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Abstract

Sub-Saharan African (SSA) countries are increasingly adopting digital finance, which generally represents a positive driver of development and growth. However, the digital finance sector is known to be a source of large CO2 emissions, thereby contributing to climate change, and SSA countries will likely be the ones that suffer most from climate change. This constitutes a negative channel through which digital finance could impair development. This article aims to disentangle these two channels to assess which effect prevails overall. We analyse the impact of mobile money and bitcoin on the Human Development Index (HDI). We find that mobile money mitigates the negative impact of CO2 emissions. Globally, through its interaction with CO2 emissions, mobile money has a positive impact on development. In contrast, we find weak evidence concerning bitcoin. On its own, bitcoin has a negative impact on HDI.

JEL Classification: Q43; Q54; G23; E42; O14; O16; O55

Keywords: CO2; climate change; economic development; growth; Africa; energy; digital finance; mobile money; cryptocurrency

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1. Introduction

Common wisdom views digital finance as a factor contributing positively to growth, development and financial inclusion. However, some tools in digital finance are known to emit significant amounts of CO_2, and the recent exponential increase in their adoption thus raises climate change issues.

We thus have two contradictory effects. One is positive and direct (digital finance fosters growth and development), and the other is negative and indirect (digital finance contributes to climate change, which is especially harmful to developing countries). This article aims to disentangle these two effects and assess which effect is more influential.

We deliberately restrict the study to sub-Saharan African (SSA) countries for two reasons. First, these countries are among those projected to suffer most from climate change (Burke et al., 2015). Second, these countries are also where digital finance is experiencing a sharp increase and is viewed as a way to bypass an inadequate banking sector and facilitate financial inclusion and financial development (Aron & Muellbauer, 2019).

We also restrict our consideration of digital finance to two particular forms. The first is the use of cryptocurrencies based on proof-of-work and blockchain technology, such as bitcoin, because they are currently viewed as the tool with the highest CO_2 emissions among forms of digital finance (de Vries, 2019). Of course, bitcoin is less used in SSA countries than in other countries, but the impact of CO_2 is by nature a global externality; hence, it is interesting to study these countries' contribution to this externality. Second, we study the mobile money industry (mobile payments and banking). This sector is not a heavy CO_2 emitter at present in comparison with transport, for example; however, the sector is projected to grow massively, and furthermore, the contribution to CO_2 emissions of mobile money is not negligible if one takes into account the whole production and life cycle of products (e.g., electricity to recharge batteries) and network infrastructures needed to use them (cables and data centres); see (Belkhir & Elmeligi, 2018).

Our data coverage starts in 2010 due to the nature of the research object: bitcoin was launched in 2009, and the first data became available from 2010; the first mobile money tools in Africa emerged in Kenya in approximately 2005, and data for most African countries became available from approximately 2010. As a result, we analyse the 2010-2018 period for 46 countries.

Concerning the Human Development Index (HDI), we find that mobile money mitigates the negative impact of CO2 emissions. Globally, through its interaction with CO2 emissions, mobile money thus has a positive impact on development. In contrast, we find weak evidence concerning bitcoin. In itself, bitcoin has a negative impact.

Our approach is novel in the sense that the interrelations of development, digital finance and climate change have rarely been studied by academics. Whereas the separate importance of digital finance for financial inclusion and development, on the one hand, and climate change, on the other, are fuelling important debates, we posit that the interaction between those two aspects must also be at the centre of attention.

Our results have important consequences for researchers, development organizations, policymakers, and the mobile phone and digital finance industry at large. For researchers, this study helps to better clarify the nexus between development and CO2 emissions and a purported driver of prosperity such as digital finance. Prosperity requires energy and hence needs CO2 emissions. However, those frequently come with negative environmental externalities that may have a detrimental impact on development. It is thus important to assess whether digital finance, and which tools within digital finance, can help support a sustainable development path. It follows that decisionmakers should integrate the carbon intensity of each financial development tool under review and trade off growth or development benefits against climate change costs and that the digital finance industry should consider proof-of-stake cryptocurrencies (which run on a carbon-lighter technology than that underpinning bitcoin) or lighter operating systems and longer-life smartphones.

This paper is organized as follows: The second section reviews the literature, the third section presents the data and methods, the fourth section presents the results, and the last section concludes.

2. Literature review

Financial development is now acknowledged as an ingredient of development and growth in developing countries (Demetriades & Hussein, 1996). Traditional variables used to measure financial development are, for example, the monetary aggregate M2, private credit, the size of the insurance industry, and stock market capitalization (Yue et al., 2019). However, the sign of the effect is less clear when CO2 emissions or energy is accounted for. As an example, (Ouyang & Li, 2018) analyse Chinese data and find, for some specifications, a negative impact of financial development on growth.

These mixed results call for greater precision in identifying the mechanism by which financial development is supposed to have an impact. More recent papers include, if not digital finance, at least information and communication technology (ICT) devices and mobile phones as factors in development and/or growth. Asongu (2013) shows that mobile phone penetration is positively related to the financial development of African countries. Philippon (2019) argues, in a theoretical model, that financial technology (fintech) democratizes access to financial services and reduce the cost of financial intermediation. Focusing on GDP growth, Cleeve & Yiheyis (2014) show that mobile penetration has a positive impact on growth. On a related basis, Mazzoni (2019) describes the status and prospects of energy access in Africa and highlights cases where mobile money offers an opportunity to access energy (electricity) [2] and financial services at the same time.

Fewer articles narrow their focus to the use of smartphones[3], on the one hand, as mobile money devices, or to bitcoin, on the other, as a potential factor related to development and/or growth. As argued in the introduction, we analyse mobile money as it is extremely fast growing in Africa[4] and because it is viewed as a way to "leapfrog" the need for a fully accessible traditional banking system (Aron & Muellbauer, 2019). We focus on bitcoin as the prototypical and most carbon-emitting technology amongst forms of digital finance. Our analysis also bears relevance for current discussions about central bank digital currencies that would adopt the same underlying technology (proof-of-work based on blockchain), or about countries tempted to give legal tender to bitcoin[5].

