Impact of Digital Technology Adoption on Employment in Senegal

Thierno Malick Diallo

Tsambou André Dumas

and

Fomba Kamga Benjamin

Working Paper DT-003

Bringing Rigour and Evidence to Economic Policy Making in Africa

AFRICAN ECONOMIC RESEARCH CONSORTIUM

CONSORTIUM POUR LA RECHERCHE ÉCONOMIQUE EN AFRIQUE

Impact of Digital Technology Adoption on Employment in Senegal

By

Thierno Malick Diallo
Gaston Berger University at Saint-Louis

Tsambou André Dumas
Yaoundé II University

and

Fomba Kamga Benjamin
Yaoundé II University

AERC Working Paper DT-003
African Economic Research Consortium
September 2022

THIS RESEARCH STUDY was supported by a grant from the African Economic Research Consortium. The findings, opinions and recommendations are those of the author, however, and do not necessarily reflect the views of the Consortium, its individual members or the AERC Secretariat.

Published by: The African Economic Research Consortium
P.O. Box 62882 - City Square
Nairobi 00200, Kenya

Contents

List of tables

List of figures

List of abbreviations and acronyms

2SLS	Two-Stage Least Squares
AfDB	African Development Bank
ANPEJ	Agence Nationale pour la Promotion de l'Emploi des Jeunes (National Bureau for the Promotion of Youth Employment)
ANSD	Agence Nationale de la Statistique et de la Démographie
ATE	Average Treatment Effect
ATT	Average treatment Effect on the Treated
ATU	Average Treatment Effect on the Untreated
CNES	Confédération Nationale des Employeurs du Sénégal (National Confederation of Employers in Senegal)
CNP	Conseil National du Patronat (National Council of Employers)
DE	Directorate of Employment
DPEASF	Déterminants de la Performance des Entreprises en Afrique Subsaharienne Francophone
EAPE	Améliorer les Politiques d'Emploi (Improving Employment Policies)
GDP	Gross Domestic Product
ICT	Information and Communications Technology
IDRC	International Development Research Centre
	IPWRA Inverse Probability Weighted Regression Adjustment
ITU	International Telecommunication Union
MCA	Multiple Correspondence Analysis
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PSM	Propensity Score Matching
PSE	Plan Sénégal Émergent (Emerging Senegal Plan)
UEMOA	West African Economic and Monetary Union
UNDP	United Nations Development Programme

Abstract

The future of developing countries lies primarily in the intensity of their uptake of digital technologies. Although these new technologies have disrupted the existence of old ones with a possible impact on productivity, employment, and competitiveness in different sectors of activity, there has been little empirical research on this possible impact. The present study aims to fill this gap by examining the impact of digital technology adoption on labour market outcomes, and on employment dynamics in the manufacturing and service sectors in Senegal. Firstly, in order to assess the effect of digital technologies on young people's awareness of public employment programmes and their access to employment, the study applied the propensity score matching method to data obtained from a survey labelled “Improving Employment Policies” (Améliorer les Politiques d’Emploi, EAPE), which was conducted in 2018 among 2,746 individuals in Senegal. Secondly, in order to measure the effect of digital technology adoption on employment dynamics in the manufacturing and service sectors, the study applied the instrumental variables method to data obtained from a survey called “Determinants of the Performance of Firms in Francophone Sub-Saharan Africa: the Case of Senegal” (Déterminants de la Performance des Entreprises en Afrique Subsaharienne Francophone: Cas du Sénégal), which was conducted in 2014 among 723 firms. The relevance of the present study lies in the fact that it will provide policy makers with guidance on the measures they should take to help young people entering the labour, and private-sector firms with guidance on how to make the most of digital technology diffusion in Senegal. By way of results, the study found that digital technology adoption helped the unemployed youth to participate in solidarity-contract programmes and to continue their active job search efforts, although it did not reduce the duration of their unemployment. It also found that digital technology adoption by Senegalese firms had a positive and significant impact on both the number of people they employed and the number of both their highly skilled and less skilled employees. Specifically, by adopting digital technologies, a firm increased the number of its highly skilled employees by 2.12% and that of its less skilled ones by 2.64%. This corresponds to a 0.52% greater impact for the less skilled employees than for the highly skilled ones.

