors on HDI by partially taking the derivatives of the equation to obtain the total impact.

4. Empirical findings

4.1. Impact of fintech on HDI

Based on the empirical strategy, table 4 shows the OLS results for our baseline models. Model 1 shows the direct effect of fintech on HDI, model 2 depicts the moderating effect of access to electricity on the relationship between fintech and HDI, and model 3 illustrates the interaction effect of fintech and access to electricity on HDI. We find that fintech positively affects HDI at the 1% significance levels across the regression models. This implies that the use of financial technology increases the social and economic conditions of the populace in sub-Saharan Africa. This conforms with the findings of Gomber et al. (2017), Apiors & Suzuki (2018), and Lyons et al. (2020), who find that financial technology enhances economic growth.

Furthermore, in line with the view of Tiwari et al. (2021) that the policies on access to electricity are germane for sustainable economic growth, we include access to electricity as a moderating variable in model 2. The results (shown on table 4) reveal that the coefficient of access to electricity is positive and significant with HDI at 1% level of significance. Hence, access to electricity is an important moderating factor that enhances the connection between fintech and HDI. This supports the expectation that the presence of adequate electricity could be a precipitator for fintech (Sarkodie & Adams, 2020; Yermack, 2018) and thus increases living conditions of people in sub-Saharan Africa.

Next in model 3, we repeat the tests in model 2 by including an interaction term (between fintech and access to electricity), an approach which has not been addressed in the literature, to the best of our knowledge. We find that the joint effect of fintech and access to electricity is positively significant. This implies that 1% increase in the interaction term will lead to an increase in the level of HDI. We also establish strong positive connection between access to electricity and HDI at 1% level. As such, the joint effect result further reinforces the strong relationship between fintech and HDI through access to electricity. This implies that access to electricity, as a key enabler of fintech, would accelerate the level of human development in sub-Saharan Africa. This corroborates the views of Sarkodie and Adams (2020) and Yermack (2018) whose separate studies suggest that constant electricity supply would encourage the use of fintech and invariably improve the standard of living of the economic units.

Consistent with other studies (such as Mbiti & Weil, 2015; Johnson, 2016; Minto-Coy and McNaughton, 2016; Yermack, 2018), the estimated coefficients of the control variables across the models show that GDP per capita, institutional quality and trade openness are positive and significantly increase HDI. Thus, they play significant roles in augmenting the socio-economic conditions of countries. Moreover, population growth is negative and significant, suggesting an increase in population without adequate policies in place could reduce the socio-economic wellbeing of the people.

Please insert table 4 here

Due to the limitations of OLS model producing spurious results, we conduct random-effect (RE) regressions to solve the problem of correlated errors in a regression model (Allison, 2009).

Moreover, we conduct Hausman test (see appendix) to choose the regression that is suitable for our model. The *p*-value of the coefficient of the Hausman-test is not significant, therefore we accept the null hypothesis which specifies that random effect is appropriate. We report the result of random-effect regression for our baseline models in table 5. Interestingly, the results of the random-effect regression are in tandem with the OLS regression estimates in table 4. These results suggest that financial technology and access to electricity ultimately improve the standard of living conditions of economic units.

Please insert table 5 here

Furthermore, in table 6, we report the Prais &Winsten (1954) regression which considers AR(1) serial correlation of the errors in the regression model. We subject the Prais-Winsten regression to follow the patterns of the OLS and random effect models in tables 4 and 5. We find that all the coefficients of the variables of interest in the three models have the expected signs and are consistent with the results that we obtain in tables 4 and 5. This further accentuates the strong relationship between fintech and HDI as well as the moderating effect of access to electricity. Consequently, our findings bolster the argument that fintech, in the context of constant electricity supply, enhances socio-economic status of individuals in a country. This is also in line with the works of Asongu & Le Roux (2017), Apiors & Suzuki (2018), Lyons et al. (2020), and Owusu-Agyei et al. (2020).

Please insert table 6 here

4.2. Moderating the effect of fintech and access to electricity based on income and regional classification of countries in sub-Saharan Africa

To address the heterogeneity of the sample characteristics, we assess the influence of fintech on HDI using the regions and income-classes of countries in sub-Saharan Africa. We adopt models in tables 4, 5 and 6, employing Prais-Winsten regression to ascertain the differences in sample characteristics.

4.2.1. Heterogeneity by income classification of countries

In table 7, we investigate whether the increasing impact of the interactive term (between fintech and access to electricity) on HDI varies across income levels. This income classification is based on the World Bank categorization of countries in sub-Saharan Africa. We establish a positive relationship between the interactive term and HDI for only upper-middle and high-income countries and insignificant effects for the low and middle-income countries. This conforms with the assertion of Bloom et al. (2010), that countries with high prevalence of energy shortage (such as the lower income countries) may not be able to harness the gains of fintech compared to their counterparts with higher income levels. Invariably, financial technology, as a growth opportunity, tends to increase the social and economic well-being in an environment of affordable and available energy supplies.

Please insert table 7 here

4.2.2. Heterogeneity by regional classification of countries

Next, table 8 reports the Prais-Winsten regression results of examining whether the effect of the interactive term (between fintech and access to electricity) on HDI differs meaningfully by regions of sub-Saharan Africa. We find that the increasing effects of the interactive term on HDI are pronounced in Eastern, Central and Southern regions. It should, however, not be surprising that an insignificant relationship is registered for the Western region. Whilst they are supposed to enjoy more growth opportunities like the adoption of fintech (Bloom et al., 2010), many countries in the Western region fall in the lower-income category, with low electrification rates acting as a major barrier to the adoption and use of fintech (Yermack, 2018; Michael, 2016). Invariably, the electricity obstacle faced by most countries in the region could best explain the insignificant effect.

