Doctoral Dissertation

Essays on Information and Communication Technology, Poverty, Environment, and Corruption

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Graduate School for International Development and Cooperation
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Summary of the Dissertation

The Sustainable Development Goals (SDGs), also known as the global goals, were adopted by all United Nations member states in 2015 as a universal call to action to end poverty, protect the planet and ensure that all people enjoy peace and prosperity by 2030. These goals are 17 and integrated so that action in one area will affect outcomes in others, and that development must balance social, economic and environmental sustainability. Through the pledge to leave no one behind, countries have committed to fast-track progress for those furthest behind first. That is why the SDGs are designed to bring the world to several life-changing 'zeros', including zero poverty, hunger, Acquired immunodeficiency syndrome (AIDS) and discrimination against women and girls. Everyone is needed to reach these ambitious targets. The creativity, knowhow, technology and financial resources from all of society is necessary to achieve the SDGs in every context, so that the need for partnerships to reach these goals which is the goal number 17 has become the most important among them. The SDG 17 is a call for all contributions at international, regional , national, community, and individual level in term of cooperation (leading coherent policy development (Target 17.14)), assistance (supporting capacity building in developing countries (17.9)), or improving access to sustainable technologies and technology development in emerging economies (17.7), etc. through academic research to make the first 16 goals realizable.

Given the importance of academic research align with the SDG 17, our individual contribution through this doctoral dissertation is to analyze the contribution of Information and Communication Technology (ICT) to reach the SDGs. To do so, we targeted three important ones among them namely SDG 1 (no poverty), SDG 13 (climate action), and SDG 16 (peace, justice, and strong institutions). The important interrogations which will legitimate our endeavor are threefold: (i) why is ICT important to reduce poverty? (ii) why is ICT important to mitigate climate change? (iii) how can ICT contribute to strengthening institutions?

Economic growth is achieved with technical progress which allows many scholars to work on the relationship between ICT and Poverty (Jack & Suri, 2014). Among various types of ICT, mobile money has attractive for the promotion of financial inclusion which is now recognized as a crucial factor for economic growth. Our first essay examines the effect of financial inclusion and mobile money on poverty in Burkina Faso where mobile money has not prevailed yet.

There are two opposite relationships between ICT and the environment namely the unfavorable effects: ICT is positively associated with CO_2 due to the life cycle of ICT production and the favorable effects: ICT is negatively associated with CO_2 due to green technology. Our second essay analyzes the overall relationship in developing countries.

Corruption is recognized to harm economic growth by weakening institutions. Some studies argue that ICT use mitigates corruption by improving institutional efficiency and transparency (Kanyam et al., 2017), so our third essay examines the relationship between ICT, corruption, and military expenditures by using country level panel data in the Sub-Saharan Africa region which is regarded as the most corrupt region in the world (Willet, 2009). Our dissertation uses different identification strategies with different indicators or measures of ICT to show the empirical analysis between ICT and the selected three SDGs.

From the results of the empirical analysis, we can notice that ICT reduces poverty, CO_2 emissions, and corrupted military expenses for the sake of developing countries.

The first chapter is the general introduction. The second one is related to financial inclusion, mobile money, and individual welfare: The case of Burkina Faso. The third chapter deals with ICT and environmental sustainability: Any differences in developing countries? The fourth chapter explores the nexus between corruption, ICT and military expenditure in Sub-Saharan Africa, and the fifth chapter is the general conclusion.

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Chapter 1: Introduction

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Chapter 2: Financial inclusion, mobile money, and individual welfare: The case of Burkina Faso.

Chapter 3: ICT and environmental sustainability: Any differences in developing countries?

Chapter 4: Corruption, ICT and military expenditure in Sub-Saharan Africa.

Chapter 5: Conclusion.

Chapter 2: Financial inclusion, mobile money, and individual welfare: The case of Burkina Faso

2.1 Introduction

The promotion of financial inclusion has been emphasized, particularly for poor people. Financial accessibility is crucial for economic growth.[1] Demirgüç-Kunt & Klapper (2012) suggest an integral role of financial inclusion in poverty reduction by facilitating saving and borrowing, which empowers poor individuals to help smooth consumption and insure themselves against vulnerabilities in their lives. However, the unfulfilled demand for financing is still substantial around the world, so that the lack of financial inclusion remains a far-reaching problem even though microcredit institutions have prevailed in many developing countries (Chaia et al., 2009). Indeed, adults without access to the banking system amount to 1.7 billion in 2017, representing almost 40 percent of adults worldwide (Grohmann et al., 2018). Traditional financial institutions, such as banks and nonbank financial institutions, have failed to provide enough financial services or financial access for low-income people who need financial credit in developing countries (Diniz et al., 2012).

The emergence of mobile money or mobile financial services is expected to resolve issues related to the difficulty in financial access to traditional financial institutions and to promote the financial inclusion of poor people in developing countries. Several studies, such as Jack and Suri (2014) and Munyegera and Matsumoto (2016), suggest that mobile money can be the best tool for individual financial inclusion because it allows individuals, especially among the financially excluded rural communities in many developing countries, to transfer purchasing power by simple Short Messaging Service (SMS) technology with the low cost of sending money across vast distances. Recently, mobile money, or rather interoperability, which is the association of mobile money and external parties such as traditional financial services, has prevailed due to rapid progress in telecommunication technology and the regulatory efforts of financial regulators. However, the penetration rates of mobile money differ substantially among developing countries. In fact, some of the least-developed countries in Africa still have a low penetration of mobile money due in part to deficiencies in the telecommunication infrastructure. For example, only 16 percent of adults are registered with mobile money services in Burkina

[1] See, e.g., King and Levine (1993), Rajan and Zingales (1998), Beck et al. (2000), Levine et al. (2000), Khan (2001), Claessens (2006), Demirguc-Kunt et al. (2008), and Ghosh (2016).

Faso. Given these arguments, this study attempts to evaluate the roles of financial inclusion and mobile money in improving individual welfare and contributing to poverty reduction in a landlocked sub-Saharan country, Burkina Faso, one of the poorest countries in the world.

Many studies have discussed the linkage of financial inclusion with welfare and poverty. Demirguc-Kunt et al. (2017) show that financial inclusion alleviates poverty and inequality through investment in the future, consumption smoothing, and financial risks management. Burgess and Pande (2005) show that a state-led rural branch expansion is associated with poverty reduction in India. Bruhn and Love (2014) state that more access to financial services promotes income growth for low-income people by enabling informal business holders to maintain their businesses functional and thus creates an overall increase in employment. Moreover, Brune et al. (2016) assess that offering financial access to individual savings accounts not only increases banking transactions but also improves measures of household welfares, such as investments in inputs and subsequent agricultural yields, profits, and expenditures. Furthermore, Klapper et al. (2016) sum up the advantages of financial inclusion by showing how it can help achieve Sustainable Development Goals (SDGs).

At the same time, there has been a growing literature on the effects of mobile money on poverty, particularly in the context of poor countries. The report of the Global System for Mobile communications Association (GSMA) (2017a) states that mobile money contributes to 11 of the 17 United Nations SDGs, decreasing inequality by enabling households to lift themselves out of poverty and empowering underserved segments of the population. Suri and Jack (2016) find that access to the Kenyan mobile money system M-PESA[2] increased per capita consumption and lifted 194,000 households, or two percent of households, out of poverty. In addition, Munyegera and Matsumoto (2016) reveal a positive effect of mobile money access on household welfare in Uganda. Moreover, Riley (2018) finds that after a village-level rainfall shock, users of mobile money could prevent a drop in their consumption in Tanzania. Furthermore, Danquah and Iddrisu (2018) show that mobile money access leads to higher sales revenues for nonfarm enterprises and households and improves the chances of not being in poverty in Ghana.

This paper makes three main contributions to the existing literature. First, we estimate the effects of mobile money use on an individual's poverty indicators of nutrition, health, and education, which would reflect basic needs as proxies of welfare, rather than monetary poverty measures such as income and savings, which are known as one-dimensional

[2] M-PESA: "M" is for mobile and "PESA" means money in Swahili (the local language of Kenya).

poverty (Batana et al., 2013). Second, we analyze the role of the combination of financial inclusion and mobile money in determining poverty reduction at the individual level, unlike other studies that focus separately on financial inclusion and mobile money (Munyegera & Matsumoto, 2016; Riley, 2018; Danquah & Iddrisu, 2018). Third, our study fills the gap in empirical studies on mobile money and poverty reduction in low-income countries, such as members of the West African Economic and Monetary Union (WAEMU),[3] where mobile money is at an early stage, and the penetration rate is low. Although some studies evaluate the effects of mobile money in Africa (Munyegera & Matsumoto, 2016; Riley, 2018), most of their targeted countries are at a more matured stage of mobile money systems in the East African Community (EAC), [4]which differ from the financial conditions of WAEMU members in terms of mobile money penetration. One of the closest studies related to our work is Ky and Rugemintwari (2015). However, their study on Burkina Faso contexts examines the relationship between mobile money and savings without taking poverty reduction into account. Thus, examining the case of a low-income country with low mobile money penetration, Burkina Faso, would enable us to discuss the role of financial inclusion and mobile money at the early stage of mobile money systems.

This study evaluates the effects of financial inclusion and mobile money use on an individual's poverty status using data on 5,066 individuals in Burkina Faso taken from the Finscope Consumer Survey (2016). The survey primarily aims to describe the levels of financial inclusion, to describe the landscape of financial access, to identify the drivers of and barriers to financial access, to stimulate evidence-based dialogue and to create a baseline for financial inclusion in the country. The survey data include three measures of multidimensional poverty status: (i) nutrition, (ii) healthcare, and (iii) education, which are among the main Millennium Development Goals (MDGs) agreed upon by 189 heads of state in 2000; they are known today as the SDGs goals and have been designated as basic needs by Beck et al. (2007). Moreover, our three measures are widely used in comparative analysis in Sub-Saharan Africa (SSA) for practical, theoretical, and methodological reasons (Batana, 2013).

One critical challenge is that our treatment variable representing individuals' choice of financial inclusion and mobile money use is not random and may have possible relationships with their

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[3] The WAEMU comprises Benin, Burkina Faso, Cote d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal, and Togo. They use FCFA as currency, which is pegged on the euro. 1€≈656 FCFA, and they are listed in the worst ranked countries based on the United Nations Development Programme (UNDP)'s 2016 Human Development Index; Burkina Faso ranks 185th out of 188 countries, and Niger ranks 187th.

[4] The EAC comprises six countries in the African Great Lakes region in eastern Africa: Burundi, Kenya, Rwanda, South Sudan, Tanzania, and Uganda. In the EAC, over 40 percent of the adult population use mobile money on an active basis (90-day) (GSMA, 2017a).

characteristics, which would cause selection biases. To mitigate such an endogeneity problem, this study estimates the treatment effects by applying two matching methodologies: propensity score matching (PSM) and inverse-probability-weighted regression adjustment (IPWRA). The main results reveal that financial inclusion reduces poverty at the individual level. More importantly, once individuals access financial services through mobile money, such favorable effects on poverty alleviation become more substantial, so that policy makers in low-income countries, such as Burkina Faso, should emphasize the promotion of mobile money in their financial inclusion programs to enhance individual welfare. Our results also support the 'interoperability' of financial services and mobile money to encourage financial institutions to provide swift financial transactions for people anywhere, which would engender a deep sense of financial inclusion (GSMA, 2017b; Peric et al., 2018). In addition, financial regulators should create a sound environment for the prevalence of mobile money through financial regulations with supply- and demand-side considerations, as suggested by the International Monetary Fund (IMF) (2019).

The rest of the paper is organized as follows. In Section 2, we provide a selective review of the literature on financial inclusion, mobile money, and poverty reduction. Section 3 explains the overview of financial conditions and poverty in Burkina Faso. Section 4 deals with the empirical analysis of financial inclusion and poverty reduction, and Section 5 incorporates the role of mobile money in our empirical analysis. Section 6 concludes with some policy discussions.

2.2 Literature review

2.2.1 Financial inclusion and poverty reduction

The primary objective of financial inclusion is the pursuit of making financial services accessible at affordable costs to all individuals and businesses (Diniz et al., 2012), and it is expected to be a key driving force in reducing poverty and boosting prosperity (Beck et al., 2007; Han & Melecky, 2013; Bruhn & Love, 2014). The importance of financial inclusion was first recognized by the United Nations Capital Development Fund (UNCDF) in the late 1990s through the support of microcredit institutions including poor people in financial systems. This has been widely acknowledged as a crucial agenda to be achieved in many developing countries.

Many studies have shown that financial inclusion by traditional financial institutions (banks and nonbanks) helps to decrease rural poverty and improve various economic and financial conditions, such as credit, employment, insurance, and savings (Sapienza, 2004; Kaboski & Townsend, 2011, 2012; Bruhn & Love, 2014; Cai et al., 2015; Dupas & Robinson, 2013). Sapienza (2004), using a panel data during the period 1991 to 1995, shows that state-owned banks help firms located in depressed areas, which mitigates rural poverty in Italy. Kaboski and Townsend (2011, 2012) describe the favorable impacts of microcredit loans in the context of Thailand's Million Baht Village Fund Program, where every village received 1 million Baht (about $24,000) to initiate a village bank that provided funds available to villagers. Bruhn and Love (2014) find that reaching low-income individuals by financial access, with over 800 branches opening almost overnight in 2002, has a considerable positive effect on economic activity through the labor market (employment) in the case of Banco Azteca in Mexico. Cai et al. (2015) conduct field experiments in China and show that promoting the adoption of insurance significantly increases farmers' sow production, and this effect seems to persist in the long run. Dupas and Robinson (2013) show that having access to savings accounts encourages women to economize and to increase the size of their business in Kenya.

On the other hand, some studies fail to show clear evidence supporting the favorable effect of financial inclusion on poverty reduction. In summarized studies in Uganda, Malawi, and Chile, Dupas et al. (2016) find no evidence that reaching basic bank accounts for the rural poor results in improving welfare or reducing poverty. Their study comments that accounts not geared to particular needs and expensive costs due to the use of accounts are the main hindrances to overall increases in savings or to improvements in developmental outcomes such as consumption, schooling, and health. Banerjee et al. (2015a) summarize results across studies and mention unclear evidence of financial inclusion by revealing a merely positive, but not transformative, effect of microcredit on poverty reduction under different specifications in Europe with the case of Bosnia and Herzegovina (Augsburg et al., 2015), Africa with the case of Ethiopia (Tarozzi et al., 2015), and Morocco (Crepon et al., 2015), Asia with the case of India (Banerjee et al., 2015b) and Mongolia (Attanasio et al., 2015), and America with the case of Mexico (Angelucci et al., 2015). They generally suggest that though businesses can obtain profit from loans, it is less clear that this profit is translated into developmental impacts, such as increased incomes and broader welfare benefits for individuals. Such unfavorable evidence is consistent with the argument of Demirguc-Kunt et al. (2015), who claim that over 40 percent of adults worldwide remain financially excluded due to various barriers, such as physical access, affordability, and eligibility. Owing to the limited traditional financial access, particularly in rural areas, associated with low infrastructure levels in developing countries, it has widely been acknowledged that financial institutions should make use of advanced telecommunication technology, such as mobile phones, to enhance financial accessibility, especially for poor people (Claessens, 2006; Mas & Kumar, 2008; He et al., 2017).

2.2.2 Mobile money and poverty reduction

Mobile money is a financial innovation through Short Message Service (SMS) technology with a commission system to remunerate the providers of the different services (Jack & Suri, 2014). Through a mobile phone, mobile money enables people to use various financial services, including (1) person-to-person transfer of funds, including domestic and international remittances, (2) person-to-business payments for sales and purchases of goods and services, and (3) mobile banking, through which customers can access their bank accounts to pay bills or deposit and withdraw funds (Dolan, 2009; Riley, 2018). On the one hand, several studies have examined the effects of mobile money on welfare in the context of poor countries. Among them, GSMA (2017a) states that mobile money contributes to eleven (including the three proxies in this study) of the seventeen UN SDGs by enabling households to lift poor people out of poverty and by empowering underserved segments of the population. Suri and Jack

(2016) show that mobile money enables two percent of households to escape from extreme poverty and its impacts are more pronounced for female-headed households in Kenya. Munyegera and Matsumoto (2016) also find a positive effect of mobile money access on household welfare, measured by real per capital consumption, in Uganda using a combination of household fixed effects, instrumental variables, and matching methods. Riley (2018) reveals that after a village-level rainfall shock in Tanzania, only users of mobile money can prevent a drop in their consumption by applying difference-in-difference specification. Danquah and Iddrisu (2018) find that mobile money improves the chances of not being in poverty by leading to higher sales and revenues for nonfarm enterprises and households in Ghana.

On the other hand, a few studies have cast doubt on the positive effects of mobile money on poverty reduction by revealing some risks stemming from the use of mobile money, which may diminish the positive effects and renew the debate around this relationship for researchers at the Consultative Group to Assist the Poor (CGAP) (2017). There is a growing interest in possible win-to-win collaboration or interoperability between mobile money and external parties, such as bank and nonbank services. Indeed, mobile money covers two distinct industries (telecommunication and banking) with separate business models, so that the development of the necessary cross-sectoral partnership must include bridging cultures and regulations (World Bank, 2012). Such complex social and business forms could be difficult, and often risky, to manage for both providers and users. In addition, profitability in this industry needs a large scale, and business operators are faced with the trade-off between higher costs to recoup their investments and lower costs to build a mass market with a large scale (Mas & Radcliffe, 2010). Moreover, the Consultative Group to Assist the Poor (CGAP) (2017) reveals that mobile financial services could become a conduit for fraud and other criminal activities, as explained in more detail in a document related to financial crimes on mobile money (Chatain et al., 2011). Furthermore, Raphael (2016) reveals the risks and barriers for mobile money users in mobile money transactions (MMT) and the frequencies of their incidences using primary data collected in a survey conducted in Ilala district, Tanzania.

2.3 Financial inclusion and mobile money in Burkina Faso

Financial inclusion is expected to play an integral role in reducing poverty and insuring poor people against several vulnerabilities in their lives (Demirgüç-Kunt & Klapper, 2012). Burkina Faso is a landlocked Sahel country between the Sahara desert and the Gulf of Guinea and shares borders with six nations (Mali, Niger, Benin, Togo, Ghana, and Côte d'Ivoire). In the country, a large portion of people remains financially excluded, despite ongoing efforts by the new government. Indeed, the country's report no. 19/16 of the International Monetary Fund in 2019 on Burkina Faso states that less than 25 percent of the population owns an account at financial institutions, and among them, less than 10 percent have accessed loans from financial institutions. In addition, the 2019 World Bank's Doing Business Report argues that access to credit in Burkina Faso is difficult and broadly comparable to its WAEMU peers. Financial accessibility is generally constrained in rural areas, particularly for lower-income women. There are also substantial informational and collateral barriers to affordable credit for small and medium sized enterprises (SMEs), which also hampers private sector-led development in dealing with poverty reduction. Although the government prioritizes the development of microfinance institutions, microfinance remains relatively underdeveloped due to a lack of information technology infrastructure, a shortage of scale economies, and fragility in business operations. Thus, the prevalence of mobile money is more imminently needed in Burkina Faso to alleviate poverty.

