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Does digitalization promote net job creation? Empirical evidence from WAEMU countries

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ABSTRACT

This article aims to study the impact of the adoption of Information and Communication Technologies (ICTs) in terms of net job creation, from the countries of the West Africa Economic and Monetary Union (WAEMU). In other words, do ICTs create more than they destroy jobs? To answer this question, this study focuses on a panel data econometrics technique covering the period from 2000 to 2017. The results indicate that ICT destroys 0.03% of low and medium-skilled jobs on the one hand and driving demand and creating 0.05% of high-skilled jobs on the other hand. The total effect of ICT on jobs is therefore positive and concludes in net creation. We therefore suggest to the leaders of concerned countries to accentuate policies to match training and employment with particular emphasis on training in electronics, telecommunications and especially digitalization.

1. Introduction

Once considered as an exogenous variable comparable to a manna fallen from the sky (Schumpeter, 1913), Information and Communication Technologies (ICTs) have gradually become essential in the production system (Acemoglu & Restrepo, 2019b; Antonelli, 2009; Baldwin et al., 2003; Cariolle et al., 2019; Cette et al., 2004; Heckel, 2006; Kossaï et al., 2010). Their adoption and dissemination have experienced significant growth in recent years. In 2018 for example, apart from the rate of fixed-telephone subscribers which is idling (around 12.4%), the rate of mobile telephony and Internet subscriptions worldwide stood at 107.0% and 57.8%, respectively (IUT, 2019). These statistics will experience an unprecedented increase over years to come for the whole world is more convinced of their importance in the daily experience especially, and because of the high demand on these technologies in solving the global health crisis caused by the coronavirus. In fact, since the start of the Covid-19 pandemic, a large proportion of daily activities have been carried out through digital channels (televisions, telephones, computers, etc. with a strong demand for Internet access). Thus, online transactions operations; online courses, meetings and seminars (webinars or videoconferences) have soared. This situation further imposes ICTs in the production, distribution and even consumption process.

However, the adoption and use of ICTs cause persistent problems of human capital, the existence of telecommunications

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infrastructure and problems of regulating telecommunications markets (Akue-Kpakpo, 2013). Indeed, the technological revolution and especially the advanced digitization of our economies raises the fear of technological unemployment. That is to say, the use of new production techniques, particularly numerical controlled machine tools, the robots, trams, fully digital banks, online services, adoption of integrated management systems (GIS), etc. induce major upheavals in the job market (Cariolle, 2018; Hjort & Poulsen, 2019; Mercier, 2007). This market is becoming more and more polarized towards skilled jobs (Acemoglu & Restrepo, 2019a; Autor et al., 2006). Because, individuals, organizations and even nations are all aware that a high level of knowledge and skill is essential for their security and success. Thus, the digital revolution favors capital over labor and skilled labor over unskilled labor (Jorgenson, 2001; Quah, 2001; Youssef & M'Henni, 2004; Nomaler & Verspagen, 2020; Baek et al., 2020). This leads to the loss of some unskilled jobs (those not having the ability to use ICT tools) and a strong demand for skilled jobs (IT specialists, engineers, system analysts, programmers, telecom engineers, etc.). As a result, the job market in highly digitalized countries was disrupted very early on (Bartoloni & Baussola, 2020). In the United States (USA) for example, there were 70% of new positions in the year 2000. We also note that 47% of total jobs in the USA; 35% in the UK; 42% in France; 49% in Japan and 54% in the European Union are undergoing gradual automation. These studies have also shown that since 1980 employment growth has been stronger in new occupations (Frey & Osborne, 2017).

In Africa, task automation is still in an embryonic stage due to the low level of ICT development. Indeed, according to the International Telecommunications Union (ITU) report, the most digitized nation in Africa (Mauritius) ranks 49th globally. Likewise, while the ICT Development Index (IDI) in developed and emerging countries is estimated at 7%, Africa has an average rate of 2.64% or about half of the world average which is equivalent to 5.11% (IUT, 2019). It follows then that reducing the digital divide between the most connected countries and those less connected still remains a very important issue (Asongu et al., 2020). In 2017, the gap between the countries with the highest indices and those with the lowest indices widened and reached 8.02 points out of 10 because, the growth rate of the IDI is 0.15% in LDCs compared to 0.22% in developing countries (IUT, 2019). This shows that the digital revolution is slower in LDCs and in Africa in particular. In the WAEMU, on the other hand, since 1990, countries have been gradually adopting and disseminating ICTs (see A1 and A2). Even though these technologies are limited to posts and telecommunications, their use has upset the way all sectors of activity operate. There are thus changes in the field of finance; trade; tourism; crafts; the method of teaching; agriculture; etc. (Goujon & Cariolle, 2019; Wamboye et al., 2015). However, the expected effects of these technologies on growth and employment are slow to materialize and benefit all populations. This is due in particular to the glaring lack of qualified human resources for ICT. As can be seen from the following graph, highly skilled jobs exist in very insignificant numbers in WAEMU (see Fig. 1).

The number of employed people with a very high level of professional qualification is very low (3.47%) while those with a low level of professional qualification are very high (67.34%). There is evidence that the human capital of sub-Saharan African countries is inferior in quantity and quality to that of economically advanced countries (Kigotho, 2014). This is why, while the productivity of the labor factor is gradually decreasing in developed countries, the WAEMU countries are experiencing an increase (see Fig. 2).

The declining trend in labor input productivity in other economic regions means that the production process in these regions is increasingly digitalized and therefore requires more machines than men. At the same time, low-income countries like those in the WAEMU still exhibit relatively high labor factor productivity. This is justified by a weak computerization of tasks and overall by a weak structural transformation of their economies. Taken together, these facts corroborate the extent of the digital divide between WAEMU and high-income countries.

Based on these stylized facts, which clearly show the specificity of the WAEMU countries in the adoption and diffusion of ICTs, it seems necessary to analyze the effects of ICTs on jobs and professional qualifications. In other words, do ICTs create more jobs than they destroy? Thus, the relationship between ICT and human capital has particularly attracted our attention because of the fact that the WAEMU countries adopt these technologies on a massive scale without first having a highly qualified workforce in the digital sector while studies that have been carried out showed that the adoption of ICT requires a high level of professional qualification. This paper therefore aims to investigate the effects of ICT on jobs and professional qualifications. The paper pursues two interests. First, it extends the debates raised by Solow's productivity paradox[1] by showing the effects of technical progress on labor. Second, the paper experiences the concerns raised by the "capital deepening" mechanism[2] and that of the "creation/destruction" effect in the specific case of the WAEMU countries.

The rest of this article is organized around four sections. The first presents a synthesis of studies that have analyzed the relationships between ICT and jobs. The second provides details on the methodology and data used. The third section presents and analyzes the results of the econometric estimates. Finally, the fourth and last section concludes and presents the implications of economic policies.

2. Literature review

The literature on the link between ICT and employment is very diverse. It is evoked by work that focuses on the link between human capital and ICTs, work on the main determinants of ICT adoption and also work on the creation/destruction effects induced by the advent of ICTs.

[1] Computers are seen everywhere except in statistics. It also refers to the coexistence of an acceleration in technical progress and a slowdown in growth.

[2] It refers to the relative increase in the share of capital compared to labor in the use of inputs, where ICTs are viewed as biased technologies. Because, they lead to favoring capital over labor and skilled labor over unskilled labor (Jorgenson, 2001; Quah, 2001).