In regards to the related literature, first, Beck et al. (2015) build a dynamic general equilibrium model in which mobile money has a positive impact on output, mainly by alleviating transaction frictions in SME–supplier relationships. An application to Kenya covering the 2006-2013 period (one of the first countries to see a mass deployment of mobile money, with the emergence of the fintech firm M-Pesa) shows that mobile money was responsible for 0.33 to 0.47 percentage points of the average GDP growth in that period. Building on several GSMA reports (among them GSMA, 2019), Aron & Muellbauer (2019) argue that there are several reasons to expect a positive microeconomic impact of mobile money. It serves financial inclusion because the unbanked poor, who are an unprofitable target for commercial banks, can easily access an

[2] Countries like Nigeria still have more than 60% of the population without access to electricity, which strongly constraints access to digital finance.
[3] For readability, we will use indifferently the terms mobile phones and smartphones in the remainder of the article.
[4] An IMF study directed by A. Sy from the African Department (Maino et al., 2019) shows that Africa is a global leader in mobile money adoption and use, and that in SSA the number of mobile money accounts per 1000 adults exceeds the number of traditional deposits accounts per 1000 adults, since 2015. About the complementarity between mobile money and financial accounts, see also Gourène & Soumaré, (2021).
[5] Salvador voted legal tender for bitcoin on September 7, 2021.The president put forward the same type of arguments as those of the literature (as presented later in the text).

electronic account, deposit cash and transfer electronic money at an affordable cost. It also helps decrease the information asymmetry faced by conventional banks, as user transaction records can be used as individual credit scores that can eventually serve as a pathway to accessing formal financial services. Mobile money can facilitate services such as interest-bearing savings, small loans, or insurance products. Thompson (2017) analyses different channels for aid distribution[6] and concludes that benefit distribution via mobile money may lower transaction costs and enable more frequent payments. It could also improve the privacy, transparency, traceability, and security of disbursements.

In regards to the second literature stream, bitcoin has also been analysed in terms of its impact on development. Ammous (2015) argues that bitcoin could help secure remittances and increase the efficiency of microfinance. The traceability features of this technology could help facilitate distribution of development aid and help countries with weak national money integrate into international trade with potentially less unfavourable terms of exchange. Although its exchange rate is volatile, bitcoin may offer an inflation haven—i.e., serve as a store of value. The author above posits that currency devaluation, hyperinflation, banking failures, liquidity crises, and bank account confiscations are frequent events in many developing countries and that bitcoin could be more accessible and convenient for the poor than safe foreign currencies and precious metals. Parino et al. (2018) show a relatively high Spearman correlation (between 0.76 and 0.80) between bitcoin usage and HDI. However, the authors underline that they do not analyse causality.

Concerning the impact of digital finance on environmental degradation and CO2 emissions in particular, reducing greenhouse gas emissions is a challenge for sustainable development. SSA countries are among those that will suffer the most from the negative externalities of global

[6] In the context of, for example, the Payment for Ecosystemic Services (PES) and Reducing Emissions from Deforestation and forest Degradation (REDD+) programmes.

warming (Burke et al., 2015)[7]. It is thus important to assess the impact of development tools on CO_2 emissions.

We first review the ICT sector at large, and then we focus on mobile money and bitcoin.

Belkhir & Elmeligi (2018) implement linear and exponential extrapolations from 2007-2016 data to assess the global ICT footprint. Restricting their analysis to smartphones, the authors estimate that these devices would represent 11% of total greenhouse gas emissions (GHGEs) of the ICT sector in 2020. Under a business-as-usual scenario, smartphones alone would represent 1.4% of total global emissions in 2040, i.e., approximately 520 Mt CO2e[8]. These authors' measurement includes smartphone production, energy consumption of the device, and energy consumption of the infrastructure needed to operate the devices (servers, data centres)[9].

Asongu et al. (2017) provide one of the first studies to analyse the interaction between the positive effects of ICT on development and inequality with the potentially negative effect of CO_2 emissions. They show that in some configurations, mobile phone penetration and internet penetration modulate the potentially negative effect of CO_2. Their intuition is that ICT can prevent unnecessary transportation costs.

Beyond the ICT sector in general, some rare studies focus on the CO_2 impact of mobile money and bitcoin in particular.

First, as mobile money represents only a fraction of the total use of smartphones, there are practically no studies that try to assess its specific impact[10]. In view of the estimation of 125 Mt CO2e in smartphone emissions for 2020 from Belkhir & Elmeligi (2018), we can suppose only that mobile money will represent an important component of the corresponding figures for this

[7] For SSA countries, the authors predict a drop in GDP of –75% in 2100 under a business-as-usual scenario in comparison with projections based on constant 1980-2010 average temperatures.

[8] This figure is approximately 66% of the 2010-2018 average total CO_2 emissions for all 46 SSA countries in our sample (773 Mt CO2e).

[9] One problem is that the average lifecycle of smartphones is around two years, adding to this impact the problem of electronic waste. E-waste from mobile phone has been proven to harm development in African countries (Moletsane R., Zuva, 2018).

[10] However, Jacolin et al. (2021) make one attempt to analyse mobile money using a dummy variable equal to 1 if mobile financial services are offered in the country.

indicator over the decades to come as long as it substitutes for cash. Second, the estimations for bitcoin vary from 19 to 29.6 Mt CO2e in 2018 (de Vries, 2019) to a range of 21.5 Mt CO2 to 53.6 Mt CO2 as of November 2018 in Stoll et al. (2019). With respect to its carbon footprint, bitcoin emits between 233.4 and 363.5 kg of CO2 per transaction in comparison with 0.4 to 3 g of CO2 per VISA transaction[11]. Using prediction models, Mora et al. (2018) build a scenario in which bitcoin is adopted as a means of payment at the same rate as broadly used technologies (i.e., credit cards) in the XXth century. Under this scenario, bitcoin alone could push global warming beyond 2°C in 2040-2050. Beyond bitcoin, it is urgent to raise the debate about the emissions entailed by such technologies[12] in whatever areas in which they apply.

3. Data and methods

3.1 Data

This study examines 46 countries in Africa for the period of 2010-2018, with 414 country-year observations. Our dependent variable is HDI, which measures the level of income as well as the level of basic living standards in health and education[13]. Digital finance is measured with a proxy for domestic usage of bitcoin (bitcoin client download statistics) and with mobile money

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[11] Proponents of this digital currency argue that this energy comes mainly from Chinese renewable hydropower; however, de Vries (2019) replies that this energy source has high seasonality and that the consumption is balanced out with coal. Furthermore, turning to environmental degradation beyond energy use, the machines used to mine bitcoin have a limited lifetime and are specifically created for bitcoin mining (they immediately become e-waste after their use). This amounted to an average of 134.5 g of e-waste per bitcoin transaction in 2018, in comparison with an estimate of 0.0045 g of e-waste per VISA transaction.

[12] The same distributed ledger technologies based on blockchain have been applied to various fintech innovations in SSA countries (cf. Maino et al., 2019).