Mobile money use started increasing in Burkina Faso at the same time as its WAEMU peers, ever since instruction N^0 01/2006/SP DU 31 JUIL. 2006 (Banque Centrale des Etats de l'Afrique de l'Ouest (BCEAO), 2006), which enables a nonfinancial entity (mostly telecommunication companies) to issue mobile money services in the WAEMU under the agreement of BCEAO. The two pioneers of mobile money in Burkina Faso are Airtel and

Telmob. Both are telecommunication companies, and they launched mobile money services in 2012 and 2013, respectively. Airtel money was launched further to a partnership between Airtel Burkina and Ecobank Bank in 2012 and later became Orange money. In 2013, a partnership between Telmob and BICIA-Burkina (a subsidiary of BNP Paribas) gave rise to mobicash, which is the second mobile payment service (money transfers and bill payments) in Burkina Faso. Currently, the evolution of the mobile payments market is impressive, such that they compete with traditional banks at some locations. In addition, BCEAO (2016) revealed that the flow of mobile money transactions in 2016 in Burkina Faso reached 2,415 billion FCFA ($4,488,847,584 USD) but still recognized that it still has a huge potential of growth, which can be seen in the economic literature. Indeed, according to Mothobi and Grzybowski (2017), mobile phone users who live in areas with poor infrastructure tend to rely on mobile phones to make financial transactions than individuals living in areas with better infrastructure. Ky and Rugemintwari (2015) find that using mobile money services increases the ability of individuals to save for health emergencies in the case of Burkina Faso, but they did not rely directly on poverty reduction in their study.

2.4 Financial inclusion and poverty reduction

This study first assesses the effects of financial inclusion on poverty status at the individual level and then evaluates the role of mobile money in accelerating financial inclusion in a later section. We took the data at the individual level in Burkina Faso from the Finscope Consumer Survey (2016). The survey primarily aims to describe the degrees of financial inclusion, to describe the landscape of financial access, to identify the drivers of and barriers to financial access, to stimulate evidence-based dialogue, and to create a baseline for financial inclusion in the country. The survey targeted adults who are 15 years old or older in a comprehensive listing of 675 enumeration areas within the 13 regions of Burkina Faso with 85,513 eligible households, and face-to-face interviews were conducted by an international study group during the period from May 2016 to September 2016. The sample was randomly drawn by the Institut National de la Statistique et de la Démographie (INSD). The sampling method broadly resembled a stratified multistage random sampling with confirmation of quality control and data validation.[5] After removing observations with missing variables, our sample comprises 5,066 individuals, which includes demographic, socioeconomic, and geographic characteristics.

Monetary-based poverty measures (such as income) have widely been used to examine the poverty status. However, several studies have emphasized the argument that in addition to these money-metric poverty measures, other dimensions of poverty, such as education and health conditions, should be incorporated to examine the poverty status. In fact, obtaining the precise information of income and expenditures are often difficult in developing countries, especially in Sub-Saharan Africa which is generally regarded as having the highest levels of poverty and extreme poverty (Batana, 2013). Moreover, monetary-based poverty measures do not capture all forms of deprivation. For example, although South Asian countries have reduced monetary-based poverty at an impressive pace over the past decade, the region lags in the non-monetary dimensions of the poverty status (World Bank, 2018). Accounting for the multidimensional concept of poverty (Sen, 1976), this study focuses on three outcome variables related to poverty status: (i) lack of nutrition (skipped a meal because of lack of food, $\mathtt{LON}$), (ii) lack of healthcare (stayed without medical treatment or medicine because of lack of money, $\mathtt{LOH}$), and (iii) lack of education (not been able to send children to school because of lack of money, $\mathtt{LOE}$), using a four-point Likert-type scale (1 = never; 2 = rarely; 3 = sometimes; 4 = often). Financial inclusion and exclusion at the individual level are captured by the dummy variable (FI), which equals one if an individual uses financial access provided by financial institutions (banks or nonbank financial institutions) and zero otherwise. Our specification

[5] See the Finscope Consumer Survey (2016) for the details.

implies that individuals with $\mathrm{FI} = 1$ are financially included, while those with $\mathrm{FI} = 0$ are financially excluded.

2.4.1 Methodology

This study first measures the effects of financial inclusion on individual poverty status to verify the conventional wisdom that financial inclusion improves welfare in the case of Burkina Faso. The reasons for using financial services could reflect individuals' characteristics related to their level of poverty status, so that linear regression models may be biased due to potential endogeneity problems.[6] Past literature suggests various methods to address such a selection bias issue. Among them, many studies employ instrumental variables (IVs). However, finding valid instruments is a challenge for many empirical studies. To mitigate potential endogeneity, our study uses matching methods. Our analysis is based on the idea that the use of financial services or financial inclusion represents a treatment, where individuals using financial services comprise the treatment group, while nonusers represent the counterfactual group (control group). Our measure of interest is the average treatment effect on the treated (ATT).[7]

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[6] The standard ordinary least squares (OLS) estimation of the model with poverty status as the outcome and the decision to use financial inclusion as the independent variable creates the issue of self-selection bias, because the decision could be affected by unobservable characteristics, such as an individual's knowledge, that are already part of the error term. The literature applies several empirical procedures to fix the selection bias. Among them, many studies employ the instrumental variables (IV) method.

[7] Following Imbens and Wooldridge (2009), the ATT is described as $\mathrm{ATT} = \mathrm{E}[\mathrm{Y}_1|\mathrm{D} = 1] - \mathrm{E}[\mathrm{Y}_0|\mathrm{D} = 1]$, where D is the financial inclusion dummy; Y_1 and Y_0 are potential outcomes of the users and nonusers (two counterfactual situations), respectively; $\mathrm{Y}_0|\mathrm{D} = 1$ is the value of the outcome of our interest that would have been observed if the individual had not chosen to use financial services (counterfactual outcome); and $\mathrm{Y}_1|\mathrm{D} = 1$ is the value of the outcome that is actually observed for the same individual. A fundamental problem is the difficulty in estimating the ATT because the counterfactual outcome is the unobservable value of $\mathrm{E}[\mathrm{Y}_0|\mathrm{D} = 1]$. When an individual's choice of financial inclusion is random, the average outcome of individuals not exposed to treatment, $\mathrm{E}[\mathrm{Y}_0|\mathrm{D} = 1]$ is an adequate substitute, meaning that the ATT can be obtained from the differences in the sample means of the outcome variable between the treatment and the control groups. However, the choice of financial inclusion can be endogenous.

In nonexperimental analysis, the treatment is nonrandom (De Janvry et al., 2010; Heckman & Vytlacil, 2007). In the case of nonrandomized assignments, observed and unobserved backgrounds of individuals may influence treatments as well as dependent variables so that selection bias can be persistent. The concept of matching methods is to imitate randomization regarding the assignment of the treatment. The unobserved counterfactual dependent variable is imputed by matching the treated individuals with untreated individuals that are as close as possible regarding all pretreatment characteristics. The estimate of the ATT is described as follows:

$$\mathrm{ATT(x)} = \mathrm{E}[\mathrm{Y_1}|\mathrm{D} = 1, \mathrm{X} = \mathrm{x}] - \mathrm{E}[\mathrm{Y_0}|\mathrm{D} = 0, \mathrm{X} = \mathrm{x}],$$

where x is a set of relevant pretreatment characteristics, $\mathrm{E}[\mathrm{Y_1}|\mathrm{D} = 1, \mathrm{X} = \mathrm{x}]$ is the expected outcome for the units that received treatment, and $\mathrm{E}[\mathrm{Y_0}|\mathrm{D} = 0, \mathrm{X} = \mathrm{x}]$ is the expected outcome for the treated units' best matches. This study first estimates the ATT by applying the propensity score matching (PSM) method, which could mitigate selection bias issues. Once the treated units are matched, the PSM assumes no systematic differences in unobservable characteristics between treated and untreated units. Given the estimated propensity scores $\mathrm{P(x)}$ under the main assumptions, i.e., conditional independence, the independent and identically distributed observations, and the common support assumptions, the ATT can be computed as follows:[8]

$$\mathrm{ATT} = \mathrm{E}[\mathrm{Y_1}|\mathrm{D} = 1, \mathrm{P(x)}] - \mathrm{E}[\mathrm{Y_0}|\mathrm{D} = 0, \mathrm{P(x)}].$$

In the matching process, a sufficient overlap is assumed to exist between the control and

[8] As underlined in several studies, such as Rosenbaum and Rubin (1985) and Heinrich et al. (2010), PSM approaches work under the following assumptions. The first assumption is the conditional independence assumption (CIA) or confoundedness. This assumption states that no unobservable variable affects both the likelihood of treatment and the outcome of interest after conditioning on covariates. CIA is the strong assumption and does not consider any unobservable differences. The second assumption is the independent and identically distributed observations assumption, which requests the potential outcomes and treatment status of each unit to be independent of the potential outcomes and treatment status of all other units in the sample. The third assumption is the common support or overlap requirement, which suggests that every observation comes with a positive probability of being both treated and controlled. In addition, the PSM should satisfy the balancing property, i.e., the mean value of covariates between treatment and control groups should be similar after matching.

treatment groups (i.e., common support). Furthermore, even when the overlap assumption is satisfied, there may be a large gap between the propensity scores of the two closest individuals available for match, leading to poor matches. To avoid this situation, this study uses the caliper restriction (Caliendo & Kopeinig, 2008), which imposes a threshold for the maximum distance between matched units. If the distance is above this threshold, the treated observation is dropped to avoid obtaining biased estimates. In this study, common practice is applied with a caliper of 0.05.

However, the ATT estimated from PSM can still suffer from biased results in the presence of misspecification in the propensity score model (Robins et al., 2007; Wooldridge, 2007, 2010).

One potential remedy for such a problem is to apply inverse-probability-weighted regression adjustment (IPWRA) estimation methods (Imbens & Wooldridge, 2009). IPWRA estimators use weighted regression coefficients to calculate averages of treatment-level predicted outcomes, where the weights are the estimated inverse probabilities of treatment.[9] Unlike PSM, IPWRA has a double robust property that ensures consistent results, as it allows the outcome and the treatment models to account for misspecification. PSM will provide inconsistent estimates if the treatment model is mis-specified. Moreover, with IPWRA, if the treatment model is misspecified, the estimates of the treatment effect can still be consistent if the outcome model is not misspecified. In addition, if the treatment model is not misspecified, IPWRA can also provide consistent estimates even when the outcome model is misspecified. That is why IPWRA estimates are consistent in the presence of misspecification in the treatment or outcome model, but not both (Imbens & Wooldridge, 2009; Wooldridge, 2010).[10] To estimate treatment

[9] The use of IPWRA also requires several assumptions, such as the conditional independence, the independent and identically distributed observations, and the overlap assumptions.

[10] In addition to the misspecification issue, IPWRA improves on PSM in two ways. The first one is the inclusion of controls for the observation's baseline characteristics in the outcome model. Both IPWRA and PSM must satisfy the conditional independence assumption, which states that no unobservable variable affects both the likelihood of treatment and the outcome of interest after conditioning on covariates. Since IPWRA includes more covariates in the outcome model than PSM, which includes only the covariates in the treatment model, this

effects using IPWRA, we start by estimating the parameters of the treatment model and derive inverse-probability weights. By using the estimated inverse-probability weights, we fit weighted regression outcome models for each treatment level and obtain the treatment-specific predicted outcomes for each subject. At the end, we compute the means of the treatment-specific predicted outcomes so that the contrasts of these averages provide the estimates of the average treatment effects.

This study evaluates the effects of financial inclusion on three measures of an individual's poverty status related to lack of nutrition, healthcare, and education (LON, LOH, and LOE). To construct a control group of untreated units that is as similar as possible to the treatment group, we need to select appropriate covariates representing the pretreatment an individual's characteristics. Following the studies by Ogutu et al. (2014) and Barnett et al. (2019), we select relevant pretreatment individual characteristics, including the age of the respondent in years (AGE), a gender dummy (FEMALE) that is equal to one if the respondent is female and zero otherwise, the family size or the number of household members (HSIZE), a distance dummy (TTM) that indicates the time to reach the market by using a six-point Likert-type scale (1=less than 10 minutes; 2=11-20 minutes; 3=21-30 minutes; 4=31-60 minutes; 5=61 minutes-2 hours; 6= more than 5 hours), and a mobile phone dummy (MP) that equals one if the respondent owns a mobile phone and zero otherwise. We also control for the primary education attendance of each respondent by including a dummy (PEDUC) which equals one when the respondent attended primary education and zero otherwise, the land (hectares) owned by each respondent (LSIZE) and an area dummy (RURAL) which equals one when the

assumption is more likely to hold with IPWRA than with PSM. The second improvement is that, unlike PSM, which compares each treatment observation to control observations that have a similar likelihood of being treated in a restrictive way, IPWRA implicitly compares every unit to every other unit while placing higher weights on observations that have a similar likelihood of being treated and lower weights on observations that are dissimilar.

respondent lives in a rural area and zero otherwise.[11] Table 2.1 displays the descriptions of variables used in this study.

Table 2.1. Description of variables.

variables	Description
Dependent variables	
LON	Lack of nutrition (skipped a meal because you did not have food (1= Never/ 2 = Rarely/ 3 = Sometimes/ 4 = Often))
LOH	Lack of healthcare (stayed without medical treatment or medicine because you did not have money (1= Never/ 2 = Rarely/ 3 = Sometimes/ 4 = Often))
LOE	Lack of education (not been able to send children to school because of lack of money for transport or uniform or other school costs (1= Never/ 2 = Rarely/ 3 = Sometimes/ 4 = Often))
Treatment variables	
FI	Use of financial services (1 for formal financial access and 0 for otherwise)
MM	Use of mobile money (1 for mobile money use and 0 for otherwise
Covariates	
AGE	Age of respondent (years)
FEMALE	Dummy for gender of respondent (1=female/ 0=male)
HSIZE	Household size
TTM	Dummy for Time to Market (1= "Less than 10 minutes"/ 2= "11 -20 minutes"/ 3= "21 - 30 minutes"/ 4= "31 - 60 minutes"/ 5= "61 minutes - 2 hours"/ 6= "More than 5 hours")
MP	Dummy for Mobile Phone (1= own a Mobile Phone; 0= Otherwise)
PEDUC	Dummy for Primary Education (primary school (1= No formal schooling or Preschool or Primary/ 0 = Otherwise))
LSIZE	Land size (hectares)
RURAL	Dummy for area (1 = Rural; 0 = Otherwise)

2.4.2 Results

Table 2.2 shows the summary statistics of the variables. The sampled individuals are divided into the treatment (financial inclusion) group with 1,148 individuals (29.8 percent) and the control (financial exclusion) group with 2,703 individuals (70.2 percent). There are significant

[11] In Burkina Faso, most of the total adult population (76%) live in rural areas. The definition of the rural area is decided by the Institut National de la Statistique et de la Démographie (INSD. The rural area is an area where there is less than 5,000 people living further than 2 km from a rood in good or fair condition (World Bank, 2019).

differences in means for poverty status measures and pretreatment variables between financially included and excluded groups. Financially excluded individuals tend to be poorer than financially included individuals in terms of nutrition, healthcare, and education. The process in this study begins with the estimation of propensity scores for the treatment variable by applying a logistic regression model, where the probability of financial inclusion is regressed on our individual characteristics.

Table 2.2. Descriptive statistics

	Whole sample (1)		Financial inclusion (2)		Financial exclusion (3)		Mean diff (3)-(2)
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev	Mean
LON	1.8886	1.0692	1.7247	1.0130	1.9582	1.0849	0.2334***
LOH	1.8489	1.0482	1.6881	0.9732	1.9171	1.0714	0.2290***
LOE	1.6964	1.0566	1.5174	0.9171	1.7725	1.1019	0.2550***
FI	0.2981	0.4575	-	-	-	-	-
MM	0.1898	0.3922	-	-	-	-	-
AGE	34.8169	14.8407	37.3850	14.5673	33.7262	14.8240	-3.6588***
FEMALE	0.4827	0.4998	0.3606	0.4804	0.5346	0.4989	0.1740***
HSIZE	8.8437	4.7546	9.4347	5.0114	8.5927	4.6193	-0.8420***
TTM	2.4025	1.0959	2.3545	1.0908	2.4229	1.0977	0.0683*
MP	0.8250	0.3800	0.8841	0.3202	0.7998	0.4002	-0.0843***
PEDUC	0.8873	0.3163	0.8632	0.3437	0.8975	0.3033	0.0343***
LSIZE	5.0321	4.6823	6.0233	6.7015	4.6111	3.4030	-1.4121***
RURAL	0.9182	0.2741	0.8615	0.3456	0.9423	0.2332	0.0808***
No of obs.	3,851		1,148		2,703		

Note: ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Table 2.3 displays the estimated results of the logistic regression. The results confirm that female, young, and less educated people are more likely to be financially excluded. In addition, people in rural regions tend to be financially excluded. Moreover, people without assets, such as a mobile phone and land, are more likely to be financially excluded. In the matching process, sufficient overlap exists between the control and treatment groups, i.e., common support (Caliendo & Kopeinig, 2008). In addition, large gaps may exist between the propensity scores of the closest individuals available for match, which leads to poor matches. To mitigate this issue, we implement a restriction of a 0.05 caliper. Moreover, the density distribution of the propensity scores in the treatment and control groups confirms that differences in the density distributions prior to the matching have been removed.

Table 2.3. Logistic regression

	Coefficient
AGE	0.0182***
	(0.0026)
FEMALE	-0.6640***
	(0.0762)
HSIZE	0.0110
	(0.0082)
TTM	-0.0162
	(0.0342)
MP	0.6361***
	(0.1090)
PEDUC	-0.3081**
	(0.1218)
LSIZE	0.0701***
	(0.0096)
RURAL	-1.0787***
	(0.1256)
Constant	-0.9168***
	(0.2100)
No. of obs.	3,851
LR chi2(8)	338.67
Prob>chi2	0.0000
Pseudo R-squared	0.0722
log likelihood	-2176.8834

Notes: (1) Standard errors are in parentheses. (2) ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively

The balancing property in Table 2.4 shows that the p-values related to the differences in means of covariates between the two groups after matching are insignificant, indicating that our matching achieves appropriate balancing properties.

Table 2.4. Balancing property

	Mean		Bias	P-value
	Treated	Control	reduction	
Before matching				
AGE	37.385	33.726		0.000
FEMALE	0.3606	0.5346		0.000
HSIZE	9.4347	8.5927		0.000
TTM	2.3545	2.4229		0.077
MP	0.8841	0.7998		0.000
PEDUC	0.8632	0.8975		0.002
LSIZE	6.0233	4.6112		0.000
RURAL	0.8615	0.9423		0.000
After matching				
AGE	36.968	36.647	91.2	0.632
FEMALE	0.3802	0.3840	97.8	0.858
HSIZE	9.1906	9.1943	99.6	0.986
TTM	2.3792	2.3943	77.9	0.751
MP	0.8755	0.8792	95.5	0.791
PEDUC	0.8802	0.8651	56.0	0.297
LSIZE	5.3807	5.3605	98.6	0.918
RURAL	0.8981	0.8840	82.5	0.296

Table 2.5 displays the estimated ATTs of financial inclusion on our three proxies of individual welfare related to lack of nutrition, healthcare, and education (LON, LOH, and LOE) under the PSM and IPWRA frameworks. The results present clear evidence supporting that financial inclusion guided by financial services induces poverty reduction at the individual level. Once an individual is financially included, the three measures of poverty status (LON, LOH, and LOE) are reduced by 0.16-0.20, 0.17-0.24, and 0.24-0.30 points, respectively.