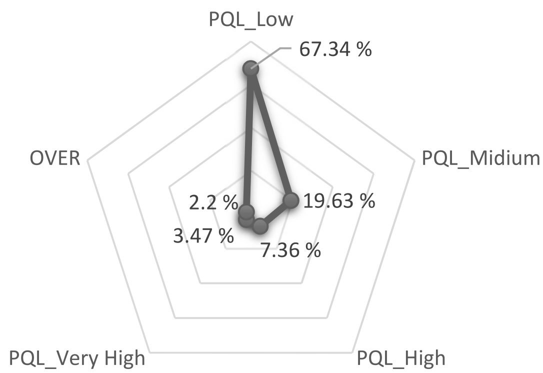


Fig. 1. Jobs by level of professional qualification in WAEMU. Source. Our calculations based on data from ILOstat and PWT, 2020

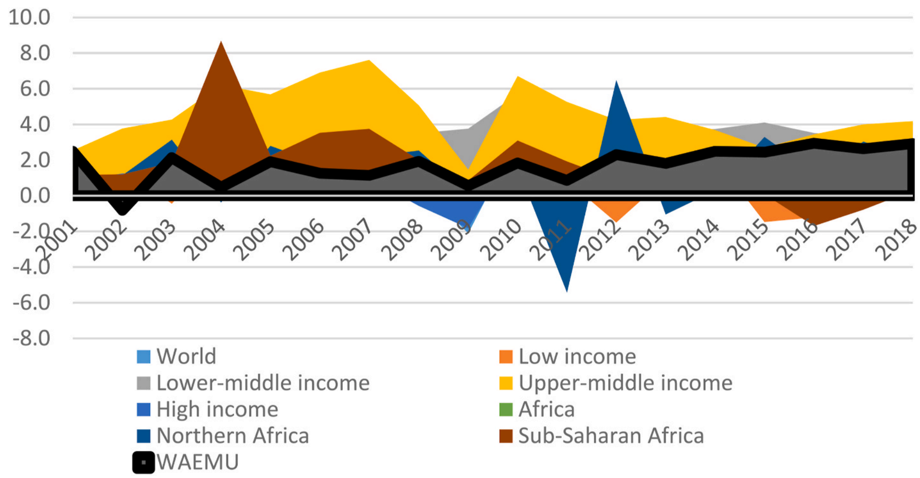


Fig. 2. The evolution of labor productivity by major economic region.
Source. ILOstat, 2020

2.1. Link between level of professional qualification and degree of ICT adoption

The adoption of ICT is positively correlated with the skill levels of individuals, firms and countries (Altinok, 2007; Freeman & Soete, 2009; Heckel, 2006). Indeed, the information society demands knowledge, skills, training, education and learning as essential complementary assets (Freeman & Soete, 1997). Thus, following the pioneering article by Nelson et Phelps (1966), an abundant empirical literature has developed analyzing the relationship between human capital and the adoption of new technologies at both the macroeconomic and microeconomic levels. Despite the methodological diversity of these different studies, the vast majority show that a better level of human capital is necessary for the adoption of ICTs (Acemoglu & Restrepo, 2019b; Ben Khalifa, 2010; Bessen, 2017; Bobillier-Chaumon & Dubois, 2009; De la Fuente & Ciccone, 2002; Doms et al., 1997; Valenduc & Vendramin, 2019). These studies have therefore identified the level of professional qualification of the manager and employees, the size of the firm and research and development predispositions as the main determinants of the adoption of ICT. As we could see, the first of these determinants is human capital. How and by what mechanism does human capital determine the adoption of ICT?

First, the adoption of new technologies is strongly influenced by the level of professional qualification of the entrepreneur (Dosi, 1993; Lal, 1998; Utterback & Suárez, 1993). Indeed, the acquisition, deployment and use of new technologies require qualified leaders that is to say with a high professional qualification. Because, for Earl (1989) et Brown (1992) knowledge of the potential of new technologies is the main factor influencing their adoption. As a result, the entrepreneur likely to recognize the essentiality of digital technologies in the production process is one who has a high level of qualification (Kossaï et al., 2010).

Second, the technologies adopted by the leader must be accepted and used by the employees. They must therefore also have a certain capacity for appropriation and use of said technologies. Thus, several studies have shown that companies with a large share of skilled labor are characterized by a high level of ICT. In other words, a workforce with high-level professional qualification is needed to facilitate the adoption of new technologies. Specifically, Dunne and Troske (2004) showed from American data that there is a positive and significant correlation between computerization and the share of skilled labor. The same study was carried out with French data by Mairesse et al. (2000). These show a significant and positive correlation between variation in the share of skilled labor and the level of

ICT within French companies. Very recent studies like those of Reshef and Toubal (2017); Cirera and Sabetti (2019); Crespi et al. (2019); Hou et al. (2019); Hjort and Poulsen (2019); Woltjer et al. (2019); Acemoglu and Restrepo (2019b) have also shown the importance of high professional qualification in ICT adoption.

Thus, the advent of ICT is leading to a strong demand for a skilled workforce, very well trained and willing to adapt to technological developments. What then happens as soon as these technologies are adopted? Are they destroying jobs or creating more?

2.2. The net effects of ICT on jobs

Most studies of the effects of adoption and use of ICTs have shown that they have controversial effects on jobs. They generate two significantly opposite effects: positive effects and negative effects (Acemoglu & Restrepo, 2019a; Asongu, 2015; Cariolle, 2018; Peña-Casas et al., 2018). Indeed, the adoption of ICTs leads to a polarization of the labor market, by increasing the demand for skilled workers at the expense of less skilled workers. This hypothesis has been verified in several empirical cases. Autor et al. (2006); Michaels et al. (2014); Crespi et al. (2019); Cirera and Sabetti (2019) tested it using data from Japan, the United States, and European countries. Their studies show that firms with high growth in ICT capital have shifted from a demand for medium-skilled workers to a demand for highly skilled workers. These are also the results of Akerman et al. (2015); Valenduc and Vendramin (2019) who analyzed the effect of broadband on productivity and employment in a wide range of developed and developing countries. For them, high-speed internet improves the productivity and employment of skilled workers and deteriorates that of unskilled workers. It is therefore complementary to qualified work and participates in the performance of their tasks. While conversely, it is a substitute for unskilled labor, replacing unskilled workers in certain tasks. New technologies can therefore destroy jobs if they aim to substitute capital for labor and increase its productivity (Greenan, 1996).

Despite the low level of human capital in African countries, the empirical cases carried out on the link between ICT and jobs give results in accordance with the literature. Indeed, the work of Wamboye et al. (2016); Cariolle (2018); Hjort and Poulsen (2016); Hjort and Poulsen (2019) confirm the hypothesis of polarization of the labor market and that of increasing employee productivity. Specifically, on a sample of 43 countries in Sub-Saharan Africa (SSA), Wamboye et al. (2016) show that the development of fixed and mobile phones stimulates productivity growth in a process of increasing returns, confirming the existence of a network effect. Likewise, Hjort and Poulsen studied the impact of the improvement of high-speed Internet on jobs by looking at the deployment of submarine telecommunication cables on a sample nearly 600,000 companies in 12 SSA countries. They find as the main result that the probability of employment of an individual following the arrival of broadband increases between 6.9% and 13.2% depending on the African country studied (Hjort and Poulsen, 2016, 2019).

