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Does ICT access and usage reduce growth inefficiency in Sub-Saharan Africa?*

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Abstract

This paper investigates whether or not the access to and use of ICT can help African countries reduce their growth inefficiencies. Inefficiency is measured, on the one hand, by the gap between a country's growth rate and its own frontier, and on the other hand by the relative position of each country compared to the best achievers. We find that if countries were doing a better job of controlling corruption and improving citizen participation in politics, they would achieve higher growth efficiency performance by using ICT. When countries are compared with each other, considering the growth "frontier" as countries in the sample, then growth differentials are explained primarily by non-ICT factors of growth (human capital, schooling rates, capital growth rates, etc.). The role of ICT factors is secondary. But they contribute to growth to a greater extent for the best achievers (compared to the lowest and middle achievers) because they are better endowed with ICT factors than the others.

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1.- Introduction

We use the latest survey data from Research ICT Africa to investigate whether the diversity of internet access and usage across Sub-Saharan African countries (hereafter SSA) can explain heterogeneity in their growth performance. The survey covers 17 African countries over the years 2007 and 2008. The data concern nearly a hundred indicators providing information on several dimensions of ICT use by households. The main headings covered are fixed telephony, cell phones, the degree of ICT penetration in household use, ICT expenditure, internet use, and many behavioural variables on why people choose to use or refrain from using ICT. These variables are used to capture idiosyncratic effects in growth models estimated on panel data between 2004 and 2019. Our paper makes two contributions to the literature.

First, it is the first time that data on household ICT use behaviour are used to investigate the links between ICT and growth in SSA countries. Indeed, most studies usually rely on aggregate variables to capture the growth effect of ICT, such as the number of fixed-line telephone users, the number of people with internet access, the number of people with cell phones, or the number of people using specific services such as mobile payment. We therefore mix two types of data. We consider standard aggregate data (such as the percentage of internet and fixed telephone users and mobile cellular subscriptions), and microeconomic behavioural data on ICT. This mix, a difference to most of the preceding literature, allows us to highlight heterogeneity in the effects of ICT on growth in the African countries where their use is most widespread.

Second, our methodology departs from much of the literature on the topic. ICTs have two effects. In the short run, they have an influence on economic growth. In the medium/long term, they have an impact on the productive capacity of economies, i.e. on potential growth. This second effect is rarely studied in the literature. Yet, for developing countries in Sub-Saharan Africa, the issue is important. Indeed, beyond economic growth, the question of raising the population's standard of living is an objective that will make it possible to reduce poverty in the long term. The literature has focused on the obstacles to development (insufficient human capital, weak diversification of economies, governance and institutional problems, low investment rates, poor quality of electrical and sanitary infrastructures, etc.). Here, we investigate whether the suboptimal use of ICTs can be a hindrance to the achievement of countries' potential growth. Two distinctive features of this paper in measuring potential growth is the following. First, we focus on an individual perspective by estimating stochastic frontiers on GDP growth rates, i.e. we measure the maximum growth rates that each individual country can reach. Differences between frontier growth and actual growth are interpreted as inefficiency. We thus seek to see whether, conditional on the use of ICT, each country is far from its frontier in terms of economic growth or not. The second perspective we consider is comparative. We estimate a growth model using the quantile method and consider as potential growth rate the growth estimated for the highest quantiles of the observations (above the 80% quantile). Any discrepancy between the observed growth rates and the estimated growth of the highest quantiles is also interpreted as a sign of inefficiency. We then seek to understand whether these discrepancies are due to cross-country differences in ICT endowments, or whether countries are not optimally mobilizing their ICT resources.

Stochastic frontier regressions lead two interesting results. First, ICT use and access reduce growth inefficiencies in a majority of countries (10 out of 15). Second, if countries were doing a better job of controlling corruption and improving citizen participation in politics, they would achieve higher growth efficiency performance than they do with current anti-corruption policies and civil society inclusion in politics. The worst performing countries are Nigeria and Zambia. In the case of Nigeria, we find that given the state of corruption and politics, even if the country were to pursue anti-corruption and political inclusion policies at the level of the best performing countries in the region (Botswana), their productive efficiency would be increased tenfold, but the growth efficiency gains would remain very small compared to other African countries. Growth efficiency gains from the use of ICT are highest in Ghana, Namibia, Senegal, and Mozambique.

Quantile regressions, which account for heterogeneous responses of growth to ICT usage and access, reveal other additional interesting results. When countries are compared with each other, considering the growth "frontier" as countries in the sample, then growth differentials are explained primarily by non-ICT factors of growth (human capital, schooling rates, capital growth rates, etc.). The role of ICT factors is secondary. But they contribute to growth to a greater extent for the best achievers (compared to the lowest and middle achievers) because they are better endowed with ICT factors than the others.

The remainder of the paper is organized as follows. Section 2 contains a literature review on the impact of ICT on economic growth in SSA countries. Section 3 presents the data. Section 4 contains our estimations based on stochastic frontier models. Section 5 discusses our contributions from quantile regressions. Section 6 concludes.

2.- Literature review

The theory of economic growth has progressed since the 18th century as researchers looked for causes of increased output. Smith (1776) and Ricardo (1814) listed capital and labor as the main forces at play in economic analysis. Solow (1956) underlined the importance of technical advancement as a factor generating externalities on the productivity of capital and labor elements, despite the fact that it occurred several centuries after the event. It was deemed exogenous since it occurred outside of the control of the individuals involved. However, later research demonstrated that human effort is necessary for the full realization of these technological advances. The notion of endogenous growth relies on this work, which first emerged in the 1980s. This theory explores the ways in which human intervention might boost the effectiveness of time-honored techniques. The seminal articles in this stream are those of Romer (1986) and Lucas (1988). Following on from this pioneering work, a slew of authors have investigated alternative drivers of growth, including public investment (Barro, 1990); innovations, creative destruction, and specialization (Aghion and Howitt, 1992); financial development (Pagano, 1993); and institutions (North, 1990).

Empirical tests have shown a plethora of endogenous growth sources. Sala-i-Martin (1997), for example, ran two million regressions. His investigation uncovered over sixty elements. Without attempting to be exhaustive, studies have highlighted the role of institutional factors (Alesina and Perotti 1994; Acemoglu et al., 2005), financial development (King and Levine, 1993; Bernanke and Gertler, 1990; Law and Singh, 2014; Arcand et al, 2015), historical context (Putterman, 2000), income inequality (Alesina and Rodrik 1996), ethnic diversity (Easterly and Levine 1997), trade openness (Levine and Renelt 1992; Frankel and Romer, 1999), environment (Mariani et al., 2010; Constant and Raffin, 2016), inflation (Fischer, 1993), foreign direct investment (Dunning, 1973), etc. The impact of information and communication technologies (ICT) on growth and economic development in general has been underlined since the turn of the century (Gordon, 2000; Roller and Waverman, 2001).

Indeed, economic prosperity nowadays is inextricably linked to the advancement of ICTs. ICTs have an impact on practically every element of human existence, including time savings, knowledge diffusion, ease of communication and networking, information access, and automation through artificial intelligence. They can increase productivity by facilitating exchanges, boosting transparency and governance, and building social capital. They can, however, obstruct it by increasing the risks of cyber-attacks and privacy vulnerability, or by digitally dividing persons in society. This mixed finding is supported by a body of research. To be more specific, there are two types of empirical validations. The first collection of studies (Cardona et al., 2013; Stanley et al., 2018) demonstrates that ICT investment leads to increased productivity and, eventually, economic development. The second group (Brynjolfsson and Yang, 1996; Hajli et al., 2015) challenges the impact of ICT on growth by citing Solow's (1987) "productivity paradox." Computers are present everywhere except in productivity data, implying that increased ICT use in enterprises, manufacturing industries, and countries does not boost labor productivity.

Nonetheless, given the importance of ICTs in modern economies, an assessment of their influence on key economic indices has been conducted. These include human capital (Asongu and Le Roux, 2017) through health (Venkatesh et al., 2020; Farasat et al., 2007) or education (Wadi and Sonia, 2002); institutional quality (Elbahnasawy, 2014; Martins and Gonçalves Veiga, 2022); employment polarisation (Catherine et al, 2015; Dadegnon et al, 2020); financial development (Venkatesh et al., 2020; Chen et al., 2021); environmental quality (Avom et al., 2020); etc. Some of these variables then influence growth, increasing the number of potential indirect relationships between ICT and growth. As a result, the impact of ICT on growth includes both direct and indirect consequences.

The direct effect of ICT on economic growth

The direct effect of ICT is often examined within the context of the neoclassical model that serves as the foundation of growth accounting (Draca, et al., 2007). This model consists of a Solow residual and a function that connects output growth to input growth (capital and labor). The capital input includes a portion of computer capital (computers, telephones, or, more broadly, ICT) and a portion of non-computer capital (buildings, land, etc.). The percentage of computer capital investment in the evolution of production for a country assesses the impact of ICT on economic growth. As a result, equipping businesses with ICT leads to faster growth. The notion that the Keynesian ICT investment multiplier mechanism is more essential than the non-ICT investment multiplier mechanism supports this idea (Mairesse, et al., 2000; Vu, 2013).

However, this method of determining the direct benefits of ICT has certain drawbacks. One is that the proportion of ICT externalities represented in the Solow residual is understated by the accounting technique. This is highlighted by proponents of endogenous growth theory who claim that, for instance, there are significant knowledge spillovers in human capital owing to ICT, especially among highly trained individuals (Aghion and Howitt, 1998). Such indirect impacts are routinely disregarded in traditional growth accounting. They do, however, go through a variety of pathways, which impact development.