Please insert table 8 here

4.3. Robustness tests

To further verify the preceding results, we adopt Generalized Method of Moments (GMM) technique for our baseline models in tables 4, 5 and 6. This model is considered superior because it is robust to endogeneity, simultaneity, and heterogeneity (Arellano and Bond, 1991). The estimated coefficients of fintech and access to electricity, and interactively specifically show positive effects on human development. Given the positive signs of the interactive term in the baseline regression models (OLS, RE and Prais-Winsten) and GMM, we infer that financial technology and access to electricity complement each other in explaining the socio-economic wellbeing of the countries in sub-Saharan Africa. Additionally, all the control variables have the predicted signs and do not materially differ from the baseline regression results. Moreover, the *p*-values in table 9 from the Hansen test indicate that the instruments used are valid while AR(2) being insignificant means that no second order autocorrelation exists.

Please insert table 9 here

Furthermore, we employ a non-linear regression technique (the MM-quantile regression), as a check on our baseline models. This is used to express the conditional quantiles of HDI as a function of fintech and other predictors. Thus, we divide HDI into 0.25, 0.50, 0.75 and 0.90 quantiles. As predicted, the models in tables 10, 11 and 12 generate significant positive median coefficients for our variables of interest (fintech, access to electricity and their interaction term) and the control variables across all quantiles of the HDI. Thus, these suggest that the use of financial technology drives the social and economic wellbeing of the economic units. Besides, the availability of electricity is a stimulus for fintech in enhancing high socio-economic status. The results further give support to our baseline regression outcomes. Even though the positive effects are registered in all the quantiles, the coefficients increase as the quantiles level of the HDI increases. For example, in table 12 (which uses the model 3 of table 4), the coefficient is 0.0280 at 0.25 quantile but increased gradually to 0.0452 at 0.90 quantile. Similar outcomes can be observed in the results presented in tables 10 and 11 for model 1 and model 2, respectively.

Please insert tables 10 and 11 here

We also show the marginal effects of fintech at the mean and percentile levels of 5%-99%. The results in table 12 show that the marginal effects of fintech at the mean level of access to electricity is positive for HDI. Interestingly, while the results vary at percentile levels, they tend to increase at higher levels but reduce at lower levels. It is important to note that countries with HDI percentile below 0.50 fall into the lower income category, while above 0.50 are higher income countries. This further provides support to the findings in table 7, that the low income and low-middle income countries are less likely to appropriate the potential benefits inherent in the adoption of fintech as a growth opportunity, and may, therefore, not improve the socio-economic conditions of their economic units because of energy poverty. Overall, fintech and more importantly, the proposed moderating factor, access to electricity, are essential mechanisms that could accelerate levels of human development in sub-Saharan Africa. Indeed, our findings resonate the importance of access to electricity as a good moderating variable in explaining the effects of fintech on HDI. This corroborates the assertion of Bloom et al. (2010) that countries with stable energy supply are more likely to exploit the gains of fintech and thus improve the socio-economic conditions of their citizens.

Please insert table 12 here

5 Conclusion

The availability of, and access to, fintech tools has been identified as one of several factors that can help improve human development, as measured by Human Development Index (HDI), which has been used over the years to assess the socio-economic status of individuals in a country, as well as study how human development compares across countries. However, fintech adoption is also largely dependent on the availability of, and access to, constant electricity supply. Noting that access to power supply is a challenge in some parts of sub-Saharan Africa, this study specifically investigates the effect of fintech adoption on HDI with electricity playing a moderating role in 43 sub-Saharan African countries for the period 2002 to 2020. Employing robust regression techniques that account for heteroscedasticity, cross-dependence, endogeneity, and non-linearity of data, our findings show that fintech and electricity enhance HDI in the countries under investigation.

When fintech and electricity are interacted and the sample is split by income and regional classifications, we find positive effects for only the upper-middle income and high-income countries and Eastern, Central and Southern regions, respectively. These results imply that low- and middle-income countries as well as those in the Western region of sub-Saharan Africa are not importantly reaping the expected reward from fintech adoption. This is, however, not surprising given the challenge of electricity supply they are faced with.

Policy wise, it becomes important for countries in the Western region as well as low- and middle-income sub-Saharan African countries to put in place measures and infrastructures that would address the energy poverty being experienced by their populace. This action would ensure that they do not miss out on the benefits of fintech adoption and at the same time, do not suffer a lag in HDI.

References

Allison, P. D. (2009). *Fixed effects regression models*. SAGE publications.

Ang, J. B. (2008). Survey of recent developments in the literature of finance and growth. *Journal of Economic Surveys, 22*, 536-576.

Apiors, E. K., and Suzuki, A. (2018). Mobile money, individuals' payments, remittances, and investments: Evidence from the Ashanti Region, Ghana. *Sustainability*, 10(5),1409.

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte-Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58 (2):277–297.

Asongu, A.S & Nwachukwu, J.C, (2016). The role of governance in mobile phones for inclusive human development in Sub-Saharan Africa. *Technovation*, 55-56, 1–13.

Asongu, S. A., & Le Roux, S. (2017). Enhancing ICT for inclusive human development in Sub-Saharan Africa. *Technological Forecasting and Social Change*, *118*, 44-54.

Baur, D. G. (2013). The structure and degree of dependence: A quantile regression approach. *Journal of Banking & Finance*, *37*(3), 786-798.

Bloom, N., Mahajan, A., McKenzie, D., and Roberts, J. (2010). Why do firms in developing countries have low productivity? *American Economic Review*, 100(2):619–23.

Breusch, T.S., Pagan, A.R., 1980. The Lagrange Multiplier test and its applications to model specification in econometrics. Review of Economic Studies 47 (1), 239–253

Chakravarty, S. R. (2003). A generalized human development index. *Review of Development Economics*, *7*(1), 99-114.

Chhorn, D (2021). Financial development, poverty, and human development in the fintech age: a regional analysis of the Southeast Asian states. DANS. 2021

Chinoda, T., & Mashamba, T. (2021). Fintech, financial inclusion, and income inequality nexus in Africa. *Cogent Economics & Finance*, *9*(1). Available at https://doi.org/10.1080/23322039.2021.1986926

Choi, C., & Yi, M. H. (2009). The effect of the Internet on economic growth: Evidence from cross-country panel data. *Economics Letters*, *105*(1), 39-41.

Daniela, G & Sally, B (2017). The digital revolution in financial inclusion: international development in the fintech era. New Political Econ. 2017; 22(4): 423–436.