Table 2.5. ATTs of financial inclusion

	PSM	IPWRA
LON	-0.1635***	-0.2032***
	(0.0449)	(0.0394)
LOH	-0.1673***	-0.2354***
	(0.0435)	(0.0395)
LOE	-0.2401***	-0.3018***
	(0.0433)	(0.0391)

Notes: (1) Standard errors are in parentheses. (2) ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

For robustness checks, we also conduct ordinary least squares (OLS) regressions (Table 2.A1 in the appendix). The coefficients of LON, LOH, and LOE are significantly negative, which support the PSM and IPWRA results.[12] Our results in the case of Burkina Faso are consistent with the conventional relationship between financial inclusion and poverty reduction (Burgess & Pande, 2005; Demirguc-Kunt et al., 2017). Enabling people to access financial services would help achieve poverty reduction, which is emphasized in the Sustainable Development Goals (SDGs). Since limited capital or credit is the main hindrance for entrepreneurs to access inputs and high-end markets for their output (Okello, 2010) and for households to smooth consumption (Demirgüç-Kunt & Klapper, 2012), financial services could help eliminate extreme poverty. Deepening financial inclusion can induce favorable welfare effects that extend beyond benefits in the financial realm to the real economy (Grohmann et al., 2018).

2.5 Incorporating the role of mobile money

This section extends the analysis to evaluate how an individual's welfare is affected by the introduction of mobile money. In the previous section, we consider two categories based on whether or not an individual has financial accounts in financial institutions (FI): financially included individuals (treatment group) ($\mathrm{FI} = 1$) and financially excluded individuals (control group) ($\mathrm{FI} = 0$). A mobile money user is captured by the dummy variable (MM) which equals one if an individual uses mobile money and zero otherwise. To evaluate the role of mobile money, we further divide financially included individuals (financial inclusion) into two groups based on the usage of mobile money, and our whole sample now comprises three groups: (i)

[12] Recently, matching techniques have moved away from the PSM towards other matching techniques. King and Nielsen (2019) emphasize the weakness of the PSM, which often suffers from increasing imbalance, inefficiency, model dependence, and bias, and they suggest other matching methods, such as Mahalanobis Distance Matching (MDM) and Coarsened Exact Matching (CEM), which approximate a fully blocked experimental design. Thus, in addition to the PSM, we also conduct the robustness checks by applying two alternative matching methods, (i) kernel matching and (ii) 2-nearest neighbor matching. Table 2.A2 in the appendix shows the estimated ATTs of these two methods, which confirm the results of the PSM and IPWRA.

financially included individuals without mobile money (financial inclusion without mobile money) ($\mathrm{FI} = 1$ and $\mathrm{MM} = 0$), (ii) financially included individuals with mobile money (financial inclusion with mobile money) ($\mathrm{FI} = 1$ and $\mathrm{MM} = 1$), and (iii) financially excluded individuals (financial exclusion) ($\mathrm{FI} = 0$ and $\mathrm{MM} = 0$). In the data set, there exist a small number of individuals who do not have financial accounts in financial institutions but who use mobile money (27 out of 3,878). This case is extremely rare because people need to open financial accounts in financial institutions to use mobile money. Thus, we exclude such samples from our data set. Table 6 shows the descriptive statistics for our whole sample and each of the three groups. Among 1,148 financially included individuals, there are 731 who used mobile money (63.68 percent) and 417 who did not use mobile money (36.32 percent). We observe that the differences in means of the three poverty statuses appear to be substantial among the three groups.

Table 2.6. Descriptive statistics

	Whole sample (1)		Financial inclusion Without mobile money (2)		Financial inclusion With mobile money (3)		Financial exclusion (4)		Mean diff (4)-(2)	(4)-(3)
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev	Mean	
LON	1.8886	1.0692	1.8201	1.0533	1.6703	0.9859	1.9582	1.0849	0.1380**	0.2879***
LOH	1.8489	1.0482	1.7746	0.9937	1.6388	0.9585	1.9171	1.0714	0.1425***	0.2783***
LOE	1.6964	1.0566	1.6499	1.0177	1.4419	0.8458	1.7725	1.1019	0.1226**	0.3306***
FI	0.2981	0.4575	-	-	-	-	-	-	-	-
AGE	34.8169	14.8407	37.6834	15.1887	37.2148	14.2084	33.7262	14.8240	-3.9572***	-3.4885***
FEMALE	0.4827	0.4998	0.4245	0.4948	0.3242	0.4684	0.5346	0.4989	0.1101***	0.2104***
HSIZE	8.8437	4.7546	9.0288	4.5662	9.6662	5.2374	8.5927	4.6193	-0.4361*	-1.0735***
TTM	2.4025	1.0959	2.4988	1.1522	2.2722	1.0461	2.4229	1.0977	0.0759	0.1506***
MP	0.8250	0.3800	0.8297	0.3763	0.9152	0.2788	0.7998	0.4002	-0.0299	0.1153***
PEDUC	0.8873	0.3800	0.9161	0.2776	0.8331	0.3731	0.8975	0.3033	-0.0185	0.0644***
LSIZE	5.0321	4.6823	6.0460	6.6839	6.0103	6.7160	4.6111	3.4030	-1.4348***	-1.3992***
RURAL	0.9182	0.2741	0.9113	0.2847	0.8331	0.3731	0.9423	0.2332	0.0310**	0.1092***
No of obs.	3,851		417		731		2,703			

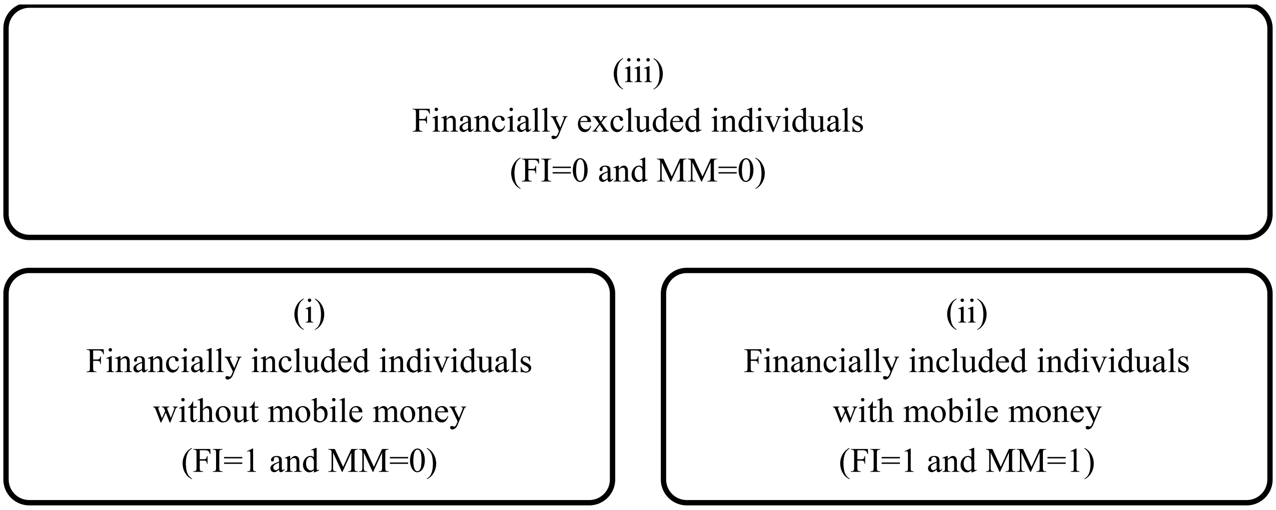
Note: ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

To evaluate the effects of mobile money, this study applies two matching methods (PSM and IPWRA) after the satisfaction of the balancing properties of our covariates over each of the following three subsamples separately.[13] The first subsample (subsample 1) consists of (i) financially included individuals without mobile money (financial inclusion without mobile money) and (iii) financially excluded individuals (financial exclusion), where the treatment and control groups comprise financial inclusion without mobile money and financial exclusion, respectively. Subsample 1 allows us to examine how financially excluded individuals improve their poverty status by accessing financial services without mobile money. The second subsample (subsample 2) consists of (ii) financially included individuals with mobile money (financial inclusion with mobile money) and (iii) financially excluded individuals (financial exclusion), where the treatment and control groups comprise financial inclusion with mobile

[13] The results of the balancing properties regarding each binary treatment variable are displayed in Tables 2.A5, 2.A6, and 2.A7 in the appendix and show how best ours matching methods reduce controls variables bias after matching.

money and financial exclusion, respectively. Subsample 2 enables us to evaluate how financially excluded individuals enhance their poverty status by accessing financial services with mobile money. The third subsample (subsample 3) consists of (ii) financially included individuals with mobile money (financial inclusion with mobile money) and (i) financially included individuals without mobile money (financial inclusion without mobile money), where the treatment and control groups comprise financial inclusion with and without mobile money, respectively. Subsample 3 allows us to evaluate how financially included, but without mobile money, individuals enhance their poverty status by using mobile money, i.e., the value added of mobile money for individuals who have already accessed financial services. Figure 2.1 presents the three groups (financially excluded individuals, financial inclusion without mobile money, and financially included individuals with mobile money) and three subsamples (subsamples 1, 2, and 3). For each of the three subsample analyses, we use the same pretreatment variables or covariates as those in the previous section.

Figure 2.1. Incorporating mobile money use



	Treatment group	Control group
Subsample 1	(i) Financially included individuals without mobile money	(iii) Financially excluded individuals
Subsample 2	(ii) Financially included individuals with mobile money	(iii) Financially excluded individuals
Subsample 3	(ii) Financially included individuals with mobile money	(i) Financially included individuals without mobile money

Table 2.7 shows the estimated results of logistic regressions, which enable us to obtain propensity scores of the PSM method for each subsample analysis. The estimated results generally coincide with the findings in the previous case of the full sample, where the treatment and control groups comprise financially included individuals and financially excluded individuals, respectively.

Table 2.7. Logistic regression

	Subsample 1 Financial inclusion without mobile money vs financial exclusion	Subsample 2 Financial inclusion with mobile money vs financial exclusion	Subsample 3 Financial inclusion with mobile money vs financial inclusion without mobile money
AGE	0.0161***	0.0195***	0.0008
	(0.0036)	(0.0031)	(0.0046)
FEMALE	-0.4208***	-0.8086***	-0.4655***
	(0.1098)	(0.0927)	(0.1337)
HSIZE	-0.0106	0.0245***	0.0410***
	(0.0124)	(0.0094)	(0.0149)
TTM	0.0812*	-0.0791*	-0.1781***
	(0.0484)	(0.0419)	(0.0581)
MP	0.2383*	0.9905***	0.7492***
	(0.1435)	(0.1476)	(0.1924)
PEDUC	0.1231	-0.5041***	-0.6590***
	(0.2050)	(0.1376)	(0.2169)
LSIZE	0.0747***	0.0629***	-0.0110
	(0.0121)	(0.0110)	(0.0104)
RURAL	-0.6206***	-1.2530***	-0.6265***
	(0.1964)	(0.1397)	(0.2097)
Constant	-2.4633***	-1.3122***	1.3443***
	(0.3246)	(0.2503)	(0.3626)
No. of obs.	3,120	3,434	1,148
LR chi2(8)	90.51	352.23	71.70
Prob>chi2	0.0000	0.0000	0.0000
Pseudo R-squared	0.0369	0.0991	0.0477
log likelihood	-1181.7611	-1601.7893	-716.3887

Notes: (1) Standard errors are in parentheses. (2) ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively

Table 2.8 presents the estimated results of the ATTs based on the PSM and IPWRA methods for each of the three subsamples. We also conduct OLS regressions (Table 2.A3 in the appendix), which support the PSM and IPWRA results.[14] The first two columns correspond to the first subsample, where the treatment and control groups comprise financial inclusion without mobile money and financial exclusion, respectively; the next two columns correspond to the second subsample, where the treatment and control groups comprise financial inclusion with mobile money and financial exclusion, respectively; and the last two columns correspond

[14] Similar to the previous discussions about the weakness of the PSM in footnote 12, we also conduct the robustness checks by applying two alternative matching methods, (i) kernel matching and (ii) 2-nearest neighbor matching, for each of the three subsamples. Table A4 in the appendix confirms that the estimated ATTs are consistent with those of the PSM and IPWRA.

to the third subsample, where the treatment and control groups comprise financial inclusion with and without mobile money, respectively.

Table 2.8. ATTs of financial inclusion and mobile money

	Subsample 1 Financial inclusion without mobile money vs financial exclusion without mobile money		Subsample 2 Financial inclusion with mobile money vs financial exclusion without mobile money		Subsample 3 Financial inclusion with mobile money vs financial inclusion without mobile money	
	PSM	IPWRA	PSM	IPWRA	PSM	IPWRA
LON	-0.0757	-0.1358**	-0.2586***	-0.2413***	-0.1328*	-0.1088*
	(0.0739)	(0.0569)	(0.0562)	(0.0459)	(0.0745)	(0.0647)
LOH	-0.1373*	-0.1648***	-0.2535***	-0.2765***	-0.1432**	-0.1013
	(0.0726)	(0.0544)	(0.0547)	(0.0465)	(0.0703)	(0.0629)
LOE	-0.1425*	-0.1584***	-0.3759***	-0.3845***	-0.2187***	-0.2183***
	(0.0734)	(0.0554)	(0.0538)	(0.0447)	(0.0678)	(0.0622)

Notes: (1) Standard errors are in parentheses. (2) ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Concerning the first subsample analysis, the estimated results reveal that financial inclusion, even without mobile money use, reduces our three measures of poverty status: lack of nutrition, healthcare, and education. For the second subsample analysis, the results show that financial inclusion with mobile money also reduces our three measures of poverty status. Importantly, the estimated ATTs are larger than those in the first subsample analysis, which suggests that the favorable effects of financial inclusion on an individual's welfare would be intensified by the usage of mobile money. The finding in the second subsample analysis can also be verified by the third subsample analysis showing the positive effects of mobile money use for the sample restricted to financially included individuals.[15]

[15] For the robustness check, we also estimate multivalued treatment effects (ATTs) by applying the IPWRA method. In this specification, we divide all individuals into three groups: (i) financial exclusion, (ii) financial inclusion without mobile money, and (iii) financial inclusion with mobile money. Table 2.9 shows the estimated results, which generally support the baseline findings shown in Table 2.8.

Table 2.9. ATTs of multivalued treatments

		IPWRA
LON	Financial inclusion without mobile money vs financial exclusion	-0.1351** (0.0568)
	Financial inclusion with mobile money vs financial exclusion	-0.2720*** (0.0486)
LOH	Financial inclusion without mobile money vs financial exclusion	-0.1643*** (0.0544)
	Financial inclusion with mobile money vs financial exclusion	-0.3175*** (0.0473)
LOE	Financial inclusion without mobile money vs financial exclusion	-0.1580*** (0.0554)
	Financial inclusion with mobile money vs financial exclusion	-0.3613*** (0.0431)

Notes: (1) Standard errors are in parentheses. (2) ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Our results provide clear evidence supporting the important role of mobile money in enhancing the positive effects of financial inclusion in Burkina Faso. The 'interoperability' of financial services and mobile money has been emphasized to enable financial institutions to provide swift financial transactions for people anywhere (GSMA, 2017b; Peric et al., 2018). Such convenient functions can be beneficial for people in rural areas, people who are far from branches of financial institutions, and people who often face the difficulty of accessing financial services. More specifically, our analysis confirms that the prevalence of financial inclusion through mobile money improves the welfare status related to nutrition, healthcare, and education for poor people, which helps achieve some of the seventeen goals of the SDGs (GSMA, 2017a). First, the improvement in nutrition status is related to zero hunger in Goal 2. Easy access to financial services through mobile money helps small-sized agricultural farmers, particularly in rural regions, increase crop productivity (Ogutu et al., 2014). This can inevitably curb hunger and improve the nutrition status of poor farmers in Burkina Faso, where approximately 672,000 children under 5 years old (representing 21 percent of children under 5 years old), suffer from chronic malnutrition (stunting or low height-for-age), and 10 percent of them suffer from acute malnutrition (United States Agency for International Development (USAID), 2018).

Second, the results showing the favorable effects on healthcare status support good health and wellbeing in Goal 3 of the SDGs. Communicable diseases have continued to be the primary cause of morbidity and mortality in Burkina Faso, with malaria being the largest contributor to mortality for children under 5 years of age (USAID, 2018). Financial services through mobile phones improves individuals' ability to successfully manage their own health and that of their family by tracking medical expenses, saving income, receiving remittances in times of external shocks, and purchasing health insurance. Third, the improvement in education status as the effect of financial inclusion would be consistent partly with the quality of education in Goal 4 of the SDGs. Currently, mobile money providers often work with schools as well as universities, either directly or through government authorities, to digitize the payments of various fees, including registration fees, tuition fees, and examination fees, from students, and they also digitize salary payments to school teachers and staff. Such advanced technology would help achieve access to education for children in Burkina Faso, where a third of school-age children (around one million girls and boys) do not have access to education, and where 70 percent of the adult population is illiterate (Swiss agency for Development and Cooperation, 2016). In sum, the interoperability of financial services and mobile money could be an efficient means of improving conditions related to nutrition, healthcare, and education, which are crucial nonmonetary elements of an individual's welfare. Our results in the case of Burkina Faso coincide with the argument of Suri and Jack (2016), who find that interoperability is a key driver in mitigating poverty in Kenya, as the introduction of the mobile money system (M-PESA) has increased per capita consumption levels and lifted 194,000 households, or 2 percent of households, out of poverty (Jenkis, 2008).

2.6 Conclusion

Financial inclusion is one of the important agendas for less developed countries to solve poverty issues and achieve the SDGs. The recent prevalence of mobile money services has been expected to promote financial inclusion for poor people. This study has evaluated how financial inclusion and mobile money in the context of their interoperability help reduce poverty and improve individuals' welfare in the case of a least-developed country, Burkina Faso, where the penetration rate of mobile money is relatively low compared to other developing countries. In particular, we have focused on nonmonetary poverty indicators of nutrition, healthcare, and education. Our three poverty-related indicators have been targeted to achieve poverty reduction in Burkina Faso. In fact, the proportion of households with poor or limited food consumption increased nationally from 26 percent in 2008 to 32 percent in 2012. Food consumption quality dropped significantly among urban households, with 30 percent exhibiting poor or limited food consumption compared to 12 percent in 2008 (World Food Programme, 2014). The government has emphasized the improvement of people's nutrition status since 2016 under the National Food and Nutrition Security Policy (PNSAN) (Murphy et al., 2017). In addition, 79 percent of women reported at least one problem in accessing healthcare, 72 percent of women reported a lack of money to pay for services as a barrier, 44 percent cited distance to the health center as a deterrent, and only 23 percent of women were literate in Burkina Faso (Institut National de la Statistique et de la Démographie (INSD) & Inner City Fund (ICF) International, 2012), so the government has also targeted the improvement of healthcare and education by establishing the General Directorate of Health Information and Statistics (DGISS) and the Programme Sectoriel de l'Education et de la Formation (PSEF) (Zida et al., 2017). The estimated results of the matching methods have presented the favorable effects of financial inclusion on poverty reduction in terms of individuals' nonmonetary welfares (nutrition, healthcare, and education). More importantly, once financial services are provided through mobile money, such favorable effects become more substantial. Our analysis has revealed the crucial role of the interoperability of financial services and mobile money, such that financial and telecommunication regulators should create a sound environment for the prevalence of mobile money, as suggested by Suárez (2016).