Key words: Digital technologies; employment; Senegal.
JEL classification codes: O14; O33; J01; J23.

Acknowledgements

This study has benefitted from the technical and financial support from the African Economic Research Consortium (AERC). The authors are grateful to the members of the AERC research network who served as sources of valuable comments at various stages of the study. The analyses and opinions expressed in this paper are those of the authors.This Working Paper is an output of the project entitled "For Transregional Research on Private Sector Development, Digitization and Disruptive Technologies" which was implemented in cooperation with the Economic Research Forum (ERF) and funded by the Carnegie Corporation of New York.

1.0 Introduction

While Senegal is the second largest economy in the West African Economic and Monetary Union (UEMOA), representing 19.55% of the Union's GDP (République du Sénégal [Republic of Senegal], 2019), its economic fabric remains weak and characterized largely by small and medium enterprises. That is why the country's adoption of digital technologies should enable it to improve overall productivity, accelerate economic growth, innovation, and job creation (Banque Mondiale [World Bank], 2019). For this reason, digital transformation of Senegal's economy has become a top priority for the country's government, whose popularization of digital technologies in the early 2000s translated into the creation of a set of institutions (among which the Ministry of Posts and Telecommunications) tasked with promoting the digital industry. The setting up of those institutions has made ICT adoption a reality in Senegal and the reduction of the digital divide a key goal for the country. Thus, in 2016 the penetration rate was 15%, while it was 20% for access to the Internet, 26% for private Internet access, 1.9% for the use of fixed telephony services, 98.7% for the use mobile telephone services, and 50% for the 3G Internet coverage (ANSD, 2016). In 2019, Senegal had a high rate of ICT use; it boasted one of the highest smartphone penetration rates (35.6%) in West Africa (Banque Mondiale [World Bank], 2019). In 2016, Senegal ranked 14th in Africa in the Network Readiness Index[1] and ranked 1st in Africa in terms of the relative weight of the Internet in the economy, which was estimated at 3.3% (MINPOST, 2016).

Despite all these advantages, Senegal's situation is not very bright on the continental and world levels according to the International Telecommunication Union (ITU, 2017). While it is true that Senegal's 30 administrative subdivisions are digitally connected to the central network, the country is still known to lag behind in terms of technology. Indeed, according to the ITU (2017), Senegal ranked 124th in 2012 and 142nd in 2017 out of 176 countries on the ICT Development Index. This drop by 18 places is attributable to the lack of competition on the ICT market in Senegal, to a digital

1 The Networked Readiness Index is a tool that enables public and private sector players to fully exploit the potential of ICT.

ecosystem that is not very conducive to employment and entrepreneurship, and to high prices.[2] The reduction in tariffs in recent years remains insufficient as the cost of mobile Internet represents 12% of the gross monthly per capita income in Senegal, compared to only 6% in Kenya (Banque Mondiale [World Bank], 2019). Results of a 2017 Gallup survey also revealed that broadband Internet access deteriorated between 2016 and 2017 in urban and rural areas, while the Internet divide between urban and rural areas increased by 4 percentage points over the same year. All this goes to show that Senegal is still marked by limited coverage and a significant digital divide between urban and rural areas. The development of the ICT sector requires adaptive and rapid reaction capacities, which in turn requires a high level of human capital. Yet Senegal's population is characterized by a low level of qualifications and skills, which is not conducive to the expansion of a dynamic digital economy. The country was ranked 168 out of 189 in the Human Development Index 2019 (UNDP, 2020) and 128 out of 130 in the Global Human Capital Index (WEF, 2017). Such a situation does not enable Senegal to take full advantage of ICT benefits.