Demirgüç-Kunt, A., L. Klapper, D. Singer, S. Ansar, and J. Hess. (2018). *The Global Findex Database 2017: Measuring Financial Inclusion and the FinTech Revolution*.Washington, DC: The World Bank.

Driscoll, J.C., Kraay, A.C., 1998. Consistent covariance matrix estimation with spatially dependent panel data. Review of Economics and Statistics 80 (4), 549–560.

Emara, N. (2022). Asymmetric and Threshold Effects of Fintech on Poverty in SSA Countries. *Available at http://dx.doi.org/10.2139/ssrn.4062335*.

Goel, R. K., & Hsieh, E. W. (2002). Internet growth and economic theory. *Netnomics*, *4*(2), 221-225.

Gomber, P., Koch, J. A., & Siering, M. (2017). Digital finance and fintech: Current research and future research directions. *Journal of Business Economics*, 87(5), 537-580.

Harttgen, K., & Klasen, S. (2012). A household-based human development index. *World Development*, *40*(5), 878-899.

Hickel, J. (2020). The sustainable development index: Measuring the ecological efficiencyof human development in the anthropocene. *Ecological Economics*, *167*, 106331.

Hussain, M., Ye, Z., Bashir, A., Chaudhry, N. I., & Zhao, Y. (2021). A nexus of natural resource rents, institutional quality, human capital, and financial development in resource-rich high-income economies. *Resources Policy*, *74*, 102259.

Johnson, S. (2016). Competing visions of financial inclusion in Kenya: The rift revealed by mobile money transfer. *Canadian Journal of Development Studies*/Revue [Canadienne D'études Du Développement], 37(1), 83-100.

Jones, L. (2018). Guest editorial: Poverty reduction in the FinTech age. *Enterprise Development and Microfinance,* 29(2), 99-102.

Koenker, R., Bassett, G., 1978. Regression quantiles*. Econometrica* 46 (1), 33–50.

Leong, K., & Sung, A. (2018). FinTech (Financial Technology): what is it and how to use technologies to create business value in fintech way? *International Journal of Innovation, Management and Technology*, *9*(2), 74-78.

Lyons, A., Kass-Hanna, J. and Greenlee, A. (2020). Impacts of Financial and Digital Inclusion on Poverty in South Asia and Sub-Saharan Africa. Available at *https://ssrn.com/abstract=3684265*

Matekenya, W., Moyo, C., & Jeke, L. (2021). Financial inclusion and human development: Evidence from Sub-Saharan Africa, *Development Southern Africa*, 38 (5), 683-700. DOI:10.1080/0376835X.2020.1799760

Mbiti, I., & Weil, D. N. (2015). Mobile banking: The impact of M-Pesa in Kenya. In African Successes, Volume III: Modernization and Development (pp. 247-293). Chicago, IL: University of Chicago Press.

Micheal, W.N., (2016). Understanding Africa's energy needs. World Economic Forum. Understanding Africa's energy needs |World Economic Forum (weforum.org)

Minto-Coy, I., & McNaughton, M. (2016). Barriers to entrepreneurship and innovation: an institutional analysis of mobile banking; in Jamaica and Kenya. *Social and Economic Studies*, 65 (2), 107-139

Nussbaum, M, (2000). *Women and human development*. Cambridge University Press, New York

Nelder, J. A. and Wedderburn, R. W. (1972). Generalized linear models. *Journal of the Royal Statistical Society: Series A (General)*, 135(3):370–384

Ofosu-Mensah Ababio, J., Attah-Botchwey, E., Osei-Assibey, E., & Barnor, C. (2021). Financial inclusion and human development in frontier countries. *International Journal of Finance & Economics*, *26*(1), 42-59.

Owusu-Agyei, S., Okafor, G., Chijoke-Mgbame, A. M., Ohalehi, P., & Hasan, F. (2020).Internet adoption and financial development in sub-Saharan Africa. *TechnologicalForecasting and Social Change*, *161*, 120293.

Pesaran, M.H., 2004. General Diagnostic Tests for Cross Section Dependence in Panels. Cambridge Working Papers in Economics No. 435 and CESifo Working Paper Series.

Prais, S. J., & Winsten, C. B. (1954). Trend estimators and serial correlation. *Cowles Commission*. *383*, 1-26.

Ranis, G., Stewart, F., & Samman, E. (2006). Human development: beyond the human development index. *Journal of Human Development*, *7*(3), 323-358.

Sarkodie, S. A., & Adams, S. (2020). Electricity access, human development index, governance, and income inequality in Sub-Saharan Africa. *Energy Reports*, *6*, 455-466.

Schueffel, P. (2016). Taming the beast: A scientific definition of fintech. *Journal of Innovation Management*, *4*(4), 32-54.

Tekin, B. (2020). The nexus between financial development and human development: The case of developing countries. *Bilgehan Tekin Journal of Emerging Economies and Islamic Research*, *8*(2), 73-87.

Thomas, A., Spataro, L., & Mathew, N. (2014). Pension funds and stock market volatility: An empirical analysis of OECD countries. *Journal of Financial Stability*, *11*, 92-103.

Tiwari, A. K., Eapen, L. M., and Nair, S. R. (2021). Electricity consumption and economic growth at the state and sectoral level in India: Evidence using heterogeneouspanel data methods. *Energy Economics*, 94:105064.

Wachtel, P. (2001). Growth and finance: what do we know and how do we know it? *Journal of International Finance, 4*, 335-362.

Wang, H. Y., & Wang, S. H. (2010). User acceptance of mobile internet based on the unifiedtheory of acceptance and use of technology: Investigating the determinants and gender differences. *Social Behavior and Personality: an international journal 38*(3), 415-426.

Wang, Z., Rasool, Y., Asghar, M. M., & Wang, B. (2019). Dynamic linkages among CO2 emissions, human development, financial development, and globalization: empirical evidence based on PMG long-run panel estimation. *Environmental Science and Pollution Research*, *26*(36), 36248-36263.

Wieser, C., Bruhn, M., Kinzinger, J., Ruckteschler, C., & Heitmann, S. (2019). The impact of mobile money on poor rural households: Experimental evidence from Uganda Washington, D.C.: The World Bank. (Policy Research Working Paper 8913).

Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. The MIT Press, Cambridge, Massachusetts

Yermack, D. (2018). *FinTech in sub-Saharan Africa: What has worked well, and what hasn't* (No. w25007). National Bureau of Economic Research.

Yumashev, A., Ślusarczyk, B., Kondrashev, S., & Mikhaylov, A. (2020). Global indicators of sustainable development: Evaluation of the influence of the human development index on consumption and quality of energy. *Energies*, *13*(11), 2768.

Table 1: Summary statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
HDI	645	0.505	0.022	0.463	0.538
Fintech	645	0.187	0.551	0.472	1.177
Access to electricity	645	42.773	3.482	38.523	51.103
GDP per capita	645	2.260	1.030	4.192	0.598
Institutional quality	645	0.112	0.289	0.146	0.980
Inflation	645	6.729	1.964	4.389	13.016
Trade openness	645	70.963	5.536	59.315	76.712
Population growth	645	2.472	0.944	-2.629	4.655

Note: See the text for the definition and measurement of variables.

Table 2: Correlation matrix

Variable	1 *HDI*	2 *Fintech*	3 *Access to electricity*	4 *GDP per capita*	5 *Institutional quality*	6 *Inflation*	7 *Trade openness*	8 *Population growth*
1	1.0000							
2	-0.4669*	1.0000						
3	-0.2051*	0.3152*	1.0000					
4	-0.1670*	0.1719*	0.4101*	1.0000				
5	0.5545*	-0.3689*	-0.3870*	-0.3351*	1.0000			
6	-0.2650*	0.1933*	-0.1540*	-0.4231*	-0.0341	1.0000		
7	-0.0003	0.0727	-0.2181*	-0.1910*	0.0684	-0.0846*	1.0000	
8	0.0456	-0.0624	-0.0602	-0.0366	0.0434	0.0301	-0.0110	1.0000

Note: See the text for the definition and measurement of variables. * denotes the statistical significance level at 5 percent.

Table 3: Variance inflation factor

	VIF	1/VIF
Fintech	2.023	0.494
Access to electricity	1.807	0.553
GDP per capita	1.417	0.706
Institutional quality	1.330	0.752
Inflation	1.129	0.885
Trade openness	1.012	0.988
Population growth	1.007	0.993
Mean VIF	1.389	

Note: See the text for the definition and measurement of variables.

Table 4: The impact of fintech on HDI: OLS regression results

Variables	Model 1	Model 2	Model 3
Fintech * Access to electricity			0.0396***
			(0.0020)
Fintech	0.2993***	0.2340***	0.2910***
	(0.0294)	(0.0293)	(0.0331)
Access to electricity		0.0328***	0.0371***
		(0.0032)	(0.0030)
GDP per capita	0.1043***	0.0795***	0.1150***
	(0.0110)	(0.0083)	(0.0077)
Institutional quality	0.6414***	0.4688***	0.5006***
	(0.0474)	(0.0469)	(0.0489)
Inflation	-0.0173	-0.0111	-0.0109
	(0.0164)	(0.0153)	(0.0140)
Trade openness	0.0133***	0.0134***	0.0128***
	(0.0003)	(0.0002)	(0.0002)
Population growth	-0.0189**	-0.0139	-0.0157**
	(0.0093)	(0.0085)	(0.0078)
Constant	-1.4487***	-2.8926***	-3.2250***
	(0.0457)	(0.1450)	(0.1362)
Observations	645	645	645
R-squared	0.448	0.576	0.597

Note: The table reports the result of ordinary least square (OLS) regression of our baseline models. Model 1 assesses the relationship between fintech and HDI. Model 2 illustrates the relationship between fintech and HDI with an inclusion of access to electricity as a moderating variable. Model 3 portrays the interaction effect of fintech and access to electricity on HDI. Robust standard errors are in parentheses. See the text for the definition and measurement of variables. ***, ** and * denote the statistical significance level at 1 percent, 5 percent and 10 percent respectively.

Table 5: The impact of fintech on HDI: Random-effect regression results

Variables	Model 1	Model 2	Model 3
Fintech * Access to electricity			0.0396***
			(0.0011)
Fintech	0.2995***	0.2342***	0.2912***
	(0.0176)	(0.0171)	(0.0212)
Access to electricity		0.0328***	0.0371***
		(0.0016)	(0.0015)
GDP per capita	0.1044***	0.0796***	0.1150***
	(0.0056)	(0.0046)	(0.0044)
Institutional quality	0.6414***	0.4689***	0.5007***
	(0.0243)	(0.0257)	(0.0299)
Inflation	-0.0169**	-0.0107	-0.0106
	(0.0082)	(0.0074)	(0.0077)
Trade openness	0.0133***	0.0134***	0.0128***
	(0.0001)	(0.0001)	(0.0000)
Population growth	-0.0187***	-0.0136***	-0.0155***
	(0.0048)	(0.0042)	(0.0049)
Constant	-1.4529***	-2.8974***	-3.2290***
	(0.0173)	(0.0708)	(0.0615)
Observations	645	645	645
Number of countries	43	43	43

Note: The table reports the result of random-effect regression of our baseline models. Model 1 assesses the relationship between Fintech and HDI. Model 2 illustrates the relationship between fintech and HDI with an inclusion of access to electricity as a moderating variable. Model 3 portrays the interaction effect of fintech and access to electricity on HDI. Robust standard errors are in parentheses. See the text for the definition and measurement of variables. ***, ** and * denote the statistical significance level at 1 percent, 5 percent and 10 percent respectively.