2.7 Appendix

Table 2.A1. OLS results

	Full sample analysis		
	LON	LOH	LOE
Treatment	-0.2016***	-0.2262***	-0.2791***
	(0.0377)	(0.0365)	(0.0358)
AGE	0.0063***	0.0070***	0.0050***
	(0.0012)	(0.0013)	(0.0013)
FEMALE	-0.0156	-0.0188	-0.0250
	(0.0348)	(0.0342)	(0.0347)
HSIZE	0.0105***	0.0150***	0.0282***
	(0.0039)	(0.0037)	(0.0038)
TTM	-0.0449***	-0.0218	-0.0809***
	(0.0157)	(0.0156)	(0.0159)
MP	- 0.4727***	- 0.3621***	-
	(0.0489)	(0.0475)	0.2974***
			(0.0483)
PEDUC	0.0788	0.0956*	0.0951*
	(0.0550)	(0.0529)	(0.0524)
LSIZE	-0.0209***	-0.0158***	-0.0047
	(0.0061)	(0.0047)	(0.0036)
RURAL	-0.0304	-0.1264*	-0.0866
	(0.0649)	(0.0646)	(0.0632)
Constant	2.2035***	2.0091***	1.8256***
	(0.1037)	(0.1013)	(0.1006)
No. of obs.	3,851	3,851	3,851
R-squared	0.0610	0.0502	0.0494

Notes: (1) Treatment equals one for financially included individuals and zero for financially excluded individuals in the full sample analysis. (2) Robust standard errors are in parentheses. (3) ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Table 2.A2. ATTs using Kernel matching and 2-nearest neighbor matching estimations.

	Whole sample Financial inclusion	
	Kernel matching	2-nearest neighbor matching
LON	-0.1990***	-0.1995***
	(0.0400)	(0.0479)
LOH	-0.2216***	-0.2461***
	(0.0389)	(0.0473)
LOE	-0.2958***	-0.3193***
	(0.0383)	(0.0483)

Notes: (1) Standard errors are in parentheses. (2) ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively

Table 2.A3. OLS results

	Subsample analysis 1			Subsample analysis 2			Subsample analysis 3		
	LON	LOH	LOE	LON	LOH	LOE	LON	LOH	LOE
Treatment	-0.1136**	-0.1437***	-0.1444***	-0.2525***	-0.2753***	-0.3640***	-0.1317**	-0.1319**	-0.2092***
	(0.0558)	(0.0534)	(0.0546)	(0.0436)	(0.0424)	(0.0394)	(0.0639)	(0.0608)	(0.0588)
AGE	0.0060***	0.0067***	0.0055***	0.0073***	0.0076***	0.0049***	0.0038*	0.0062***	0.0042**
	(0.0014)	(0.0014)	(0.0014)	(0.0013)	(0.0014)	(0.0014)	(0.0022)	(0.0022)	(0.0020)
FEMALE	-0.0344	-0.0264	-0.0510	-0.0325	-0.0564	-0.0675*	0.0554	0.0859	0.1423**
	(0.0384)	(0.0379)	(0.0393)	(0.0368)	(0.0362)	(0.0367)	(0.0661)	(0.0629)	(0.0590)
HSIZE	0.0081*	0.0126***	0.0280***	0.0109***	0.0160***	0.0282***	0.0205***	0.0224***	0.0328***
	(0.0043)	(0.0042)	(0.0046)	(0.0042)	(0.0040)	(0.0040)	(0.0071)	(0.0066)	(0.0061)
TTM	-0.0480***	-0.0269	-0.1043***	-0.0487***	-0.0176	-0.0824***	-0.0323	-0.0279	-0.0256
	(0.0176)	(0.0176)	(0.0182)	(0.0167)	(0.0168)	(0.0171)	(0.0274)	(0.0267)	(0.0248)
MP	-0.4587***	-0.3662***	-0.2879***	-0.4819***	-0.3535***	-0.3096***	-0.4145***	-0.3138***	-0.2005**
	(0.0520)	(0.0504)	(0.0522)	(0.0517)	(0.0506)	(0.0516)	(0.1070)	(0.1001)	(0.0942)
PEDUC	0.1213*	0.1271**	0.0951	0.0558	0.0884	0.1025*	0.0094	0.0174***	0.0235
	(0.0638)	(0.0625)	(0.0639)	(0.0576)	(0.0554)	(0.0552)	(0.0939)	(0.0866)	(0.0788)
LSIZE	-0.0284***	-0.0181***	-0.0035	-0.0234***	-0.0202***	-0.0077**	-0.0133*	-0.0102*	-0.0044
	(0.0079)	(0.0068)	(0.0052)	(0.0067)	(0.0050)	(0.0037)	(0.0074)	(0.0054)	(0.0039)
RURAL	-0.0048	-0.0986	-0.0566	-0.0466	-0.1234*	-0.1133*	-0.0590	-0.1915**	-0.1241
	(0.0842)	(0.0832)	(0.0818)	(0.0696)	(0.0691)	(0.0683)	(0.0906)	(0.0913)	(0.0556)
Constant	2.2127***	2.0191***	1.8385***	2.2398***	2.0077***	1.8972***	2.0168***	1.8529***	1.4832***
	(0.1251)	(0.1205)	(0.1226)	(0.1094)	(0.1078)	(0.1066)	(0.1868)	(0.1808)	(0.1635)
No. of obs.	3,120	3,120	3,120	3,434	3,434	3,434	1,148	1,148	1,148
R-squared	0.0582	0.0430	0.0409	0.0683	0.0556	0.0559	0.0384	0.0424	0.0566

Notes: (1) Treatment equals one for financially included individuals without mobile money and zero for financially excluded individuals in the subsample analysis 1. (2) Treatment equals one for financially included individuals with mobile money and zero for financially excluded individuals in the subsample analysis 2. (3) Treatment equals one for financially included individuals with mobile money and zero for financially included individuals without mobile money in the subsample analysis 3. (4) Robust standard errors are in parentheses. (5) ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Table 2.A4. ATTs using Kernel matching and 2-nearest neighbor matching estimations.

	Subsample 1 Financial inclusion without mobile money vs financial exclusion without mobile money		Subsample 2 Financial inclusion with mobile money vs financial exclusion without mobile money		Subsample 3 Financial inclusion with mobile money vs financial inclusion without mobile money	
	Kernel matching	2-nearest neighbor matching	Kernel matching	2-nearest neighbor matching	Kernel matching	2-nearest neighbor matching
LON	-0.1332**	-0.0915	-0.2371***	-0.2312***	-0.1117	-0.0814
	(0.0568)	(0.0674)	(0.0464)	(0.0569)	(0.0686)	(0.0719)
LOH	-0.1619***	-0.1691**	-0.2603***	-0.2629***	-0.0988	-0.0205
	(0.0540)	(0.0679)	(0.0454)	(0.0544)	(0.0653)	(0.0674)
LOE	-0.1506***	-0.2040***	-0.3725***	-0.3951***	-0.2208***	-0.1990***
	(0.0555)	(0.0712)	(0.0428)	(0.0517)	(0.0643)	(0.0680)

Notes: (1) Standard errors are in parentheses. (2) ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively

Table 2.A5. Balancing property

Subsample 1: Financial inclusion without mobile money vs financial exclusion

	Mean		Bias reduction	P-value
	Treated	Control		
Before matching				
AGE	37.683	33.726		0.000
FEMALE	0.4244	0.5346		0.000
HSIZE	9.0288	8.5927		0.072
TTM	2.4988	2.4229		0.192
MP	0.8297	0.7998		0.153
PEDUC	0.9161	0.8975		0.240
LSIZE	6.046	4.6112		0.000
RURAL	0.9113	0.9423		0.014
After matching				
AGE	37.715	37.877	95.9	0.884
FEMALE	0.4227	0.4227	100.0	1.000
HSIZE	8.9179	8.715	53.5	0.500
TTM	2.4952	2.4928	96.8	0.976
MP	0.8385	0.8382	67.7	0.710
PEDUC	0.9155	0.9082	60.9	0.713
LSIZE	5.7444	5.6289	91.9	0.754
RURAL	0.9106	0.9034	76.6	0.720

Table 2.A6. Balancing property

Subsample 2: Financial inclusion with mobile money vs financial exclusion

	Mean		Bias	P-value
	Treated	Control	reduction	
Before matching				
AGE	37.215	33.726		0.000
FEMALE	0.3242	0.5346		0.000
HSIZE	9.6662	8.5927		0.000
TTM	2.2722	2.4229		0.001
MP	0.9152	0.7998		0.000
PEDUC	0.8331	0.8975		0.000
LSIZE	6.0103	4.6112		0.000
RURAL	0.8331	0.9423		0.000
After matching				
AGE	36.933	36.339	83.0	0.483
FEMALE	0.3416	0.3504	95.8	0.734
HSIZE	9.5124	9.7942	73.8	0.325
TTM	2.292	2.3036	92.2	0.838
MP	0.9095	0.9080	98.7	0.925
PEDUC	0.8525	0.8467	90.9	0.763
LSIZE	5.5519	5.5454	99.5	0.980
RURAL	0.8701	0.8496	81.3	0.276

Table 2.A7. Balancing property

Subsample 3: Financial inclusion with mobile money vs financial inclusion without mobile money

	Mean		Bias	P-value
	Treated	Control	reduction	
Before matching				
AGE	37.215	33.683		0.600
FEMALE	0.3242	0.4245		0.001
HSIZE	9.6662	9.0288		0.038
TTM	2.2722	2.4988		0.001
MP	0.9152	0.8297		0.000
PEDUC	0.8331	0.9161		0.000
LSIZE	6.0103	6.046		0.931
RURAL	0.8331	0.9113		0.000
After matching				
AGE	37.32	37.877	50.0	0.822
FEMALE	0.4088	0.4227	55.8	0.216
HSIZE	9.1536	8.715	32.2	0.175
TTM	2.4271	2.4928	31.0	0.052
MP	0.8776	0.8382	81.7	0.521
PEDUC	0.9088	0.9082	52.9	0.036
LSIZE	6.1163	5.6289	-152.6	0.857
RURAL	0.9036	0.9034	50.0	0.042

Chapter 3: ICT and environmental sustainability: Any differences in developing countries?

3.1 Introduction

Information and communication technology (ICT) is an important contributor to economic growth (Hoffert et al., 2002; Middlemist and Hitt, 1981). During the last decades, ICT has brought about substantial changes in a global economy by increasing productivity, promoting global supply chains, and uplifting economic growth (OECD, 2000). The swift decline in the price of ICT equipment has caused substitution of ICT equipment for other forms of capital, reducing the production expenses. This substitution has also facilitated investors to increase ICT investments and restructure the corresponding economic activities (Jorgenson and Stiroh, 1999).

Many empirical studies have shown a significantly positive effect of ICT capital on output growth (O'Mahony and Vecchi, 2005, for the UK; Dimelis and Papaioannou, 2011, for the US). The relationship between ICT and economic growth in the US reveals economically significant contributions of ICT capital to economic growth after the mid-1990s (Jorgenson and Stiroh, 2000). In addition, ICT has a potential to help reduce poverty, increase productivity, and boost economic performance in emerging and developing countries (Sanz and Hellström, 2011). The impact of ICT is more substantial in developing countries than in developed countries (Dimelis and Papaioannou, 2010).

Responsible consumption and production are highlighted as one of the 17 sustainable development goals (SDGs) set by the United Nation (United Nations, 2015). The ICT sector has become recognized as ever more significant in ensuring sustainable development (Klimova et al., 2016). Since the 2000s, ICT has become an essential player in the journey toward a low carbon economy. The "green ICT" initiative targets to reduce the unfavorable effect of ICT on the environment. Green ICT represents the efficiency and effectiveness of this sector with minimal or no impact on the environment (Askarzai, 2011). ICT is an important tool to reduce carbon dioxide (CO_2) emissions by building smarter cities, transportation systems, electrical grids, and industrial processes (Danish et al., 2017).

Despite the Kyoto Protocol and the Paris Agreement, CO_2 emissions are still increasing. Several studies focus on the relationship between ICT and CO_2 emissions. ICT products and services cause environmental degradation (Arushanyan et al., 2014; Malmodin et al., 2010), but they also have a large potential for reducing environmental degradation by substituting ICT products for environmentally unfriendly products and making production processes more efficient (Erdmann and Hilty, 2010). Table 1 summarizes several studies on unfavorable and favorable effects of ICT on the environment.

Mingay (2007) argues that the ICT sector is estimated to produce 2% of global GHG emissions. Danish et al. (2017) confirm that ICT products increase CO_2 emissions throughout their life cycle (production, use, and disposal). Dedrick (2010) and Molla et al. (2009) emphasize the emergency to mitigate the unfavorable effects of ICT on the environment. Amri (2018) examines the linkage between CO_2 emissions and ICT in Tunisia and fails to show the favorable effect of ICT on the environment. The darker and more ominous side of the ICT industry is its exponentially growing energy consumption. As our reliance on ICT devices and services grows rapidly, so does our need for energy in manufacturing and electricity industries to power these devices. The generation of the much-needed energy to make and operate all the ICT devices on the market today is a crucial cause towards the creation of carbon dioxide, a leading Green House Gas (GHG), as well as other global warming pollutants (Belkhir and Elmeligi, 2018). Overall energy consumption of ICT suggests that in 2007, the ICT sector produced 1.3% of global GHG emissions with the corresponding global electricity consumption of 3.9% (Malmodin et al., 2010). A forecast indicates that the ICT sector expansion will cause the carbon footprint to reach 1.1 Gt by year 2020 (Malmodin et al., 2013).

Table 3.1. Summary of literature review

Authors	Period	Study area	Variables	Method.	Interpretations
I) Studies focusing on the unfavourable effect of ICT on the environment.					
Amri (2018)	1975-2014	Tunisia	CO_2, total factor productivity, ICT, trade, energy consumption, and financial development.	ARDL with break point.	Insignificant impact of ICT on CO_2 emissions.
Mingay (2007)	2008-2009	IT organizations	CO_2, ICT, and GHG.	Compilation of many studies.	ICT sector has been estimated to produce 2% of global greenhouse gas emissions.
GeSI (2008)	2007-2020	ICT industry (Worldwide)	CO_2, ICT, and GHG	Estimation approach "cradle-to-grave"	Global greenhouse gas will increase to an estimated of 2.8% by 2020.
II) Studies displaying the favourable effects of ICT on the environment.					
Lee and Brahmasrene (2014)	1991-2009	Nine members from the Association of Southeast Asian Nations (ASEAN).	CO_2, ICT, and economic growth	Co-integrating regression estimation	ICT shows significant favourable relationship with environment.
Zhang and Liu (2015)	2000–2010	China	Population, ICT industry, Urbanization, GDP per capital, Industrial structure, total CO_2 emission, and Energy Intensity.	STIRPAT	ICT industry contributes to reducing China's CO_2 emissions.
Asongu (2018)	2000-2012	44 Sub-Saharan African countries	CO_2 per capita, Educational quality, internet, mobile phones, GDP growth, population growth, Foreign investment, trade openness and regulation quality	GMM	ICT can be employed to dampen the potentially favourable effect on environment.
Aldakhil et al. (2019)	1975-2016	South Asia	ICT, R&D, FDI, Trade, GDP per capita, Energy efficiency, agricultural technology	Robust Least Squares Regression (RLS)	ICT applications used in diversified economic restructuring are helpful in reducing high-mass carbon-fossil emissions to achieve environmental sustainability in South Asia.

On the other hand, ICT is expected to be a possible solution to many environmental problems (Higón et al., 2017). ICT broadens the opportunities to reduce the human impact on nature. For example, e-commerce, tele-working, and video conferencing have reduced the worldwide travelling of both people and goods and hence the consumption of petroleum and the emission of greenhouse gases (Yi and Thomas, 2007). Weber et al. (2008) estimate that compared to traditional retails, e-commerce has approximately 30% lower energy consumption and GHG emissions. If air travel is replaced for teleconferencing by 10% within the next 10 years in the United States, approximately 200 million tons of GHG abatement could be achieved. Shifting all newspaper subscriptions from paper to online has the potential to reduce 57.4 million tons of CO_2 emissions over the next decade. Furthermore, Lee and Brahmasrene (2014) examine the relationships among ICT, CO_2 emissions, and economic growth from a panel of ASEAN during the period from 1991 to 2009 and find a significantly favorable effect of ICT on economic growth and CO_2 emissions. Concerning regional differences in China, Zhang and Liu (2015) consider the impact of the ICT industry on CO_2 emission using the Stochastic Impacts by Regression on Population, Affluence, and Technology (STRIPAT) model with provincial data. Their finding concludes that the ICT industry mitigates the problem of CO_2 emission in China. In addition, Asongu (2018) analyzes the nexus between ICT, openness, and CO_2 emission in Africa, and the empirical findings based on the generalized method of moments (GMM) approach suggest that ICT can be a useful tool to reduce the globalization driven CO_2 emissions.

Given the arguments related to favorable and unfavorable effects of ICT on global warming and environmental sustainability, this study intends to find out which effect of ICT on the environment is dominant in the case of developing countries. This study focuses on developing countries, which provides an empirical contribution to curb the scarcity of empirical evidences on the relationship between ICT and environment. Following Amri (2018) among others, we use the sum of mobile and fixed telephone subscription data per 100 people as a suitable proxy for ICT, since they are common, less costly, and less polluting among ICTs products in developing countries (Cheng et al., 2013). Moreover, this study applies a panel pooled mean group autoregressive distributive lag (PMG-ARDL) analysis, known as a modern econometric method (Alola et al., 2019), to a comprehensive panel data for 58 developing countries in the world during the period of 1990-2014. The sample countries are classified into two groups: (i) relatively low-income group (GNI per capita of $1025 or less) and (ii) relatively high-income group (middle- income countries[16]), which will enable us to capture how development stages affects the long-run relationships among variables.

The original contributions of our study are three-fold. Firstly, our study presents that the long-run relationship between CO_2 emissions and ICT depends on countries' income level, i.e., the development stage. In fact, CO_2 emissions are negatively and significantly associated with ICT for "relatively low-income" developing countries, while this relationship is less clear (negative but not significant) for "relatively high-income" developing countries. Secondly, our results support the favorable effect of ICT on the environment under the 'greening through ICT' argument and present ICT as a powerful tool to reduce CO_2 emissions especially at the early stages of economic development. Thirdly, our finding is a good news for developing countries in general and particularly for the relatively low-income ones, which mostly complain about the expensive costs of renewable energy sources. To enjoy the advantages in the context of ICT in developing countries, decision makers can encourage the population to use ICT products by promoting various policies, for instance, facilitating foreign investment in ICT sectors.

The remainder of this study is organized as follows. Section 2 describes data and methodology used in this study. In section 3, we present the empirical results of our analysis, including panel unit root tests, panel cointegration tests, the long-run estimates under PMG-ARDL method, and the Dumitrescu and Hurlin (2012) causality test, and we discuss some implications derived from our empirical results. Final section 4 provides the conclusion.

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[16] According to the World Bank (2015), lower middle-income countries are identified with a GNI per capita between $1026 and $4035 and the upper middle-income countries with a GNI per capita between $4036 and $12,475.