Indirect effects of ICT on economic growth and transmission channels

Externalities from ICT spread across the economy. The Solow residual rises as a result of this dispersion to technical development. As a result, the components of this residue serve as ICT transmission channels for economic growth. These channels comprise a diverse variety of components, the majority of which have been emphasized empirically. This assessment focuses on the following channels: human capital, institutions, financial development, the environment, employment, inflation, the capital/labor ratio, trade openness, and foreign direct investment.

The human capital channel

Human capital determines growth (Lucas, 1988) and is seen as an ICT transmission channel. Indeed, the usage of ICT boosts users' human capital, which leads to growth. According to Asongu and Le Roux (2017), estimating instrumental Tobit regressions on a sample of 49 Sub-Saharan African nations from 2000 to 2012 yields a result along these lines. They demonstrate explicitly that growing ICT (mobile phone, internet, telephone) increases inclusive human development. Meltzer (2015) sees benefits for organizations' human capital in the Internet. It raises individuals' educational levels by providing simple access to knowledge (online courses), which boosts their productivity. Venkatesh et al (2020) demonstrate that ICT-based counselling networks facilitate the seeking of contemporary medical treatment and minimize maternal mortality in India when it comes to women's health. Farasat et al. (2007) present econometric evidence in developing countries showing a relationship between public health spending and two health outcomes, namely under-five mortality and maternal mortality. N'Dede demonstrates that the use of ICTs positively alters the means of access to information and, more particularly, the connection between the instructor and the student in secondary education in Côte d'Ivoire. Finally, according to Wadi and Sonia (2002), information and communication technology (ICT) helps to cover gaps in academic services such as a lack of well-stocked libraries or laboratories.

The quality channel of institutions

In certain research, the quality of institutions emerges as a transmission channel for ICT and contributes to growth (North, 1990; Acemoglu et al., 2005). Elbahnasawy (2014) discovers, for example, that ICT in e-government decreases corruption due to communications infrastructure and the quality of online services by estimating a dynamic model on a broad range of panel nations. Similarly, Jiménez et al. (2022) discover that an e-procurement system is successful in combating corporate corruption if it gets supranational backing, after researching 8373 enterprises in 72 countries from 2008 to 2019. Finally, Martins and Gonçalves Veiga (2022) found that developments in digital government contribute to lower administrative and regulatory burdens, providing a more business-friendly environment, in a panel of 169 nations from 2004 to 2018.

The financial development channel

Financial development promotes growth and also serves as a transmission channel for ICT (Bernanke and Gertler, 1990; Law and Singh, 2014; Arcand et al., 2015). Indeed, Chen et al. (2021) demonstrate that financial development has a negative influence on growth in high-income nations, but that the interaction effect of financial development with ICT is relatively good. This suggests that ICT promotes to growth through interactions with finance. In the countries of the Economic Community of West African States, Traore and Ouedraogo (2020) discover threshold impacts of ICT on growth via the channel of financial development. The authors demonstrate conditional effects around ICT diffusion thresholds of 82.43 percent for mobile phones and 34.75 percent for the internet by calculating a quadratic model. Finally, according to Levine (2001), "financial sector expansion and ICT dissemination can both effect economic growth."

The Environmental Quality Channel

Environment quality affects growth (Mariani et al., 2010; Constant and Raffin, 2016) and has been identified as a conduit for ICT transmission. In 21 sub-Saharan African countries from 1996 to 2014, Avom et al. (2020) demonstrate that ICT use (as assessed by mobile phone and internet penetration) increases CO2. In doing so, ICTs degrade the environment's quality. Yu Cheng et al. (2022) discover an inverted U-shaped association between the urban digital economy and carbon intensity in China using a quadratic model. They infer that the intensity of carbon emissions reduces when the digital economy index exceeds 0.4219.

The employment polarisation channel

Employment contributes to the traditional growth factor of labor (Solow, 1956) and also serves as a conduit for ICT. Concern has emerged regarding the impact of ICT on employment. Due to automation, this is the polarisation of the labor market, which tends to eliminate jobs associated to "routine" occupations. Catherine et al. (2015) demonstrate that professions in the middle of the wage distribution tend to grow scarcer in France between 1990 and 2012, while high-paying, highly-skilled employment and low-paying, low-skilled, non-routine jobs are produced (a construction worker for example). Dadegnon et al. (2020) conclude that more jobs are generated than destroyed in the countries of the West African Economic and Monetary Union, and that the majority of the jobs lost are unskilled. In order to prevent an increase in unemployment, it is essential that training programs be tailored to the demands of ICTs. On this issue, Coffinet and Perillaud (2017) note that the Internet increases the efficiency of the labor market due to the transparency it enables. Indeed, faster access to job listings by a greater number of candidates is advantageous for both businesses and job seekers.

The technology deflator channel of inflation

Inflation is a growth determinant (Fischer, 1993) and looks to be another ICT transmission channel. Beginning point is the decline in ICT and computer pricing in general. This persistent decline in the price of microprocessors prompts businesses to boost their investments in this industry. According to Gordon (2002), a significant decline in ICT prices between 1996 and 1998 led to overinvestment by U.S. companies. Then, productivity gains in the ICT sector worked as a technology deflator, controlling inflation and supporting economic growth. Collecchia and Schreyer (2001) have identified similar technology deflator mechanism in nine OECD nations.

The capital-labour substitution channel

The substitution of traditional growth elements such as capital and labor (Solow, 1956) creates a conduit for ICT transmission. Indeed, with the arrival of ICTs, this substitution favors capital over labor. The resulting expansion leads to capital accumulation and a decline in labor employment. Gordon (2002) estimates that the substitution impact accounted for two-thirds of the acceleration in the US economy between 1996 and 2001.

The trade opening channel

Trade openness leads to economic development (Levine and Renelt, 1992; Frankel and Romer, 1999) and serves as a conduit for ICT transmission. Due to the speed of information flow and the scope of the network, ICT enables businesses to rapidly reach a much bigger target audience. This ease of entry into new markets has a favorable effect on enterprises' exports and, consequently, their growth (Clarke and Wallsten, 2004; Biswas and Lynn Kennedy, 2016). Fink et al. (2005) demonstrate that the Internet and ICTs assist international trade by lowering the risks and costs associated with locating market information. The trade openness of nations that invest more in ICT is anticipated to be greater (Demirkan et al., 2009; Liu and Nath, 2013). Using data from 178 countries from 1995 to 2012, Keita (2016) demonstrates that the elasticity of trade costs with respect to ICT increases with distance, but reduces as ICT levels rise. He concludes that the Internet and ICT have a cost-reduction effect on international trade, and that this benefit grows as the distance between trading partners rises. Freund and Weinhold (2004) demonstrate a favorable correlation between Internet development and trade flows.

The channel of opening to Foreign Direct Investment

Financial openness fosters growth via Foreign Direct Investment (Dunning, 1973), which also serves as a transmission mechanism for ICTs. According to Harris (1995), the role of ICTs is to enable cooperation within an organization, as well as between the organization and its suppliers. Therefore, he expects that unfavorable network externalities, such as internet congestion, will inhibit market growth. Choi (2003) identifies a positive correlation between internet growth and FDI. FDI flows grow by 2.58 percent if the number of internet servers increases by 10 percent, and by 1.84 percent if the number of internet users increases by 10 percent. Ko (2007) presents a two-step game to demonstrate that the positive (negative) network externalities connected with the use of the Internet stimulate (discourage) foreign direct investment.

3.- Data

The number of countries (16) and the period (from 2004 to 2019) is dictated by the availability of data. We organize our series as panel data.

3.1.- ICT access and usage data

We use data from the ICT research Africa survey on access to and use of ICT by African households. This survey covers 17 countries during 2007 and 2008 and 23,000 individuals and households were interviewed. The survey has one advantage. It includes nearly 80 variables that provide information on the habits and perceptions of households, but also on the factors that may inhibit or accelerate their digital divide: the cost of telephone communications, illiteracy in digital matters, the possibility of using an individual cell phone or from a public call center, etc. The survey was initially used to highlight the sub-optimal use of ICT by households and the exclusion of many from services using new technologies. The results of the survey are available at: www.researchICTafrica.net. The areas of questions cover several dimensions: access to and use of fixed lines, motivations and use of cell phones and the Internet, the role of telecommunication costs and payment methods, the share of ICT expenditure in the household budget, international calls, computer ownership, frequency of Internet use, and the quality of ICT infrastructure.

The large number of variables in this survey (more than 80), leads us to conduct a principal component analysis in order to work with factors that summarize the information they contain. We initially select the first 10 factors, which represent more than 90% of the total variance. Then a BMA analysis leads us to select only 6 factors whose influence on growth is robust (see the details of the BMA analysis in the next section). For each factor, we can see which survey variables are most correlated with it. Tables 1a and 1b contain this information. As can be seen, many variables relate to perceptions and motivations in accessing ICT, while others highlight supply-side constraints (quality of services provided by operators, costs, access to ICT through public telephone services, etc.).

3.2.- Other variables

To select the determinants of potential growth, this paper draws on the extensive literature on neoclassical and endogenous growth models. Taking account of the constraints related to the availability of statistical data for SSA countries, we retain the following variables.

The endogenous variable is the growth rate of real GDP per employed person. Data for real GDP and employed people is taken from Penn World Table (PWT) 9.1. We compute the logarithmic first-difference of the ratio. Since our focus is on investigating medium-term effect of ICT on growth, we eliminate the short-term fluctuations by smoothing the data and compute a four moving-average of the differentiated series.