Faced with those many shortcomings, in 2016 the country's government devised the National Strategy for the Digital Economy, whose aim is to breathe new life into the sector by providing players in the sector with new engines and sources of growth. Based on the guidelines set by the Emerging Senegal Plan (Plan Sénégal Émergent, PSE), the goal to be achieved by 2025 by the new strategy is to raise the contribution of digital technology to GDP to 10%, to generate an induced increase in GDP of CFAF 300 billion, and to create 35,000 direct jobs in the digital industry (MINPOST, 2016). The other progress indicators expected by 2025 will be measured by international rankings based on two main indices: first, with regard to the World Economic Forum's Networked Readiness Index, the goal for Senegal is to rank 70th in the world and 4th in Africa; second, in relation to the ITU's ICT Development Index, the goal is to rank 90th in the world and 4th in Africa. Through this strategy and the Electronic Communications Code (adopted in December 2018), Senegal intends to make the most of the strong potential of ICT in its socioeconomic development.

Numerous studies have analysed the effect of digital technologies on economic development (Freeman & Soete, 1997; Brynjolfsson & Yang, 1996; Galddfarb & Tucker, 2019). On the one hand, drawing on the productivity paradox (Solow, 1987), some authors have laid emphasis on the impact of digital technologies on productivity growth (Cusolito & Maloney, 2018). They have shown that investment in information and communications technology (ICT) leads to an increase in the stock of capital, improves labour productivity, and increases total factor productivity (O'Mahony & Van Ark, 2003). In the same vein, others have recently shown that a greater use of digital technologies increases factor productivity and efficiency (Brynjolfsson et al., 2018). Some authors have been more concerned about the risk that increased digitization will destroy jobs or increase the demand for skilled jobs at the expense of unskilled jobs (Acemoglu & Restrepo, 2019). In this regard, they have shown that the use of

2 There are three mobile telephony operators in Senegal: SONATEL, TIGO and EXPRESSO.

digital technologies has had an effect on the demand for skilled workers and on the reduction in the wage gap between skilled and unskilled workers depending on the sectors of activity (Lacovone & Pereira-Lopez, 2018). These digital technologies can also be associated with job rotation in the form of employee turnover, elimination of certain occupations, creation of new occupations, and a decline in the proportion of unskilled workers (Brambilla & Tortarolo, 2018).

While the importance of digital technologies has been widely demonstrated in the case of developed countries, little research has been done about it in the case of Africa in general and of Senegal in particular. The present study fills this gap on two levels: firstly, it improves our understanding of how ICT diffusion changes the labour market behaviour of the unemployed and facilitates their access to employment; secondly, it examines the extent to which ICT diffusion influences job dynamics by causing firms to introduce new jobs while eliminating a number of others.

That is why the study sought to answer the following two research questions:

- What is the effect of digital technology adoption on young people's awareness of public employment programmes and their access to employment?
- What is the effect of digital technology adoption on productivity and employment dynamics in the manufacturing and service sectors?

Deriving from these questions were the following research objectives:

- To measure the effect of digital technology adoption on young people's awareness of public employment programmes and their access to employment.
- To measure the effect of digital technology adoption on productivity and employment dynamics in the manufacturing and service sectors.

The rest of this study is structured as follows: Section 2 is a review of the literature; Section 3 describes the study's methodology; Section 4 describes the profile of jobseekers who adopt digital technologies; Section 5 analyses the impact of digital technology adoption on jobseekers' participation in public employment programmes and job search; Section 6 analyses the effect of digital technology adoption on employment dynamics; Section 7 discusses the robustness and heterogeneity of the study's results; while Section 8 is the conclusion, which contains some policy implications of the findings.