[13] The focus on HDI rather than GDP growth can also be justified by a climate policy concern: Van den Bergh & Botzen (2018) compute the emissions pathway for 2015-2050 with an allowance for countries with HDI<0.8 to increase their CO2 emissions while developed countries (HDI>0.8) restrain emissions such that the global temperature remains within 2°C. They find that HDI per ton of CO2 per capita continues to rise for rich countries as well, whereas when measured with GDP, the welfare costs of climate policy are likely to be overestimated.

variables (the number of registered mobile money accounts per 1,000 adults, the number of active mobile money accounts per 1,000 adults, the number of mobile money transactions per 1000 adults, and the value of mobile money transactions as a percent of GDP). We use the amount of fossil fuel CO2 emissions by country as a proxy for environmental degradation and contribution to climate change. Additionally, four control variables (foreign aid, private domestic credit, education and foreign direct investment) are included in the model to prevent variable omission bias. Definitions and sources are in Appendix A, summary statistics are in Appendices B and D, and the correlation matrix is in Appendix C.

3.2 Hypotheses

We address our research questions by formulating the following hypotheses.

H1: Bitcoin helps mitigate the potentially negative impact of CO2 emissions on development.

H2: Mobile money helps mitigate the potentially negative impact of CO2 emissions on development.

We consider H1 (H2) to be valid if, when we account for the interaction between CO2 and bitcoin (mobile money), the total marginal effect of CO2 on HDI is significantly positive, provided that the direct unconditional effect of bitcoin (mobile money) on HDI is significant and positive.

3.3 Model

To test our hypotheses, we use the following panel OLS fixed effect model (Greene, 2000, Baltagi, 2005):

$$HDI_{it} = \beta_0 + \beta_1 DF_{it} + \beta_2 CO2_{it} + \beta_3 CO2_{it}^2 + \beta_4 \left(CO2_{it}^2 \times DF_{it}\right) + \sum_{c=1}^{C} \gamma_c W_{cit} + \alpha_i + \varepsilon_{it} \quad (1)$$

where HDI_{it} is the HDI of country i in year t; DF_{it} is the digital finance variable; $CO2_{it}$ is CO2 emissions; W_{cit} denotes the control variables c; α_i is the country fixed effect, which controls for country-level unobserved heterogeneity; and ε_{it} is the stochastic error term.

We first have to disentangle the positive and negative impacts on CO2 emissions. We thus introduce a squared CO2 term to capture the nonlinearity in the relationship between CO2 and HDI. This allows us to check whether an inverted U-shaped relationship exists, i.e., whether β_2 is positive (illustrating that the development process needs to allow for CO2 emissions) and β_3 is negative (illustrating that pollution costs and the exacerbation of climate change can impair development). Second, we interact the digital finance variable with squared CO2 to detect whether digital finance mitigates the negative impact of CO2 emissions, in accordance with our main hypotheses.

The closest models to ours are those of Asongu et al. (2017, 2019), although we depart from these authors in several important aspects. First, we use explicit digital finance variables and not mobile phone or ICT variables at large. Second, we introduce nonlinearity in the CO2 and HDI relationship. Third, we interact our variable of interest with the squared term. Finally, we explicitly assess the significance of marginal effects, as explained later.

We believe that neither a time fixed effect nor a dynamic panel generalized method of moments (GMM) model would be appropriate in the present case. Our sample reflects a specific context in which all variables evolve slowly over time except the variables of interest (digital finance), which show a real boom in SSA countries for 2010-2018[14]. We derive from this context that a

[14] These are the evolutions of annual averages between 2010 and 2018. HDI increased by +9.2% and CO2 emissions by +11.6% in this period. In contrast, bitcoin usage (the number of client downloads) multiplied by a factor of 200, the number of registered mobile money accounts by a factor of 6.5, the number of active mobile money accounts by a factor of 210, the number of mobile money transactions by a factor of 15.9, and the volume of mobile money transactions by a factor of 7.3 (from 3.5% to 25.4% of GDP, whereas at the same time, mean GDP grew by a factor of 1.062). The control variables moved slightly more than HDI and CO2 (between 17% and 43% in the same period), but these evolutions remain far lower to those of the digital finance variables. An earlier version of this article used GMM, and most variables were not significant or had unstable signs throughout the specifications.

time fixed effect or a lagged dependent variable could unduly attract all significant effects and cannibalize the genuine effect of the boom in digital finance.

An important concern for our topic is the endogeneity problem: one could suppose that more developed countries are prone to producing more CO2 emissions. In that case, CO2 would be an endogenous explanatory variable (Wooldridge, 2010). The endogeneity problem, which can be caused by simultaneous causality (Shepherd, 2008), can produce biased and inconsistent panel OLS parameter estimates. Researchers often try to address these bias problems by using the instrumental variables (IV) approach and/or Hausman tests (Nakamura and Nakamura, 1998).

The idea is to compare estimates from panel OLS with those of IV estimates. In our setting, the null of the Hausman test is that CO2 is exogenous. If this is the case, panel OLS is preferable to the IV approach[15].

As the interpretation of interaction variables is not straightforward (β_4 in equation (1) must be interpreted together with β_2 and β_3), we prefer to assess our main hypothesis through the overall marginal effect of CO2 emissions on HDI. This is computed as follows:

$$\frac{\partial HDI}{\partial CO2} = \beta_2 + 2\beta_3\overline{CO2} + 2\beta_4\overline{CO2} \cdot \overline{DF} \qquad (2)$$

where $\overline{CO2}$ and $\overline{DF}$ are the mean values in the sample for CO2 emissions and for the digital finance variable.

If, for a given specification, we find that β_1 is positive and significant and that the marginal effect computed in equation (2) is positive and significant, then we determine that we cannot

[15] We build our IV model as follows. CO2 must first be explained by exogenous instruments (Wooldridge, 2010; Baum, 2006 and Ao, 2009). Natural resources endowments are a good candidate. For example, oil is an important factor in CO2 emissions for both Norway and Libya, whereas these two countries have very different HDI indices. Another resource of this type is forests. Thus, in the first stage, we run a regression of CO2 explained with oil (the percent of oil sector in GDP, from World Bank data) and forests (the percent of forestry in GDP, idem) and obtain significant coefficients with a R2 of 0.17. (We also attempt to introduce the coal sector, but the available data were not sufficient. We observe that like all variables in our sample except for the digital finance variables, *oil* and *forests* move slowly through time.) In the second stage, we run an IV regression from equation (1) but instrument CO2 with oil and forests.

reject the null hypothesis that bitcoin (H1) or mobile money (H2) helps mitigate the potential negative effect of CO2 emissions on development.