Table 6: The impact of fintech on HDI: Prais-Winsten regression results

Variables	Model 1	Model 2	Model 3
Fintech * Access to electricity			0.0452***
			(0.0024)
Fintech	0.2781***	0.2465***	0.3300***
	(0.0319)	(0.0273)	(0.0295)
Access to electricity		0.0350***	0.0415***
		(0.0028)	(0.0025)
GDP per capita	0.0923***	0.0871***	0.1419***
	(0.0099)	(0.0086)	(0.0075)
Institutional quality	0.5893***	0.5049***	0.5734***
	(0.0578)	(0.0489)	(0.0641)
Inflation	-0.0208	-0.0083	-0.0067
	(0.0189)	(0.0131)	(0.0107)
Trade openness	0.0132***	0.0136***	0.0124***
	(0.0003)	(0.0002)	(0.0001)
Population growth	-0.0215**	-0.0117	-0.0114*
	(0.0104)	(0.0074)	(0.0061)
Constant	-1.4602***	-2.9829***	-3.3798***
	(0.0461)	(0.1275)	(0.1148)
Observations	645	645	645
R-squared	0.545	0.491	0.522

Note: The table reports the result of Prais-Winsten regression of our baseline models. Model 1 assesses the relationship between fintech and HDI. Model 2 illustrates the relationship between fintech and HDI with an inclusion of access to electricity as a moderating variable. Model 3 portrays the interaction effect of fintech and access to electricity on HDI. Robust standard errors are in parentheses. See the text for the definition and measurement of variables. ***, ** and * denote the statistical significance level at 1 percent, 5 percent and 10 percent respectively.

Table 7: The impact of fintech on HDI: Prais-Winsten regression results by income classification

Variables	(1) Low	(2) Low-middle	(3) Upper-middle	(4) High
Fintech*Access to electricity	0.0435	0.0460	0.0675***	0.0401***
	(0.0318)	(0.0039)	(0.0079)	(0.0036)
Fintech	2.1993*	0.3345***	0.4055***	0.2941***
	(0.8315)	(0.0464)	(0.0715)	(0.0510)
Access to electricity	0.0418*	0.0415*	0.0434***	0.0933***
	(0.0041)	(0.0041)	(0.0060)	(0.0125)
GDP per capita	0.1190***	0.1445***	0.1971***	-0.0115
	(0.0117)	(0.0119)	(0.0191)	(0.1195)
Institutional quality	0.5237***	0.5947***	0.6649***	-1.5455
	(0.0922)	(0.1140)	(0.1853)	(2.0707)
Inflation	-0.0327	-0.0078	-0.0065	-6.1310**
	(0.0456)	(0.0154)	(0.0227)	(1.6312)
Trade openness	0.0126***	0.0124***	0.0114***	0.0105***
	(0.0002)	(0.0002)	(0.0004)	(0.0022)
Population growth	-0.0283	-0.0191*	-0.0047	0.0661
	(0.0173)	(0.0103)	(0.0103)	(0.0506)
Constant	-3.3559***	-3.3622***	-3.4631***	4.7618
	(0.1930)	(0.1884)	(0.2709)	(2.4335)
Observations	270	240	120	15
R-squared	0.418	0.421	0.548	0.493

Note: The table reports the result of Prais-Winsten regression of our baseline models based on income classification of sub-Saharan African countries. Model 1 assesses the relationship between fintech and HDI. Model 2 illustrates the relationship between fintech and HDI with an inclusion of access to electricity as a moderating variable. Model 3 portrays the interaction effect of fintech and access to electricity on HDI. Robust standard errors are in parentheses. See the text for the definition and measurement of variables. ***, ** and * denote the statistical significance level at 1 percent, 5 percent, and 10 percent respectively.

Table 8: The impact of fintech on HDI: Prais-Winsten regression results by regional classification

Variables	(1) Western	(2) Southern	(3) Eastern	(4) Central
Fintech*Access to electricity	0.0436	0.0600***	0.0423***	0.0593***
	(0.0040)	(0.0091)	(0.0038)	(0.0070)
Fintech	0.3049***	0.4415***	0.2990***	0.4685***
	(0.0459)	(0.1154)	(0.0442)	(0.1132)
Access to electricity	0.0413*	0.0428***	0.0423***	0.0400***
	(0.0044)	(0.0070)	(0.0044)	(0.0054)
GDP per capita	0.1429***	0.1619***	0.1365***	0.1488***
	(0.0128)	(0.0250)	(0.0126)	(0.0193)
Institutional quality	0.5408***	0.7535**	0.5152***	0.8333***
	(0.0986)	(0.3139)	(0.0905)	(0.2951)
Inflation	-0.0131	-0.0126	-0.0096	-0.0310
	(0.0182)	(0.0279)	(0.0211)	(0.0362)
Trade openness	0.0125***	0.0119***	0.0125***	0.0119***
	(0.0002)	(0.0005)	(0.0002)	(0.0003)
Population growth	-0.0077	-0.0288	-0.0168*	-0.0099
	(0.0183)	(0.0353)	(0.0101)	(0.0117)
Constant	-3.3693***	-3.4679***	-3.3771***	-3.4178***
	(0.2089)	(0.2968)	(0.2063)	(0.2213)
Observations	225	60	225	135
R-squared	0.317	0.550	0.415	0.456

Note: The table reports the result of Prais-Winsten regression of our baseline models based on region classification of sub-Saharan African countries. Model 1 assesses the relationship between fintech and HDI. Model 2 illustrates the relationship between fintech and HDI with an inclusion of access to electricity as a moderating variable. Model 3 portrays the interaction effect of fintech and access to electricity on HDI. Robust standard errors are in parentheses. See the text for the definition and measurement of variables. ***, ** and * denote the statistical significance level at 1 percent, 5 percent, and 10 percent respectively.