The synthesis of the literature on the net effect can be drawn from the model of Acemoglu and Restrepo (2019b). These indicate that the adoption of a new technology induces a two-headed innovation: the automation of certain existing tasks and the creation of new ones. The automation of some of the existing tasks would have the consequences of reducing the share, productivity and wages of unskilled labor, while the creation of new tasks would increase the share, productivity and wages of qualified labor. De facto, if in the short term new technologies increase unemployment and increase economic inequalities, the adaptation of the skills of the workforce to the needs of this new technology suggests a positive impact on employment in the long term (Acemoglu and Restrepo, 2016, 2019a, 2019b). These conclusions are consistent with Hjort and Poulsen's caricature of the specific case of SSA countries (see Fig. 3).

This graph therefore sufficiently shows the effect of job polarization following the adoption of new technology. In the short term, jobs with high professional qualifications will be solicited and promoted while those with low professional qualifications will be negatively impacted and less in demand. But since the economy in general and the labor market in particular is in a state of perpetual adjustment, vulnerable employees will improve their profile to adapt to ICT requirements. Hence the positive long-term effect.

This paper is part of an empirical verification of this polarization hypothesis described above on the specific case of WAEMU countries. It has the merit of enriching the literature with a case study on an economic and monetary union of underdeveloped countries with a very low technological level.

3. Methodology

3.1. Specification of model

Based on the theoretical framework carefully set out in Appendix 3 (A3), and to highlight the creation/destruction effect, we propose to start from the specific effect of ICTs on each socio-professional category of employed persons. In this way, we will know the nature of the jobs destroyed and those created. To do this, we start from the following simple linear model:

$$Y_{it} = ICT_{it}^{\alpha_0} . Z_{it}^{\alpha_0} \quad With\ i = 1, 2\ldots, N\ and\ t = 1, 2, \ldots, T \tag{1a}$$

N represented the number of country and T, the number of period.

The dependent variable Y_{it} represents the Professional Qualification Level (PQL) of employed people. Based on the International Labor Office's (ILO[3]) categorization of jobs by level of education and continuing Greenan's[4] preliminary work on the subject, we

[3] Employment by education (Downloaded from ILOSTAT. Last update on 23DEC19)https://www.ilo.org/ilostat/faces/oracle/webcenter/portalapp/pagehierarchy/Page3.jspx?locale=EN&MBI_ID=11.

[4] (Greenan, 1996 P.41).

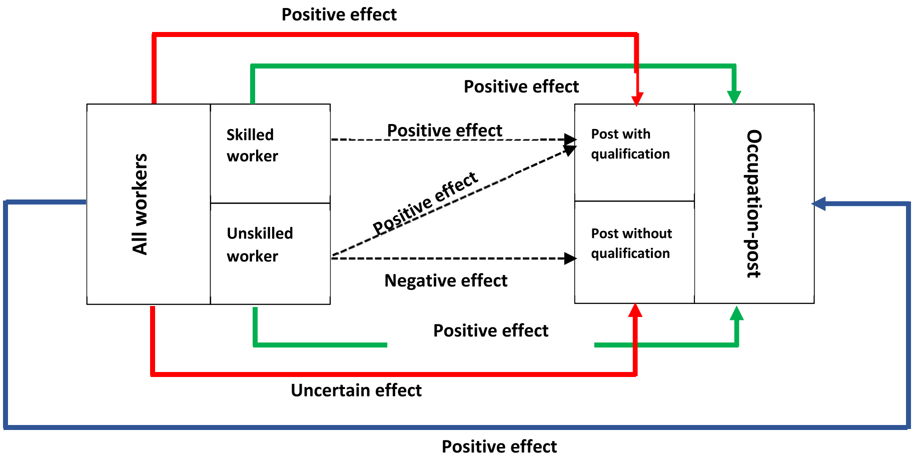


Fig. 3. Effects of ICT on jobs.
Source: Hjort & Poulsen, 2016.

disaggregate this level into four sub-levels as follows:

PQL_Low: employees with at most PSC (Primary Study Certificate) or a Qualification Certificate for Professional Trades. This category occupies 67.34% of the total employed in the WAEMU;

PQL_Midium: these are workers with a secondary diploma (Lower secondary school leaving certificate; Certificate of Professional Aptitude; Baccalaureate). They occupy 19.63% of total union jobs;

PQL_High: these are employed people with an undergraduate degree (Superior technician's certificate; License). They are on average 7.36% of the total number of people employed in the various WAEMU countries.

PQL_Very High: employed people with a second and third university degree followed by an ability to adapt and the opportunity to practice in R&D. They are very few in public and private administrations. We can estimate their workforce at 3.47% of total jobs.

Several variables can influence the professional qualification of employees. We are particularly interested in Information and Communication Technology (ICT). It is the set of digital predispositions (Computers, Telephones, Internet access, Investments in ICTs) which can affect the qualification of employees. Mathematically it is obtained in the following way:

$$ICT_{it} = \sum_{i=1}^{N} \tau_i X_i \tag{2a}$$

It is constructed as a composite variable using the Principal Component Analysis (PCA) method (Dadegnon & Igue, 2020) (See appendix A4). According to the literature developed above, ICT can negatively influence low-skilled jobs and positively influence high-skilled jobs (Hou et al. (2019); Hjort and Poulsen (2019); Woltjer et al. (2019); Acemoglu and Restrepo (2019b)). After this main variable, we integrate control variables such as Human Capital Index (HCI) which indicates the level of human capital in the country. We first use it as a dependent variable to measure the effect of ICT adoption and diffusion on the level of human capital in WAEMU countries. In a second step, this variable is used as an explicative variable in order to capture its effect on the level of professional qualification of the persons employed. This index has a significant influence on the level of qualification of employees and, consequently, on the level of adoption of ICT capital (Earl, 1989 et; Brown, 1992); Subsidies to Employees (SubEmpl) which can allow them to improve their level of professional qualification; Self-employment (Selfempl) which can have perverse effects on professional qualification if its rate is very high; Vulnerability Rate of Jobs (VRJ) whose knowledge should encourage employees to improve; Industrialization Rate (IR) of the country which can influence the choice of sectors and the nature of retraining; Remuneration of Employees (RemEmpl) which can be a factor favoring the improvement of the level of professional qualification of the worker; Public Education Expenditure (PubEducEx) which could influence training offers and, in turn, the level of professional qualification.

The combination of all those variables gives the model developed in the following linear form:

$$lnPQL_{it} = \alpha_0 + \alpha_1 lnICT_{it} + \alpha_2 lnHCI_{it} + \alpha_3 lnSubEmpl_{it} + \alpha_4 lnSelfEmpl_{it} + \alpha_5 lnVRJ_{it} + \alpha_6 lnIR_{it} + \alpha_7 lnRemEmpl_{it} + \alpha_8 lnPubEduExp_{it} + \varepsilon_{it} \tag{3a}$$

With ln the neperian logarithm.

The estimation of this model was carried out in two scenarios, the first of which consists in capturing the cluster effect of ICTs on the dependent variable and the second captures the individual effect of each of the ICT components on the dependent variables.

After the econometric regressions, we will proceed to calculate the net effect (NE) of ICT on employment using the following method:

$$NE = \gamma \sum X - \phi \sum Z \tag{4a}$$

With X jobs created and Z jobs destroyed.