Finally, to provide policy-oriented conclusions, we propose a turning (or "tipping") point analysis. If the inverted U-shape holds for the relationship between CO2 and HDI, then it is important to know at which level of emissions a country can pass from the "positive" to the "negative" side of CO2 emissions. Because the computed turning point depends on the digital finance variable under study, it can provide insightful policy implications as to which financial tools should be prioritized. Tipping points have recently become widely used in the fields of climate change, ecology and health (Livina et al., 2015); we consider the latest panel techniques that have proven reliable in dynamic contexts with persistent data (cf. Bernard et al., 2011). Using equation (2), the turning point is the amount of CO2 emissions such that the right-hand side of equation (2) is zero, i.e.:

$$turning\ point = -\frac{\beta_2}{2\beta_3 + 2\beta_4.\overline{DF}} \tag{3}$$

This makes sense only if, as explained earlier, β_2 is positive and β_3 is negative.

4. Results

4.1 Development, digital finance, and environmental degradation

Table 1 presents our main results. Specifications with even (odd) numbers include (exclude) the control variables. Unsurprisingly, the R-squared values are systematically larger for specifications including the control variables. Specifications (1)-(2) are a base case without the digital finance variables. Specifications (3)-(4) study bitcoin, specifications (5)-(6) study the number of registered mobile money accounts, specifications (7)-(8) study the number of active mobile money accounts, specifications (9)-(10) study the number of mobile money transactions, and specifications (11)-(12) study the volume of mobile money transactions.

First, we observe an inverted U-shape for the CO2 variable, as the CO2 coefficient is positive and the coefficient on its squared term is negative for each of specifications (1)-(12). These two variables have significant coefficients in all specifications (except the squared term in specification (8)). This seems to confirm that CO2 emissions have countervailing impacts—both positive and negative—on development. Based on these results, we believe that integrating the squared term for CO2 in the specifications is an improvement and that not including this squared term might explain the unstable results obtained in the literature (for example, in Asongu et al., 2017).

The results of the Hausman endogeneity tests favour panel OLS with fixed effects (those presented in the tables) instead of the IV approach. Most specifications exhibit p-values above 5% for the test statistic. The only exception is specification (1), which does not include our variable of interest and serves only for comparison purposes. However, for specifications (8) and (10), the p-value is only slightly above 5%; thus, these results must be interpreted with caution. We believe that this is related to the fact that these two specifications are also those with the fewest observations.

Concerning the control variables, their sign and significance are mostly in line with results in the literature. When significant, *aid* has a negative impact on HDI ((2) and (4)). In Asongu et al. (2017), this variable bears a negative—albeit not significant—sign in most specifications, and Asongu (2014) concludes that foreign aid negatively affects inequality-adjusted HDI (IHDI) in Africa. The conclusions of other studies (Clements, 2020; Pickbourn & Ndikumana, 2016) are less categorical and show that there is no consensus on the impact of foreign aid on development. *Credit* is positive only when mobile money variables are included and is significant in (6), (8) and (10). There seems to be a positive association between mobile money and access to credit that fosters development. In the literature, private domestic credit is viewed as a traditional driver of development (Mbate, 2013; Mlachila et al., 2016). Education is a component of HDI and has been documented to be associated with development (e.g., Gyimah-Brempong, 2011). Our variable *edu* is the pupil/teacher ratio, thus it should have a negative coefficient. This is the case in half of the specifications, and when significant (in (2) and (4)), it is negative, as expected. Finally, foreign direct investment (*fdi*) is never significant (whereas it is significant and positive in half of the specifications in Asongu et al., 2017).

Let us now turn to the digital finance variables.

We observe that bitcoin, when control variables are included, has a direct negative impact on development (a negative coefficient for *cumulBTC* in specification (4)) and a positive impact when controls are excluded in (3). This unstable relation casts doubts on the impact of bitcoin on development. In contrast, all other money variables have a direct positive impact on development ((5) to (12)).

Moving beyond this direct impact, we investigate the marginal effects to assess the overall effect of the complementarity of digital finance and CO2 emissions in affecting development. The marginal effects are applicable (all coefficients involving CO2 are significant) in most specifications. In those cases, the marginal effects are positive and significant, with p-values below 1% in specifications (4), (5), (7), (9), (10), and (12) and just above 1% for (6). In (3), which concerns bitcoin without control variables, the interaction between bitcoin and CO2 emissions is not significant; hence, the marginal effect is not applicable. This is also the case for active mobile money accounts with controls in (8) and for the value of mobile money transactions without controls in (11).

For bitcoin (4), the overall marginal effect is positive and significant; however, as we explained above, the direct effect is negative. We interpret this as follows: Although both the negative aspect of environmental degradation (the negative sign for squared CO2) and bitcoin exert negative pressure on development, the unconditional positive direct effect of CO_2 (emissions needed for development) is strong enough to lead to an overall positive marginal effect[16]. For this reason, we reject H1, as bitcoin is not responsible for this overall positive marginal effect.

In contrast, for mobile money in (5), (6), (7), (9), (10), and (12), the variable coefficient themselves are positive, and the marginal effects are, too: The interpretation is then straightforward[17]. As the overall marginal effect of the complementarity between mobile money and CO_2 is positive, it illustrates that mobile money helps mitigate the negative aspect of CO_2 emissions on development. Thus, we do not reject H2.

[16] Unsurprisingly, as HDI is an index taking values between 0 and 1, the coefficients appear to be small, as in Asongu et al. (2017). For readability, Table 1 stops at the third decimal. The (heretofore unreported) next decimals for specification (4) are as follows: It appears that the coefficient of the interaction term is extremely small (3.17 E-11), whereas the coefficient for the negative direct effect of bitcoin is a greater in absolute terms (-5.43 E-6). In addition, the coefficient for squared CO_2 is greater in absolute terms (-0000.1), and finally, the coefficient for the direct effect of CO_2 is the largest (0.00945); i.e., this last coefficient makes the most important contribution to the overall marginal effect, substantiating our interpretation.

[17] As an example, we report in this note the full decimals for registered mobile money accounts in specification (6): The coefficient of the interaction term is 4.16 E-10 and of CO_2 squared is -5.13 E-6, while the direct positive effect of registered mobile money accounts is 0.0000181 and 0.0045 for CO_2.