Robustness Checks

Table 9: The impact of fintech on HDI: GMM regression results

Variables	Model 1	Model 2	Model 3
HDI lagged	3.8361***	2.8690***	6.2847***
	(0.4337)	(0.4645)	(0.3567)
Fintech*Access to electricity			0.0616***
			(0.0017)
Fintech	0.3917***	0.3970***	0.3817***
	(0.0988)	(0.0967)	(0.0951)
Access to electricity		0.0263***	0.0233***
		(0.0047)	(0.0022)
GDP per capita	2.0076***	1.5051***	3.2915***
	(0.2205)	(0.2363)	(0.1822)
Institutional quality	0.3278***	0.3237***	0.0395
	(0.0884)	(0.0817)	(0.0728)
Inflation	-0.9312***	-1.0226***	-0.4222*
	(0.3013)	(0.3138)	(0.2427)
Trade openness	0.0137***	0.0135***	0.0132***
	(0.0001)	(0.0002)	(0.0001)
Population	-0.05883	-0.0364	-0.0641**
	(0.0671)	(0.0328)	(0.0280)
Model Diagnostics:			
AR(1)	-0.88 (0.000)	-1.29 (0.000)	-2.53 (0.012)
AR(2)	0.62 (0.536)	-1.43 (0.153)	0.74 (0.457)
Hansen (*p*-value)	36.28 (0.379)	39.10 (0.196)	39.45 (0.206)
Number of groups	43	43	43
Number of instruments	17	17	17

Note: The table reports the result of GMM regression of our baseline models. Model 1 assesses the relationship between fintech and HDI. Model 2 illustrates the relationship between fintech and HDI with an inclusion of access to electricity as a moderating variable. Model 3 portrays the interaction effect of fintech and access to electricity on HDI. The AR(1), AR(2), and Hansen tests are within the acceptable thresholds with their *p*-values in parentheses. Robust standard errors are in parentheses. See the text for the definition and measurement of variables. ***, ** and * denote the statistical significance level at 1 percent, 5 percent and 10 percent respectively.

Table 10: The impact of fintech on HDI: MM-quantile regression results using model 1

Variables	Location	Scale	(0.25) HDI	(0.50) HDI	(0.75) HDI	(0.90) HDI
Fintech	0.2993***	-0.1333***	0.0871***	0.1933***	0.2488***	0.4284***
	(0.0292)	(0.0139)	(0.0216)	(0.0277)	(0.0299)	(0.0379)
GDP per capita	0.1043***	0.0402***	0.1684***	0.1363***	0.1196***	0.0654***
	(0.0109)	(0.0034)	(0.0088)	(0.0103)	(0.0113)	(0.0138)
Institutional quality	0.6414***	-0.3159***	0.1384***	0.3903***	0.5216***	0.9471***
	(0.0470)	(0.0228)	(0.0335)	(0.0465)	(0.0529)	(0.0617)
Inflation	-0.0173	0.0044	-0.0102	-0.0137	-0.0156	-0.0216
	(0.0163)	(0.0079)	(0.0152)	(0.0144)	(0.0151)	(0.0210)
Trade openness	0.0133***	0.0002***	0.0136***	0.0135***	0.0134***	0.0131***
	(0.0003)	(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Population growth	-0.0189**	0.0078*	-0.0065	-0.0127	-0.0160*	-0.0265**
	(0.0093)	(0.0046)	(0.0088)	(0.0083)	(0.0086)	(0.0120)
Constant	-1.4487***	0.2342***	-1.0757***	-1.2625***	-1.3599***	-1.6754***
	(0.0453)	(0.0177)	(0.0383)	(0.0443)	(0.0479)	(0.0587)
Observations	645	645	645	645	645	645

Note: The table reports the result of MM-quantile regression of model 1. This assesses the relationship between fintech and HDI. Robust standard errors are in parentheses. See the text for the definition and measurement of variables. ***, ** and * denote the statistical significance level at 1 percent, 5 percent, and 10 percent respectively.

Table 11: The impact of fintech on HDI: MM-quantile regression results using model 2

Variables	Location	Scale	(0.25) HDI	(0.50) HDI	(0.75) HDI	(0.90) HDI
Fintech	0.2340***	-0.1521***	0.0076***	0.0804***	0.2484***	0.3728***
	(0.0290)	(0.0146)	(0.0214)	(0.0211)	(0.0309)	(0.0375)
Access to electricity	0.0328***	0.0012	0.0317***	0.03270***	0.0340***	0.0347***
	(0.0032)	(0.0015)	(0.0029)	(0.0027)	(0.0032)	(0.0039)
GDP per capita	0.0795***	-0.0189***	0.0495***	0.0604***	0.0813***	0.0968***
	(0.0082)	(0.0042)	(0.0093)	(0.0094)	(0.0082)	(0.0094)
Institutional quality	0.4688***	-0.2565***	0.0613	0.2097***	0.4932***	0.7029***
	(0.0464)	(0.0271)	(0.0462)	(0.0358)	(0.0489)	(0.0617)
Inflation	-0.0111	0.0032	-0.0060	-0.0079	-0.0114	-0.0140
	(0.0152)	(0.0081)	(0.0174)	(0.0154)	(0.0154)	(0.0184)
Trade openness	0.0134***	-0.0004***	0.0128***	0.0130***	0.0134***	0.0137***
	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Population growth	-0.0139	0.0054	-0.0053	-0.0084	-0.0144*	-0.0188*
	(0.0084)	(0.0044)	(0.0100)	(0.0089)	(0.0085)	(0.0100)
country_id	-0.0002	0.0000	-0.0002	-0.0002	-0.0002	-0.0002
	(0.0006)	(0.0003)	(0.0008)	(0.0007)	(0.0006)	(0.0008)
Constant	-2.8926***	0.0391	-2.8306***	-2.8532***	-2.8964***	-2.9283***
	(0.1436)	(0.0659)	(0.1269)	(0.1251)	(0.1473)	(0.1820)
Observations	645	645	645	645	645	645

Note: The table reports the result of MM-quantile regression of model 2. This reports the relationship between fintech and HDI with an inclusion of access to electricity as a moderating variable. Robust standard errors are in parentheses. See the text for the definition and measurement of variables. ***, ** and * denote the statistical significance level at 1 percent, 5 percent, and 10 percent respectively.