3.2 Methodology and data

3.2.1 Model specification

This study attempts to discuss how ICT relates to CO_2 emissions in developing countries. To identify the relationship between ICT and CO_2 emissions, controlling for other explanatory variables, we consider the following empirical model:

$$\mathrm{lnCO2PC}_{i,t} = \alpha_0 + \alpha_1 \mathrm{ICT}_{i,t} + \sum_k \beta_k x_{k,i,t} + \mu_i + \varepsilon_{it}, \quad (1)$$

where $\mathrm{lnCO2PC}_{i,t}$ is the log of CO_2 emissions per capita in country i at year t; $\mathrm{ICT}_{i,t}$ is the measure of the level of ICT; $x_{k,i,t}$'s are other control variables which are expected to relate to CO_2 emissions; μ_i is the country-specific fixed effects; and ε_{it} is the error term. As a proxy for the level of ICT, we use the sum of mobile and fixed telephone subscriptions data per 100 people. In the ICT related literature, mobile and fixed telephone subscriptions are commonly used to measure the ICT access in developing countries (Amri, 2018; Amri et al., 2019; Higón et al., 2017; ITU, 2017).

As other control variables, we include the log of total energy consumption per capita ($\mathrm{lnTECPC}_{i,t}$), and renewable energy penetration ($\mathrm{RREP}_{i,t}$), which is measured by the ratio of renewable energy consumption to total energy consumption penetration. Total energy consumption and renewable energy penetration are crucial factors to determine CO_2 emissions (Balsalobre-Lorente et al., 2018). In addition, the model includes the log of real GDP per capita ($\mathrm{lnRGDPPC}_{i,t}$), to control for a country's income level, which is related to the well-known environmental Kuznets curve (EKC) argument. The EKC argument claims that the income-emission relationship depends on a country's income level, which suggests the important role of the development stages. To account for different income-emission relationships, this study classifies our sample of developing countries into two country groups: (i) relatively low-income developing countries and (ii) relatively high-income developing countries. By doing so, we can discuss the links of development stages with the relationships among the variables and their possible differences between the two groups.

To estimate the short- and long-run associations of CO_2 emissions with ICT and other variables for each of the two income groups, this study employs a panel ARDL framework that includes the lags of both dependent and independent variables in Eq. (1):

$$\mathrm{lnCO2PC}_{i,t} = \sum_{j=1}^{p} \delta_{i,j}\mathrm{lnCO2PC}_{i,t-j} + \sum_{j=0}^{q} X_{i,t-j}\varphi_{i,j} + \mu_i + \varepsilon_{it}, \quad (2)$$

where $X_{i,t-j}$ is a vector of the independent variables (ICT, lnTECPC, lnRGDPPC, RREP) with equal lags across individual countries; p is the lags of the dependent variable; q is the lags of the independent variables; μ_i is the country fixed effects; and ε_{it} is the error term. The panel ARDL model allows for different coefficients across countries. Assuming the existence of cointegration among the variables in Eq. (2), the error term would follow the process that is integrated of order zero. In this case, countries have the long-run equilibrium relationship among the variables, and the time paths of the variables reflect the deviation from their long-run equilibrium. The re-parametrizing model turns into an error correction form, where the short-run adjustment can be explained by the deviation from the long-run equilibrium:

$$\Delta\mathrm{lnCO2PC}_{i,t} = \phi_i \mathrm{ECT}_{i,t} + \sum_{j=1}^{p-1} \delta_{i,j}^{*}\Delta\mathrm{lnCO2PC}_{i,t-j} + \sum_{j=0}^{q-1} \Delta X_{i,t-j}\varphi_{i,j}^{*} + \varepsilon_{it}, \quad (3)$$

where Δ is the difference operator, and $\mathrm{ECT}_{i,t} = \mathrm{lnCO2PC}_{i,t-1} - X_{i,t}\theta_i$ is the error correction term (ECT). The first part $\phi_i \mathrm{ECT}_{i,t}$ captures the convergence speed, and the latter part depicts the short-run dynamics. The parameter $\phi_i = -(1 - \sum_{j=1}^{p} \delta_{i,j})$ is the coefficient of the short-run adjustment or the group specific speed of adjustment, and the parameter $\theta_i = -(\sum_{j=0}^{q} \varphi_{i,j})/\phi_i$ is the long-run coefficients. The parameters $\delta_{i,j}^{*}$ and $\varphi_{i,j}^{*}$ are the short run dynamic coefficients of the dependent and independent variables, where $\delta_{i,j}^{*} = -\sum_{d=j+1}^{p} \delta_{i,d}$ and $\varphi_{i,j}^{*} = -\sum_{d=j+1}^{q} \varphi_{i,d}$. It should be noticed that the coefficient of ECT is significantly negative, i.e., $\phi_i < 0$.

The panel ARDL technique has been applied recently to empirical works in various contexts (Mensah et al., 2019; Alola et al., 2019; Essandoh et al., 2020). Pesaran and Smith (1995) and Pesaran et al. (1999) suggest that a panel ARDL model is more appropriate, since it can be applied even when the variables follow different orders of integration (I (0) or/and I (1) but certainly not I (2)) or a mixture of both. The panel ARDL model has advantages over other dynamic panel methods, such as the fixed effects and the Generalized Methods of Moment (GMM) estimators proposed by Anderson and Hsiao (1982, 1981), Arellano (1989), and Arellano and Bover (1995), which may produce inconsistent estimates of the average value of the parameters unless the coefficients are identical across countries (da Silva et al., 2018). In addition, the panel ARDL can mitigate some endogeneity issues and simultaneously estimate both short-run and long-run parameters in a single fitted model. Moreover, the panel ARDL model can be estimated by employing the mean group (MG) estimator, which estimates the parameters for each country and then averages for the group. Assuming the homogeneous long-run coefficients across countries, the PMG estimators are more efficient, allowing the short-run coefficients to vary across countries but with the homogenous long-run coefficients (Pesaran and Smith, 1995; Pesaran et al., 1999). In this study, we conduct the Hausman test to confirm that the PMG estimator is more adequate than the MG estimator.

3.2.2 Data

In this study, we use panel data of 58 developing countries during the period from 1990 to 2014. Based on the World Bank's income classification, all sample countries are divided into two income groups: "relatively low-income" and "relatively high-income" developing countries (Table 3.2). For the definitions of the variables (Table 3.3), CO_2 emission per capita is measured in kilotons of oil equivalent (ktoe), and total energy consumption per capita is captured by total energy use per capita in kilotons of oil equivalent (ktoe). Real GDP per capita is measured by GDP per capita in constant 2010 US dollars. Renewable energy penetration is measured by the ratio of renewable energy to total energy consumption (Bekun et al., 2019). The level of ICT is measured by the sum of mobile and fixed telephone subscription data per 100 people (Amri, 2018). The data of all variables are taken from the World Bank's World Development Indicators (WDI) database. Table 3.4 and table 3.5 present the summary statistics and the correlation matrix of the variables used in our analysis, respectively. The average measure of ICT in relatively high-income developing countries is larger than that in relatively low-income developing countries. In addition, the simple correlation analysis shows that ICT is positively correlated with the log of CO_2 emission per capita, irrespective of the income groups. As in most of the time series literature, this study first conducts panel unit root tests and panel cointegration tests. Then we evaluate the long-run relationships among variables with the short-run dynamics by applying the panel ARDL model. Finally, we apply the Granger causality test of Dumitrescu and Hurlin (2012) to identify the directional relationships among the variables, i.e., whether one time series is useful in forecasting another.

Table 3.2. List of sample countries

Relatively low-income developing countries			
Benin	Guatemala	Mongolia	Philippines
Bangladesh	Haiti	Morocco	Senegal
Bolivia	Honduras	Mozambique	Sudan
Côte d'Ivoire	India	Nepal	Tanzania
Cameroon	Indonesia	Nicaragua	Togo
Egypt, Arab Rep.	Iraq	Nigeria	
El Salvador	Kenya	Pakistan	
Ghana	Sri Lanka	Paraguay	
Relatively high-income developing countries			
Albania	Colombia	Jordan	South Africa
Algeria	Costa Rica	Lebanon	Thailand
Argentina	Cuba	Mexico	Tunisia
Botswana	Dominican Republic	Mauritius	Turkey
Brazil	Ecuador	Malaysia	Uruguay
Bulgaria	Gabon	Panama	
Chile	Iran, Islamic Rep.	Peru	
China	Jamaica	Romania	

Table 3.3. Variable definitions

Variable	Variable	Variables definitions (measurements)	Logarithm
CO_2 per capita	lnCO2PC	CO2 emissions per capita in kilotons of oil equivalent (ktoe)	yes
Total energy consumption per capita	lnTECPC	Total energy use in kilotons of oil equivalent (ktoe)	yes
Real GDP per capita	lnRGDPPC	Real GDP per capita (constant 2010 US dollars)	yes
Ratio of renewable energy penetration	RREP	Ratio of renewable energy on total energy consumption	no
Information Communication Technology	ICT	Sum of mobile and fixed telephone subscription data per 100 people (ratio)	no

Table 3.4. Descriptive statistics

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
Relatively low-income developing countries					
lnCO2PC	725	-0.6169	0.9930	-3.3945	2.5988
lnTECPC	725	6.1575	0.4455	4.7783	7.5316
lnRGDPPC	725	7.1455	0.6544	5.1056	8.6140
RREP	725	57.1529	26.7035	0.3240	95.1776
ICT	725	0.2946	0.3860	0.0021	1.6119
Relatively high-income developing countries					
lnCO2PC	725	1.0569	0.5381	-0.7126	2.3005
lnTECPC	725	7.0450	0.4626	5.9522	8.0825
lnRGDPPC	725	8.5951	0.4758	6.5919	9.5861
RREP	725	23.0425	17.3154	0.0686	88.0958
ICT	725	0.5520	0.5108	0.0058	1.9726

Table 3.5. Correlation matrix

	lnCO2PC	lnTECPC	lnRGDPPC	REP	ICT
Relatively low-income developing countries					
lnCO2PC	1.0000				
t-Statistic	-				
Prob.	-				
lnTECPC	0.7115***	1.0000			
t-Statistic	27.2253	-			
Prob.	0.0000	-			
lnRGDPPC	0.7824***	0.6489***	1.0000		
t-Statistic	33.7770	22.9318	-		
Prob.	0.0000	0.0000	-		
RREP	-0.8844***	-0.4847***	-0.5993***	1.0000	
t-Statistic	-50.9562	-14.9011	-20.1303	-	
Prob.	0.0000	0.0000	0.0000	-	
ICT	0.3574***	0.3127***	0.4520	-0.3020***	1.0000
t-Statistic	10.2893	8.8533	13.6241***	-8.5187	-
Prob.	0.0000	0.0000	0.0000	0.0000	-
Relatively high-income developing countries					
lnCO2PC	1.0000				
t-Statistic	-				
Prob.	-				
lnTECPC	0.9086***	1.0000			
t-Statistic	58.5120	-			
Prob.	0.0000	-			
lnRGDPPC	0.3328***	0.4904***	1.0000		
t-Statistic	9.4907	15.1296	-		
Prob.	0.0000	0.0000	-		
RREP	-0.4915***	-0.2538***	0.1588***	1.0000	
t-Statistic	-15.1764	-7.0557	4.3241	-	
Prob.	0.0000	0.0000	0.0000	-	
ICT	0.2663***	0.3590***	0.4929***	-0.0882**	1.0000
t-Statistic	7.4287	10.3419	15.2325	-2.3798	-
Prob.	0.0000	0.0000	0.0000	0.0176	-

Notes: *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively

3.3 Results and discussion

3.3.1 Panel stationarity tests

With the panel data, we need to check the stationarity of the variables to ensure that they fluctuate around a constant mean, since running regression models with nonstationary variables often leads to unreliable results. To check the stationarity of the variables, this study conducts five types of panel unit root tests: (i) Levin-Lin- Chu (Levin et al., 2002); (ii) Breitung (Breitung, 2005; Breitung and Das, 2005); (iii) Im-Pesaran-Shin (Im et al., 2003); (iv) Fisher-

ADF (Maddala and Wu, 1999); and (v) Fisher-PP (Choi, 2001) tests. All the tests employ a null hypothesis that all the panels contain a unit root. Table 3.6 presents the results of the panel unit root tests (level and first difference) on the variables used in this study ($\mathrm{lnCO2PC}$, $\mathrm{lnTECPC}$, $\mathrm{lnRGDPPC}$, RREP, and ICT) for each income group. The test results confirm that for each income group, all variables are integrated of order either zero or one, i.e., $\mathrm{I}(0)$ or $\mathrm{I}(1)$, which satisfies the requirement for applying the panel ARDL analysis.

Table 3.6. Panel unit root tests (1990 - 2014)

	Null: unit root									
	Levin, Lin & Chu		Breitung		Im, Pesaran and Shin		ADF-Fisher		PP-Fisher	
Relatively low-income developing countries										
lnCO2PC	0.2741	[0.608]	2.6811	[0.996]	-0.0107	[0.496]	63.2932	[0.295]	58.9177	[0.442]
ΔlnCO2PC	-16.1773***	[0.000]	-8.1009***	[0.000]	-17.1443***	[0.000]	333.719***	[0.000]	725.665***	[0.000]
lnTECPC	-0.6821	[0.248]	3.9942	[1.000]	-0.0680	[0.473]	67.7097	[0.180]	66.1958	[0.215]
ΔlnTECPC	-16.8787***	[0.000]	-9.0239***	[0.000]	-15.9658***	[0.000]	314.860***	[0.000]	804.696***	[0.000]
lnRGDPPC	-2.5319***	[0.006]	3.7127	[1.000]	-0.8155	[0.207]	98.7347***	[0.001]	78.0274**	[0.041]
ΔlnRGDPPC	-14.4934***	[0.000]	-8.2036***	[0.000]	-13.9471***	[0.000]	289.336***	[0.000]	299.753***	[0.000]
RREP	-1.1121	[0.133]	-0.0947	[0.462]	-0.2165	[0.414]	63.7203	[0.282]	56.9150	[0.516]
ΔRREP	-17.1219***	[0.000]	-10.9220***	[0.000]	-16.7841***	[0.000]	329.233***	[0.000]	510.575***	[0.000]
ICT	1.8636	[0.969]	13.3999	[1.000]	5.1877	[1.000]	76.3120*	[0.054]	9.0821	[1.000]
ΔICT	1.2480	[0.894]	3.4580	[1.000]	-4.2883***	[0.000]	113.473***	[0.000]	67.4393	[0.186]
Relatively high-income developing countries										
lnCO2PC	-2.5706***	[0.005]	0.0407	[0.516]	-2.5959***	[0.005]	88.0865***	[0.007]	84.1825**	[0.014]
ΔlnCO2PC	-18.1730***	[0.000]	-13.1437***	[0.000]	-18.8901***	[0.000]	372.550***	[0.000]	556.019***	[0.000]
lnTECPC	-1.4105*	[0.079]	0.4741	[0.682]	-1.5408*	[0.062]	84.5783**	[0.013]	82.1570**	[0.020]
ΔlnTECPC	-16.8268***	[0.000]	-9.5852***	[0.000]	-17.2304***	[0.000]	334.383***	[0.000]	528.869***	[0.000]
lnRGDPPC	-1.6562**	[0.049]	1.0808	[0.860]	-3.3072***	[0.000]	104.019***	[0.000]	90.4040***	[0.004]
ΔlnRGDPPC	-11.8146***	[0.000]	-6.6594***	[0.000]	-11.0120***	[0.000]	224.370***	[0.000]	608.102***	[0.000]
RREP	-2.3748***	[0.009]	0.3406	[0.633]	-1.2161	[0.112]	63.6946	[0.283]	62.2625	[0.327]
ΔRREP	-16.6073***	[0.000]	-10.4363***	[0.000]	-15.9469***	[0.000]	312.377	[0.000]	726.224***	[0.000]
ICT	-2.5639***	[0.005]	8.0804	[1.00]	0.7120	[0.762]	52.0950	[0.693]	28.3499	[1.000]
ΔICT	0.0072	[0.503]	1.9198	[0.973]	-4.0402***	[0.000]	127.634***	[0.000]	91.5258***	[0.003]

Notes: (1) Figures in the parenthesis indicate p-values. (1) Optimal lag lengths are determined by Schwarz Info Criterion (SIC). (3) Individual intercept and individual linear trend are included. (4) *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively.

3.3.2 Panel cointegration tests

Although cointegration of the variables is not strictly required, if it exists, the panel ARDL model has an error correction model interpretation and there is a strong evidence that the long run estimates are common across all countries, supporting the application of the PMG estimators. This study applies two panel cointegration tests developed by Pedroni (2004, 1999) and Kao (1999), which extend the two-step residual-based cointegration tests of Engle and Granger (1987). Both tests have the null hypothesis of no cointegration and allow the panel-specific cointegrating vectors and the AR coefficients in the auxiliary regression to vary over panels with heterogeneous intercepts and trend coefficients across cross-sections. Table 3.7 presents the results of the Pedroni cointegration tests. For each income group, six test statistics are statistically significant, although some test statistics show less significance. Therefore, the Pedroni panel cointegration tests indicate that the null of no cointegration can be rejected, so that there exists a long-term relationship among lnCO2PC, lnTECPC, lnRGDPPC, RREP, and ICT. As another method, the panel cointegration tests proposed by Kao (1999) take a similar approach as the Pedroni tests but requires cross-section specific intercepts and homogeneous coefficients on the regressors in the first stage estimation. Tables 3.8 shows the results of the Kao cointegration tests, which coincides with the results of the Pedroni panel cointegration tests.

Table 3.7. Pedroni panel cointegration tests (1990-2014)

	Within-dimension (panel statistics)			Between-dimension (individual statistics)		
	Test	Statistic	Prob.	Test	Statistic	Prob.
Relatively low-income developing countries						
Pedroni (1999)	Panel v-Statistic	-1.3059	0.9042	Group rho-Statistic	2.9187	0.9982
	Panel rho-Statistic	0.7312	0.7677	Group PP-Statistic	-6.6668***	0.0000
	Panel PP-Statistic	-6.1706***	0.0000	Group ADF-Statistic	-6.6760***	0.0000
	Panel ADF-Statistic	-6.0676***	0.0000			
Pedroni (2004) Weighted Statistic	Panel v-Statistic	-3.0431	0.9988			
	Panel rho-Statistic	0.2336	0.5923			
	Panel PP-Statistic	-8.9530***	0.0000			
	Panel ADF-Statistic	-9.1069***	0.0000			
Relatively high-income developing countries						
Pedroni (1999)	Panel v-Statistic	-2.9308	0.9983	Group rho-Statistic	1.8983	0.9712
	Panel rho-Statistic	-0.5546	0.2896	Group PP-Statistic	-16.7476***	0.0000
	Panel PP-Statistic	-13.6707***	0.0000	Group ADF-Statistic	-8.4060***	0.0000
	Panel ADF-Statistic	-7.8420***	0.000			
Pedroni (2004) Weighted Statistic	Panel v-Statistic	-3.4656	0.9997			
	Panel rho-Statistic	0.7000	0.7581			
	Panel PP-Statistic	-11.7356***	0.0000			
	Panel ADF-Statistic	-6.8674***	0.0000			

Notes: Optimal lag lengths are determined by Schwarz Info Criterion (SIC). Individual intercept and individual linear trend are included in the test regressions. *, **, and *** represent the 10%, 5% and1% significance levels, respectively.