Table 1 Development (HDI), digital finance, and environmental degradation

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	HDI	HDI	HDI	HDI	HDI	HDI
CO2_t	0.008***	0.008***	0.006***	0.009***	0.004***	0.005**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
CO2_t#CO2_t	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
aid		-0.001***		-0.001***		0.001
		(0.000)		(0.000)		(0.001)
credit		-0.000		-0.000		0.002**
		(0.000)		(0.000)		(0.001)
edu		-0.001*		-0.001**		0.000
		(0.001)		(0.000)		(0.000)
fdi		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)
cumulBTC			0.000**	-0.000*		
			(0.000)	(0.000)		
cumulBTC#CO2_t#CO2_t			-0.000	0.000**		
			(0.000)	(0.000)		
NRMMA					0.000***	0.000***
					(0.000)	(0.000)
NRMMA#CO2_t#CO2_t					0.000***	0.000***
					(0.000)	(0.000)
Constant	0.422***	0.471***	0.437***	0.472***	0.462***	0.406***
	(0.016)	(0.027)	(0.015)	(0.026)	(0.016)	(0.044)
Observations	352	237	352	237	188	134
R-squared	0.307	0.474	0.364	0.488	0.667	0.701
Number of countries	44	42	44	42	35	29
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
CO2 marginal effect (at means)	0.00736	0.00819	na	0.00912	0.00360	0.00441
Margin st. err.	0.00125	0.00151		0.00140	0.00111	0.00187
Margin p-value	3.66e-09	5.61e-08		6.92e-11	0.00121	0.0186
Hausman endog. test chi2	6.209	7.370	5.501	7.880	1.034	4.482
p-value	0.0449	0.195	0.139	0.247	0.793	0.612

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 1 gives fixed effect panel regressions for several specifications of our model for sub-Saharan African countries from 2010 to 2018. # is the multiplication operator. *CO2_t* is the amount of fossil fuel emissions of CO2 in million tons, *aid* is net official development assistance (ODA) received (percent of GNI), *credit* is domestic credit to the private sector by banks (percent of GDP), *edu* is the pupil-teacher ratio in primary education, *fdi* is foreign direct investment inflows (percent of GDP), *cumulBTC* is the cumulated number of downloads of bitcoin client software in a country, *NRMMA* is the number of registered mobile money accounts per 1000 adults, *NAMMA* is the number of active mobile money accounts per 1,000 adults, *NMMT* is the number of mobile money transactions per 1,000 adults, and *VMMT* is the value of mobile money transactions (percent of GDP). The *CO2 marginal effect* gives the overall variation in HDI due to the variation in all CO2 variables, computed at the means, and which we consider significant if *Margin p-value*<0.05. When at least one of the CO2 variables is not significant, we consider the marginal effect not applicable (*na*). The *Hausman endogeneity test* compares panel OLS versus instrumental variable (IV) coefficients and determines that panel OLS is preferable if *p-value*>0.05.

Table 1, continued

VARIABLES	(7) HDI	(8) HDI	(9) HDI	(10) HDI	(11) HDI	(12) HDI
CO2_t	0.009***	0.008***	0.006**	0.007**	0.007**	0.009***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
CO2_t#CO2_t	-0.000**	-0.000	-0.000**	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
aid		0.000		0.001		-0.000
		(0.001)		(0.001)		(0.001)
credit		0.003***		0.002**		0.001
		(0.001)		(0.001)		(0.001)
edu		-0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
fdi		0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)
NAMMA	0.000***	0.000				
	(0.000)	(0.000)				
NAMMA#CO2_t#CO2_t	-0.000***	-0.000**				
	(0.000)	(0.000)				
NMMT			0.000***	0.000***		
			(0.000)	(0.000)		
NMMT#CO2_t#CO2_t			-0.000*	-0.000**		
			(0.000)	(0.000)		
VMMT					0.001***	0.000***
					(0.000)	(0.000)
VMMT#CO2_t#CO2_t					-0.000	-0.000***
					(0.000)	(0.000)
Constant	0.387***	0.321***	0.438***	0.369***	0.416***	0.382***
	(0.032)	(0.051)	(0.032)	(0.051)	(0.041)	(0.048)
Observations	134	97	165	114	168	119
R-squared	0.613	0.673	0.534	0.644	0.496	0.589
Number of countries	28	23	32	28	33	28
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
CO2 marginal effect (at means)	0.00857	na	0.00510	0.00608	na	0.00771
Margin st. err.	0.00257		0.00197	0.00233		0.00259
Margin p-value	0.000845		0.00973	0.00902		0.00287
Hausman endog. Test chi2	2.664	12.95	0.154	11.01	0.159	10.14
p-value	0.446	0.0734	0.926	0.0512	0.984	0.119

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 1 gives fixed effect panel regressions for several specifications of our model for sub-Saharan African countries from 2010 to 2018. # is the multiplication operator. *CO2_t* is the amount of fossil fuel emissions of CO2 in million tons, *aid* is net official development assistance (ODA) received (percent of GNI), *credit* is domestic credit to the private sector by banks (percent of GDP), *edu* is the pupil-teacher ratio in primary education, *fdi* is foreign direct investment inflows (percent of GDP), *cumulBTC* is the cumulated number of downloads of bitcoin client software in a country, *NRMMA* is the number of registered mobile money accounts per 1,000 adults, *NAMMA* is the number of active mobile money accounts per 1,000 adults, *NMMT* is the number of mobile money transactions per 1,000 adults, *VMMT* is the value of mobile money transactions (percent of GDP). The *CO2 marginal effect* gives the overall variation in HDI due to the variation in all CO2 variables, computed at the means, and which we consider significant if *Margin p-value*<0.05. When at least one of the CO2 variables is not significant, we consider the margin effect not applicable (*na*). The *Hausman endogeneity test* compares panel OLS *versus* instrumental variable (IV) coefficients and determines that panel OLS is preferable if *p-value*>0.05.

4.2 Analysis of turning points

Because we have shown an inverted U-shaped relationship between CO2 emissions and HDI, it is important to compute the turning (or tipping) point, which represents the amount of CO2 emissions that separates the positive and negative net impacts of CO2 emissions. For CO2 values below that point, the positive effect prevails: It is necessary to pollute to develop. Beyond that point, the negative effect prevails: environmental degradation negatively impacts development, probably through health expenses and income losses.

It is thus important to assess whether the turning point that we compute from the regression in Table 1 is within realistic bounds; otherwise, this could mean that our model is misspecified.

Table 2 gives the turning points computed from Table 1 (regressions (1)-(12)) and, when applicable, (3)-(12) by means of the respective digital finance variables. We set aside our base case specifications ((1) and (2)) for which the turning point values are beyond the sample range. Of the 10 remaining specifications, eight are within the sample range, and only two specifications ((7) and (8)) are beyond this range, one of which ((8)) is the regression with the fewest observations. We conclude that this shows that our model is correctly specified.