Table 1a. Factors and survey variables

Factor 2	**Factor3**	**Factor 4**
(1) 16+ having used public phones with mobile phone	**(1)** Less than once a month	**(1)** I prefer to use the fixed-line phone at work or at school
(2) 16+ having used public phones: all	**(2)** Convenience	**(2)** Share of HH with fixed phone
(3) The same as I do now	**(3)** Monthly mobile expenditure/monthly individual income: /Bottom 75% in terms of disposable income	**(3)** I do not have access to a computer
(4) 16+ having used public phones with mobile phone	**(4)** Billingprep	**(4)** Monthly mobile expenditure/monthly individual income: all individual
(5) Once a month	**(5)** Public phone use in the last three months: calling mobile phone	**(5)** Too expensive
(6) Lack of time	**(6)** Monthly mobile expenditure/monthly individual income:All disposable	**(6)** At least once a month
(7) Only a very little more (up to 10% increase a month)	**(7)** Public phone use in the last three months: international	**(7)** I have no one to e-mail to
(8) Quite a bit more (11-30% increase a month)	**(8)** What billing type is it? Monthly	**(8)** Price of calls
(9) Knowledge about how use the Internet	**(9)** I have no one to e-mail to	**(9)** Average number of SIM cards per user
(10) 16+ knowing what the Internet is: all	**(10)** Public phone use in the last three months: calling fixed-line	**(10)** Public phone use in the last three months: calling mobile phone

The explanatory variables are the following :

(1) a human capital index and the schooling rate (tertiary) to capture the influence of the labor factor,

(2) the growth rate of physical capital per employed people.

Both series are also taken from PWT 9.1. For the physical capital per employed people we proceed in a similar way as for GDP. These variables are usually considered as basic variables in empirical growth models.

We further consider a set of control variables (all taken from the World Bank):

(3) imports of ICT goods (% of total imports) and access to electricity (% population). We take the log of both variables,

(4) a set of variables capturing the functioning of institutions and good governance (rule of law, control of corruption, quality of regulation, effectiveness of government, political stability and absence of violence, voice and accountability),

(5) finally, we also consider 3 aggregate ICT variables: fixed and mobile telephone subscriptions (per 100 people) as well as the percentage of individuals using internet (out of total population). All three variables are measured in log.

3.3.- Preliminary analysis to select the explanatory variables: BMA and WALS regressions

As a preliminary analysis, we investigate which of our explanatory variables can be formally considered as significant determinant of growth. We account for model uncertainty, using a Bayesian Model Averaging analysis (BMA) and Weighted Average Least Squares (WALS)[2].

Table 1b. Factors and survey variables (next)

Factor 5	Factor 6	Factor 8
(1) Average public phone expenditure in US$	**(1)** Once a day	**(1)** Household without fixed-line that do not want it
(2) Lack of local language content	**(2)** Operator would not provide because of lack of regular income	**(2)** I do not want to use the Internet
(3) Too inconvenient	**(3)** Security while using	**(3)** No interesting content
(4) Slowness of Internet	**(4)** Cannot read/write	**(4)** At least once a week
(5) Active Sim urban	**(5)** Cost of access	**(5)** Lack of local language content
(6) Very much more than I use now (51+% increase a month)	**(6)** I use public phones because I do not have a mobile phone	**(6)** Every day or almost every day
(7) Monthly mobile expenditure/monthly individual income:/Bottom 75% in terms of disposable income	**(7)** Monthly mobile expenditure/monthly individual income: all disposable	**(7)** I do not have access to a computer
(8) Monthly mobile expenditure/monthly individual income: /Top 25% in terms of disposable income	**(8)** Public phone use in the last three months: international	**(8)** Average monthly fixed-line expenditure in US$ using implied PPP conversion rate
(9) Share of prepaid users	**(9)** Monthly mobile expenditure/monthly individual income: Bottom 75% in terms of individual income	**(9)** Households that applied for a fixed-line phone and never received it
(10) Monthly mobile expenditure/monthly individual	**(10)** Households that applied for a fixed-line phone and never received it	**(10)** I have no one to e- mail to

[2] For a detailed presentation of these estimators, see De Luca and Magnus (2011 and 2016).

income: /Top 25% in terms of individual income	

We consider as « focus variables » the growth rate of physical capital and the index of human capital (these are the variables we absolutely want in the model). For the BMA estimator, the selection of the variables is based on the posterior inclusion probability (PIP). A variable is considered to be significantly correlated with the growth rate of GDP per employed people if the PIP is above the 0.5 threshold. The WALS estimator uses a preliminary orthogonal transformation of the data to ensure that the estimates are invariant to scale transformation and to improve accuracy of the estimator. The selection of the variables that are significantly linked to the endogenous variables is based on the t-ratio.

Table 2 shows the results of BMA and WALS analysis. The PIP of the focus variables equals 1 since we impose their inclusion in the model (excluding them would be meaningless from an economic viewpoint). A percentage increase in investment (per employed people) increases the probability that growth per employed people ends by 0.3%, while an increase in the index of human capital is also associated with a higher probability of growth increase.

Among the auxiliary variables, the aggregate variable of access to internet is not significantly correlated with growth, since the probability of inclusion is only roughly one-third. The BMA analysis suggests that only but a few governance variables are strongly correlated with the growth rate of GDP (voice accountability and control of corruption are the two variables with a PIP higher than 50%). For the internet usage factors (factors from ICT factor data), seven of the ten selected factors have a significant effect on growth.

The WALS regression leads to conflicting results compared to the BMA analysis. The sign of the influence of the human capital indicator is reversed (negative). One explanation may be that the effects of human capital are non-linear: the beneficial effects on growth appear once the country crosses a threshold of human capital development. Before that, the costs outweigh the benefits (Okunade et al. 2022 highlight this type of effect for the productivity growth rate). Access to electricity no longer appears to be a significant factor in growth. In contrast, we find a significant effect for many more governance variables. The number of factors from ICT survey data is about the same as for the BMA analysis.

These contradictory results illustrate the uncertainty model phenomenon. We select the variables based on the BMA analysis for the following reason. The probabilistic approach is more reliable, because the PIP is obtained from the best combination of explanatory variables after estimating 4,194,304 different models.

Based on the results of this preliminary analysis, we therefore eventually select the variables reported in Table 3. In addition to the variables in the BMA analysis, we add dummies to capture different legal regimes based on colonization (French, Portuguese/Spanish, English). Colonial legal systems have left different legal rules across countries (e.g., civil law and common law traditions).

Table 2. BMA and WALS estimates

	BMA			WALS		
	Coef.	Std. Err.	pip	Coef.	Std. Err.	t-ratio
				Focus variables		
Intercept	**9.788**	8.069	1.00	**10.722**	5.542	1.93
Growth rate of physical capital	**0.300**	0.153	1.00	**0.233**	0.138	1.69
Index of human capital	**-12.085**	4.775	1.00	**-10.191**	2.479	-4.11
				Auxiliary variables		
Control variables						
Imports of ICTs	**3.909**	1.349	0.97	**4.413**	1.038	4.25
Access to electricity	**2.669**	1.947	0.73	0.536	1.255	0.43
Enrolment rate	**1.557**	1.940	0.49	**3.251**	1.056	3.08
Access to internet	-0.263	0.485	0.29	0.199	0.534	0.37
Fixed tel subscription	**2.626**	0.509	1.00	**2.103**	0.476	4.42
Mobile cellular subscription	-0.444	0.644	0.40	-0.778	0.478	-1.63
Governance variable						
Voice accountability	**4.401**	2.588	0.79	**3.461**	1.645	2.10
Political stability	0.581	1.075	0.30	**2.538**	0.950	2.67
Government effectiveness	3.218	4.195	0.45	**8.340**	2.770	3.01
Regulatory quality	-1.076	1.988	0.28	-2.278	1.901	-1.20
Rule of law	-0.910	2.157	0.22	**-5.053**	2.509	-2.01
Control of corruption	**-2.449**	2.788	0.54	-2.749	1.759	-1.56
Factors from ICT survey data						
PC1	0.008	0.057	0.07	0.050	0.159	0.31
PC2	**-0.233**	0.199	0.66	-0.132	0.117	-1.12
PC3	**-0.981**	0.329	0.98	**-0.664**	0.199	-3.34
PC4	**0.549**	0.179	0.99	**0.567**	0.147	3.87
PC5	**0.952**	0.506	0.83	**0.735**	0.259	2.84
PC6	**1.308**	0.302	1.00	**1.290**	0.218	5.91
PC7	-0.199	0.336	0.33	**-0.540**	0.199	-2.71
PC8	**0.481**	0.311	0.78	**0.470**	0.168	2.79
PC9	-0.250	0.438	0.30	-0.208	0.284	-0.73
PC10	-0.186	0.404	0.27	**-0.829**	0.316	-2.62

Note: the coefficients in bold indicate the variables that have a high probability of influencing GDP growth. For BMA, we look at the PIP and select those variables with a PIP higher than 0.5. For

WALS, we consider the t-ratios and select the variables with a ratio higher than 1.64 (which corresponds to a 10% level of significance.