Table 3.8. Kao panel cointegration tests (1990-2014)

	Statistic	Prob.
Relatively low-income developing countries		
ADF	-7.0010***	0.0000
Residual variance	0.0143	
HAC variance	0.0124	
Relatively high-income developing countries		
ADF	-3.5090***	0.0002
Residual variance	0.0054	
HAC variance	0.0031	

Notes: *, **, and *** represent the 10%, 5% and 1% significance levels, respectively.

3.3.3 Long- and short-run estimates

Table 3.9 presents the results of the PMG-ARDL model for the groups of relatively high-income and low-income developing countries. The Hausman test results fail to reject the null of long-run cross-section parameter homogeneity, which supports that the PMG estimator is more appropriate than the MG estimator. The short-run estimates vary across countries, so that the mean group may not provide a good accuracy on the differences between countries. In addition, the estimated coefficients of the error correction term (ECT), which indicate the convergence speed, are significantly negative at the values of -0.4814 and -0.3700 for relatively high-income and low-income developing countries, respectively. These results suggest that the half-life values are approximately 1.1 years for relatively high-income developing countries and approximately 1.5 years for relatively low-income developing countries.[17]

[17] The half-life value indicates the length of time after a shock before the deviation shrinks to half of its impact (Chari et al., 2000). The half-life is calculated as $\ln(0.5)/\log(1+\phi)$.

Table 3.9. Pooled mean group with dynamic autoregressive distributed lag: PMG-ARDL (1,1,1,1,1)

	Relatively high-income Developing countries	Relatively low-income Developing countries
Long-run equation		
lnTECPC	1.0202***	0.4951***
	(0.0000)	(0.0000)
lnRGDPPC	-0.0609***	0.8697***
	(0.0084)	(0.0000)
RREP	-0.0097***	-0.0090***
	(0.0000)	(0.0000)
ICT	-0.0053	-0.1626***
	(0.4934)	(0.0000)
Short-run equation		
ECT(-1)	-0.4814***	-0.3700***
	(0.0000)	(0.0000)
lnTECPC	0.3324***	0.6996***
	(0.0002)	(0.0041)
lnRGDPPC	0.1439**	0.1323
	(0.0123)	(0.4444)
RREP	0.0038	-0.0205***
	(0.8161)	(0.0002)
ICT	0.0427	0.0615
	(0.5322)	(0.5896)
Constant	-2.5852***	-3.4144***
	(0.0000)	(0.0000)
Hausman	0.97	3.41
	(0.9148)	(0.4924)
No of obs.	696	696

Notes: (1) *, **, and *** represent the 10%, 5% and 1% significance, respectively. (2) The dependent variable is lnCO2P.

The panel PMG-ARDL analysis shows a clear difference in the long-run ICT-emissions relationship between the two income groups. The coefficient of ICT is significantly negative for relatively low-income developing countries, while it is insignificant for relatively high-income developing countries. Given the arguments of the favorable and unfavorable effects of ICT on the environment, CO_2 emission in this study, our results suggest that the favorable effect of ICT dominates the unfavorable one in relatively low-income developing countries, while the favorable and unfavorable effects of ICT are balanced in relatively high-income developing countries. In relatively low-income developing countries, a 1 percent increase in the ICT penetration rate (mobile and fixed phone penetration) is associated with a 0.16 percent decline in CO_2 emission per capita. This result is in contrast to the finding of the Tunisia case in Amri (2018) but is consistent with the finding of the Africa case in Asongu (2018). The introduction of ICT enables the economy to replace traditional and inefficient technology for advanced technology, including green ICT, and to mitigate the environmental degradation. This favorable effect of ICT on CO_2 emissions is more substantial for least-developed countries where ICT is less prevalent. On the other hand, the installment of ICT is often accompanied with more demand for energy due to its life cycle of production, use, and disposal, which would increase CO_2 emissions and induce the environmental degradation (Danish et al., 2017). However, this unfavorable effect of ICT may be relatively small for least-developed countries, where the energy demand associated with ICT is not so large. These arguments support that the favorable ICT effect, or the green ICT, plays a dominant role in determining CO_2 emissions in relatively low-income developing countries.

Concerning the long-run relationship of CO_2 emissions with other explanatory variables ($\ln RGDPPC$, $\ln TECPC$, and $RREP$), the ARDL analysis first reveals the positive and negative relationships between CO_2 emissions and real GDP per capita for relatively low-income developing countries and relatively high-income developing countries, respectively. A 1 percent increase in real GDP per capita is associated with a 0.06 percent decrease in CO_2 emission per capita in relatively high-income developing countries. On the other hand, a 1 percent increase in real GDP per capita is associated with a 0.87 percent increase in CO_2 emissions in relatively low-income developing countries. These findings are consistent with the EKC hypothesis that postulates an inverted-U-shaped relationship between pollutions and per capita income. Second, our results identify the unfavorable impact of per capita energy consumption on the environment. This unfavorable impact is more substantial for relatively high-income developing countries. A 1 percent increase in per capita energy consumption is associated with a 1.02 percent increase and a 0.50 percent increase in CO_2 emissions per capita for relatively high-income and relatively low-income developing countries, respectively. Third, our analysis also finds the negative relationship between renewable energy penetration and CO_2 emissions for both country groups. When a country increases the share of renewable energy by 1 percent, CO_2 emissions would be decreased by approximately 1 percent for both country groups.

The ARDL analysis also provides several results of the short-run dynamics. First, similar to the long-run relationship, energy consumption per capita and CO_2 emissions per capita have a positive relationship in the short-run for both country groups. Second, the short-run relationship between real GDP per capita and CO_2 emissions per capita is significantly positive for relatively high-income developing countries, which is in contrast to the result of their negative long-run relationship. On the other hand, there is no clear short-run relationship between real GDP per capita and CO_2 emissions per capita for relatively low-income developing countries. Third, our results reveal that relatively low-income developing countries experience the negative short-run relationship between renewable energy penetration and CO_2 emissions per capita, while relatively high-income developing countries have the less clear short-run relationship.

3.3.4 Dumitrescu and Hurlin panel causality tests

This subsection employs the panel Granger causality test, initiated by Dumitrescu and Hurlin (2012), to evaluate the direction of the relationship between variables used in the model. The standard Granger causality test can be applied to the panel data, assuming the homogenous panel with identical intercepts and slope coefficients (Granger, 1969). Recent studies such as Koçak and Şarkgüneşi (2017), Bekun et al. (2019), and Essandoh et al. (2020) have applied the Dumitrescu-Hurlin panel causality test, which is based on the heterogeneous assumption, to evaluate Granger causality in various energy and environmentally related fields. The

Dumitrescu-Hurlin panel causality test accounts for two-dimensional heterogeneities: the heterogeneity of the regression model for Granger causality test and the heterogeneity of the causality relationship. Given the fact that countries are generally heterogeneous in terms of their energy and ICT use patterns, this study also applies the heterogeneous Dumitrescu-Hurlin panel causality test. Specifically, Dumitrescu and Hurlin (2012) propose the following linear model:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t},$$

where x and y are two stationary variables for country i in year t. The model allows slope and lag parameters, $\beta_i^{(k)}$ and $\gamma_i^{(k)}$, to vary across cross-sections but are assumed to be fixed over time. The null hypothesis is no causal relationship for any cross-section of the panel, known as the homogeneous noncausality hypothesis (H_0: $\beta_i = 0$ for any $i = 1, 2, \cdots, N$), and the alternative hypothesis is the existence of a causal relationship in at least one cross-section unit. The individual Wald statistics are calculated for each cross-section, and then the test statistic for the panel is calculated by taking the average of all individual Wald statistics (Dumitrescu and Hurlin, 2012), $W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}$, where $W_{i,T}$ is the individual Wald statistic for country i in year T, and N is the number of countries.[18] To investigate the Granger causality, all variables must be stationary. Thus, we use the first differences of variables ($\mathrm{lnCO2PC}$, $\mathrm{lnTECPC}$, $\mathrm{lnRGDPPC}$, RREP, and ICT).

Table 3.10 displays the results of Dumitrescu-Hurlin panel causality tests. It is observed that there are some differences in Granger's causality between relatively low-income

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[18] Given the test statistic $W_{N,T}^{HNC}$, Dumitrescu and Hurlin (2012) derive its limiting distribution and show that an alternative test statistic, $Z_{N,T}^{HNC} = \sqrt{\frac{N}{2K}}\left(W_{N,T}^{HNC} - K\right)$, converges to the normal distribution $N(0,1)$, where K is the number of lags. For the practical use, $W_{N,T}^{HNC}$ is recommended if the time dimension is lower than the cross-section one, while $Z_{N,T}^{HNC}$ is recommended if the time dimension is higher than the cross-section one (Dumitrescu and Hurlin, 2012).

developing countries and relatively high-income developing countries. For the group of relatively high-income developing countries, the test results show several causal relationships. First, one-way Granger causal relationships exist from ICT to lnCO2PC, lnTECPC, and RREP, which supports the significant role of ICT in predicting the variation of all variables except for lnRGDPPC. Second, the analysis also presents one-way Granger causal relationships from lnRGDPPC to lnTECPC and from RREP to lnRGDPPC. Real GDP per capita is an important predictor for total energy consumption per capita, and renewable energy penetration is an important predictor for real GDP per capita. On the other hand, the test results for the group of relatively low-income developing countries also reveal several causal relationships. First, it is observed that there are one-way Granger causal relationships from ICT to lnCO2PC and from lnTECPC to ICT. Total energy consumption per capita is an effective predictor for ICT, which in turn is an effective predictor for CO_2 emissions per capita. Second, the results also present a one-way Granger causality from RREP to lnCO2PC, which is consistent with the conventional argument that renewable energy use helps reduce CO_2 emissions. Third, the analysis observes a two-way or reciprocal Granger causality between ICT and RREP. This two-way relationship could be justified by the argument of a virtuous cycle that the prevalence of ICT is one important determinant of renewable energy production, which could also increase the demand for ICT products. Accounting for the causality from RREP to lnCO2PC, sound management of ICT policy is a possible remedy for environmental sustainability through green ICT.

Table 3.10. Dumitrescu and Hurlin panel causality test

Null Hypothesis	Relatively low-income developing countries			Relatively high-income developing countries		
	W-Stat.	Prob.	Causality	W-Stat	Prob	Causality
DlnTECPC does not homogeneously cause DlnCO2PC	1.3900	0.3804		0.9455	0.6026	
DlnCO2PC does not homogeneously cause DlnTECPC	1.2966	0.5598		1.5469	0.1706	
DlnRGDPPC does not homogeneously cause DlnCO2PC	0.9316	0.5725		1.3082	0.5353	
DlnCO2PC does not homogeneously cause DlnRGDPPC	1.2656	0.6271		1.0173	0.7680	
DRREP does not homogeneously cause DlnCO2PC	1.6795*	0.0739	RREP → lnCO2PC	1.4200	0.3313	
DlnCO2PC does not homogeneously cause DRREP	1.1640	0.8678		0.8482	0.4084	
DICT does not homogeneously cause DlnCO2PC	3.0601***	0.0000	ICT → lnCO2PC	0.5175*	0.0619	ICT → lnCO2PC
DlnCO2PC does not homogeneously cause DICT	0.9482	0.6084		1.0402	0.8236	
DlnRGDPPC does not homogeneously cause DlnTECPC	1.2888	0.5764		1.7991**	0.0305	lnRGDPPC → lnTECPC
DlnTECPC does not homogeneously cause DlnRGDPPC	1.0752	0.9101		1.2967	0.5594	
DRREP does not homogeneously cause DlnTECPC	1.4685	0.2610		1.1259	0.9628	
DlnTECPC does not homogeneously cause DRREP	1.2094	0.7571		0.9279	0.5645	
DICT does not homogeneously cause DlnTECPC	1.3297	0.4919		0.5177*	0.0620	ICT → lnTECPC
DlnTECPC does not homogeneously cause DICT	2.3711***	0.0001	lnTECPC →ICT	1.2794	0.5966	
DRREP does not homogeneously cause DlnRGDPPC	0.8959	0.4986		1.8712**	0.0168	RREP → lnRGDPPC
DlnRGDPPC does not homogeneously cause DRREP	1.0337	0.8076		1.1191	0.9800	
DICT does not homogeneously cause DlnRGDPPC	1.5350	0.1825		0.6138	0.1178	
DlnRGDPPC does not homogeneously cause DICT	1.5944	0.1285		0.7949	0.3200	
DICT does not homogeneously cause DRREP	2.4962***	0.0000		2.0482***	0.0032	ICT → RREP
DREP does not homogeneously cause DICT	2.01788***	0.0043	ICT ←→RREP	0.8938	0.4943	

Note: ***, ** and * means statistical rejection level. While → and ↔ represent one-way causality and bi-directional causality, respectively.

3.3.5 Robustness checks

To confirm the empirical validity of our estimated results in the previous subsections, we conduct a robustness check by including two additional variables that are expected to relate to CO_2 emissions into the baseline model. The first variable is urbanization (URBAN), and the second is trade openness (TRADE). Many studies have discussed the role of international trade in determining the environment, and recent focus has been on the principles of carbon emission responsibility in international trade from different perspectives (Dogan and Seker, 2016; Kim et al., 2018; Long et al., 2018; Essandoh et al., 2020). In addition, many works have existed on the relationship between urbanization and CO_2 emissions, given the arguments that changes in urbanization could affect patterns of energy use and CO_2 emissions (Poumanyvong and Kaneko, 2010; Sadorsky, 2014).

The results of the extended model as a robustness check are generally consistent with the findings of our baseline analysis (Tables 3.A1 to 3.A7 in the appendix). The long-run relationship between CO_2 emissions and ICT depends on countries' income level, i.e., the development stage. In the long run, the prevalence of ICT is associated with the reduction of CO_2 emissions in relatively low-income developing countries, while no clear relationship exists between ICT and CO_2 emissions in relatively high-income developing countries. Moreover, the estimations of the extended model show some evidences supportive of clear differences in the long-run relationships between the two groups. First, CO_2 emissions per capita is positively associated with trade openness only for relatively high-income developing countries. Second, CO_2 emissions per capita is negatively associated with urbanization for relatively high-income developing countries, while it is positively associated with urbanization for relatively low-income developing countries.

3.4 Conclusion

This research work has aimed to examine the relationship between CO_2 emissions and ICT and how the relationship is affected by development stages. We have employed a panel ARDL analysis with PMG estimators to a panel of 58 developing countries, which are divided into two income groups (relatively low- and relatively high-income developing countries), during the sample period from 1990 to 2014. Our analysis has revealed that the long-run relationship between CO_2 emissions and ICT differs, depending on a country's development stage. The prevalence of ICT is associated with the low level of CO_2 emissions in relatively low-income developing countries, but ICT and CO_2 emissions have no clear relationship in relatively high-income developing countries. In addition, the estimated results have confirmed the argument of the environmental Kuznets curve (EKC) that the income level, captured by real GDP per capita, is positively associated with CO_2 emissions at the earlier stage development, while it is negatively associated with CO_2 emissions at the later stage development.

Our results could provide important policy implications about ICT and environmental sustainability in developing countries. Less-developed countries at the earlier stage of development tend to prioritize economic growth or poverty reduction over the environmental issues and to use a large amount of nonrenewable energy due to the high cost of clean or renewable energy, which would consequently intensify the environmental degradation with large CO_2 emissions. Since our results suggest the favorable effect of ICT on the environment, ICT promotion can be a powerful tool to fight such environmental degradation, particularly for less-developed countries.

Developing countries, particularly least-developed countries, with the substantial use of ICT need to emphasize "greening ICT" strands. Policymakers should implement various ICT policies toward the prevalence of ICT products and services, such as attracting foreign direct investment (FDI) with advanced and green ICT from developed countries. Another potential benefit of ICT for developing countries is that advanced technology reduces energy use and improve energy efficiency. From an economic point of view, building infrastructure to produce eco-friendly renewable energy is expensive for most developing countries. As an alternative solution, ICT can guide these countries to achieve their climate targets by the reduction in energy use. For instance, in the transportation sector, introducing ICT based intelligent operation ensures more resource-efficient operation and reduced-physical transportation. By optimizing the performance of energy-using systems, ICT helps conserve energy and reduce fossil-fuel use, which enables sustainable development in least-developing

3.5 Appendix

Table 3.A1. The definitions of additional variables

Variable	Variable	Variables definitions (measurements)
Urbanization	URBAN	The percentage of the urban population in the total population
Trade openness	TRADE	Imports plus exports of goods and services (% of GDP)

Table 3.A2. Descriptive statistics of additional variables

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
Relatively low-income developing countries					
URBAN	725	0.4123	0.1415	0.0885	0.6976
TRADE	725	0.6203	0.2599	0.0002	1.5423
Relatively high-income developing countries					
URBAN	725	0.6597	0.1535	0.2644	0.9494
TRADE	725	0.7307	0.3820	0.1375	2.2040

Table 3.A3. Panel unit root tests for additional variables (1990-2014)

	Null: unit root									
	Levin, Lin & Chu		Breitung		Im, Pesaran and Shin		ADF - Fisher		PP - Fisher	
Relatively low-income developing countries										
URBAN	-6.4952***	[0.000]	-2.6235***	[0.004]	-1.5259*	[0.063]	253.409***	[0.000]	189.305***	[0.000]
ΔURBAN	-6.1594***	[0.000]	-6.5317***	[0.000]	-2.1671**	[0.015]	311.854***	[0.000]	77.5900**	[0.044]
TRADE	-2.3774***	[0.009]	-0.8883	[0.187]	-1.4467*	[0.074]	77.2320**	[0.046]	87.8969***	[0.007]
ΔTRADE	-22.1606***	[0.000]	-13.6814***	[0.000]	-20.3147***	[0.000]	467.543***	[0.000]	1354.94***	[0.000]
Relatively high-income developing countries										
URBAN	3.0774	[0.999]	3.3953	[1.000]	0.2661	[0.605]	117.703***	[0.000]	63.9496	[0.276]
ΔURBAN	2.2699	[0.988]	1.6731	[0.953]	-1.3639*	[0.086]	97.4551***	[0.001]	316.020***	[0.000]
TRADE	-4.3577***	[0.000]	-1.2945*	[0.098]	-4.0101***	[0.000]	111.523***	[0.000]	91.4409***	[0.003]
ΔTRADE	-19.2031***	[0.000]	-12.2570***	[0.000]	-17.3807***	[0.000]	334.266***	[0.000]	471.163***	[0.000]

Notes: (1) Figures in the parenthesis indicate p-values. (1) Optimal lag lengths are determined by Schwarz Info Criterion (SIC).
(3) Individual intercept and individual linear trend are included. (4) *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively.