3.2. Description of the data, data sources and descriptive statistics

The data used for this research cover the period from 2000 to 2017. Their definitions, descriptions and sources are recorded in the following Table 1:

The descriptive statistics for these different variables are presented in the following Table 2. They indicate high volatility between the values of the PQL variables; Remuneration of employees; ICT and employee subsidy. This volatility is due to a very rapid change in the values of said variables over time. It also indicates a heterogeneity of the WAEMU countries with regard to the evolution of these variables with high standard deviations.

With regard specifically to the dependent variable (Professional Qualification Level), we see that employees with a low level of qualification dominate all jobs in each of the countries of the union (2,882,572 on average). They are followed by those with a medium level of qualification (909,259.2 on average). Those with very high qualifications are the least numerous. We also note that some variables contain some missing data, but this does not affect the quality of the results obtained.

In these statistical tests, specifically in the correlation tests (see Appendix 7), there is a high correlation between employee subsidies and the level of professional qualification in some scenarios. This is also the case for public spending on education and some ICT components. These correlations, which could a priori bias the results of the regressions, did not affect them in any way, because in each of the scenarios, ICT carefully played the role of a moderating variable[5] (Sharma et al., 1981). In fact, it strongly influenced the relationship between these explicative variables and the dependent variable. Furthermore, all correlated variables were not estimated together in the same model since our models are estimated separately.

3.3. Estimation techniques

Our models were estimated by the Generalized Least Squares (GLS) method to minimize the impact of measurement errors and to correct t-student's statistics for their possible heterogeneity (Goaied & Sassi, 2012). In practice, we separately estimated the effect of ICT on the human capital index and then on the four levels of professional qualification that we have described above. In each of the models, we capture the effect of ICT in an aggregate manner and then we disaggregate it to have the individual effect of each of its components.

After this step, as a sensitivity test, we checked whether our variable of interest (TIC) is really exogenous. To do this, we first looked for the existence of endogenous variables by the Nakamura & Nakamura, 1981 test. This test is done in two steps: (1) each suspected endogenous variable is regressed on the exogenous variables of the model and its instruments; (2) the residuals from the first step are recovered and included in the original model. A Fisher test is then performed on the overall significance of the coefficients of the residuals; the null hypothesis being that all the coefficients of the residuals are not different from 0. If the coefficients of the residuals are jointly significant, then the endogeneity of the variables tested cannot be rejected (Igue, 2013).

Then, we identify and test the validity of the instruments and estimate our different models with the Double Least Squares method.

4. Results, analyses and discussions

The following table compiles the result of the estimates. The first two columns show the econometric link between ICT and Human Capital Index (HCI) and the following columns present the ICT regression on each level of professional qualification (see Table 3).

The results of the first model show that the current level of human capital in WAEMU countries is not sufficient to reap the benefits of ICTs in general. This low level inhibits the very beneficial adoption of ICTs. In return, the latter are gradually trying to improve it, but so far its effect has been insignificant.

From the results of models 2 and 3, we note that ICT has a negative effect on low and medium-skilled jobs. Indeed, an additional adoption of 1% of ICT destroys 0.01% of low-skilled jobs and 0.02% of medium-skilled jobs. This result supports the first aspect of the polarization hypothesis which states that the adoption of ICTs destroys unskilled jobs in the short term (Acemoglu & Restrepo, 2016; Méda, 2017).

On the other hand, models 4 and 5 indicate that jobs with high professional qualifications are resistant to the advent of ICT. They are even sought after and promoted. Thus, when the adoption of ICT grows by 1%, the demand for skilled jobs increases by 0.02% and that of highly skilled jobs increases by 0.03%. This corroborates the second aspect of the polarization hypothesis, which states that the advent of new technologies induces a demand for increasingly skilled labor (Acemoglu & Restrepo, 2019a). These results are also consistent with empirical work in several other countries and economic regions which has shown that ICT adoption is positively correlated with the level of professional skills and qualifications of entrepreneurs and employees (Cirera & Sabetti, 2019; Freeman & Soete, 2009; Hou et al., 2019; Reshef & Toubal, 2017; Woltjer et al., 2019). Despite the atypical adoption of ICTs[6] in the WAEMU region, the effects of these technologies on employment are similar to those obtained in high-income countries.

[5] A moderator variable is a variable that essentially affects the relationship between two other variables. It systematically modifies the magnitude, intensity, direction and/or form of the effect of the independent variable on the dependent variable (Sharma et al., 1981).

[6] A facade adoption where all the ICT equipment used is imported without exception.

Table 1
Description of variables and data sources.

Indicator name	Label	Definition and measurement
Dependent variable Professional Qualification Level	PQL	It refers to the number of persons employed by level of education. Source. Penn World Table (PWT: www.ggdc.net/pwt)
Independent variables Information and Communication Technology	ICT	It is a composite variable that combines investment in ICTs, subscriptions to fixed-telephone, mobile telephony and the Internet. It is constructed using the PCA method (see A4). Source. (ITU: http://www.itu.int/en/ITU-D/Statistics)
Human Capital Index	HCI	It is constructed on the basis of the level of schooling and the rate of education. Source. (PWT: www.ggdc.net/pwt)
Subsidy to employees	SubEmpl	This is the amount granted to employees as an advance on salary and as a contribution to the employees' diplomatic training. They are in current currency. Source. (http://data.worldbank.org/data-catalog/world-development-indicators)
Self-employment	Selfempl	This is the part of those employed that is self-employed. It is as a percentage of the total number of employment. Source. (http://data.worldbank.org/data-catalog/world-development-indicators)
Vulnerability rate of jobs	VRJ	It represents the % share of vulnerable jobs. Source. (http://data.worldbank.org/data-catalog/world-development-indicators)
Industrialization rate	IR	This is the share of the added value of the industry sector in the GDP. Source. (http://data.worldbank.org/data-catalog/world-development-indicators)
Remuneration of employees	RemEmpl	It is the % share of the wage burden in the total expenditure of countries. Source: (http://data.worldbank.org/data-catalog/world-development-indicators)
Public expenditure on education	PubEduExp	It measures the amount in current currency of total public expenditure on education. Source. (http://data.worldbank.org/data-catalog/world-development-indicators)
Investment in ICTs	InvTIC	This is the amount of investment in telecommunications with private participation. It is measured in current dollars. Source. (http://data.worldbank.org/data-catalog/world-development-indicators)
Subscription to fixed-telephone	FixTelSub	It measures the number of people subscribing to fixed-line telephony. Source. (http://www.itu.int/en/ITU-D/Statistics)
Mobile phone subscription	MobTelSub	It measures the number of people who subscribe to mobile telephony. Source. (http://www.itu.int/en/ITU-D/Statistics)
Internet subscription	InterSub	It measures the number of people who subscribe to the Internet. Source: (http://www.itu.int/en/ITU-D/Statistics)

Source. Authors

Table 2
Descriptive statistics of the variables under study.