2.0 Literature review

The theoretical and empirical literature essentially distinguishes between two effects of ICT on the economy depending on whether one considers the impact on productivity growth or employment. Several studies have already examined the impact of ICT on productivity growth. The early studies of the 1970s and 1980s found that ICT had a limited, if not negative, impact on productivity. These findings prompted the economist Robert Solow to point out the productivity paradox, according to which computers were seen everywhere except in productivity statistics (Solow, 1987). In their review of the literature, Brynjolfsson & Yang (1996) pointed out that there were various reasons for this productivity paradox: firstly, this paradox could be an issue of measurement error arising from the fact that output and input statistics were not properly taken into account. Secondly, it could also be a delay issue to the extent that the benefits of ICT adoption may have taken time to materialize. Thirdly, it could be a redistribution issue to the extent that the ICT benefits were only reaped by businesses and their customers but without any real impact on total output. Finally, it could be a mismanagement issue to the extent that ICT investment had not been profitable enough.

However, later studies have rigorously shown that there is a positive impact of ICT on productivity (Maliranta & Rouvinen, 2004; Pilat & Wölfl, 2004). Pilat and Wölfl (2004) studied the impact of ICT on productivity growth in OECD countries and found that ICT adoption improved the productivity of both the manufacturing and the service sectors. However, Maliranta and Rouvinen (2004) found that the productivity gains resulting from ICT adoption seemed to be greater in the service sector than in the manufacturing one. Cardona et al. (2013) reviewed 150 studies and found that the majority of them had confirmed the positive impact of ICT adoption on productivity. For their part, Stanley et al. (2018), applying a meta-regression analysis to 59 econometric studies, also highlighted the positive effect of ICT on productivity. However, they observed that the developed countries seemed to benefit more from ICT adoption than the developing ones. More recent studies have also shown that ICT adoption has a positive impact on economic growth (see, for example, Fernandez-Portillo et al., 2020; Myovella et al., 2020). In their study of 41 countries from sub-Saharan Africa and 33 countries from the OECD area, Myovella et al. (2020) found that ICT use was positively correlated with economic growth, but with considerable variation depending on the indicator used. Their study revealed that the use of mobile telephony had a greater impact on the economic growth of sub-Saharan African countries, while access to broadband connectivity contributed more to economic growth in the OECD countries.

Many other studies have also examined the effects of ICT on employment. Those conducted in developed countries have revealed that digital technology adoption increases the volume of employment, with a greater effect in rural than in urban areas (Fabritz, 2013; Ivus & Boland, 2015), and a greater impact in the service sector than in the manufacturing sector (Crandall et al., 2007). Using a sample of 45 countries from sub-Saharan Africa covering the period 1996–2017, Ndubuisi et al. (2021) found that ICT adoption significantly increased the volume of employment in the services sector. This finding can be explained by the fact that the use of ICT, in particular the Internet, facilitates access to employment by reducing the costs of acquiring information on employers and employees (Autor, 2001). Likewise, the use of high-speed Internet promotes job creation by facilitating the entry of enterprises into business and their survival (Kandilov et al., 2011; Kim & Orazem, 2012; De Stefano et al., 2014). Hasbi (2017) examined the effect of the presence of a high-speed network on the creation of new local enterprises and on unemployment. He found that the deployment of a very high speed network facilitated the creation of new enterprises operating in the tertiary sector, but had no significant impact on the creation of those in the construction industry and the industrial sector. He further found that the presence of a very high-speed network enabled the development of entrepreneurship and reduced unemployment. Studies carried out in the USA and France have also found a positive relationship between ICT adoption, in particular the use of high-speed Internet, and employment (Crandall et al., 2007; Gillett et al., 2006).

A number of studies have also analysed the impact of ICT on job-search strategies. Gürtzgen et al. (2021) have found that access to the Internet primarily changes the jobseekers' search behaviour by enabling them to increase their online searches and number of job applications. By comparing individuals who got their jobs through online search with those who got theirs offline (through friends, newspaper ads, or other channels), Mang (2012) observed that online job search led to better jobs. For their part, in a study analysing the different channels used to search for a job, Kuhn and Mansour (2013) found that searching for a job on the Internet reduced the duration of unemployment by about 25%. However, all these findings vary from one context to another. For example, in the case of the United States, Kroft and Pope (2014) found that expanding Craigslist[3] drastically reduced job advertisements in newspapers, but had no effect on the unemployment rate. In a similar vein, Brenzel et al. (2016) observed that posting jobs online and its success rate seemed to be more relevant for high-skilled jobs than for medium- and low-skilled ones.This provides the first evidence on an important selection issue, namely, the type of jobs posted online.