Table 3. Final selection of variables in the regressions

Endogenous variable	Explanatory variables
Growth rate of GDP per employed people	**(1) Factors of production** Growth rate of capital per employed people Human capital index **(2) Control variables** Imports of ICTs Access to electricity Enrolment rate Fixed telephone subscription Voice and accountability Control of corruption **(3) Factors from ICT survey data** PC2, PC3, PC4, PC5, PC6, PC8 **(4) Dummies variables for rule of law regimes** (English, French, Portuguese/Spanish

4.- Measuring the effects of ICTs on growth: stochastic frontier models

4.1.- The model

We start with the following production frontier equation:

$$y_{it} = \alpha_i + X'_{it}\beta + Z'_{it}\delta + v_{it} - u_{it}, \quad i = 1, \cdots, 15, \; t = 2004, \cdots, 2019 \qquad (1)$$

where $y_{it} = \Delta log$(GDP per employed people) in country i at time t, α_i is a country fixed effect, X_{it} is the vector of basic factors of production (capital growth and human capital index), Z_{it} is the vector of control variables excluding the ICT survey and governance variables. ,

u_{it} is the (non-negative) inefficiency variable that measures the distance from the maximum level of GDP growth. It follows a Normal-half distribution $N_+ \left(\mu \;, \sigma_u^2\right)$. $v_{it} \approx N(0, \sigma_v^2)$ is the error term. We assume that $u_{it} \perp \left(X_{it}, Z_{it}, v_{it}\right)$.

Define F_i as the vector of factors that summarize the information in the ICT survey data. This vector enters as explanatory variables of the mean of the inefficiency term μ_{it}:

$$\mu_{it} = k_0 + F'_i k_1 \qquad (2)$$

The coefficients of Equations (1) and (2) are estimated by maximum likelihood using Greene (2005a, 2005b)'s approach. The inefficiency parameter $\lambda = \sigma_u / \sigma_v$ is also computed. A significant λ indicates skewness of the distribution. The individual and mean efficiencies are estimated using Jondrow et al. (1982)'s formula. Since the coefficient of the variables in the inefficiency term do not have a direct interpretation, we calculate the marginal effects using Wang (2002)'s approach. They are based on the post-truncation mean of u_{it}.

Denoting $\Omega_{it} = (e_{it}, FI_i)$, where e_{it} is a vector of 1 and Ω_{it}^l the l^{th} element of Ω_{it} and k_l the coefficient associated to this variable, we have

$$\frac{\partial E(u_{it})}{\partial \Omega_{it}^l} = k_l \left\{1 - \nabla_{it} \frac{\phi(\nabla_{it})}{\Phi(\nabla_{it})} - \left[\frac{\phi(\nabla_{it})}{\Phi(\nabla_{it})}\right]^2\right\}, \quad (3)$$

where $\nabla_{it} = \mu_{it}/\sigma_u$, $E(u_{it}) = \sigma_u[\nabla_{it} + \phi(\nabla_{it})/\Phi(\nabla_{it})]$, ϕ and Φ denote the Normal density and distribution function, respectively.

Equations (1) and (2) account for two types of heterogeneity. First, unobserved heterogeneity is captured by country fixed effects α_i and there are as many estimated coefficients as countries. Second, we have heterogeneity due to different behaviors from one country to another in terms of access to and usage of ICTs. We assume that the survey data, even though it was conducted in 2007 and 2008, applies to each of the years in the sample, because it can be assumed that, over the period of time we are considering, ICT access and usage behaviors have inertia. While considering the average effect of the F_i variables on the growth rate (a single coefficient is estimated for all countries), the heterogeneity of the impact on growth is captured by the inefficiency term in the regression.

The role of institutions for economic growth has been the subject of an extensive literature since the seminal work of North (1991). They have experienced a revival of interest in the 1990s and 2000s (for a survey, see Acemoglu 2010). The reason why we consider them as variables in the inefficiency term, and not as explanatory variables of the frontier, is that growth theories consider them as background forces that can inhibit or promote growth, and not as factors of production as such. They are used primarily to exploit the potential economic benefits of technology. We give the same status to the factors summarizing access to and use of ICT. When introduced into the frontier equation, they have no significant explanatory power. They are variables that can support growth by causing the effects to reach their growth potential. On the other hand, they can have a blocking power for potential growth, if they are used in a suboptimal way.

4.2.- Results

The results of the regression can be found in Table 4. The dummies representing the nationality of the colonizing country are collinear, which leads to only one dummy being entered into the regression. We will briefly comment on the regression results, and focus on the topic of the paper, i.e. the role of access and use variables on growth efficiency gains/losses.

For the variables that define the frontier, the addition of ICT factors in the inefficiency term has several consequences. First, the positive and significant influence of investment on potential growth increases by about 31% (the coefficient increases from 0.39 to 0.51). The sign of the human capital variable becomes positive. Second, we see the importance of infrastructure constraints. The electricity access variable becomes significant when ICT factors are included in the regression. Their sign is negative. This reflects the fact that, on average in SSA countries, access to electricity has been a constraint to economic growth, which can be explained by the critical low level of electricity infrastructure and the poor quality of service provision. The regression also shows a favorable effect of imports of ICT goods and services on potential growth.

Table 4. Stochastic frontier regressions

	Without ICT usage			**With ICT usage**			**Marginal effect**	
	Coeff		z-ratio	Coeff		z-ratio	**Mean**	**St. Dev**
Frontier								
Investment	0.39	***	3.49	0.51	***	6.20	-	
Human capital	-12.45	***	-2.44	10.55	***	3.48	-	
ICT imports	1.13		1.02	5.44	***	7.04	-	
Electricity access	2.39		1.31	-4.67	***	-3.47	-	
Enrolment	-0.60		-0.72	-0.11		-0.17	-	
Fixed tel	1.80	***	3.31	-0.34		-0.82	-	
Inefficiency								
voice	9.50	***	3.04	37.02	***	2.51	4.45	9.74
corruption	-21.13	***	-4.32	7.39		0.39	0.88	1.94
english	16.80	***	2.51	-	-	-	-	-
Factor 2	-	-	-	5.82	***	2.86	0.7	1.53
Factor 3	-	-	-	0.24		0.05	-	-
Factor 4	-	-	-	13.36	***	2.68	1.61	3.52
Factor 5	-	-	-	29.47	***	2.89	3.54	7.76
Factor 6	-	-	-	23.90	***	3.25	2.87	6.29
Factor 8	-	-	-	21.42	***	2.24	2.57	5.64
Constant	-20.24	***	-2.15	-86.53	***	-3.25	-	-
σ_u	5.44	***	6.99	9.45	***	6.96		
σ_v	1.43	***	3.75	1.59	***	8.58		
λ	3.80	***	4.17	5.93	***	4.08		

Note: *** means that the variables are statistically significant at 1% level of confidence

Let us examine the role of ICT variables. The marginal effects reported in Table 4 are average effects for all countries. By applying the formula in Equation (3), we calculate the marginal effects of factors by country. Table 5 shows these calculations for the factors that are significant in the regressions. For all countries, the obtained coefficients are positive, which means that access to and use of ICT is a source of growth inefficiency. This is consistent with the idea that in SSA countries, ICTs are likely to be used in a sub-optimal way (which does not only reflect a supply-side problem - e.g. the quality of ICT infrastructure or costs - but also demand-side phenomena related to users' perception and use of the technology). But the important point in Table 5 is that inefficiencies are very important in Nigeria and Zambia. Indeed, we can see the difference in the coefficients obtained for these countries compared to the others. On the contrary, for Ghana, Namibia, Senegal and Mozambique, ICTs generate few inefficiencies in growth.

Table 5. Marginal effects for ICT factors by country

	Factor 2	**Factor 4**	**Factor 5**	**Factor 6**	**Factor 8**
Nigeria	5.66	12.99	28.67	23.24	20.84
Zambia	2.96	6.80	15.00	12.16	10.90
Cote d'Ivoire	0.74	1.69	3.72	3.02	2.70
Botswana	0.38	0.88	1.94	1.57	1.41
Burkina Faso	0.20	0.45	1.00	0.81	0.73
Benin	0.13	0.29	0.65	0.52	0.47
Ethiopia	0.10	0.24	0.52	0.43	0.38
Rwanda	0.09	0.21	0.46	0.37	0.33
Kenya	0.08	0.17	0.38	0.31	0.28
Uganda	0.06	0.14	0.32	0.26	0.23
Cameroon	0.06	0.14	0.31	0.25	0.22
Ghana	0.03	0.06	0.14	0.11	0.10
Namibia	0.01	0.03	0.07	0.05	0.05
Senegal	0.00	0.01	0.02	0.02	0.02
Mozambique	0.00	0.01	0.02	0.02	0.02

These results explain Figure 1 which shows the efficiency of growth by comparing countries. We observe that, in a majority of countries, since the inefficiencies caused to growth by ICT are low, the degree of efficiency of growth increases with their use. Indeed, the figure compares, for each country, the efficiency without ICT variables and then the situation when they are considered. For 10 of the 15 countries, the difference is positive. The very beneficial effect can be seen for Ghana and Mozambique, but also for Kenya and Uganda, where the efficiency term is almost zero when

ICT variables are not taken into account, and then increases significantly when the factors are included in the inefficiency term. In contrast, for Nigeria, Zambia, Côte d'Ivoire and Botswana, the difference in efficiency with and without the ICT variables is negative. Another striking fact is that the ICT variables increase heterogeneity in growth efficiency across countries. In the model with the ICT variables, the standard deviation of efficiency is 0.23, which is roughly double the standard deviation without these variables (0.12). We can see from the graph that with the ICT variables, some countries are close to their growth frontier with an efficiency term of more than 70% (Senegal, Namibia, Mozambique). The other countries are more than 60% away from their growth frontier. For Nigeria and Zambia, the degree of growth inefficiency is enormous (over 90%).