Furthermore, these computed thresholds make economic sense and can be useful to decisionmakers or policymakers. Whereas the analysis in Table 1 casts doubts on the use of bitcoin as a tool for preserving development while mitigating the negative impact of CO2 emissions, it is worth noting that with specifications (3) and (4), the threshold at which CO2 emissions begin to impair development is quite high (near the maximum observed in the sample) but realistic. This is the same when the digital finance variable is the number of registered mobile money accounts ((5) and (6)). Unsurprisingly, CO2 emissions are highly skewed, and only South Africa approaches thresholds beyond 400 Mtons of CO2 emissions, while most countries are at approximately 3 to 4 Mtons of CO2 (see Appendices B and D for descriptive statistics). In turn, for a large majority of countries, there is room for the use of digital finance tools without fears of reaching the point at which CO2 emissions become unfavourable. More precisely, in view of (5) and (6), countries can seek to provide individuals and firms with mobile money devices without fearing that the contribution of these devices to CO2 emissions will compromise development. Instead, the mitigating role of mobile money, probably through avoided use of transport and other factors highlighted in the arguments noted in the literature review section, outweighs the sector's contribution to emissions.

This is less true for specifications (9)-(12), for which the turning points are lower (from 115.3 to 146.7 Mtons of CO2). We interpret this result as follows: In terms of the *prevalence of equipment* (the number of registered accounts), the threshold at which emissions become problematic is quite high, whereas based on the *intensity of usage* of such equipment (the number and value of transactions), the level at which emissions are problematic is much lower. The interest of a country, strictly concerning the positive complementarities between digital finance and CO2 emissions, lie in the population being widely equipped but not using their devices excessively intensively. However, again, besides South Africa, only Nigeria approaches the aforementioned threshold, and for a large number of countries, the thresholds are high enough to inspire confidence in the promotion of mobile money.

Table 2 Turning point analysis

Table 1 regression number	(1)	(2)	(3)	(4)	(5)	(6)
Digital finance variable	No	No	CumulBTC	CumulBTC	NRMMA	NRMMA
CO2 turning point	527	521.4	477.1	455.8	458.4	462
Within sample range	No	No	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes	No	Yes
Observations	352	237	352	237	188	134
Number of countries	44	42	44	42	35	29

Table 1 regression number	(7)	(8)	(9)	(10)	(11)	(12)
Digital finance variable	NAMMA	NAMMA	NMMT	NMMT	VMMT	VMMT
CO2 turning point	599.1	646.4	146.7	115.3	130.4	124.5
Within sample range	No	No	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes	No	Yes
Observations	134	97	165	114	168	119
Number of countries	28	23	32	28	33	28

Table 2 computes the turning points of CO2 based on the coefficients presented in Table 1. The maximum sample observation for CO2 is 484.2, and the 99th percentile is 472.7. When applicable, the turning point is computed by means of the digital finance variable. See Table 1 and the descriptive statistics table for other figures. *cumulBTC* is the cumulated number of downloads of bitcoin client software in a country, *NRMMA* is the number of registered mobile money accounts per 1,000 adults, *NAMMA* is the number of active mobile money accounts per 1,000 adults, *NMMT* is the number of mobile money transactions per 1,000 adults, and *VMMT* is the value of mobile money transactions (percent of GDP).

Analysing Table 2 jointly with the table of descriptive statistics by country (Appendix D), we derive that even countries already well equipped with mobile money devices (e.g., Kenya, with 1,035 registered accounts per 1,000 adults on average) have room to increase this level without reaching the point at which CO2 emissions impair development (e.g., 18.6 Mtons maximum emissions for Kenya in 2010-2018, whereas the turning point is 462 Mtons with RMMA including controls).

4.3 Robustness checks

We use several variants to check the consistency of our results.

First, we lag all right-hand-side (RHS) variables to further correct for potential endogeneity bias. One might think that current HDI is influenced by past explanatory variables. We explore whether previous-year RHS variables have different signs and significance from our those in our baseline approach. The results[18] are qualitatively identical. The CO2 variables, digital finance variables, and the interaction term bear the same signs and, most of the time, the same significance level. The marginal effects of CO2 also have the same signs and significance. The only *caveat* is that there are only 9 specifications out of 12 (against 11 out of 12 in our baseline results) for which the Hausman test concludes in favour of panel fixed effects over IV estimation. We also compute the CO2 turning points in this context and again find very similar results.

Second, we use different variables for CO2 emissions to check whether our results are biased by the specific variable that we use. We replace CO2 total emissions with CO2 emissions per capita, carbon intensity (emissions per dollar of GDP) and CO2 emissions from electricity and heat. Taken as a whole, these variants show that our results are mostly stable: At worst, we find less evidence or no evidence in some specifications, but we never find contradictory evidence. We still confirm the rejection of H1 about bitcoin. For H2 and mobile money, the interaction term is also less often significant and/or the p-value of the marginal effect is sometimes above 10%, but we still find (less numerous) cases when we cannot reject H2 and no contradictory evidence and thus confirm that mobile money helps mitigate the negative effect of CO2[19].

Third, to check that our main result is not biased by the marginal effect of CO2 being computed at the means, we compute for all 12 specifications in Table 1 the CO2 marginal effect at the median (p50), at the 25% lowest CO2 emissions (p25), and at the 75% lowest CO2 emissions. By definition, except for margins, the results are simply those in Table 1. Hence, margins are

[18] The results are available from the authors upon request.

[19] Finally, we also run the specifications with both RHS lags and alternate CO2 variables and confirm that we find qualitatively similar results. The results are available from the authors upon request.

not applicable for regressions (3), (8) and (11). We confirm that all marginal effects are positive and significant[20]. Due to the distribution of CO_2 emissions, we find that margins are lowest when computed at the 25th percentile and highest when computed at the means; however, they are stable overall. Consequently, we confirm our main results for different computations of margins.

5. Conclusions

Our research was designed to address the question of whether policy- or decisionmakers or citizens should encourage the spread of digital finance to promote development. We attempt to disentangle the advantages of digital finance in terms of development from its costs through its contribution to CO2 emissions. The results contrast depending on the digital finance device.

For bitcoin, we cannot show evidence of a contribution to development. Its direct effect is negative, and its contribution to mitigating the negative impact of CO2 emissions is very low. These results confirm previous alerts concerning the environmental cost of decentralized blockchain technology applied to money.

Concerning mobile money devices, we do not reject the hypothesis that they help mitigate the potentially negative impact of CO2 emissions on development. Incidentally, we show an inverted U-shaped relationship between CO2 emissions and development. Our data allow us to distinguish between the prevalence of equipment (the number of registered and active mobile money accounts) and the intensity of usage (the number and volume of mobile money transactions) of such devices.

[20] These results are available from the authors upon request.

Concerning the prevalence of equipment, all countries except South Africa have room to increase this level because they all have CO_2 emissions far below the turning point at which CO_2 emissions become unfavourable to development, even in already widely equipped countries such as Kenya or Tanzania.

Concerning the intensity of usage, the turning points are lower (from 115.3 to 146.7 Mtons of CO_2). We interpret this as an acknowledgement that the intensity of usage of mobile money devices is more related to the negative impact of CO_2 emissions on development than the prevalence of mobile money equipment per se. South Africa again lies above the turning points for all years. However, the second nearest country (Nigeria) emits 90.4 Mtons of CO_2 on average, which again leaves room to promote the intensity of usage without risking an approach to the turning point in the medium term.