Table 3.A4. Pedroni panel cointegration tests (1990-2014)

	Within-dimension (panel statistics)			Between-dimension (individual statistics)		
	Test	Statistic	Prob.	Test	Statistic	Prob.
Relatively low-income developing countries						
Pedroni (1999)	Panel v-Statistic	-2.3845	0.9914	Group rho-Statistic	5.5355	1.000
	Panel rho-Statistic	3.4634	0.9997	Group PP-Statistic	-14.3201***	0.0000
	Panel PP-Statistic	-7.1872***	0.0000	Group ADF-Statistic	-8.9739***	0.0000
	Panel ADF-Statistic	-5.0381***	0.0000			
Pedroni (2004) Weighted Statistic	Panel v-Statistic	-5.5226	1.0000			
	Panel rho-Statistic	3.8001	0.9999			
	Panel PP-Statistic	-12.4858***	0.0000			
	Panel ADF-Statistic	--9.5535***	0.0000			
Relatively high-income developing countries						
Pedroni (1999)	Panel v-Statistic	-4.261301	1.0000	Group rho-Statistic	5.0910	1.0000
	Panel rho-Statistic	2.6323	0.9958	Group PP-Statistic	-22.3647***	0.0000
	Panel PP-Statistic	-16.1786***	0.0000	Group ADF-Statistic	-10.3463***	0.0000
	Panel ADF-Statistic	-12.7960***	0.0000			
Pedroni (2004) Weighted Statistic	Panel v-Statistic	-6.3742	1.0000			
	Panel rho-Statistic	3.9842	1.0000			
	Panel PP-Statistic	-15.2395***	0.0000			
	Panel ADF-Statistic	-9.6394***	0.0000			

Notes: (1) Optimal lag lengths are determined by Schwarz Info Criterion (SIC). (2) Individual intercept and individual linear trend are included in the test regressions. (3) *, **, and *** represent the 10%, 5% and1% significance, respectively.

Table 3.A5. Kao panel cointegration tests (1990-2014)

	Statistic	Prob.
Relatively low-income developing countries		
ADF	-7.1164***	0.0000
Residual variance	0.0142	
HAC variance	0.0122	
Relatively high-income developing countries		
ADF	-3.6887***	0.0001
Residual variance	0.0054	
HAC variance	0.0040	

Notes: *, **, and *** represent the 10%, 5% and 1% significance, respectively.

Table 3.A6. Pooled mean group with dynamic autoregressive distributed lag: PMG-ARDL (1,1,1,1,1)

	Relatively high-income developing countries	Relatively low-income developing countries
Long-run equation		
lnTECPC	1.0232***	0.6291***
	(0.0000)	(0.0000)
lnRGDPPC	-0.0208	0.2264***
	(0.3138)	(0.0000)
RREP	-0.0121***	-0.0135***
	(0.0000)	(0.0000)
ICT	-0.0083	-0.0491***
	(0.3093)	(0.0024)
URBAN	-0.5975***	0.0089**
	(0.0000)	(0.0103)
TRADE	0.0687***	-0.0003
	(0.0090)	(0.4451)
Short-run equation		
ECT(-1)	-0.5763***	--0.4836***
	(0.0000)	(0.0000)
lnTECPC	0.2519**	0.6115***
	(0.0154)	(0.0080)
lnRGDPPC	0.0629	0.1870
	(0.4797)	(0.3198)
RREP	0.0053	-0.0143**
	(0.7540)	(0.0162)
ICT	-0.0974	0.0415
	(0.2087)	(0.7570)
URBAN	-5.3383	0.1207
	(0.3194)	(0.5422)
TRADE	-0.0518*	0.0011**
	(0.0971)	(0.0308)
Constant	-3.0786***	-2.7350***
	(0.0000)	(0.0000)
Hausman	1.15	2.40
	(0.9794)	(0.8797)
No of obs.	696	696

Notes: (1) *, **, and *** represent the 10%, 5% and 1% significance, respectively. (2) The dependent variable is lnCO2PC.

Table 3.A7. Dumitrescu and Hurlin panel causality test

Null Hypothesis	Low-income countries			Middle-income countries		
	W-Stat.	Prob.	Causality	W-Stat	Prob.	Causality
DlnTECPC does not homogeneously cause DlnCO2PC	1.3900	0.3804		0.9455	0.6026	
DlnCO2PC does not homogeneously cause DlnTECPC	1.2966	0.5598		1.5469	0.1706	
DlnRGDPPC does not homogeneously cause DlnCO2PC	0.9316	0.5725		1.3082	0.5353	
DlnCO2PC does not homogeneously cause DlnRGDPPC	1.2656	0.6271		1.0173	0.7680	
DRREP does not homogeneously cause DlnCO2PC	1.6795*	0.0739	RREP→ lnCO2PC	1.4200	0.3313	
DlnCO2PC does not homogeneously cause DRREP	1.16405	0.8678		0.8482	0.4084	
DICT does not homogeneously cause DlnCO2PC	3.0601***	0.0000	ICT → lnCO2PC	0.5175*	0.0619	ICT → lnCO2PC
DlnCO2PC does not homogeneously cause DICT	0.9482	0.6084		1.0402	0.8236	
DURBAN does not homogeneously cause DlnCO2PC	1.0471	0.8405		0.9740	0.6664	
DlnCO2PC does not homogeneously cause DURBAN	2.1927***	0.0007	lnCO2PC →URBAN	0.7643	0.2754	
DTRADE does not homogeneously cause DlnCO2PC	1.2025	0.7737		1.2766	0.6027	
DlnCO2PC does not homogeneously cause DTRADE	0.9235	0.5552		1.0891	0.9447	
DlnRGDPPC does not homogeneously cause DlnTECPC	1.2888	0.5764		1.7991**	0.0305	lnRGDPPC → lnTECPC
DlnTECPC does not homogeneously cause DlnRGDPPC	1.0752	0.9101		1.2967	0.5594	
DRREP does not homogeneously cause DlnTECPC	1.4685	0.2610		1.1259	0.9628	
DlnTECPC does not homogeneously cause DRREP	1.2094	0.7571		0.9279	0.5645	
DICT does not homogeneously cause DlnTECPC	1.3297	0.4919		0.5177*	0.0620	ICT → lnTECPC
DlnTECPC does not homogeneously cause DICT	2.3711***	0.0001	lnTECPC → ICT	1.2794	0.5966	
DURBAN does not homogeneously cause DlnTECPC	1.1835	0.8200		1.3859	0.3874	
DlnTECPC does not homogeneously cause DURBAN	1.8715**	0.0168	lnTECPC → URBAN	1.3415	0.4687	
DTRADE does not homogeneously cause DlnTECPC	1.4986	0.2230		1.9211**	0.0109	TRADE → lnTECPC
DlnTECPC does not homogeneously cause DTRADE	0.4538**	0.0387	lnTECPC→ TRADE	1.4462	0.2919	
DRREP does not homogeneously cause DlnRGDPPC	0.8959	0.4986		1.8712**	0.0168	RREP → lnRGDPPC
DlnRGDPPC does not homogeneously cause DRREP	1.0337	0.8076		1.1191	0.9800	
DICT does not homogeneously cause DlnRGDPPC	1.5350	0.1825		0.6138	0.1178	
DlnRGDPPC does not homogeneously cause DICT	1.5944	0.1285		0.7949	0.3200	
DURBAN does not homogeneously cause DlnRGDPPC	2.0610***	0.0028	URBAN→ lnRGDPPC	0.7690	0.2819	
DlnRGDPPC does not homogeneously cause DURBAN	1.0880	0.9421		1.7947**	0.0316	lnRGDPPC → URBAN
DTRADE does not homogeneously cause DlnRGDPPC	1.3659	0.4229		1.3237	0.5037	
DlnRGDPPC does not homogeneously cause DTRADE	1.1205	0.9765		2.1972***	0.0006	lnRGDPPC → TRADE
DICT does not homogeneously cause DRREP	2.4962***	0.0000		2.0482***	0.0032	ICT → RREP
DRREP does not homogeneously cause DICT	2.0179***	0.0043	ICT ←→RREP	0.8938	0.4943	
DURBAN does not homogeneously cause DRREP	1.7620**	0.0407	URBAN→RREP	0.9762	0.6713	
DRREP does not homogeneously cause DURBAN	1.2896	0.5746		1.0106	0.7519	
DTRADE does not homogeneously cause DRREP	0.9183	0.5442		3.5001***	0.0000	TRADE ←→ RREP
DRREP does not homogeneously cause DTRADE	0.9854	0.6925		1.9513***	0.0082	
DURBAN does not homogeneously cause DICT	2.8051***	0.0000	URBAN → ICT	1.5566	0.1612	
DICT does not homogeneously cause DURBAN	0.65870	0.1548		3.2755***	0.0000	ICT → URBAN
DTRADE does not homogeneously cause DICT	0.9594	0.6332		0.9230	0.5542	
DICT does not homogeneously cause DTRADE	1.3733	0.4096		1.04103	0.8255	
DTRADE does not homogeneously cause DURBAN	1.9802***	0.0063	TRADE → URBAN	1.3880	0.3839	
DURBAN does not homogeneously cause DTRADE	1.0561	0.8625		1.8166**	0.0265	URBAN → TRADE

Note: ***, ** and * means statistical rejection level. While → and ↔ represent one-way causality and bi-directional causality respectively.

Chapter 4: Corruption, ICT and military expenditure in Sub-Saharan Africa.

4.1 Introduction

National security is listed among the priorities of nations (Gupta et al., 2001), but there is no transparency in the military department. This department is associated with the occurrence of plenty corruption cases for secret defense purpose. Governments are typically the sole providers of defense services and the opacity of defense information make certain aspects of defense provision subjected to corruption. In fact, regulations typically confer power on the officials in charge of authorizing contracts so the secrecy surrounding defense outlays gives rise to corruption, particularly in the procurement of military equipment. Furthermore, defense contracts are often excluded from freedom of information legislation, where available; and are also often drawn in secrecy and under considerable discretionary power by the authorities. Moreover, administrative procedures in military spending may not be closely monitored by tax and customs administration authorities and defense contracts may not be liable to standard budget oversight such as auditing and legislative approval.

Corruption is a major concern for developing countries as it can have a seriously damaging effect on development and welfare through the weakening of the institutions (d'Algostino et al, 2016). Moreover, one scholar observes that corruption "is not markedly worse than in many other parts of the developing and the former communist world, yet corruption in Africa is universally perceived, by external observers and by local reformers alike, as being 'catastrophic' in its impact on development" (Szeftel, 2000). In fact, Sub-Saharan Africa countries are listed among the most corrupted ones in the world and this phenomenon occurs mostly in the states where the military are in charge and specially in the military expenditure. For instance, in the Congo (Zaire) late General Mobute Sese Seko president of the state was not free from corruption allegation as he was accused of hiring a concord jet for shopping trip and built a palace fitted with a nuclear garget (Momoh, 2015). In Nigeria, the late military junta General Sani Abacha was accused to have looted billions of dollars in which former Head of State General Abdulsalami Abubakar regime recovered about US $ 750 million while former President Olusegun Obasanjo administration convinced the Swiss banking authorities to freeze more than US$600 million in late General Sani Abacha deposit and return nearly US$ 140 million to the Nigerian government (Momoh, 2013). In the same vein, there was an allegation of bribery involving the role of BAE systems and other weapons firms in the South Africa's biggest arm deal (the sale of Hawk and Gripen Warplanes for 1.66 billion pounces) (Momoh, 2015).

To deal with the endemic nature of corruption in Sub-Saharan Africa at the institutional levels especially in the military expenditure, head of states have promulgated the control of corruption through the implementation of anti-corruption laws (administrative reform, law enforcement, social capital) (Shim and Eom, 2009). Unfortunately, these anti-corruption laws faced tremendous internal and external challenges. The internal ones are classified as political, economic, socio-cultural, technological and environmental factors such as discretionary anti-corruption laws which grant immunities to some political leaders by making the procedure of prosecuting such leader when found guilty of corruption charges difficult Momoh (2013) and the external ones such as money derived from serious crime like financing terrorism, make the anti-corruption laws ineffective to reduce the military expenditure.

To overcome the ineffectiveness of the anti-corruption laws, appears the Information and Communication Technology (ICT). In fact, the literature on ICT supports the argument that ICT plays an important role in public management reform (Asgarkhani,2005) by delivering better quality public services with less waiting time and cost (Breen, 2000), helping citizens find jobs and better public services (Brueckner, 2005), facilitating public engagement (Goodwin, 2005), and helping community development (Hammerman, 2005). Ultimately, it can be argued that ICT enhances public

productivity (Yang and Rho, 2007), supports good governance (Basu, 2004), and improves government accountability (Rose, 2004; Wong and Welch, 2004; Yang and Rho, 2007). As a resume, ICT offers remarkable opportunities for promoting good governance, increasing transparency, and reducing corruption (Kanyam et al., 2017), so it is expected to reduce the misuse of the military expenditure. In fact, most studies are related to corruption and military expenditures (Gupta et al., 2001); corruption and growth in Africa (D'Agostino et al., 2016); government spending, corruption, and growth (D'Agostino et al., 2016); ICT and corruption (Kanyam et al., 2017). Few studies have attempted to look at the contribution of ICT to reduce the misuse of military expenses. Our main objective is to examine how ICT as a policy variable is associated with the relationship between control of corruption and military expenditure in Sub-Saharan Africa. To reach that objective we formulated one hypothesis which states that the interaction of the control of corruption (traditional anti-corruption factors) and the use of ICT is negatively correlated with the military expenditure. To test our hypothesis, we use a panel data of 48 Sub-Saharan Africa countries from 2003 to 2015 and apply Arellano and Bond GMM estimation as identification strategy the main result is that the relationship between control of corruption and military expenditure depends on the level of ICT. When ICT level is low, there is less clear relationship between control of corruption and military expenditure. However, when ICT prevails, there is negative relationship between control of corruption and military expenditure. Policymakers should use ICT as a key policy variable to fight corruption in the defense sector, especially for the military expenditure through good regulation of telecommunication sector, encouraging foreign investments in ICT sector, educating and encouraging the population to be familiar to ICT tools especially internet.

The remainder of this study is organized as follows. In section 2, we provide a selective review of the literature on corruption, ICT, and military expenditure. Section 3 describes data and methodology used in this study. In section 4, we present the empirical results of our analysis, and we discuss some implications derived from our empirical results. Final section 5 provides the conclusion.

4.2 Literature review

4.2.1 Corruption and military expenditure

The complex and clandestine nature of corruption makes it difficult to observe, measure, and to estimate its extent precisely. While there is no direct mechanism for measuring corruption, researchers, scholars, and development practitioners have deduced several indirect ways of getting information about its prevalence in a country or institution (Tanzi,1998). Over time, research has shown that people's perceptions offer a reliable estimate of the nature and scope of corruption in a given country. The most preferred and widely disseminated measures utilized by scholars and policy makers are the corruption perception index (CPI) presented by Transparency International and the ‘‘control of corruption” (CoC) by the World Bank. The CPI is a composite index including opinion survey data which captures the informed views of independent institutions specializing in governance and business climate analysis, country experts, business people, global analysts, and experts who are residents of the evaluated countries (Svensson, 2005; Transparency International, 2013). The CoC index, on the other hand, captures the ‘‘perception of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as ‘capture' of the state by elites and private interest.” It draws on surveys from households and firms, commercial business information providers, non-governmental organizations, and public sector organizations (World Bank, 2010). Even though the two measures are highly correlated (Tanzi,1998), the CoC indicator is much broader than the CPI (Aidt,Dutta, & Sena, 2008) and it is the one used in this study. It incorporates a variety of aspects of corruption ranging from the frequency with which firms make additional payments to get things done, to the effects of corruption on the business environment, to measuring grand corruption in the political arena (Olken & Pande, 2011). Gupta et al. (2001) distinguished the supply side and the demand side of corruption related to the military spending. by using a panel data from four different sources for up to 120 countries during 1985–1998. Their study reveals that corruption is associated with higher military spending as a share of both GDP and total government spending, as well as with arms procurement in relation to GDP and total government spending. Langlotz and Potrafke (2019) confirmed that corrupt recipients of aid are likely to spend a higher share of their GDP on military expenditure than less corrupt countries by using instrumental variable (IV) approach to a dataset that includes new data on military expenditure for 124 recipient countries over the 1975–2012 period. d'Algostino et al. (2016) by using Arellano and Bond GMM estimation to a comprehensive panel of 106 countries found that corruption and military spending have strong negative impacts on economic growth. In the case of Africa d'Algostino et al. (2016) by using the same identification strategy confirmed the negative effect of corruption and military spending on growth, but also showed that corruption interacts with military burden, through indirect and complementary effects, to further increase its negative effect.

4.2.2 ICT and military expenditure

ICT can reduce unnecessary interventions by public employees that engender the abuse of power and help to monitor and reveal public employees' behaviors at a low cost through audit. ICT also contributes by transparently providing information to the public and can build social capital by increasing interactions among individuals. Foremost, ICT helps to prevent public employees' corrupt behavior by transparently providing information about governmental policymaking and service delivery processes to the public. The public can access governmental websites and download information as they desire, keeping track of governmental policymaking processes through the Internet. In this approach, basic governmental operations are not altered, and relatively simple information is delivered to information seekers. This approach can prevent corrupt behavior of public workers by systematically reducing their arbitrary behavior in a centralized system as well as when public organizations are decentralized (Zuurmond, 2005), which enables horizontal networks among different agencies easily. As a result, public service delivery becomes more accessible to the public, and thus government workers will feel that they are more likely to be exposed if they decide to pursue corrupt behavior. Some countries have adopted e-government initiatives as an anticorruption solution, and successful cases have been reported from several countries, including South Korea, India, Russia, Argentina, and Chile (Bhatnagar, 2001a, 2001b; Chawla and Bhatnagar, 2001; Im, 2001; Shim and Eom, 2008). Several researchers have argued that e-government approaches have greater potential to succeed when they are integrated with an e-participation approach (Bruszt et al., 2005; Saxena, 2005). The Organization for Economic Co-operation and Development (OECD, 2001) argues that democratic participation processes should reflect the policy agenda of citizens, and that ICT enhances government responsiveness by supporting the citizen participation process with e-participation applications. As government service delivery is essentially a monopoly, an information delivery-oriented e-government initiative could be perceived as a digital mandate (Tan et al., 2005) that might prevent citizens from being active users of e-government services. In this context, the e-participation approach is important in that it gives the public an opportunity to observe and supervise policy implementation and participate in the government policy-making processes (Saxena, 2005). By strengthening representative democracy, e-participation prevents small interest groups controlled by political elites from dominating public policy (Macintosh, 2002). This approach is better described as 'e-governance' compared to 'e-government', in that it aims to transform the policy decision-making process into a 'citizen-centric, cooperative, and seamless but polycentric modern governance '(Saxena, 2005).