Figure 1. Growth Efficiency

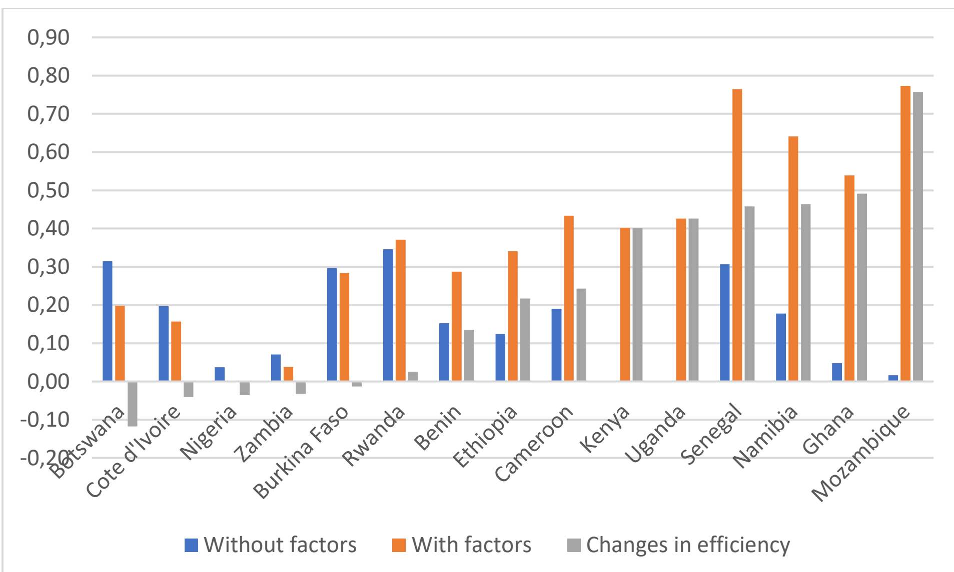
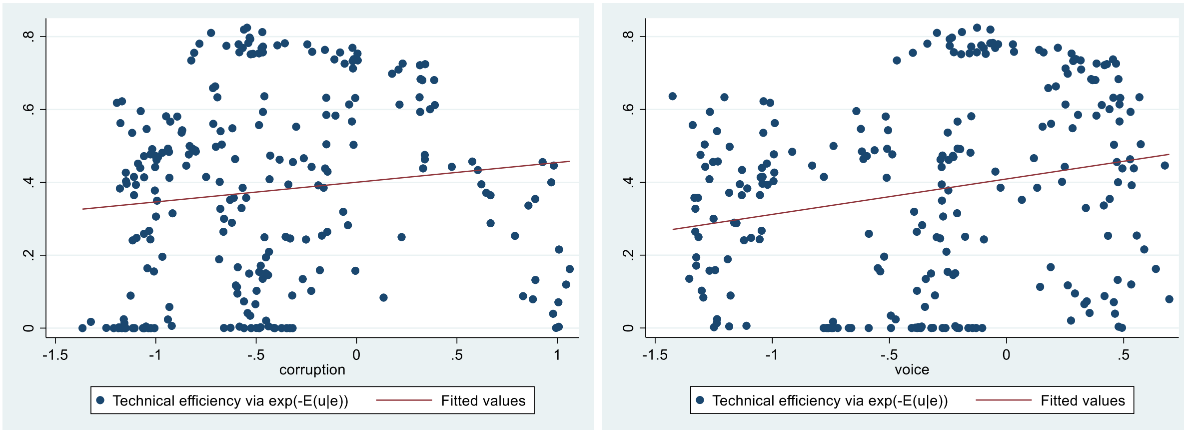


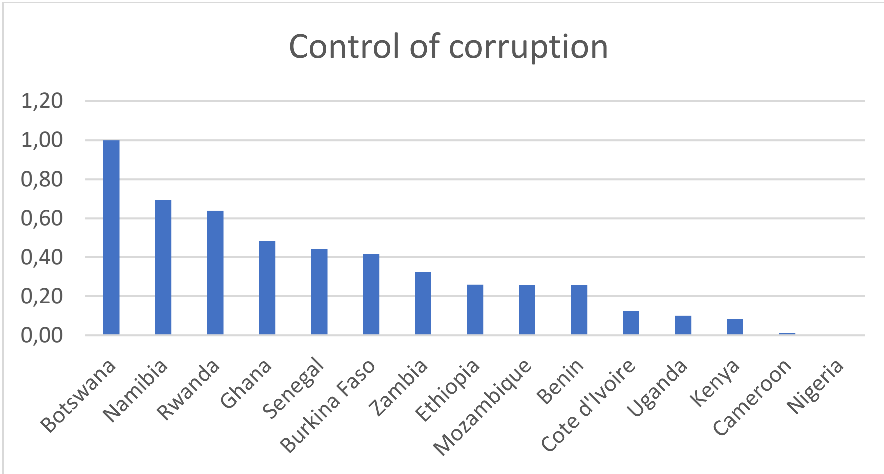
Figure 2. Scatterplot of growth efficiency versus control of corruption and voice and accountability

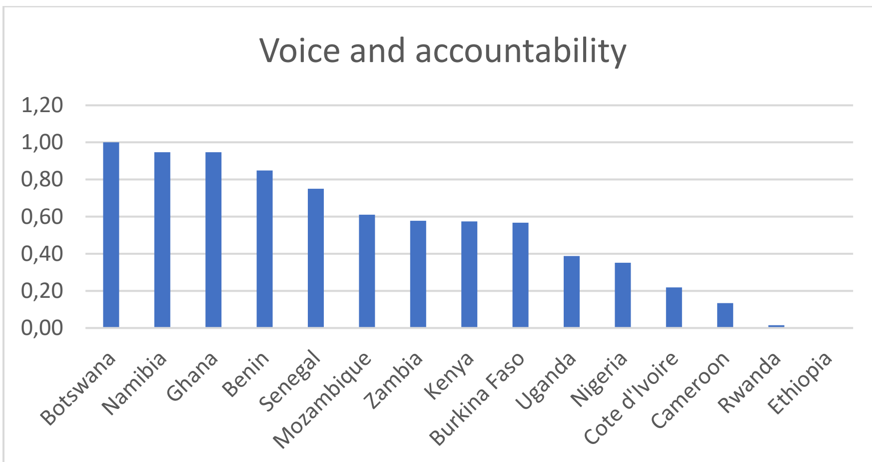


Our explanation for this heterogeneity is that the factors that handicap the beneficial effects of ICT on growth are related to the quality of institutions. Indeed, we show in Figures 2 the scatterplots representing the efficiency terms calculated using the formula in Equation 3 as a function of the two variables of control of corruption and voice and accountability. The first variable is an index. When it increases it means that anti-corruption policies are more effective. For the second variable, an increase means that citizen participation in politics is more inclusive. The figure shows a positive correlation between both variables and growth efficiency.

To understand the role of the ICT variables, we perform a counterfactual analysis. Figure 3 shows that the country with the highest ranking for both governance variables is Botswana. Suppose that all countries had the same ranking as Botswana for control of corruption and voice and accountability. Would this increase the degree of growth efficiency? Could this change be explained by a reduction in inefficiencies caused by ICT to economic growth?

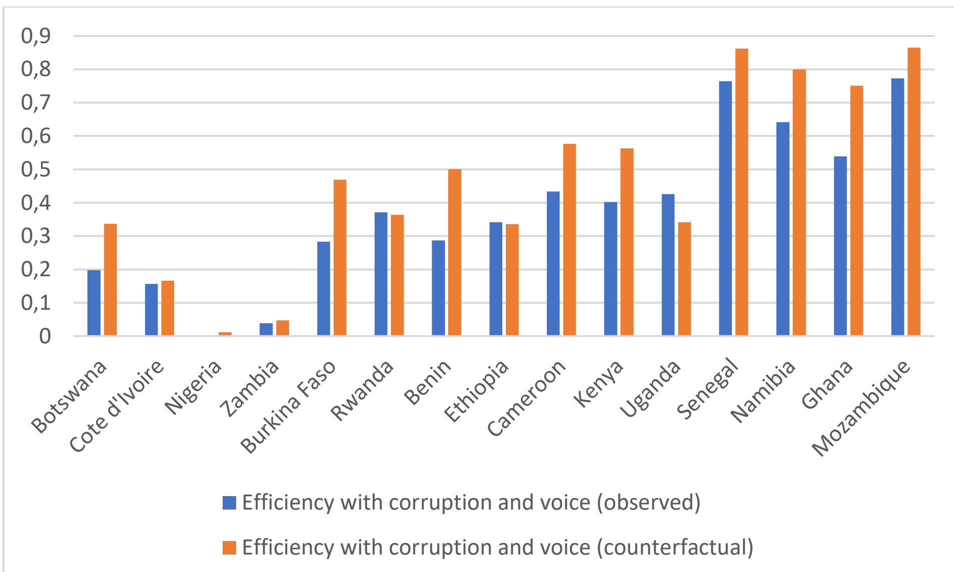
Figure 3. Ranking of countries (variables rescaled between 0 and 1)





We re-estimate the model under the counterfactual and compare the indicators of inefficiencies and changes in the marginal effects of ICT on the efficiency term. Figure 4 shows encouraging results. In a large number of countries, growth efficiency is higher under the counterfactual. This means that more inclusive policy decisions and better control of corruption reduce growth inefficiencies. Table 6 shows that such an improvement could be explained by better use of ICT. Indeed, the table shows the variation in the marginal effects of ICT on the inefficiency term. A positive sign indicates that changes in ICT increase inefficiency. On the contrary, a negative sign indicates that they decrease it. The table shows negative signs for a majority of countries. There are four exceptions: Côte d'Ivoire, Ethiopia, Rwanda and Uganda. In Figure 4, we see that these are also the countries for which we observe no difference between the efficiency calculated under the counterfactual hypothesis and the observed situation of corruption and voice accountability for these countries.