Table 12: The impact of fintech on HDI: MM-quantile regression results using model 3

Variables	Location	Scale	(0.25) HDI	(0.50) HDI	(0.75) HDI	(0.90) HDI
Fintech*Access to electricity	0.0396***	-0.0066***	0.0280***	0.0333***	0.0404***	0.0452***
	(0.0020)	(0.0013)	(0.0027)	(0.0022)	(0.0021)	(0.0023)
Fintech	0.2910***	-0.1656***	0.0032	0.1341***	0.3107***	0.4325***
	(0.0327)	(0.0136)	(0.0257)	(0.0239)	(0.0384)	(0.0375)
Access to electricity	0.0371***	0.0094***	0.0534***	0.0460***	0.0360***	0.0291***
	(0.0030)	(0.0015)	(0.0034)	(0.0030)	(0.0032)	(0.0033)
GDP per capita	0.1150***	0.0023	0.1190***	0.1172***	0.1147***	0.1130***
	(0.0076)	(0.0050)	(0.0096)	(0.0076)	(0.0078)	(0.0098)
Institutional quality	0.5006***	-0.3673***	-0.1379***	0.1526***	0.5444***	0.8147***
	(0.0484)	(0.0249)	(0.0365)	(0.0364)	(0.0631)	(0.0564)
Inflation	-0.0109	0.0028	-0.0060	-0.0082	-0.0113	-0.0134
	(0.0139)	(0.0073)	(0.0138)	(0.0124)	(0.0143)	(0.0176)
Trade openness	0.0128***	-0.0003***	0.0122***	0.0124***	0.0128***	0.0131***
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Population growth	-0.0157**	0.0030	-0.0105	-0.0129*	-0.0161**	-0.0183*
	(0.0077)	(0.0039)	(0.0082)	(0.0072)	(0.0079)	(0.0095)
Constant	-3.2250***	-0.2109***	-3.5916***	-3.4248***	-3.1999***	-3.0447***
	(0.1348)	(0.0678)	(0.1526)	(0.1337)	(0.1370)	(0.1542)
Marginal effects of fintech						
Mean	0.0669***	0.0400	0.0981****	0.0982***	0.0983***	0.0987***
	(0.0343)	(0.0278)	(0.0711)	(0.0647)	(0.0277)	(0.0225)
Percentiles						
5%	0.3392***	0.2983	0.2666***	0.2802***	0.3159***	0.3565***
	(0.0243)	(0.0178)	(0.0577)	(0.0617)	(0.0125)	(0.0172)
10%	0.3866***	0.3043	0.2726***	0.2511***	0.3229***	0.3625***
	(0.0771)	(0.0027)	(0.0047)	(0.0017)	(0.0020)	(0.0077)
25%	0.3602***	0.3079	0.2372***	0.2547***	0.3265***	0.3505***
	(0.0034)	(0.0020)	(0.0320)	(0.0310)	(0.0035)	(0.0207)
50%	0.4092	0.3269	0.2952	0.2737	0.3455	0.3851
	(0.0377)	(0.0287)	(0.0344)	(0.0278)	(0.0253)	(0.0267)
75%	0.4401***	0.3578	0.3261***	0.3046***	0.3764***	0.4160***
	(0.0376)	(0.0211)	(0.0232)	(0.0215)	(0.0300)	(0.0324)
90%	0.4744***	0.3921	0.3604***	0.3389***	0.4107***	0.4503***
	(0.0276)	(0.0139)	(0.0172)	(0.0182)	(0.0179)	(0.0195)
99%	0.5064***	0.4241	0.3924***	0.3709***	0.4427***	0.4823***
	(0.0390)	(0.0267)	(0.0157)	(0.0146)	(0.0304)	(0.0333)
Observations	645	645	645	645	645	645

Note: The table reports the result of MM-quantile regression of model 3. This portrays the interaction effect of fintech and access to electricity on HDI. The marginal effect of fintech and percentiles of each quantile are reported. Robust standard errors are in parentheses. See the text for the definition and measurement of variables. ***, ** and * denote the statistical significance level at 1 percent, 5 percent, and 10 percent respectively.

Appendices

Appendix 1: Hausman specification test

	Coefficient
Chi-square test value	9.279
P-value	0.158

Note: This table reports the result of Hausman specification test for fixed and random effect regression.

Decision rules- H0: Random effect is appropriate; H1: Fixed effect is appropriate.

Appendix 2: Tests for cross sectional dependence	Coefficient	P-value
Pesaran's test of cross-sectional independence	-0.337	1.1809
Friedman's test of cross-sectional independence	7.211	0.7731

Appendix 3: Test for first order serial correlation

	Coefficient	P-value
Wooldridge test for autocorrelation F (1,42)	11.019	0.0002

Appendix 4: Wald test for heteroscedasticity

	Coefficient	P-value
Wald test (X^2) (43)	983.11	0.0000

Appendix 5: List of African countries in the sample

S/No	Country	Regional classification	Income classification
1	Angola	Central	Low-middle income
2	Benin	Western	Low-middle income
3	Botswana	Southern	Upper-middle income
4	Burkina Faso	Western	Low-middle income
5	Burundi	Eastern	Low-income
6	Cabo Verde	Western	Low-middle income
7	Cameroon	Central	Low-middle income
8	Chad	Central	Low- income
9	Comoros	Eastern	Low-middle income
10	Cote d'Ivoire	Western	Low-middle income
11	Equatorial Guinea	Central	Upper-middle income
12	Eritrea	Eastern	Low-income
13	Eswatini	Southern	Low-middle income
14	Ethiopia	Eastern	Low-income
15	Gabon	Central	Upper-middle income
16	Gambia	Western	Low-income
17	Ghana	Western	Low-middle income
18	Guinea	Western	Upper-middle income
19	Guinea-Bissau	Western	Low-income
20	Kenya	Eastern	Low-middle income
21	Lesotho	Southern	Low-middle income
22	Liberia	Western	Low-income
23	Madagascar	Eastern	Low-income
24	Malawi	Eastern	Low-income
25	Mali	Western	Low-income
26	Mauritania	Western	Low-middle income
27	Mauritius	Eastern	Upper-middle income
28	Mozambique	Eastern	Upper-middle income
29	Namibia	Southern	Upper-middle income
30	Niger	Western	Low-income
31	Nigeria	Western	Low-middle income
32	Rwanda	Eastern	Low-income
33	Senegal	Western	Low-middle income
34	Seychelles	Eastern	High-income
35	Sierra Leone	Western	Low-income
36	Somalia	Western	Low-income
37	South Africa	Southern	Upper-middle income
38	South Sudan	Eastern	Low-income
39	Tanzania	Eastern	Low-middle income
40	Togo	Western	Low-income
41	Uganda	Eastern	Low-income
42	Zambia	Eastern	Low-income
43	Zimbabwe	Eastern	Low-middle income