3 Craigslist is one of the leading online job-posting sites in the United States.

This issue is particularly relevant because the jobs that people seek online may besystematically different from those that they seek through other job search channels (Gürtzgen et al., 2021).

All in all, while there is abundant literature on the economic impact of ICT adoption in developed countries and in some developing ones, as evidenced by the studies mentioned above, there is still little in the case of sub-Saharan Africa in general and of Senegal in particular.

3.0 Methodology

Sources of data

The present study used data from two sources. The first one is the survey called "Improving Employment Policies" (Améliorer les Politiques d'Emploi, EAPE), which was conducted in Senegal in 2018 with the technical and financial support from the International Development Research Centre (IDRC). This survey provides information on the respondents' level of education and training, their awareness of employment programmes, their employment status, their main occupation, and their job prospects before and after their participation in a training programme organiszd by the National Bureau for the Promotion of Youth Employment (Agence Nationale pour la Promotion de l'Emploi des Jeunes, ANPEJ) between 2012 and 2015. Specifically, data was collected from the information stored by the ANPEJ about all jobseekers. This information enabled us to set up a sampling base from which it was possible to identify some of the jobseekers who sought the ANPEJ's services between 2012 and 2015. From the various ANPEJ programmes, the survey focused on people who had sought the assistance of the National State-Employer Agreement signed in 1987 and renewed in 2000 and 2009 (République du Sénégal [Republic of Senegal], 2014)

The individuals surveyed were drawn at random and contacted by telephone for a direct interview appointment. When the phone number was not reachable, a new random draw was made. Also, when an initially contacted person was not available for the appointment, another one was randomly drawn and contacted. In addition, another group of individuals who had never sought the assistance of the National State-Employer Agreement was also surveyed. A classical household survey was used to find the individuals in this latter group. In all, 2,746 individuals were surveyed, of whom 41.26% were women and 58.74% men. Although the information collected was likely to have changed between the date of registration with the public employment services and that of survey, it transpired that 33.07% of the individuals surveyed had not sought the assistance of the National State-Employer Agreement, while 66.94% had. Of the latter, 41.19% had been assisted at least once, while 55.81% had not been at all.

One of the advantages of this survey is that it enabled the present study to measure the impact of digital technologies on the popularization of public employment programmes. Indeed, answers to the question (during the survey) of what the main channel that young people used to obtain information on public employment programmes has enabled us to analyse the relationship between young people's awareness of public employment programmes and their use of ICT.

The second source of data is the survey called "Determinants of Firm Performance in Francophone Sub-Saharan Africa: The Case of Senegal", which was conducted in 2014 among 723 firms, 34.6% of which were from the manufacturing sector and 65.4% from the services sector. It was conducted by the Cheikh Anta Diop University's Laboratory for Economic and Monetary Research, with the technical and financial support from the International Development Research Centre (IDRC). Data from this survey makes it possible to investigate the performance factors likely to influence the strategic behaviour of firms and to revitalize the productive sector in Senegal (Diene et al., 2015). Three questionnaires were used to collect information on a firm's employees, its production, and its manager. Given the present study's direction, it used only data obtained from the first two questionnaires. The first questionnaire sought information on the demographic and socioeconomic characteristics of a firm's employees: their age, gender, education level, socio-professional category, and monthly income. The second questionnaire sought detailed information on ICT and technological innovation, ICT infrastructure, the effective use of ICT tools, and investment in ICT and technological innovations. It also sought information on the performance of firms and on the changes in the number of their permanent and non-permanent staff from the time the firms were created. This combined information enabled us to analyse the effect of digital technology adoption on firm performance and on employment dynamics in the manufacturing and service sectors. A summary description of all the data is given in Table A1 (in the appendix).