Figure 4. Comparing growth efficiency



In the case of Nigeria and Zambia, we see that, in spite of a strong improvement in the role played by ICT (Table 6), the gain in terms of growth efficiency would be very small (Figure 6). For Nigeria of Nigeria, one explanation could be that the control of corruption corresponding to the real situation of the country, shows an indicator that is very low compared to other countries.

Table 6. Changes in efficiency (counterfactual minus actual governance)

	Factor 2	Factor 4	Factor 5	Factor 6	Factor 8
Benin	**-0.07**	**-0.18**	**-0.53**	**-0.31**	**-0.21**
Botswana	**-0.18**	**-0.45**	**-0.90**	**-0.80**	**-0.46**
Burkina Faso	**-0.11**	**-0.26**	**-0.54**	**-0.46**	**-0.30**
Cameroon	**-0.02**	**-0.06**	**-0.11**	**-0.10**	**-0.04**
Cote d'Ivoire	0.05	**-0.03**	0.30	0.00	0.98
Ethiopia	0.09	0.18	0.48	0.33	0.54
Ghana	**-0.02**	**-0.04**	**-0.09**	**-0.08**	**-0.06**
Kenya	**-0.03**	**-0.08**	**-0.15**	**-0.14**	**-0.07**
Mozambique	0.00	**-0.01**	**-0.01**	**-0.01**	0.00
Namibia	**-0.01**	**-0.02**	**-0.04**	**-0.03**	**-0.02**
Nigeria	**-2.82**	**-6.97**	**-14.04**	**-12.26**	**-7.43**
Rwanda	0.07	0.13	0.35	0.24	0.41
Senegal	0.00	**-0.01**	-0.01	**-0.01**	**-0.01**
Uganda	0.14	0.28	0.71	0.51	0.71
Zambia	**-0.91**	**-2.44**	**-4.43**	**-4.23**	**-1.21**

5.- Comparing growth rates using quantile regressions

In the stochastic frontier approach, each country has its own frontier. It is interesting to compare growth performance across countries against a common denominator. Specifically, we may want to compare countries to others in the sample that appear to achieve better growth rates given their endowments in ICT and other factors.

For this purpose, we need to investigate the conditional distribution of growth (growth predicted by the ICT and internet usage variables and by the control variables). From this distribution, we will be able to find the lowest achievers (those whose growth rates are close to the lowest quantiles of the conditional distribution), the best achievers (those whose growth rates are close to the highest quantiles), the upper achievers (those who are close to the highest quantiles) and the middle achievers (those whose growth rates are close to the median). This approach is interesting because it shows that the degree of productive efficiency is a relative indicator and depends on the other countries against which a country is compared. In the OLS approach, the reference is always the country representing the conditional mean of the distribution. This is not the case here. In econometric terms, this is illustrated by the fact that the place of countries in the conditional distribution of growth rates changes according to the quantile that is chosen as the reference.

Our investigation is therefore based on two stages. Step 1 consists in estimating the conditional distributions of growth, using quantile regressions. Step 2 consists in identifying which growth rates lie next to which quantiles. This is done by computing the percentile ranks of the fitted growth rates.

5.1.- Estimating conditional quantiles of growth and percentile ranks: methodology

If we consider the growth rate Y as a random variable whose distribution function is noted F_Y, its quantile function is defined from $]0,1[$ in $\mathcal{R}$ and it associates with θ belonging to $]0,1[$, the function

$$Q_Y(\theta) = inf\{y_{it}: F_Y(y_{it}) \geq \theta\}. \qquad (3)$$

The conditional quantile function for a pair of observations (i,t) where $i = 1, \dots N$, and $t = 1 \dots, T$, refer respectively to countries and years, is defined by

$$Q_Y(\theta, y_{it}|X_{1it}, X_{2i}) = X'_{1it}\beta(\theta) + X'_{2i}\gamma(\theta) + \xi(\theta, \upsilon_{it}), \qquad (4)$$

where y_{it} is country i's growth rate at time t, X_{1it} is the vector of covariates that are time-varying within countries, X_{2i} is the vector of independent variables are time-invariant within countries - these include the ICT variables and the governance variables). $\xi(\theta, \upsilon_{it})$ is a random term, which is usually written as $\xi(\theta, \upsilon_{it}) = \lambda_i(\theta) + \varepsilon_{it}(\theta)$. λ_i is a fixed effect and ε_{it} is a random noise (both are functions of the quantile θ). β and γ are vectors of parameters that differs across quantiles. We assume that $\mathbb{E}[\xi(\theta, v_{it})|X_{1it}, X_{2i}] = 0$. Denoting with a hat estimated parameters and variables, the estimated values

$$\hat{Q}_Y(\theta, \hat{y}_{it}|X_{1it}, X_{2i}) = X'_{1it}\hat{\beta}(\theta) + X'_{2i}\hat{\gamma}(\theta) + \hat{\lambda}_i(\theta). \quad (5)$$

This function gives us a distribution of conditional growth rates estimated from the smallest quantiles (representing the lower achievers) to the largest quantiles (representing the upper achievers). Suppose we are interested in deciles, i.e $\theta = 0.1, 0.2, 0.3, \ldots, 0.9$. The $\hat{y}'_{it}s$ values estimated for the 0.9 quantile give the largest values of conditional growth rates in the sample.

The model to estimate, using a quantile regression estimator, is the following:

$$y_{it}(\theta) = X'_{1it}\beta(\theta) + X'_{2i}\gamma(\theta) + \lambda_i(\theta) + \varepsilon_{it}(\theta), \;\; i = 1, \ldots, 16, t = 1, \ldots, 16. \quad (7)$$

There are two important issues. The first concerns the fixed effect $\lambda_i(\theta)$ which is either uncorrelated (random effect model) or correlated (fixed effects models) with the independent variables. The second is related to potential endogeneity of the exogenous variables. The techniques usually used to deal with both aspects combine quantile panel regressions and instrumental variables methods and are based on different types of two-step estimators[3].

The methodology used here is close to the two-stages minimum distance estimator proposed by Melly and Pons (2021).

As a first stage, the authors propose to make an individual-level quantile regression, for each quantile θ, of y_{it} on a constant, and time-variant independent variables X_{1it}. These coefficients

[3] The literature is vast. The interested reader can refer to Canay (2011), Chernozhukov and Hansen (2005), Chetverikov et al. (2016), Dai and Jin (2021), Galvao and Wang (2015), Galvao and Kato (2016), Galvao et al. (2020), Gu and Volgashev (2019), Kato et al. (2012), Galvao and Poirier (2019), Ma and Koenker (2016), Melly and Pons (2021).

capture unobserved heterogeneity in the panel. The difficulty here in capturing unobserved heterogeneity is that the time dimension within countries is small (16 years). We therefore consider the pooled data and add individual dummies in the regression of the first step. We therefore apply the following quantile estimator[4]:

$$\tilde{B}(\theta) = \left(\tilde{\lambda}(\theta), \tilde{\beta}(\theta)\right) = \underset{\lambda(\theta),\beta(\theta)}{\operatorname{argmin}} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \zeta_\theta\{\varepsilon_{it}(\theta)\}, \qquad (8)$$

where

$\varepsilon_{it}(\theta) = y_{it}(\theta) - X'_{1it}\beta(\theta) - \sum_{i=1}^{N} \lambda_i D_{it}$,

D_i is a dummy vector which equals 1 for country i and 0 otherwise,

$\zeta_\theta(x) = [\theta - \mathbb{I}(x < 0)]x$ is the check function,

$\lambda(\theta) = \left(\lambda_1(\theta), \lambda_2(\theta), \dots, \lambda_N(\theta)\right)'$.

Equation (8) is equivalent to minimizing the absolute weighted residuals where positive and negative residuals are weighted respectively by $1 - \theta$ and θ:

$$\begin{aligned}\tilde{B}(\theta) = arg \min_{\lambda(\theta),\beta(\theta)} & \frac{1}{NT} \sum_{i \in [i:\varepsilon_{it}(\theta) \geq 0]}^{N} \sum_{t \in [t:\varepsilon_{it}(\theta) \geq 0]}^{T} \theta |\varepsilon_{it}(\theta)| \\ & + \frac{1}{NT} \sum_{i \in [i:\varepsilon_{it}(\theta) \geq 0]}^{N} \sum_{t \in [t:\varepsilon_{it}(\theta) < 0]}^{T} (1-\theta) |\varepsilon_{it}(\theta)|\end{aligned} \qquad (9)$$

In the second stage, we apply an instrumental variable limited information maximum likelihood estimator (IV-LIML) to account for potential endogeneity of the regressors. To do so, let us consider the fitted values of the regression (8) for a given quantile θ:

$$\tilde{y}_{it}(\theta) = X'_{1it}\tilde{\beta}(\theta) + \tilde{\lambda}(\theta), \quad i = 1, \dots, 16, t = 1, \dots, 16. \qquad (10)$$

[4] In the first stage, we apply the standard Basset and Koenker (1978)'s estimator.

We use a IV-LIML estimator of $\tilde{y}_{it}(\theta)$ on X_{1it} and X_{2i}. We then compute the fitted values of $y_{it}(\theta)$ as follows:

$$\hat{y}_{it}(\theta) = X'_{1it}\hat{\beta}_{2SLS}(\theta) + X'_{2i}\hat{\gamma}_{2SLS}(\theta), \quad i = 1, \ldots, 16, t = 1, \ldots, 16. \tag{11}$$

The choice of the instruments determines the estimator being used:

•if the instruments are $\dot{X}_{1it} = X_{1it} - \bar{X}_{1it}$, with $\bar{X}_{1it} = \frac{1}{T}\sum_{t=1}^{T} X_{1it}$, then we get the within estimator,

•if the instruments are $\bar{X}_{1it}$ and X_{2i}, then we get the Between estimator,

•if the instruments are $\dot{X}_{1it}$, $\bar{X}_{1it}$ and X_{2i}, then we get the 3SLS estimator,

•if the instruments are $\dot{X}_{1it}$, X_{2i}, and potential external instruments, with the standard errors of the estimates clustered at the level of the countries, then we get the Haussman-Taylor estimator.