Variables	Obs.	Average	Standard Error	Min	Max
Low Qualification Level	144	2882572	1687746	405680	7394379
Medium Qualification Level	144	909259.2	526253.1	33192	2154098
High Qualification Level	144	283322.6	270009.1	1383	1005720
Very High Qualification Level	144	125937.1	85802.3	17518	325298.4
ICT composite variable	144	3.43e+07	4.93e+07	6893.243	2.51e+08
Human capital index	126	1.405059	0.228134	1.069451	1.840833
Employee subsidy	133	3.31e+11	2.79e+11	5.45e+10	1.28e+12
Self-employment rate	144	79.62061	14.24352	46.734	92.085
Job Vulnerability Rate	144	78.32192	14.80155	44.121	90.801
Industrialization rate	144	19.6889	3.970762	11.2643	29.72464
Remuneration of employees	143	39.38361	6.772613	26.36616	53.23791
Education expenditure	136	3.35e+08	3.41e+08	7897029	1.73e+09
ICT investments	142	9.11e+07	1.18e+08	0	5.67e+08
Fixed telephone subscription	143	1.00991	0.675117	0	2.82306
Mobile phone subscription	143	39.77349	37.02781	0	138.5708
Internet subscription	139	4.431935	7.118225	0.036261	43.83992

Source. Authors from Stata15.1

Thus, the net employment balance resulting from the adoption of ICT is calculated as follows:

$$\boldsymbol{NE} = \boldsymbol{\gamma}\sum \boldsymbol{X} - \boldsymbol{\phi}\sum \boldsymbol{Z}$$

$$= \gamma \sum Job\_created - \phi \sum Job\_destroyed$$

$$= + \quad 56.455$$

This balance indicates that ICTs have an overall positive effect on jobs. They create more jobs than they destroy. But specifically, our results show that the individual components of ICT (ICT investments; Fixed-telephone, mobile telephony and Internet subscriptions) tend to negatively impact the Human Capital Index and professional qualification of UEMOA countries. This is contrary to

Table 3
Estimation results.

	HCI		PQL_Low		PQL_Midium		PQL_High		PQL_Very_high	
	1.1	1.2	2.1	2.2	3.1	3.2	4.1	4.2	5.1	5.2
LnICTit	0.01		−0.01**		−0.02***		0.02*		0.03**	
	(0.67)		(-2.59)		(-3.53)		(1.79)		(2.45)	
LnHCIit			−1.62***	−1.66***	0.01	−0.09	2.11***	2.45***	1.95***	1.93***
			(-13.90)	(-12.87)	(0.16)	(-0.80)	(19.92)	(22.57)	(13.94)	(6.56)
LnSubEmplit	0.08**	0.05	0.57***	0.45***	0.54***	0.64***	0.24***	0.37***	0.18***	0.05
	(2.08)	(0.82)	(21.04)	(13.49)	(4.97)	(5.13)	(5.75)	(5.07)	(4.48)	(0.25)
LnSelfEmplit	4.28	−4.87	18.67***	12.80**	−15.09	3.10	−52.66***	−36.46***	−38.10***	−26.09
	(0.49)	(-0.52)	(3.05)	(2.05)	(-1.59)	(0.29)	(-4.59)	(-3.26)	(-3.05)	(-1.61)
LnVRJit	1.37	4.04	−17.00***	−11.59**	13.70	−3.09	49.33***	33.18***	35.84***	22.88
	(0.83)	(0.47)	(-2.99)	(-1.99)	(1.55)	(-0.31)	(4.65)	(3.16)	(3.09)	(1.50)
LnIRit	−0.59***	−0.48**	−0.32**	−0.04	0.26	−0.23	0.27	0.13	−0.03	0.13
	(-3.28)	(-1.98)	(-2.13)	(-0.24)	(1.36)	(-1.02)	(1.17)	(0.56)	(-0.14)	(0.45)
LnRemEmplit	−0.12	0.04	−0.15*	−0.28*	0.71***	0.41**	−0.43**	−0.27	−0.49**	0.38
	(-0.93)	(0.22)	(-1.75)	(-1.93)	(5.03)	(2.29)	(-2.36)	(-1.46)	(-2.48)	(0.91)
LnPuEducExpit	−0.66***	−0.81***	−0.03	0.02	−0.10	−0.05	0.11***	0.12***	0.27***	0.21*
	(-10.89)	(-7.70)	(-0.26)	(0.14)	(-1.12)	(-0.46)	(2.85)	(2.91)	(3.33)	(1.88)
LnICTInvit		0.01		0.00		−0.03*		0.03		0.04
		(0.38)		(0.07)		(-1.80)		(1.21)		(0.90)
LnfixTelSubit		−0.01		−0.02		−0.02		−0.40***		−0.56***
		(-0.23)		(-0.55)		(-0.37)		(-3.50)		(-2.64)
LnmobTelSubit		0.00		0.01***		−0.00**		−0.00		0.00
		(0.53)		(4.13)		(2.47)		(0.43)		(0.95)
LnInterSubit		−0.00		−0.01		−0.00		−0.02***		−0.01
		(-0.43)		(-1.21)		(-0.14)		(2.67)		(0.45)
Cons	3.34	7.38**	−2.46	0.56	5.02	−2.11	20.14***	16.09	17.40***	21.76***
	(1.16)	(2.21)	(-1.24)	(0.25)	(1.58)	(-0.55)	(5.21)	(4.26)	(4.28)	(3.27)
R^2	0.97	0.78	0.97	0.98	0.90	0.91	0.93	0.96	0.93	0.95
N	63	45	63	45	83	58	50	41	32	25

Note: the numbers in parentheses are Student's t. ***; ** and * respectively indicate the significance at the level of 1; 5 and 10%.
Source. Constructed by the authors from data from the estimate under Stata15.1

the results of Hasbi and Dubus (2020); Peña-Casas et al. (2018); Hjort and Poulsen (2019) due to the dominance of the use of these technologies for inappropriate purposes and above all due to the weak regulation of its market as well as the poor management of the harmful effects of their use on the environment (Akue-Kpakpo, 2013; Avom et al., 2020).

Moreover, in each of the estimated models it is noted that the employee subsidy contributes considerably to improving their level of qualification. When this increases by 100%, workers invest 40% on average in improving their performance. Conversely, the current level and especially the operating system of self-employment in the WAEMU countries greatly diminish the impetus for improving human capital. Indeed, when the desire to self-employ increases by 1%, the decision to improve one's level of professional qualification decreases by 35% on average; a very intuitive result which clearly shows that self-employment does not require a high level of professional qualification in the WAEMU area. The same is true for the compensation of employees in these countries. This significantly reduces the desire to improve human capital and professional skills.

Public spending on education in the WAEMU area has a significantly negative effect on the level of human capital and on low-skilled jobs. Rather, they are more useful at higher education levels, thus improving the level of professional qualification of employees who have received university training.

The job vulnerability rate has a negative influence on low-skilled jobs. It forces 17% of said jobs to improve their level of professional qualification. At the same time, it boosts skilled jobs to the tune of 43%. Indeed, when the job vulnerability rate increases by 1%, 43% of qualified jobs are secured.

Finally, the results show that the rate of industrialization in WAEMU countries negatively influences the human capital index and low-skilled jobs. However, its effect is insignificant on highly skilled jobs because these can benefit from international labor mobility.

Although these different results affirm the polarization hypothesis and show net job creation, they may suffer from an endogeneity bias. This bias could occur if some of the explicative variables are correlated with the error term or if there is an inverse causality between the explicative variables and the explained variable; this would bias the results obtained with the GLS estimator. To correct this bias, the literature suggests the use of the instrumental variable method (IV), in particular the Double Least Squares (2SLS) and Generalized Moments Method (GMM) of Blundell and Bond (1998). However, GMM are recommended when the number of individuals is greater than the number of periods (Goaied & Sassi, 2012). Thus, we estimated the 2SLS as sensitivity tests. The details of the preliminary tests are presented in Appendix (A5). The 2SLS allowed us to correct for endogeneity bias and, above all, to check whether the job polarization hypothesis is still valid when we change the estimation techniques. The results of this test are presented in the table below (see Table 4):

The results shown in this table are in conformity with those obtained with the Generalized Least Squares. They show on the one hand that ICTs have an insignificant effect on the improvement of human capital and on the other hand that the advent of ICTs leads a net creation of jobs.