Specification of the econometric models

The first part of the study was aimed at assessing the effect of digital technologies on participation in public employment programmes and on job search. That is why the study sample was divided into two groups: people who adopt digital technologies in their job search strategies and those who do not. Selection bias is the main concern in any study that attempts to estimate the causal effect of digital technology adoption using non-experimental data. The selection bias arises when digital technology adopters have favourable characteristics (observable and unobservable) that make it easier for them to use digital technologies in their job search. In this case, it would be inappropriate to directly compare the digital technology adopters to a randomly selected group of its non-adopters. So, to reduce the selection bias effect, the study used two statistical matching methods: the propensity score matching (PSM) and the inverse probability weighted regression adjustment (IPWRA).

For both methods, we started with a regression analysis of digital technology adoption on a set of observable characteristics that were assumed to simultaneously influence digital technology adoption and outcome variables. The parameters were estimated using a logit model while the predicted values of digital technology adoption (i.e.,propensity scores) were obtained from all covariates, irrespective of their significance levels.

The PSM ranks individuals according to their propensity score (Heckman et al., 1998). In relation to this, we used the nearest neighbour approach as a matching algorithm. This enabled us to find, for each adopter of digital technologies, the closest non-adopter of these, and for each non-adopter, the closest adopter of them. The difference in outcome was calculated for each matched pair, and the respective differences were then averaged for the whole sample so as to obtain the average treatment effect. Formally, we calculated the treatment effects of digital technology adoption on the outcome variables in the following way:

$$\delta_i = Y_i^t - Y_i^c \quad (1)$$

Following Rubin (1980), we estimated the average treatment effect (ATE) in the following way:

$$\bar{\tau} = E(\delta) = E[Y_i^t - Y_i^c] = \pi E[\delta|D = t] + (1 - \pi)E[\delta|D = c] \quad (2)$$

Where: $D = t$ and $D = c$ correspond to the treated (i.e., the adopters) and the untreated (the non-adopters) individuals, respectively; π and $1 - \pi$ designate the proportion of the treated and that of the untreated, respectively. $E[\delta|D = t]$ represents the average treatment effect on the treated (ATT), which is the difference in outcomes between the adopters and the non-adopters of digital technologies. For its part, $[\delta|D = c]$ is the average treatment effect on the untreated (ATU).

We did not use the IPWRA method to directly match the adopters and the non-adopters; instead, we used the inverse of the propensity score, $p(X)$ for the adopters, and $(1 - p(X))$ for the non-adopters. We then used the inverse of the propensity score as a weight while regressing the outcome variable in order to correct for the estimated parameters for which there were no observations.