Due to avoid collinearity problems, we consider a Hausman-Taylor type estimator. We use clustered standard errors (by country) to obtain robust variances of the estimates.

Using $\hat{y}_{it}(\theta)$, we can calculate, for each θ, the rank percentile of countries. To see how well a country performs in comparison to others we proceed as follows. First, rank percentiles are computed for the observations of $\hat{y}_{it}(\theta)$ for $i = 1, \ldots, N$ and $t = 1, \ldots, T$. Then, we compute a time average for each country of the percentile ranks. This tells us, on average over all years, what the percentile rank of a given country is.

5.2.- Empirical implications of quantile regressions

The results of the two-step quantile regressions are shown in the Appendix (Table A1). Though we show them for sake of completeness, they are not interpretable per se, but we use the estimate to derive several important features. We consider the following quantiles: $\theta = 0.3$ (lower achievers), $\theta = 0.5$ (middle achievers), $\theta = 0.7$ (upper achievers), $\theta = 0.9$ (highest achievers). From these regressions, we plot countries rank percentiles (Figure 5).

For each country, we represent its minimum, average and maximum percentile rank. The average rank is shown by a red cross. The red horizontal lines represent the quantiles for which the fitted values of the growth rates have been estimated. The lines connecting the crosses for each country show the distance between the maximum percentile rank and the minimum rank. The closer a country to the red line the more it belongs to a given category of growth performance (lowest achiever, middle achiever, upper achiever, best achiever). These graphs clearly show that the location of a country depends on the position of the others in the conditional distributions (because the latter are not fixed, but change with the quantile at which they are estimated). The case of Côte d'Ivoire is illustrative. Indeed, we see that this country "moves" with the estimated quantiles, since its average percentile rank allows it to be classified as middle, upper or best achiever. This means that, putting aside the lowest achievers, Côte d'Ivoire is the country whose growth performance is closest to that of the countries as a whole. Benin's growth performance is close to the lowest and middle achievers overall.

We also observe some countries that are too far from the overall set of countries, so that it is difficult to categorize them (it is difficult to compare their growth performance with that of others). This is the case for Mozambique and Senegal, whose percentile ranks are far from the red bars, whatever the quantile considered. For instance, in the case of Mozambique, we see that when the reference country groups are the lowest or middle achievers, this country has a high percentile rank, which suggests that it is located far from these two groups and thus could be categorized as an upper achiever. But when the upper or best achiever groups are chosen as the reference group, Mozambique's percentile rank drops.

Interpreting the case of Senegal is a slightly simpler since thought this country "moves" with the reference quantiles, it would be, at best, classified in the group of middle achievers Indeed, this is the highest position in its average percentile rank.

For the other countries, we identify their performance group more clearly. Benin and Namibia are among the lowest or middle achievers; Cameroon and Ghana are both the lowest achievers; Nigeria and Rwanda are in the group upper achievers. Some countries can be classified as best achievers, in the sense that they have systematically a high percentile rank: Zambia, Rwanda, and Côte d'Ivoire as we have seen.

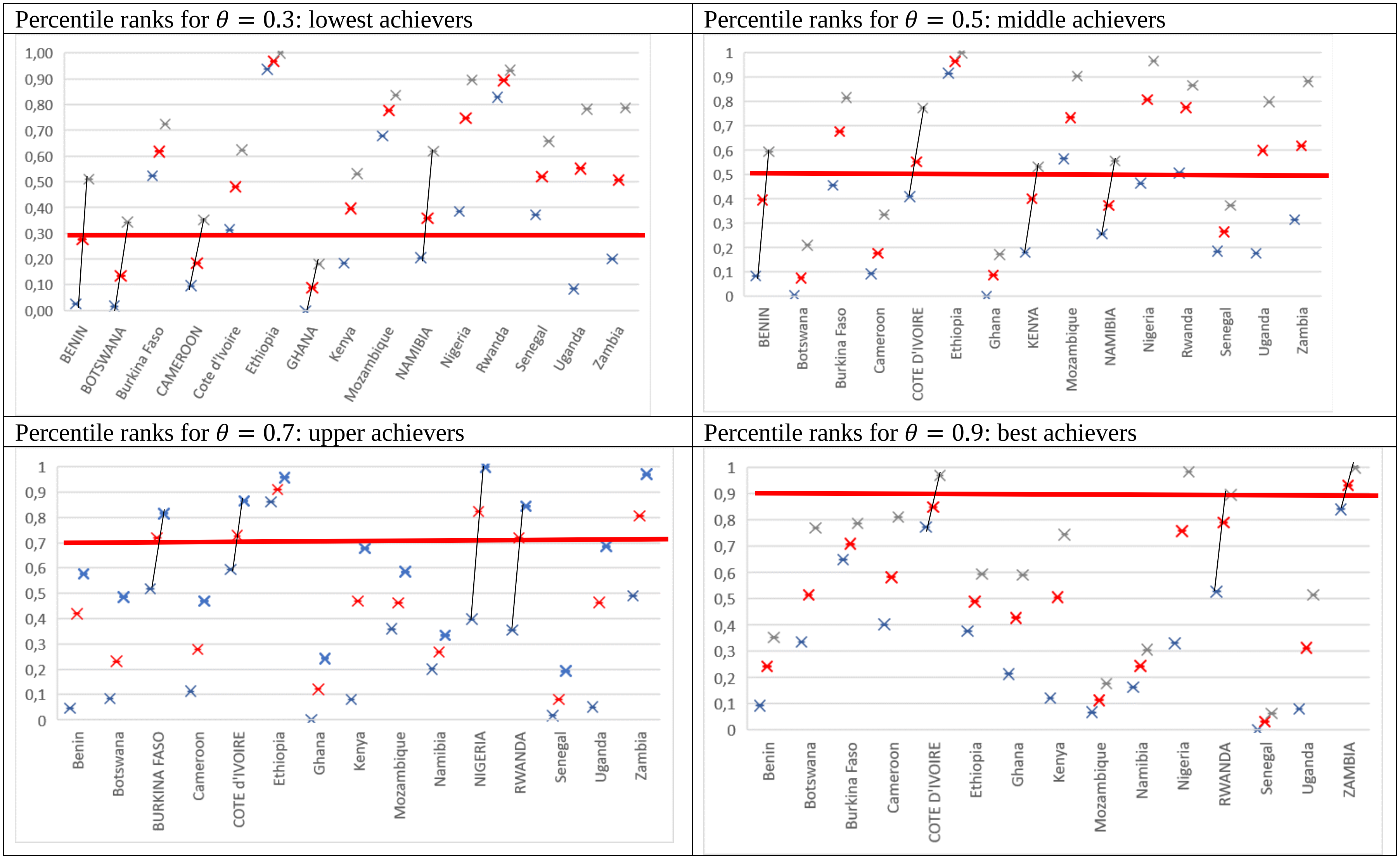
Based on these observations, we have the following classification of countries in terms of growth performance

Table 7. Classification of countries based on rank-percentiles from quantile regression

	Countries	% sample GDP
Lowest achievers	Benin, Botswana, Cameroon, Ghana, Namibia	58.77
Middle achievers	Benin, Côte d'Ivoire, Kenya, Namibia, Senegal	39.53
Upper achievers	Burkina Faso, Côte d'Ivoire, Nigeria, Rwanda	20.24
Best achievers	Rwanda, Zambia	8.48

Note: the sum in the last columns is greater than 100% because some countries belong to several categories

Figure 5. Countries' percentile ranks for different quantiles



To compare countries and measure the contributions of ICT usage to differences in growth rates, we need to perform the following exercise.

Denote $Z_{it} = (X_{1it}, X_{2i})$ and $\hat{\delta}(\theta) = \left(\hat{\beta}(\theta), \hat{\gamma}(\theta)\right)$. The following quantity represents the difference between the growth rate of best achievers at time t and the growth rate of any country close to a percentile θ at the same date:

$$d_{it}(\theta) = Z'_{it}(0.9)\,\hat{\delta}(0.9) - Z'_{it}(\theta)\,\hat{\delta}(\theta), \quad i = 1, \ldots, 16, t = 1, \ldots, 16. \qquad (12)$$

We consider $Z_{it}(\theta)$ as being specific to countries whose fitted growth rates belong to the θ^{th} quantile. $Z'_{it}(0.9)\,\hat{\delta}(0.9)$ is a vector representing the observations of fitted growth rates if all the countries in the sample were best achievers. Similarly, $Z'_{it}(\theta)\,\hat{\delta}(\theta)$ is the vector of observations of fitted growth rates if all the countries were in the θ^{th} quantile. This means that $d_{it}(\theta)$ has the same observations for all countries.