Table 4
Sensibility tests: estimation by instrumental variables (2SLS).

	HCI	PQL_Low	PQL_Midium	PQL_High	PQL_Very_high
LnICTit	0.007	−0.014	−0.021	0.020	0.029
	(0.67)	(2.59)**	(3.53)***	(1.79)*	(2.45)**
LnHCIit		−1.628	0.013	2.115	1.956
		(13.90)***	(0.16)	(19.92)***	(13.94)***
LnSubEmplit	0.079	0.565	0.537	0.238	0.189
	(2.08)**	(21.04)***	(4.97)***	(5.75)***	(4.48)***
LnSelfEmplit	4.284	18.680	−15.087	−52.660	−38.102
	(0.49)	(3.05)***	(1.59)*	(4.59)***	(3.05)***
LnVRJit	−0.600	−17.004	0.265	0.267	−0.033
	(3.28)***	(2.99)***	(1.36)*	(1.17)*	(0.14)
LnIRit	−4.306	−0.320	13.701	49.327	35.841
	(0.53)	(2.13)**	(1.55)*	(4.65)***	(3.09)***
LnRemEmplit	−0.117	−0.150	0.708	−0.432	−0.494
	(0.93)	(1.75)*	(5.03)***	(2.36)**	(2.48)**
LnPuEducExpit	−0.667	−0.025	−0.105	0.112	0.270
	(10.89)***	(0.26)	(1.12)*	(2.85)***	(3.33)***
Cons	3.345	−2.462	5.016	20.145	17.405
	(1.16)*	(1.24)*	(1.58)*	(5.21)***	(4.28)***
R^2	0.72	0.98	0.90	0.93	0.94
N	63	63	83	50	32
Sargan-Hansen P-Value	0.572	0.066	0.154	0.205	0.869
Basmann P-Value	0.597	0.080	0.173	0.244	0.888
Instrumented:	lnICT				
Instruments:	LnHCIit LnSubEmplit LnSelfEmplit LnVRJit LnIRit LnRemEmplit LnPuEducExpit				

Notes: ***$p < 0.01$; **$p < 0.05$ et * $p < 0.10$. The Sargan-Hansen and Basmann P-Values indicate the validity of the instruments used. When P>5%, the Ho hypothesis of the validity of the instruments cannot be rejected (Goaied & Sassi, 2012).
Source. Constructed by the authors from data from the estimate under Stata 15.1

5. Conclusion

Despite their important contribution to economic growth, new technologies are also a source of much scientific debates, particularly with regard to their effect on jobs. Indeed, it is feared that the machine could replace humans. This fear is deeper in developing countries which adopt and disseminate new technologies without having adequate human capital. While it is widely argued in the literature that the adoption of new technologies is strongly influenced by the existence of a high level of human capital.

In this article, we have analyzed the effect of ICTs on jobs and professional qualifications in the specific case of WAEMU countries. To achieve this, we first showed the theoretical link between ICT, employment and salary and then regress ICT on the human capital index of WAEMU countries and on each level of professional qualification in order to detect jobs vulnerable to advent of ICT. Finally, we calculated the net balance of jobs generated by ICT.

Our regressions show that the level of human capital in WAEMU countries is not yet sufficient for inclusive and profitable adoption of ICTs. We also find as results that ICT negatively impact low and medium skilled jobs. Conversely, our results indicate that the adoption of ICT is favorable to the emergence of skilled jobs. This result is very consistent with the hypothesis of job polarization and the “creation/destruction” mechanism. The net effect of this mechanism is positive and indicates that ICTs have an overall positive effect on jobs.

In view of these very intuitive results, we suggest to the leaders of the WAEMU countries to orient the training offers towards the requirements of ICT in order to take full advantage of these technologies. It is therefore necessary to increase the supply of training for computer engineers, telecom engineers, programmer analysts, call center agents, e-marketers, etc. Likewise, it is important to rethink education financing policy. Because public spending on education is at the same time weak, misguided and badly managed. WAEMU must also promote employee retraining programs and especially support them more financially in their training program. To all this is added the need to promote the establishment of manufacturing industries which can help reduce the unemployment problem and force future employees to receive better training.

APPENDIX

A1. Mapping of WAEMU countries

A2.

Table 5
Economic and numerical characteristics of WAEMU countries.

Countries	Population	Super- ficies(Km^2)	GDP (%)	Telefix (%)	Telemob (%)	Internet (%)
Benin	11,175,692	114,760	5.58	0.51	78.50	12.00
Burkina Faso	19,193,382	274,220	6.74	0.40	93.50	13.96
Ivory Coast	24,294,750	322,460	7.80	1.26	130.68	43.84

(continued on next page)

Table 5 (*continued*)

Countries	Population	Super- ficies(Km^2)	GDP (%)	Telefix (%)	Telemob (%)	Internet (%)
Guinea-Bissau	1,861,283	36,130	5.92	0.00	77.09	3.76
Mali	18,541,980	1,240,190	5.3	1.12	112.35	11.11
Niger	21,477,348	1,267,000	4.89	0.53	40.86	0.17
Senegal	15,850,567	196,710	6.79	1.83	99.42	25.66
Togo	7,797,694	56,790	5.57	0.46	79.77	12.36
WAEMU	120,192,696	3,508,260	6.07	0.76	89.02	15.36

Source. Authors from WDI and IUT 2017.

A3. The theoretical framework

The theoretical model making it possible to analyze the effects of new technologies on jobs, wages and even the overall productivity of companies has been proposed and highlighted by Acemoglu and Restrepo (2016). Their aim was to provide a unified framework in which certain tasks previously performed by the job are automated while at the same time new versions of more complex tasks are created. We present here a simplified version of their model followed by economic interpretations.

We start from a global production function of goods and services obtained by combining y (x) tasks with x ε [N-1, N].

$$\ln Y = \int_{N-1}^{N} \ln y(x)dx \tag{1b}$$

Each task can be produced by human labor ℓ (x) or by machines m (x) depending on whether it has been automated or not. In particular, the tasks x ∈ [0, I] are technologically automated, so they can be produced by labor or by machines. The others are not technologically automated, so they must be produced with human labor:

$$y(x) = \begin{cases} \gamma L(x)l(x) + \gamma M(x)m(x) & \text{si} \;\; x \in [0, I] \\ \gamma L(x)l(x) & \text{si} \;\; x \in (I, N] \end{cases} \tag{2b}$$

$\gamma L(x)$ and $\gamma M(x)$ represent respectively the productivity of labor in the task and that of machines in automated tasks. Threshold I designates the automation possibility frontier.

We assume that $\frac{\gamma L(x)}{\gamma M(x)}$ increases in and that labor has a comparative advantage in higher index tasks.

We also simplify the discussion by assuming that the supply of labor (L) and the supply of machines (K) are fixed and inelastic. This implies that changes in the demand for labor have an impact on the labor share of national income and on wages, but not on the level of employment. We describe below how this framework can be easily generalized to account for changes in employment and unemployment.