4.3 Methodology and data

4.3.1 Data

This study utilizes a balanced panel data set that consists of 48 countries in SSA (Table 4.1) spanning from 2003 to 2015 to estimate the effect of ICT as a policy variable in the relationship between the control of corruption and military expenditure. We use the corruption and transparency index (control of corruption, CoC) from the World Bank's World Governance Indicators (WGIs) (Kaufmann, Kraay, and Mastruzzi, 2011). The index ranges on a scale from -2.5 to 2.5, where a more negative or lower score indicates a greater level of corruption. Internet adoption is measured by the number of internet users (people with access to the worldwide computer network) per 100 persons. The military expenditure data from Stockholm International Peace Research Institute (SIPRI) are derived from the North Atlantic Treaty Organization (NATO) definition, which includes all current and capital expenditures on the armed forces, including peacekeeping forces; defense ministries and other government agencies engaged in defense projects; paramilitary forces, if these are judged to be trained and equipped for military operations; and military space activities. The control variables include seven non-dummy variables (lagged dependent variable, trade, net ODA received, log of real GDP, log of real GDP per capita, political stability and total natural resource rents) and one dummy variable (democracy-dictatorship regime). These control variables have been substantially documented in the literature on military expenditure (Maizels and Nissanke,1986; Gupta et al., 2001; d'Agostino et al., 2012, 2016a, 2016b; Langlotz and Potrafke, 2019 and Bjørnskov and Rode, 2020). The data of all variables are taken from the World Bank's World Development Indicators (WDI) database except the democracy-dictatorship dummy variable which from Bjørnskov and Rode (2020). Details about the variables and data sources are provided in Table 4.2. Table 4.3 displays the descriptive statistics, including variable mean, standard deviation, and minimum and maximum values. The average military expenditure in percentage of GDP is 1.73, while the average of corruption perception index and internet users per 100 people are about 0.64 and 7.7, respectively. Table 4.4 presents the correlation matrix (used to check for potential multicollinearity) for all variables in the study. The control of corruption, internet adoption, net ODA received, real GDP and political stability are negatively correlated with military expenditure while the variables trade, real GDP per capita, total natural resources rents and democray-dictatorship regime dummy variable are positively correlated with military expenditure. To mitigate the bias associated with the fact that the variables may not be normally distributed, we use an estimation technique other than Ordinary Least Squares.

Table 4.1. List of countries included in the analysis

Angola	Eswatini	Namibia
Benin	Ethiopia	Niger
Botswana	Gabon	Nigeria
Burkina Faso	The Gambia	Rwanda
Burundi	Ghana	Sao Tome and Principe
Cabo Verde	Guinea	Senegal
Cameroon	Guinea-Bissau	Seychelles
Central African Republic	Kenya	Sierra Leone
Chad	Lesotho	Somalia
Comoros	Liberia	South Africa
Congo, Dem. Rep.	Madagascar	Sudan
Congo, Rep.	Malawi	Tanzania
Cote d’Ivoire	Mali	Togo
Djibouti	Mauritania	Uganda
Equatorial Guinea	Mauritius	Zambia
Eritrea	Mozambique	Zimbabwe

Table 4.2. Variable definitions.

Variables	Signs	Variables definitions (measurements)	Sources
Military Expenditure	MILEXP	Military Expenditure (% of GDP)	World Bank (WDI)
Control of corruption	CORRUPTION	Reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Estimate (ranges from approximately -2.5 (most corrupt) to 2.5 (least corrupt).	World Bank (WGI)
Internet users (per 100 people)	INTERNET	Includes subscribers who pay for internet access (dial-up, leased line, and fixed broadband) and people with access to the worldwide computer network without paying directly, either as the member of a household or from work or school. The indicator is derived by dividing the number of internet users by total population and multiplying by 100.	World Bank (WDI)
Trade	TRADE	Trade as a percentage of GDP. Trade is the sum of exports and imports of goods and services measured as a share of the gross domestic product	World Bank (WDI)
Net ODA received (% of GNI)	NET_ODA	Net ODA received (% of GNI) agencies of the members of the Development Assistance Committee (DAC), by multilateral institutions, and by non-DAC countries to promote economic development and welfare in countries and territories in the DAC list of ODA recipients. It includes loans with a grant element of at least 25 percent (calculated at a rate of discount of 10 percent).	World Bank (WDI)
Real GDP	RGDP	GDP (constant 2010 US$)	World Bank (WDI)
Real GDP per capita	RGDPPC	GDP per capita (constant 2010 US$)	World Bank (WDI)
Political Stability	POLSTAB	Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	World Bank (WGI)
Total natural resources rents (% of GDP)	TNATRESSRENT	Total natural resources rents are the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents.	World Bank (WGI)
DD regime	DDREGIME	Regime category dummy variable, following Democracy Dictatorship dataset including colonies. "0 for Parliamentary democracy"; "1 for Mixed democratic"; "2 for Presidential democracy"; "3 for Civilian dictatorship"; "4 for Military dictatorship" and "5 for Royal dictatorship".	Bjørnskov and Rode (2020)

Table 4.3. Summary statistics of the variables included in the study.

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
MILEXP	509	1.7283	1.4313	0.1456	20.8657
CORRUPTION	624	-0.6401	0.6193	-1.8687	1.2167
INTERNET	612	7.7024	10.1991	0.0310	54.2596
TRADE	573	77.1600	39.2225	19.1008	311.3541
NET_ODA	600	9.3681	9.7660	-0.2509	92.1415
RGDP	595	2.83e+10	7.24e+10	1.33e+08	4.64e+11
RGDPPC	595	2303.421	3342.82	194.8731	20512.94
POLSTAB	624	-0.5283	0.9290	-3.3149	1.2002
TNATRESSRENT	595	12.8867	12.3344	0.0011	59.6196
DDREGIME	611	2.7119	1.1201	0	5

Table 4.4. Correlation matrix

	MIL EXP	CORRUP TION	INTER NET	TRADE	NET_ ODA	RGDP	RGD PPC	POL STAB	TNAT RESS RENT	DD REGIME
MILEXP	1.0000									
CORRUPTION	-0.1969	1.0000								
INTERNET	-0.1596	0.4403	1.0000							
TRADE	0.0328	0.2987	0.3137	1.0000						
NET_ODA	-0.1147	-0.1102	-0.3019	-0.0076	1.0000					
RGDP	-0.1255	-0.0137	0.2421	-0.2033	-0.2547	1.0000				
RGDPPC	0.0197	0.3909	0.5832	0.4814	-0.4042	0.1929	1.0000			
POLSTAB	-0.1758	0.7337	0.3391	0.3607	-0.1827	-0.1806	0.4691	1.0000		
TNATRESS RENT	0.3331	-0.5163	-0.2819	0.1168	0.1279	-0.0079	-0.0092	-0.3014	1.0000	
DDREGIME	0.2722	-0.3591	-0.1755	-0.0268	-0.0537	-0.0259	-0.0644	-0.3080	0.2602	1.0000

4.3.2 Model specification

The Generalised Method of Moments (GMM) estimation approach is adopted for the following four reasons. First, the number of countries or cross-sections (N equals 48) is substantially higher than the periodicity per cross-section (T equals 13). Second, given that the GMM estimation technique is consistent with a panel data structure, cross country variations are not eliminated in the estimations. Third, the system estimator considers inherent biases in the difference estimator. Fourth, the estimation procedure accounts for endogeneity by controlling for simultaneity in the explanatory variables using an instrumentation process. Moreover, usage of time-invariant omitted variables (or time fixed effects) also helps to mitigate the consequences of endogeneity bias. In accordance with Bond et al. (2001), the system GMM estimator (see Arellano and Bover, 1995; Blundell and Bond, 1998) has better estimation properties than the difference estimator (see Arellano and Bond, 1991). In this study, we opt for the Roodman (2009a, 2009b) extension of Arellano and Bover (1995) because it has been documented to restrict the proliferation of instruments and control for dependence among cross-sections (see Baltagi, 2008; Boateng et al., 2016; Love and Zicchino, 2006). Hence, the extended estimation procedure adopts forward orthogonal deviations as opposed to first differences. A two-step procedure is adopted instead of a one-step approach because it addresses concerns of heteroscedasticity given that the one step procedure only controls for homoscedasticity. The following equations in level (1) and first difference in (2) summarize the standard system GMM estimation procedure.

$$M_{i,t} = \alpha_0 + \alpha_1 M_{i,t-\tau} + \alpha_2 C_{i,t} + \alpha_3 I_{i,t} + \alpha_3 CI_{i,t} + \sum_{h=1}^{5} \delta_h W_{h,i,t-\tau} + \eta_i + \xi_t + \varepsilon_{i,t} \quad (1)$$

$$M_{i,t} - M_{i,t-\tau} = \alpha_1 (M_{i,t-\tau} - M_{i,t-2\tau}) + \alpha_2 (C_{i,t} - C_{i,t-\tau}) + \alpha_3 (I_{i,t} - I_{i,t-\tau}) + \alpha_4 (CI_{i,t} - CI_{i,t-\tau}) + \sum_{h=1}^{5} \delta_h (W_{h,i,t-\tau} - W_{h,i,t-2\tau}) + (\xi_t - \xi_{t-\tau}) + \varepsilon_{i,t-\tau}) \quad (2)$$

where, $M_{i,t}$ is military expenditure in country *i* at period *t*, α_0 is a constant, C is the control of corruption, *I* represents internet adoption, *CI* is the interaction between control of corruption and internet adoption, *W* is the vector of control variables (trade, net ODA received, real GDP, real GDP per capita , political stability, total natural resources rents and democracy-dictatorship regime), τ represents the coefficient of auto-regression, ξ_t is the time-specific constant, η_i is the country-specific effect and $\varepsilon_{i,t}$ the error term.

It is appropriate to devote space to discussing identification properties and exclusion restrictions in the GMM specification. All independent indicators are acknowledged as predetermined or are suspected to be endogenous. Additionally, exclusively time-invariant variables or years are considered to be strictly exogenous (also Asongu and Nwachukwu, 2016b; Boateng et al., 2016). The intuition for the consideration builds on the fact that it is not likely for the time-invariant variables to become endogenous after a first difference (Roodman, 2009b).

In the light of above emphasis, the time-invariant variables impact on the outcome variable exclusively through the predetermined variables. Furthermore, the statistical relevance of the exclusion restriction is investigated with the Difference in Hansen Test (DHT) for instrument exogeneity. Accordingly, the null hypothesis of the DHT should not be rejected for the time-invariant indicators to explain the military expenditure variable exclusively through the suspected endogenous variables. Hence, in the findings that are reported in Section 3, the assumption of exclusion restriction is validated if the alternative hypothesis of the DHT related to instrumental variables (IV) (year, eq(diff)) is not accepted. This is broadly in accordance with the standard IV procedure in which, a rejection of the null hypothesis of the Sargan Overidentifying Restrictions (OIR) test is an indication that the instruments affect the military expenditure variable beyond the suggested predetermined variable channels (see Asongu and Nwachukwu, 2016c; Beck et al., 2003).

4.4 Results and discussion

Table 4.5 shows the estimation results of the two-step system GMM with orthogonal deviation. Column (1) and (2) are identified as preliminary specifications include the control of the corruption, ICT, lagged military expenditure and the full set of controls without total natural resources rents and democracy-dictatorship regime. The third specification in Column (3) named interaction effect, controls for the same covariates but add the interaction term between the control of corruption and ICT among the regressors. Finally, the specifications in column (4) and (5) check the robustness of the third (main) specification by incorporating additional control variables (total natural resources rents and democracy-dictatorship regime). A Sargan OIR, test, a Hansen OIR test, a Difference in Hansen Test for exogeneity of instruments ‘subsets are performed for all specifications. They confirm the validity of the instruments used with the respect of the rule of Thumb about the proliferation of instruments which states that the number of instruments should be lower or equal to the number of groups, here countries. The effect of the prior level of military expenditure is positive across all models and statistically significant in all specifications except for the fifth specification. Therefore, military expenditure seems to be persistent and have inertia. The result from the columns (1) and (2) show that the control of corruption namely the traditional anti-corruption factors in Sub-Saharan Africa and ICT namely the internet adoption are not significantly associated with the military expenditure. The interaction between the control of corruption and internet adoption (column (3)) is negative and statistically significant, so the marginal effect of this interaction reduces significatively at 1% level of significance the military expenditure. From this result it appears clearly that when ICT prevails, military expenditure is negatively associated with control of corruption, so internet use in association with the control of corruption is a powerful tool to reduce military expenditure in Subsaharan African countries. This result remains robust even when we include total natural resources rents and democracy-dictatorship regime dummy variable in the specifications (4) and (5). In fact, in SSA, many African politician has made politics in Africa a means to an end and not an end itself so that African states institutions are weak as most of these institutions lack the capacity to provide basic social services for the citizens rather they are "inverted" as they tend to "look inward" rather than "outward" in their administration of social services. Furthermore, some SSA countries grant certain immunities to some political leaders by making the procedure of prosecuting such leader when found guilty of corruption charges difficult, so that the traditional anti-corruption laws are ineffective. One effective way to correct this misuse of a public or private position for direct or indirect personal gain in the military expenditure is to reveal these dishonest acts by bringing transparency back in these institutions through ICT so that the law will be respected (NATO, 2010). For instance, by doing so the UK Department for International Development (DFID) shed light on several frauds that occurred in Sub-Saharan Africa (Willet, 2009). Furthermore, some countries have adopted e-government initiatives as an anticorruption solution, and successful cases have been reported from several countries, including South Korea, India, Russia, Argentina, and Chile (Bhatnagar, 2001a, 2001b; Chawla and Bhatnagar, 2001; Im, 2001; Shim and Eom, 2008), and recently in the case of Niger (Mondafrique, 2020).

Table 4.5. Estimation results of the two-step system GMM with orthogonal deviation.

	(1)	(2)	(3)	(4)	(5)
Constant	-41.1666	-	-5.1414	-	-
	(0.552)		(0.932)		
MILEXP (-1)	0.4260**	0.3706**	0.4114***	0.4033**	0.3627
	(0.034)	(0.037)	(0.009)	(0.027)	(0.291)
CORRUPTION	0.1586	-0.9135	-0.1626	-0.2181	-0.3693
	(0.927)	(0.378)	(0.879)	(0.822)	(0.737)
INTERNET	-	0.0180	0.0247	0.0189	0.0118
		(0.546)	(0.402)	(0.485)	(0.652)
INTERNET×	-	-	-0.0381***	-0.0385**	-0.0336*
CORRUPTION			(0.010)	(0.027)	(0.089)
TRADE	-0.0093	-0.0068	-0.0124**	-0.0127	-0.0105
	(0.211)	(0.119)	(0.032)	(0.106)	(0.301)
NET_ODA	0.0016	-0.0063	-0.0110	-0.0098	-0.0072
	(0.890)	(0.389)	(0.139)	(0.270)	(0.316)
Log (RGDP)	2.4791	-0.0096	0.4541	0.1134	-0.0842
	(0.485)	(0.996)	(0.854)	(0.964)	(0.978)
Log (RGDPPC)	-2.0905	-0.8190	-0.6210	-0.3626	-0.2640
	(0.356)	(0.568)	(0.638)	(0.739)	(0.857)
POLSTAB	-0.2323	-0.1313	-0.2754	-0.3163	-0.2272
	(0.500)	(0.717)	(0.246)	(0.264)	(0.583)
TNATRESSRENT	-	-	-	0.0013	0.0019
				(0.972)	(0.961)
DDREGIME	-	-	-	-	0.0944
					(0.699)
AR(1)	(0.087)	(0.219)	(0.152)	(0.223)	(0.515)
AR(2)	(0.156)	(0.134)	(0.170)	(0.183)	(0.152)
Sargan OIR	(0.177)	(0.062)	(0.109)	(0.081)	(0.062)
Hansen OIR	(0.201)	(0.218)	(0.775)	(0.737)	(0.750)
DHT for instruments					
(a) Instruments in levels					
H excluding group	(0.170)	(0.508)	(0.685)	(0.653)	(0.595)
Dif (null, H = exogenous)	(0.440)	(0.042)	(0.702)	(0.642)	(0.876)
(b) IV (years, eq (diff))					
H excluding group	(0.165)	(0.293)	(0.145)	-	-
Dif (null, H = exogenous)	(0.292)	(0.225)	(0.873)	0.895	-
Wald $\chi2$	67.70***	62.92***	116.76***	243.42***	170.18***
Instruments	35	35	35	35	35
Countries	43	43	43	43	42
Observations	431	424	424	424	412

4.5 Conclusion

Much effort has been exerted by many governments, development practitioners, and other stakeholders to fight the secrecy on military expenditure in Sub-Saharan Africa since this region is regarded as the most corrupt in the world (Willet, 2009), especially in recent years, but this battle is still a challenge. With the advent of the internet use, policy reformers from governments and many anti-corruption organizations have recently encouraged the use of ICT systems (here internet) to bring transparency in military expenditure (NATO, 2010). This study contributes to the existing literature by empirically investigating the effect of internet adoption on the relationship between the control of corruption and military expenditure by utilizing a large panel data set. The empirical findings suggest that the relationship between control of corruption and military expenditure depends on the level of ICT. When ICT level is low, there is less clear relationship between control of corruption and military expenditure. However, when ICT prevails, there is negative relationship between control of corruption and military expenditure, so that using the internet within a supportive and regulatory environment could help deter misuse of military allocation. Policymakers should emphasize on the promotion of building integrity to reduce corruption in defense through the implementation of e-governance via internet adoption and rise the marginal cost of corruption in military expenditure much higher than the marginal benefits so that people will refrain from dishonest acts. Furthermore, policymakers should create a sound environment for the prevalence of ICT such as good regulation of telecommunication sector, encouraging foreign investments in ICT sector, educating and encouraging the population to be familiar to ICT tools especially internet. On a cautious note, it is also important to balance this finding with the fact that regulating the internet could restrict the flow of information which could suppress people from being communicative and expressive, and thus changing the way information is dealt with over the internet. From a policy perspective, by examining the influence of internet penetration on military expenditure, our study helps practitioners and policy makers to better understand the role of internet as an instrument for raising the level of transparency in the military department. Our results suggest that there is a potential external benefit of associating internet penetration to the control of corruption in order to reduce corruption in military expenditure. However, we remain cautious about any assertions of a causal linkage between the interaction term and military expenditure since our analysis rely on the marginal effect, so the need to find a net effect of our interaction term on military expenditure is laudable.

Chapter 5: Conclusion

SDGs constitute an important agenda for the international community, especially for developing countries since they are the most concerned and vulnerable to underdevelopment. To help them achieve these interrelated goals, this dissertation focuses on three important SDGs goals for developing countries namely SDG 1 (no poverty), SDG 13 (climate action), and SDG 16 (peace, justice and strong institutions. In fact, developing countries face a real challenge to reach these goals which maintain them in the trap of non-sustainability in the pursue of their development agenda. To conduct this empirical analysis, we focus on different measures and services of Information and Communication technology (ICT) in which these countries have a real potential of growth such as fixed telephone, mobile cellular penetration, internet use, and mobile money service by using different identification strategies, samples and scope. From the results it appears clearly that financial inclusion and mobile money in the context of their interoperability help reduce poverty and improve individuals' welfare in the case of a least-developed country, Burkina Faso, where the penetration rate of mobile money is relatively low compared to other developing countries. Furthermore, we found that the long-run relationship between CO_2 emissions and ICT differs, depending on a country's development stage. The prevalence of ICT is associated with the low level of CO_2 emissions in relatively low-income developing countries, but ICT and CO_2 emissions have no clear relationship in relatively high-income developing countries. Moreover, our study reveals that the control of corruption and internet adoption fail to reduce military expenditure but the interaction effect of both are statistically significant on the reduction of military expenditure, so that using the internet within a supportive and regulatory environment could help deter misuse of military allocation. This dissertation could provide important policy implications for developing countries to face their big challenges in order to reach the SDGs by 2030. In fact, policymakers could leverage on ICT to reach their SDGs goals by facilitating a good ecosystem to the growth of ICT through good regulation of the sector which will encourage foreign investments in ICT sector and stimulate the trust of the population to use ICT products. We cannot close this chapter without mentioning some limits of our study. In fact, based on the availability of data we use in our analysis some old measures of ICT which are possible to bias the accuracy of our policy recommendations, so we suggest that futures researches should focus on more contemporary measures of ICT in developing countries to do their empirical analysis.

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