Adding and subtracting $Z'_{1it}(0.9)\,\hat{\delta}(\theta)$, we get

$$d_{it}(\theta) = Z'_{it}(0.9)\left[\hat{\delta}(0.9) - \hat{\delta}(\theta)\right] + [Z'_{it}(0.9)] - Z'_{it}(\theta)\,\hat{\delta}(\theta). \qquad (13)$$

We can compute the time average (denoted $d_{i.}(\theta)$) of each $d_{it}(\theta)$. We obtain a vector of identical elements. Let us note $d_{.}(\theta)$ an element of the vector. Equation (13) implies

$$d_{.}(\theta) = \underbrace{Z'_{.}(0.9)\left[\hat{\delta}(0.9) - \hat{\delta}(\theta)\right]}_{a(\theta)} + \underbrace{[Z'_{.}(0.9) - Z'_{.}(\theta)]\,\hat{\delta}(\theta)}_{b(\theta)} \qquad (14)$$

$b(\theta)$ measures the average impact of between-quantile differences in factor endowments on the difference of growth rates productivity. It tells us that countries located at the θ^{th} quantile have a lower growth rate than the best achievers, because their fundamentals (determinants of growth) are different from those of the best achievers. $a(\theta)$ tells us that, if the highest achievers' fundamentals would apply to the other countries located at lower quantiles, growth gaps would come from the fact that the latter "under-performed" when using their fundamentals to reach a certain growth rate. We therefore have two sources of gaps: "endowment gap" (captured by $B(\theta)$) and "behavioral gap" (captured by $A(\theta)$).

Using Equation (14), we can isolate the specific contribution of ICT variables – as captured by the factors – as follows:

$$d_{.}(\theta) = \underbrace{X'_{1.}(0.9)\left[\hat{\beta}(0.9) - \hat{\beta}(\theta)\right]}_{a_{NICT}(\theta)} + \underbrace{[X'_{1.}(0.9) - X'_{1.}(\theta)]\,\hat{\beta}(\theta)}_{b_{NICT}(\theta)} + \underbrace{X'_{2.}(0.9)\,[\hat{\gamma}(0.9) - \hat{\gamma}(\theta)]}_{a_{ICT}(\theta)} + \underbrace{[X'_{2.}(0.9) - X'_{2.}(\theta)]\,\hat{\gamma}(\theta)}_{b_{ICT}(\theta)} \quad (15)$$

To compute the different elements of $d_{.}(\theta)$, we consider the average of countries in each category to compute $X'_{1.}$ and $X'_{2.}$ For instance, to compute $X'_{1.}(0.9)$, we first take the average of the variables in $X'_{1it}(0.9)$ for Côte d'Ivoire, Rwanda and Zambia. And then, from the resulting vector, we compute $X'_{1.}$ as explained above. We proceed similarly for the other quantile θ. For $\theta = 0.5$, we take the average of Benin, Botswana, Cameroon, Ghana and Namibia. And so forth.

To account for differences in the weight of countries in terms of GDP, the averages are assigned a coefficient that represents the share of GDP of the countries classified in a given group, compared to the total GDP of the countries in the sample. This avoids distortionary effects.

Table 8 shows the decomposition.

Table 8. Decomposition of conditional growth gap

	Lowest achievers $\theta = 0.3$	Middle achievers $\theta = 0.5$	Upper achievers $\theta = 0.7$
Difference of conditional growth from the best achievers: $d_{,}(\theta)$	9.27%	5.19%	1.09%
Decomposition			
1.- Non-ICT factors	8.14%	3.91%	1.29%
- Behavioural gap: $a_{NICT}(\theta)$	1.44%	1.48%	2.04%
- Endowment gap: $b_{NICT}(\theta)$	6.70%	2.43%	-0.74%
2.- ICT factors	1.13%	1.28%	-0.20%
- Behavioural gap: $a_{ICT}(\theta)$	-0.22%	-0.10%	0.05%
- Endowment gap : $b_{ICT}(\theta)$	1.35%	1.38%	-0.25%

The table shows several interesting features. First, we observe that the (conditional) growth differential decreases as the quantiles increase, which means that the growth performance gaps are smaller between the best achievers and the countries that are closer to them in the conditional growth distribution. The figures show that the degrees of growth inefficiencies-if we interpret distance in this way-have effects that are not linear. There is "only" a 1.3% growth differential between the best achievers and the uppers achievers. This figure increases to about 4% for the middle achievers, and then doubles for the lowest achievers.

Regardless of the classification of countries into different quantiles, these differences can be explained primarily by non-ICT factors, and secondarily by ICT factors. For the lowest achievers, 88% of the distance to the best achievers is explained by non-ICT factors (88%, i.e. 8.14% divided by 9.27%). For the middle achievers, it is 75% (i.e. 3.91% divided by 5.19). And for upper achievers, the figure is 118% because ICT factors have a negative contribution. For the non-ICT factors, it is the differences in factor endowments that explain the inefficiencies of growth for the lowest and middle achievers, more than behavioural factors (i.e. more than the fact that the factors of growth are combined in an inefficient way). For the upper achievers, the phenomenon is reversed. If only behavioural factors were considered (i.e. the ability to combine non-ICT growth factors), these countries would have conditional growth rates above that of the best achievers (this is shown by the negative sign -0.74%). The difference with the best achievers can then be explained solely by differences in factor endowments.

Let us now interpret the contribution of the ICT factors. The first important feature is the negative number we find for the upper achievers. Thanks to ICT, all other things being equal, countries in this category can hope to outperform the conditional growth rates of the best achievers (the contribution of ICT factors is -0.20%), by equipping themselves more (see the contribution of the endowment gap which is -0.25%). This means that when a country is sufficiently close to those at the growth "frontier", it become easier to surpass their growth rate by equipping itself with ICT. A second interesting result is that, all else being equal, for the lowest and middle achievers, any improvement in the ability to combine ICT factors would allow them to have higher growth performance than the best achievers (the behavioural gap is negative at -0.22% and -0.10% respectively), but this does not occur because of the weakness of their factor endowment in ICT compared to the best achievers (we find respective figures of 1.13% and 1.28%).

The results of the quantile regressions are not very surprising. Indeed, the fact that the differences in relative growth rate performance are explained by non-ICT factors is understandable insofar as all the countries in the sample are developing countries, a large number of them low-income countries. For this category of countries, the factors of growth are first and foremost the usual fundamentals of growth, i.e. the rate of growth of investment, the stock of human capital, the existence of basic infrastructure (such as access to electricity), or school enrolment rates. Factor productivity still depends too little on ICT for these factors to play a predominant role in conditional growth.

6.- Conclusion

In this paper, we propose two original methods to assess the effects of ICT use and access by African countries to improve their effectiveness in generating economic growth. Using survey data from 15 representative African countries, we reach two conclusions.

First, if we measure efficiency by comparing the growth rate of countries to the highest growth rate they could achieve, then we can answer in the affirmative. Not only does the use of and access to ICT improve growth performance. But, this result is valid if a country also improves its governance indicators (e.g., the effectiveness of anti-corruption policies, or whether civil society has a voice in decision-making). This result is achieved by adapting the stochastic frontier method to the analysis of the determinants of economic growth.

Secondly, if, instead of taking the growth frontier of each country as a reference for comparing their degree of efficiency, we compare them with each other by considering as best performers the countries with the highest conditional growth rates (best achievers), the conclusion is different. The ICT factors explain the relative positions of the conditional growth rates of the countries compared to the best achievers only in a secondary way. Non-ICT factors matter more.

A classification of countries can be obtained by inverting the estimated quantile functions and deriving percentile ranks.

Though our results are interesting, our analysis has a limitation. It comes from the weakness of the temporal and individual dimensions (which are imposed here by the availability of data). They concern only about 15 countries. But this is compensated by the fact that the variables capturing information on ICT use and access are very numerous (more than a hundred). The researcher must therefore arbitrate between increasing the number of years and the number of countries, by making do with very aggregated data that are few in number (classically the number of fixed telephone subscribers, the number of people with a mobile telephone and the percentage of a population using the Internet). Alternatively, micro-level data can be derived from survey data, but with the disadvantage of covering a smaller amount of data due to survey costs. The second limitation

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Appendix

Table A1. Two-step quantile regression results

	$\theta = 0.3$		$\theta = 0.5$		$\theta = 0.7$		$\theta = 0.9$	
	Coeff	sde.	Coeff	sde.	Coeff	sde	Coeff	sde
Investment	3.33***	0.056	5.39***	0.063	4.02***	0.067	3.2***	0.04
Human capital	-16.24***	0.034	-12.13***	0.037	-11.78***	0.04	-2.48***	0.030
ICT imports	5.04***	0.011	3.95***	0.013	2.51***	0.014	2.89***	0.009
Electricity access	0.35***	0.037	-1.86***	0.041	-0.84***	0.045	-2.13***	0.029
Enrolment	1.52***	0.014	1.57***	0.016	0.65***	0.018	0-.09***	0.01
Fixed tel.	0.84***	0.009	0.62***	0.011	1.81***	0.012	1.91***	0.007
Voice	1.48***	0.014	3.41***	0.016	4.05***	0.016	2.83***	0.009
Corruption	0.42***	0.019	-2.49***	0.022	-2.01***	0.024	-0.50***	0.015
Factor 2	-0.49***	0.1455	-0.35***	0.10	-0.29**	0.116	0.019	0.206
Factor 3	-0.94***	0.250	-0.48**	0.20	-0.747***	0.127	-0.105	0.2602
Factor 4	-0.27	0.32	-0.35	0.24	.0762	0.153	0.524	0.371
Factor 5	1.01**	0.43	0.95***	0.33	1.20***	0.184	0.84***	0.32
Factor 6	0.58***	0.20	0.72***	0.16	1.25***	0.15	1.61***	0.447
Factor 8	0.44	0.455	0.49	0.39	0.62***	0.208	0.21	0.448
Year	0.01***	0.0004	0.011***	0.0003	0.01***	0.0002	0.008***	.0006

Note: **,*** mean that the coefficient are statistically significant at 5%, 1% level of confidence.

sde : standard deviation error