The contributions of this article are as follows: (1) To the best of our knowledge, this is the first attempt to explicitly study the impact of digital finance (bitcoin and mobile money equipment and usage) on development; (2) we test the interaction of digital finance with the potentially negative impact of CO_2 emissions on development; and (3) we study the inverted U-shaped relationship between CO_2 emissions and development and (4) discuss the level of its turning point.

Of course, our approach has limitations and calls for future improvements. In particular, the way we take bitcoin usage into account could be discussed. In SSA countries, the overall usage of bitcoin is scarce. However, given the level of usage in some developed countries, the externalities of bitcoin usage could be taken into account even for SSA countries. The level of energy used to make the bitcoin network work is largely independent of the intensity of usage in SSA countries, and thus, the detrimental impact of bitcoin on SSA countries' development should stem from its global CO_2 emissions and not the national usage considered in our approach. However, this perspective may worsen the bitcoin's negative impact and hence may not change our general conclusion. Furthermore, it is still interesting to study countries' contribution to bitcoin usage, even if this contribution is small, precisely because domestic usage is much easier for a given country to handle than international usage. While the latter could be influenced by international agreements or information campaigns, it is easier to discourage usage in one country.

Importantly, we do not recommend not using cryptocurrencies at all but simply take into account their ecological costs. In this respect, cryptocurrencies based on centralized blockchain, with a certifying authority, are supposed to be much less energy demanding than decentralized blockchain (Pfister, 2019), thus leaving open the question of central bank digital currencies. Concerning mobile money, the scarcity of some metals used in mobile or smartphone production should also be taken into account—though this aspect is beyond the scope of this article.

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Appendix A. Variable definitions

	Variables	Description of Variables	Sources
Digital Finance	BTC	Bitcoin client download statistics	Sourceforge https://sourceforge.net/projects/bitcoin/files/stats/map?dates=2008-06-23+to+2019-09-21
	cumulBTC	Cumulated number of downloads of bitcoin client software in a country	Calculated by using BTC numbers
	Variables for Mobile Money		
	NRMMA	Number of registered mobile money accounts per 1,000 adults	International Monetary Fund
	NAMMA	Number of active mobile money accounts per 1,000 adults	International Monetary Fund
	NMMT	Number of mobile money transactions per 1,000 adults	International Monetary Fund
	VMMT	Value of mobile money transactions (% of GDP)	International Monetary Fund
Climate Change	CO2_GDP	Tons of in fossil fuel CO2 per $1,000 of 2010 GDP by country	https://edgar.jrc.ec.europa.eu/overview.php?v=booklet2018
	CO2_t	Million tons of fossil fuel CO2 emissions by country	https://edgar.jrc.ec.europa.eu/overview.php?v=booklet2018
	co2eah	CO2 emissions from electricity and heat production (% of total fuel combustion)	World Bank
	co2pc	Metric tons per cap of fossil fuel CO2 emissions by country-year	Calculated by using the formula co2pc=CO2_t*1000000/pop
Economic Indicator (Dep. Var.)	HDI	Human Development Index	http://hdr.undp.org/en/data
Control Variables	edu	Education quality: Pupil-teacher ratio, primary	World Bank: World Development Indicators
	fdi	Foreign direct investment, net inflows (% of GDP)	World Bank
	aid	Foreign aid: Net official development assistance (ODA) (% of GNI)	World Bank: World Development Indicators
	credit	Private credit: Private credit by deposit money banks and other financial institutions to GDP (%)	World Bank

Dep. Var.: Dependent Variable

Appendix B: Descriptive statistics

Variable	Obs	Mean	Std Dev	Min	Max
			Economic Indicator		
HDI	414	0.5165725	0.0996996	0.319	0.801
			Digital Finance		
BTC	236	155.5	860.8383	1	11622
cumulBTC	414	560.0942	2488.209	0	20570
NRMMA	215	448.8944	458.6397	0.0583731	1823.354
NMMT	191	12383.7	21558.05	0.0000439	195972.7
VMMT	195	12.45509	19.57556	0.0001792	142.3912
NAMMA	156	198.6319	222.93	0	940.2841
			Climate Change		
co2eah	118	24.52693	19.72449	0	70.38403
CO2_GDP	352	0.1722635	0.1312096	0.0182169	0.7580574
CO2_t	352	17.57605	70.33093	0.1330203	484.204
co2pc	352	1.078093	2.07447	0.0260396	12.88304
			Control Variables		
edu	279	39.78043	13.17043	12.54703	84.32027
fdi	409	5.718765	10.691	-6.10498	103.3374
aid	406	7.671188	7.62106	0.0035144	77.86814
credit	348	33.13999	90.88847	0.347333	972.205

Appendix C: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) HDI	1.000														
(2) co2eah	0.4419	1.0000													
(3) CO2_GDP	0.4091	0.6107	1.0000												
(4) CO2_t	0.4559	0.5693	0.8783	1.0000											
(5) co2pc	0.6740	0.6626	0.8616	0.9338	1.0000										
(6) BTC	0.3386	0.4431	0.6530	0.7522	0.6966	1.0000									
(7) cumulBTC	0.4544	0.5688	0.8561	0.9917	0.9172	0.7426	1.0000								
(8) NRMMA	-0.0162	0.1267	-0.2912	-0.1849	-0.1788	-0.0950	-0.114	1.0000							
(9) NMMT	-0.1600	0.0704	-0.1752	-0.1251	-0.1888	-0.0251	-0.0500	0.8856	1.0000						
(10) VMMT	-0.1990	0.0227	-0.2112	-0.1206	-0.2033	-0.0265	-0.0465	0.8947	0.9901	1.0000					
(11) NAMMA	0.1367	0.3821	-0.1807	-0.2005	-0.0610	-0.1295	-0.1507	0.8005	0.6405	0.6190	1.0000				
(12) edu	-0.5169	-0.5016	-0.3239	-0.1855	-0.4339	-0.1534	-0.1909	0.0659	0.1954	0.2416	-0.1689	1.0000			
(13) fdi	-0.4587	-0.4012	-0.3337	-0.1875	-0.3056	-0.1100	-0.1777	-0.0417	-0.0262	0.0005	-0.3290	0.1337	1.0000		
(14) aid	-0.8678	-0.3850	-0.3417	-0.3726	-0.5371	-0.2680	-0.3730	0.1620	0.2915	0.3197	-0.0961	0.3368	0.6327	1.0000	
(15) credit	0.5259	0.5178	0.9051	0.9635	0.9572	0.7087	0.9459	-0.2618	-0.2100	-0.2109	-0.2071	-0.3150	-0.2847	-0.4326	1.0000