Thus, an equilibrium forces companies to choose how to minimize the production costs of each task, and the labor and capital markets to be released. To simplify the discussion, we make the following hypothesis:

$$\frac{\gamma L(N)}{\gamma M(N-1)} \succ \frac{W}{R} \succ \frac{\gamma L(I)}{\gamma M(I)} \tag{A1}$$

W and *R* represent the equilibrium wage rate and the equilibrium cost of the machine, respectively. The second inequality implies that all the tasks of [N - 1, I] will be produced by machines. In contrast, the first inequality indicates that the introduction of new tasks (an increase in N) will increase overall output. Therefore, the aggregate equilibrium production takes the following form:

$$Y = B\left(\frac{K}{I-N+1}\right)^{I-N+1}\left(\frac{L}{N-I}\right)^{N-I} \tag{3b}$$

With

$$B = \exp\left(\int_{N-1}^{I} \ln \gamma M(x)dx + \int_{I}^{N} \ln \gamma L(x)dx\right) \tag{4b}$$

This Cobb-Douglas-type aggregate production function is itself derived from the allocation of the two production factors to tasks. The peculiarity here is that the exponents of capital and labor depend on the extent of automation (I) and the creation of new tasks (N).

From this equation of overall production, we can deduce that of labor demand:

$$W = (N-I)\frac{Y}{L} \tag{5}$$

This equation can be inverted to obtain a downward sloping labor demand curve as a function of wage. It therefore implies that the share of labor in national income is given by:

$$s_L = \frac{WL}{L} = N - I \tag{6}$$

- **The economic implications of automation: the displacement effect**
- **The effect on jobs and wages**

The first results of this theoretical analysis show that automation (especially when it is extensive) creates a displacement effect, reducing the demand for labor, but that it is also thwarted by a productivity effect pushing towards a greater demand for labor. More precisely, from equation (5), we obtain directly:

$$\frac{d\ \ln W}{dI} = \underbrace{\frac{d\ \ln(N-I)}{dI}}_{displacement\_effect \prec 0} + \underbrace{\frac{d\ \ln(Y/L)}{dI}}_{productivity\_effect \succ 0} \tag{7}$$

Were it not for the effect on productivity, automation would reduce the demand for labor, as it directly replaces labor in tasks that were previously performed by workers. Therefore, if the effect on productivity is small, automation will reduce the demand for labor and wages.

To explore this point further and better understand the implications of the productivity of automation technologies, let us also express the effect of productivity in terms of physical productivity of labor and machines and factor prices as follows:

$$\frac{d\ \ln(Y/L)}{dI} = \ln\left(\frac{W}{\gamma L(I)}\right) - \ln\left(\frac{R}{\gamma M(I)}\right) \succ 0$$

Using this expression, the overall impact on the demand for labor can be written:

$$\frac{d\ \ln W}{dI} = -\underbrace{\frac{1}{N-I}}_{Displacement\_effect \prec 0} + \underbrace{\ln\left(\frac{W}{\gamma L(I)}\right) - \ln\left(\frac{R}{\gamma M(I)}\right)}_{Productivity\_effect \succ 0} \tag{8}$$

This expression clarifies that the displacement effect of automation will dominate the productivity effect and thus reduce the demand for labor (and wages) when $\frac{\gamma M(I)}{R} \approx \frac{\gamma L(I)}{W}$, which is exactly the case when new technologies are little better than labor. On the other hand, when $\frac{\gamma M(I)}{R} \gg \frac{\gamma L(I)}{W}$, automation sufficiently impacts productivity and indirectly, the demand for labor and wages.

- **The effect on the labor share of income**

From equation (6), we can see the implication of automation on the share of labor in national income as follows:

$$\frac{ds_L}{dI} = -1 \prec 0 \tag{9}$$

This will mean that, whatever the size of the productivity effect, automation always reduces the share of labor in national income. This negative impact on the labor share is a direct consequence of the fact that automation always increases productivity more than wages ($\frac{d\ \ln(Y/L)}{dI} \succ \frac{d\ \ln W}{dI}$).

- **New tasks and comparative advantages of work**

Unlike capital accumulation and deepening automation, which increases the demand for labor but does not affect the labor share, equation (6) implies that new tasks increase the labor share, that is to say $\frac{ds_L}{dN} = 1$:

In conclusion, it can be noted that digitization has a positive effect on jobs and wages thanks to the advent of new tasks which require new labor, which leads to higher wages and indirectly, higher share of labor in national income.

A4. Construction of the ICT composite variable

The construction of a composite variable can be done in three different ways.

The simple average

Here, equal weighting is used. That is, the sum of the components is added to their total number. This is considered arbitrary and could lead to an overweighting of some of the less important variables or an underweighting of the more important ones.

Average weighted by expert judgement

Expert judgement can also be used to assign weights to each variable. But this approach seems to be too subjective and is often limited by the availability of experts in the field or by the lack of consensus among the experts themselves.

Weighted average by the Principal Component Analysis (PCA) method

Weight assignment by Principal Component Analysis (PCA) is thus preferred over the two older methods. It tacitly allows a weighting to be assigned to each variable proportionally to the weight of each variable.

We therefore choose to use this method for the choice of weights associated with each of the variables that make up the ICT variable. The contributions of the variables to the first component of the CPA are used as weights according to the following formula:

$$TICit = \sum_{i=1}^{k} \zeta iXi \tag{1c}$$

With ζi the weighting coefficient linked to each of the variables. Xi is the set that makes up the ICT variable. It consists of: Investment in ICT (InvTIC). Fixed-line telephone subscriptions (Telefix). Mobile telephone subscriptions (Telemob) and Internet subscriptions (Inter).

The weights assigned to each variable vary between −1 and +1. The sign of the coefficient indicates the direction of the relationships of one variable with the others to construct the composite variable. The importance of the weights describes the contribution of each variable to the value of the ICT composite variable.

The following table shows the weights obtained for each variable under stata 15.

Table 6
Weighting coefficient.

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
InvTICit	0.4377	0.7177	0.4939	0.2222	0
AboTéléfixit	0.4976	0.2943	−0.8027	−0.1464	0
AboTélémobit	0.5409	−0.3463	0.3341	−0.6898	0
AboInterit	0.5179	−0.5277	0.0048	0.6733	0

Source: Authors from stata15.1.

The coefficients of component 1 are used to weight the ICT composite variable according to formula (1)

A5. Endogeneity test of Nakamura and Nakamura (1981)

First step:
We regress the suspected endogenous explicative variable (TIC) on the exogenous variables and instruments.

ICT					
	(1)	(2)	(3)	(4)	(5)
LnHCIit		1.974	1.249	1.168	0.557
		(0.56)	(0.76)	(0.72)	(0.27)
LnSubEmplit	1.888	0.167	−4.532	0.205	−0.232
	(3.90)***	(0.27)	(1.79)*	(0.49)	(0.25)
LnSelfEmplit	115.882	96.251	−140.445	−52.252	17.174
	(1.20)*	(0.65)	(0.76)	(0.37)	(0.07)
LnVRJit	−108.191	−89.356	128.225	47.705	−19.868
	(1.21)*	(0.66)	(0.75)	(0.37)	(0.08)
LnIRit	−3.620	3.583	8.400	3.232	2.397
	(1.64)*	(0.95)	(2.34)**	(1.04)*	(0.52)
LnRemEmplit	1.726	0.698	6.305	4.289	7.432
	(0.96)	(0.34)	(2.03)**	(1.93)*	(1.95)*
LnPuEducExpit	0.308	2.059	3.724	0.814	−0.850
	(0.30)	(0.70)	(1.87)*	(1.53)*	(0.62)
Cons	−64.774	−42.084	71.249	5.078	5.270
	(2.05)**	(0.73)	(0.99)	(0.10)	(0.06)
R^2	0.52	0.16	0.17	0.32	0.27
N	63	63	83	50	32

***$p < 0.01$; **$p < 0.05$ et *$p < 0.1$.

2nd step:
We recover from the estimates of the first step, the prediction of the endogenous variable that we include in the initial model.