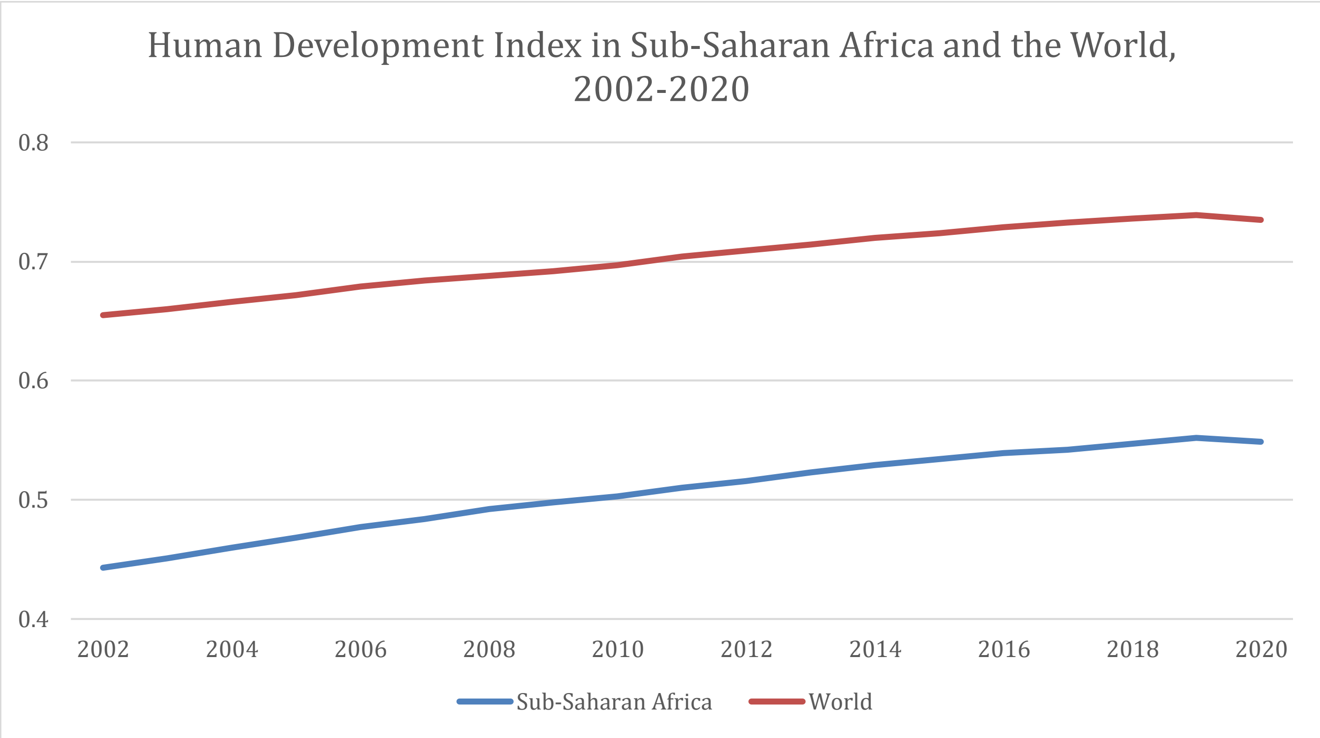

Figure 1: ***Human Development Index in Sub-Saharan Africa and the world.***

Figure 2: ***The figure shows the changes in access to electricity over time for selected African countries.***

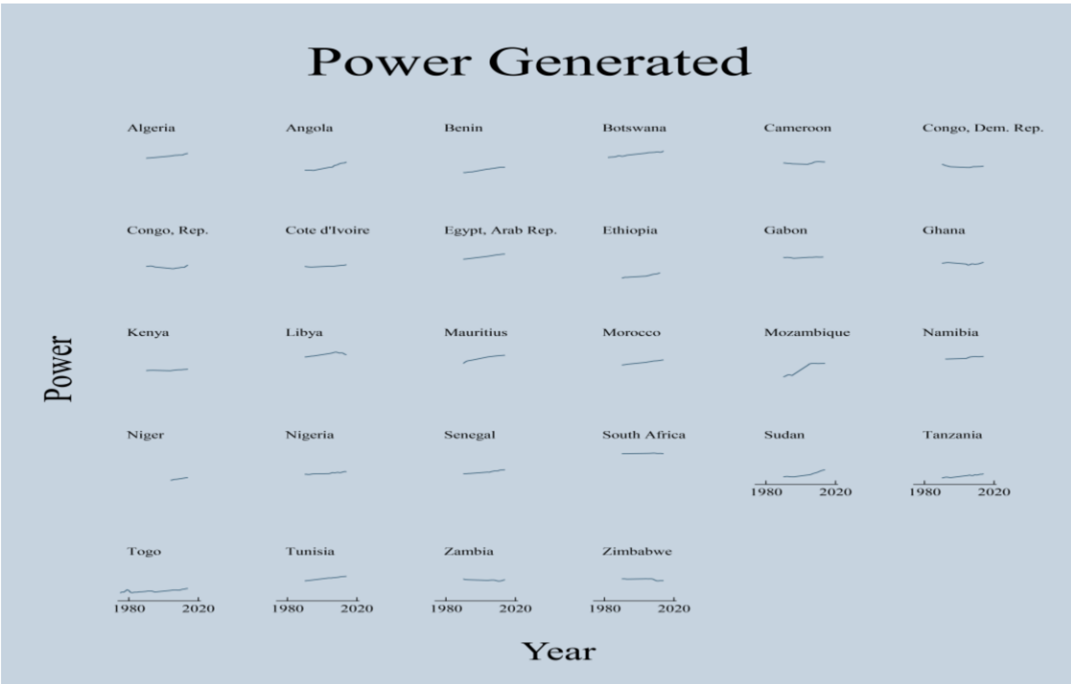

Figure 3: ***The figure shows the trend in power generated (kwh per capita) for selected African countries.***