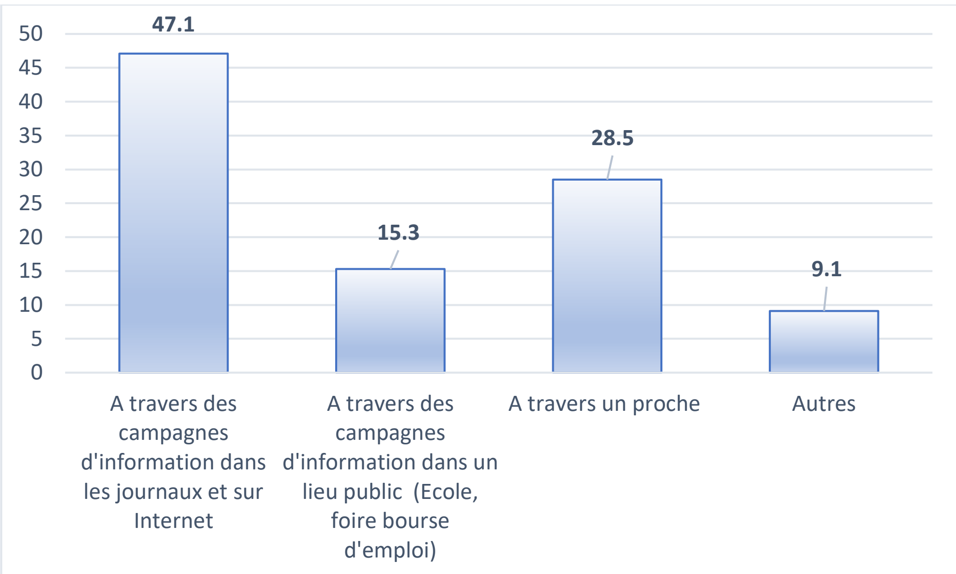
The IPWRA method is an improvement on the PSM in more than one way: while the PSM assigns a weight of 1 to the nearest untreated individual and a weight of 0 to all the others, the IPWRA method implicitly compares each individual with all the others, while assigning higher weights to individuals with a similar probability of being in the treatment or comparison group, and lower weights to individuals who are different. Given that more observations are included in the model comparing a treatment unit to its hypothetical counterfactual, statistical precision gets increased. Another interesting feature of the IPWRA method, compared to the PSM, is that it is doubly robust. Indeed, if the treatment model is misspecified (i.e., a variable is missing in the model or its functional form is incorrect), the PSM will provide inconsistent estimations. But in the case of the IPWRA method, if the treatment model is misspecified, the treatment effect estimations will remain consistent so long as the outcome variable model is not also misspecified. The inverse is also true: if the treatment model is correctly specified but the model of the outcome variable is misspecified, the IPWRA method will still provide consistent estimations. In view of these advantages, the present study's estimations were done using the IPWRA model, while the PSM was used in parallel to test for the robustness of the results.

The study's variables

The explanatory variables

The explanatory variable of interest (i.e., the treatment variable) is digital technology adoption. Figure 1 shows that most of the respondents (47.1%) learnt about the Directorate of Employment (DE) and the National Bureau for the Promotion of Youth Employment (ANPEJ) through information and communications technologies, in particular through awareness campaigns in newspapers and on the Internet. Since there were two sources of information, a binary treatment variable was used: it was assigned the value 1 if the respondent declared that he/she became aware of the two employment promotion structures through digital technologies (i.e., awareness campaigns in newspapers and on the Internet), and 0 if he/she became aware of them through awareness campaigns in a public place, or through a friend or other sources.

Figure 1: Channel through which the respondents learnt about the DE/ANPEJ



Notes: [47.1] Through awareness campaigns in newspapers and on the Internet.
[15.3] Through awareness campaigns in a public place (e.g., a school, a job fair).
[28.5] Through a friend.
[9.1] Through other sources.

Source: Compiled by the authors based on the EAPE (2018) survey.

The other explanatory variables used in the study related to the jobseekers' socioeconomic, demographic, and geographical characteristics: age, gender, and marital status. We controlled for the job seekers' education, political party affiliation, and district of residence. We also created several discrete variables: the first one was about the jobseekers' level of knowledge of Wolof, the second about their level of knowledge of Arabic, the third about their level of knowledge of French, and the last one about their level of knowledge of English.

The outcome variables

To determine the effect of digital technology adoption on participation in public employment programmes, we compared the adopters with the non-adopters of digital technologies on the basis of five outcome variables, with each being assigned the value 1 if the jobseeker benefited from a given programme, and 0 if not. Five types of programmes were concerned: the internship and apprenticeship programme, the adaptation or retraining internship programme, the incubation internship programme, the solidarity contract programme, and the spin-off contract programme. A description of each of these programmes is provided in Appendix B. The aim was to empirically test whether adopters of digital technologies were more likely to benefit from public employment programmes than the non-adopters.

On the other hand, to determine the effect of digital technology adoption on job search, we compared the adopters and the non-adopters on three outcome variables: unemployment, unemployment duration, and level of discouragement. A formal distinction between the unemployed and the discouraged provides a more in-depth analysis of job search activity. This is because unlike the unemployed, the discouraged are not part of the labour force. Specifically, the discouraged are unemployed persons who want a job, and are available for it, but have not looked for one in the last four weeks, either because they believe there are no jobs available or because they believe there are no jobs for which they are qualified. For its part, unemployment duration is calculated based on those who are already employed: it is captured by the number of months a person who used to be unemployed spent before eventually finding a job. In this regard, the question is whether or not, and to what extent, digital technology adoption can keep the unemployed in the labour force and reduce their propensity to withdraw from the labour market and if it can reduce the time spent in unemployment.