	HCI	PQL_Low	PQL_Midium	PQL_High	PQL_Very_high
LnICTit	0.044	0.180	0.086	1.028	−2.190
	(0.58)	(3.21)***	(1.49)*	(4.20)***	(2.40)**
res_LnICTit	−0.037	−0.194	−0.107	−1.008	2.219
	(0.044)	(3.50)***	(1.84)	(4.05)***	(2.43)**

(continued on next page)

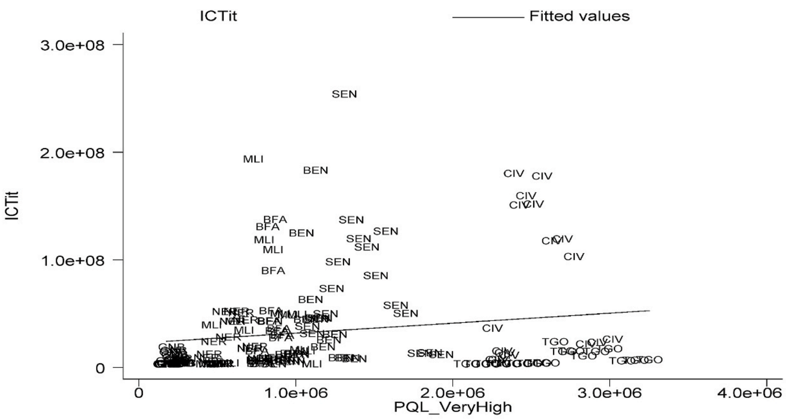
(*continued*)

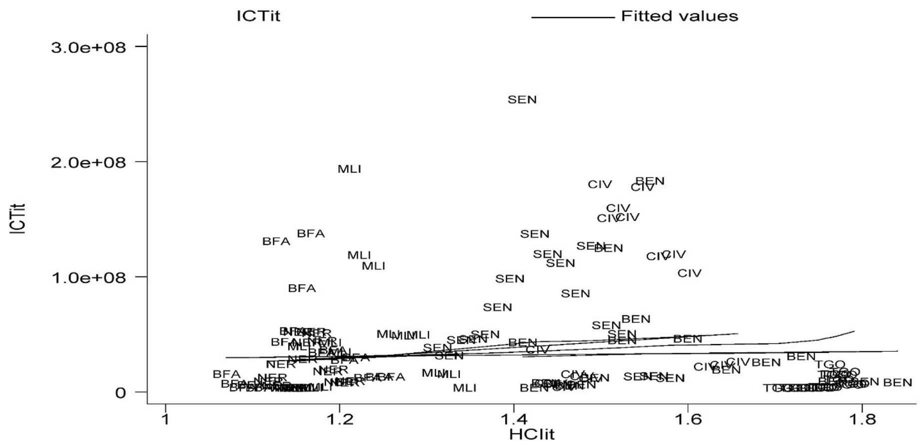
	HCI	PQL_Low	PQL_Midium	PQL_High	PQL_Very_high
LnHCIit		−2.012	−0.121	0.938	3.191
		(11.00)***	(1.06)*	(3.04)***	(6.04)***
LnSubEmplit	0.009	0.533	1.024	0.031	−0.327
	(0.07)	0.180	(4.18)***	(0.43)	(1.45)*
LnVRJit	−0.466	0.338	−0.073	1.250	−8.237
	(2.71)***	(4.17)***	(0.52)	(5.43)***	(2.35)**
LnIRit	−0.307	−1.016	−0.638	−2.990	5.286
	(2.90)***	(3.24)***	(1.70)*	(5.29)***	(2.16)**
LnRemEmplit	−0.181	−0.285	0.031	−4.754	15.995
	(0.85)	(3.53)***	(0.09)	(4.53)***	(2.38)**
LnPuEducExpit	−0.679	−0.424	−0.505	−0.709	−1.617
	(10.22)***	(2.66)**	(2.38)**	(3.42)***	(2.16)**
Cons	5.740	5.705	−2.638	15.027	29.097
	(2.51)**	(5.95)***	(1.47)*	(5.21)***	(3.06)***
R^2	0.72	0.98	0.90	0.93	0.94
N	63	63	83	50	32

***$p < 0.01$; **$p < 0.05$ et *$p < 0.1$.

Considering the value of Fisher's test on the residuals, we note that there is an endogeneity bias, particularly in models 2, 4 and 5. Hence the need to use the instrumental variables method.

A6. Some additional graphics





Source. Authors from stata15.1

A 7. Correlation test between variables

Variables	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)	(m)	(n)	(o)	(p)
Low Qualification Level (a)	1.0000															
Medium Qualification Level (b)	0.5424	1.0000														
High Qualification Level (c)	0.3124	0.8695	1.0000													
Very High Qualification Level (d)	−0.3204	0.4219	0.4833	1.0000												
ICT composite variable (e)	0.3710	0.4503	0.3923	0.0844	1.0000											
Human capital index (f)	−0.6716	0.0407	0.2726	0.8037	−0.0258	1.0000										
Employee subsidy (g)	0.5000	0.9247	0.8625	0.4710	0.5077	0.1455	1.0000									
Self-employment rate (h)	0.1970	−0.2777	−0.1034	−0.2880	−0.1755	−0.2402	−0.2875	1.0000								
Job Vulnerability Rate (i)	0.2021	−0.2787	−0.1111	−0.2871	−0.1767	−0.2454	−0.2898	0.9998	1.0000							
Industrialization rate (j)	0.0927	0.2546	0.4959	−0.1022	0.2075	−0.0142	0.3531	0.0696	0.0559	1.0000						
Compensation of employees (k)	0.3291	0.5542	0.5475	0.0559	0.2376	0.0201	0.4631	0.1939	0.1896	0.1636	1.0000					
Education expenditure (l)	0.5124	0.8531	0.7637	0.3963	0.5670	0.1311	0.9598	−0.3745	−0.3764	0.3227	0.3535	1.0000				
ICT investments (m)	0.3477	0.4280	0.3756	0.0730	0.9983	−0.0336	0.4755	−0.1658	−0.1670	0.2045	0.2281	0.5298	1.0000			
Fixed telephone subscription (n)	−0.3332	0.2919	0.2640	0.4347	0.1689	0.5146	0.2597	−0.7669	−0.7700	−0.0788	0.0926	0.2948	0.1637	1.0000		
Mobile phone subscription (o)	0.3385	0.3340	0.2737	0.1768	0.4509	0.2401	0.5051	−0.2202	−0.2202	0.0016	0.2213	0.6459	0.4039	0.2427	1.0000	
Internet subscription (p)	0.1243	0.3539	0.1937	0.2390	0.2445	0.2534	0.5228	−0.5500	−0.5503	0.0693	0.0963	0.6581	0.2029	0.3725	0.7023	1.0000

Source. Authors from stata15.1.

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