Appendix D: Descriptive statistics by country

Country	Mean CO2 t	Median CO2 t	Min CO2 t	Max CO2 t	Mean co2pc	Mean HDI	Mean RMMA	Min RMMA	Max RMMA	Mean NMMT	Min NMMT	Max NMMT	Mean VMMT	Min VMMT	Max VMMT
Angola	27.5	27.1	23.7	32.1	1.0	0,55	4	0	9	52	2	164	0.0%	0.0%	0.1%
Benin	5.6	5.2	4.8	7.1	0.5	0,50	625	64	1 347	11 121	408	30 022	19.8%	0.4%	41.5%
Botswana	5.9	6.3	3.5	7.9	2.8	0,70	655	3	1 411	7 067	4	21 278	1.6%	0.0%	5.2%
Burkina Faso	2.8	3.1	1.9	3.4	0.2	0,41	302	8	881	17 183	1 495	45 628	29.7%	1.6%	58.2%
Burundi	0.3	0.3	0.2	0.3	0.0	0,42									
Cabo Verde	0.7	0.7	0.3	1.0	1.3	0,64									
Cameroon	8.3	8.0	7.2	9.8	0.4	0,53	217	5	455	7 781	2	39 645	5.9%	0.0%	30.2%
Central African Republic	0.4	0.4	0.4	0.5	0.1	0,36	2	1	3	1	1	1	0.0%	0.0%	0.0%
Chad	0.7	0.7	0.4	1.0	0.1	0,40	2	2	2	1	0	2	0.0%	0.0%	0.1%
Comoros	0.2	0.2	0.1	0.2	0.2	0,53									
Congo, Democratic Republic of	3.7	3.5	3.1	5.5	0.1	0,44									
Congo, Republic of	5.2	5.3	4.5	5.5	1.1	0,59	239	200	277						
Cote d'Ivoire	10.0	10.2	7.3	12.5	0.4	0,48	759	120	1 695	20 354	4 873	39 354	22.6%	7.8%	40.6%
Djibouti	1.1	1.0	0.9	1.4	1.2	0,47									
Equatorial Guinea	3.4	2.9	2.5	4.7	3.1	0,59									
Ethiopia	11.2	11.4	6.9	14.9	0.1	0,44									
Gabon	6.2	6.2	5.8	6.6	3.4	0,68	21	21	21						
Gambia, The						0,45									
Ghana	15.0	15.3	11.4	18.6	0.6	0,58	850	239	1 774	27 381	1 144	79 242	28.8%	0.8%	74.3%
Guinea	2.2	2.4	1.4	2.7	0.2	0,44	213	8	624	9 790	20	32 336	10.6%	0.0%	33.3%
Guinea-Bissau	0.4	0.4	0.3	0.5	0.2	0,45	325	125	586	739	262	1 821	0.6%	0.1%	1.8%
Kenya	15.1	14.3	12.5	18.6	0.3	0,56	1 035	689	1 548	35 000	13 038	56 469	39.6%	23.1%	47.8%
Lesotho	0.6	0.7	0.2	0.8	0.3	0,49	748	347	995	18 429	455	40 780	10.0%	0.2%	21.8%
Liberia	0.9	1.0	0.6	1.1	0.2	0,46	366	16	961	1 441	473	3 673	1.0%	0.6%	1.3%
Madagascar	3.5	3.8	2.2	4.2	0.1	0,51	170	11	413	1 633	4	5 830	6.0%	0.0%	20.5%
Malawi	1.4	1.4	1.3	1.6	0.1	0,47	51	21	81	690	55	1 325	1.4%	0.1%	3.4%
Mali	0.8	0.8	0.6	1.0	0.0	0,41	343	21	733	13 851	1 453	25 640	21.0%	3.0%	33.8%
Mauritania	2.6	2.7	2.1	3.0	0.7	0,51	34	14	53				0.6%	0.1%	1.9%
Mauritius	3.8	3.8	3.7	4.0	3.1	0,78	112	5	200	63	60	70	0.0%	0.0%	0.0%
Mozambique	5.4	4.9	3.7	7.8	0.2	0,42	330	187	488	7 826	356	15 962	5.9%	0.2%	18.4%
Namibia	3.8	3.8	3.1	4.3	1.7	0,62	430	3	1 358	1 665	2	7 287	1.3%	0.0%	5.7%
Niger	2.0	2.1	1.4	2.5	0.1	0,35	161	63	272	2 407	913	3 910	3.7%	1.3%	4.8%
Nigeria	90.4	90.2	85.4	95.1	0.5	0,52	65	37	106	301	25	453	0.6%	0.0%	1.5%
Rwanda	0.9	0.9	0.8	1.1	0.1	0,51	785	34	1 494	19 871	116	40 489	12.2%	0.2%	22.1%
Sao Tome and Principe	0.1	0.1	0.1	0.2	0.8	0,58									
Senegal	8.1	7.9	7.0	9.7	0.6	0,50	372	14	783	10 924	1 316	32 902	6.7%	0.6%	20.3%
Seychelles	1.0	0.9	0.9	1.1	10.5	0,79	26	21	29	619	168	1 093	0.1%	0.0%	0.1%
Sierra Leone	1.1	1.1	0.7	1.3	0.2	0,42									
South Africa	468.8	470.2	445.8	484.2	8.7	0,69	121	73	173	162	90	206	0.0%	0.0%	0.1%
South Sudan						0,43									
Sudan	18.1	17.3	16.0	21.1	0.5	0,49	95	19	225	215	0	405	0.1%	0.0%	0.2%
Tanzania	11.4	11.4	7.1	14.7	0.2	0,51	1 11	423	1 823	25 457	730	46 998	30.8%	2.2%	51.9%
Togo	2.5	2.4	2.2	2.8	0.3	0,49	349	21	834	4 864	30	13 558	8.2%	0.0%	20.7%
Uganda	4.5	4.5	3.7	5.0	0.1	0,51	756	102	1 089	31 657	1 752	83 617	35.8%	2.4%	71.0%
Zambia	3.8	4.0	2.2	5.0	0.2	0,56	568	13	1 443	1 111	87	4 764	0.6%	0.1%	2.1%

Descriptive statistics 2010-2018 by country for CO2_t (emissions in million tons), co2pc (emissions per capita), HDI, and variables for which our main hypothesis is not rejected and for which the turning points are within the sample range, as indicated in Table 2: RMMA (number of registered mobile money accounts per 1,000 adults), NMMT (number of mobile money transactions per 1,000 adults) and VMMT (value of mobile money transactions as % of GDP).