As a second step, a comparative analysis was done of the firms in the manufacturing sector and those in the services sector so as to measure the effect of digital technology adoption on productivity first and then on employment dynamics. Such a comparison enabled us to identify which of the two sectors of activity was most affected by digital technology adoption. Employment dynamics were measured by the turnover in a firm's permanent workforce between the year of its creation and the survey year normalized by the firm's age, since the firms under study were not created in the same year. Unlike recent studies that used various indicators of ICT (Brambilla & Tortarolo, 2018), the present study followed Chinoracky and Corejovaa (2019) and Ndubuisi et al. (2021) in measuring digital technology adoption by a composite index constructed using the Multiple Correspondence Analysis (MCA), a method that enabled us to transform all the underlying indicators (possession of computers, use of fixed and mobile telephony, the Internet, the intranet, faxes, websites, etc.) into a linear factor.

To test the hypothesis of this part of the work, we considered the following reduced-form specification that relates firm-level digital technology adoption to employment dynamics. Then, we evaluated the effect of ICT adoption on the variation in the number of jobs within firms.

$$Ln\Delta(EMP_i) = \alpha + \beta_1 IndexICT_i + \beta_2 X_i + \beta_3 Z_i + \varepsilon_i \tag{4}$$

Where: $\Delta(EMP_i) = EMP_{2012} - EMP_{creation}$ and $\Delta(EMP_i)$ is the difference in the number of (skilled and unskilled) jobs for firm i between the year of its creation and 2012. EMP_{2012} is the number of jobs in the firm in 2012. $EMP_{creation}$ is the number of jobs available when the firm was created. $IndexICT_i$ is the index of digital technology adoption constructed using the MCA method. X_i is the vector of the control variables that are related to the observable characteristics of the firm and its manager. β_1, β_2 , β_3 are the parameters to be estimated, while B_1 is the impact of digital technology adoption on the dynamics of job demand in the firm.

The estimation was done progressively by introducing a set of additional explanatory variables aimed at controlling for certain factors that are specific to the sector of activity and are likely to affect employment dynamics. These control variables enabled us to take account of significant heterogeneities that could affect the relationship between digital technology and employment dynamics. With the kind of specification we have in Equation 4, an ordinary least squares (OLS) estimation is required, but it would be biased because it assumes that digital technology adoption is exogenously determined, whereas it is potentially endogenous. Firms are likely to make their digital technology adoption and employment decisions concomitantly based on unobservable characteristics such as the quality of their management. In addition, the decision to adopt or not adopt a digital technology is voluntary and may be based on an individual firm's self-selection. Firms that have adopted digital technologies may have systematically different characteristics from those that have not. They may have decided to adopt digital technologies based on their expected performance. It is quite conceivable that the unobservable characteristics of firms and those of their managers may influence both the technology adoption decision and employment dynamics. The decision to adopt digital technologies may itself depend on the employment dynamics in the firm.

To address this endogeneity problem, we adopted an instrumental variable approach by using, at the sub-regional level, a more aggregated measure of digital technologies: the sub-regional (town/city) number of firms that had at least one computer in use and the intensity of digital technology use in each sector of activity (Lacovone et al., 2016; Almeida et al., 2017).

We expected that computer use by firms at the level of each sub-region (17 towns/ cities in three regions of Senegal) would be positively correlated with those firms' adoption of digital technologies. The rationale for using these two instruments was that the degree of technological progress at the sub-regional level might have a different impact on firms depending on the intensity of ICT use in their sectors of activity. Thus, to mitigate endogeneity effects, we used a specification that controlled for region-specific technology adoption patterns and the intensity of ICT use in each sector of activity. So, the first step of our specification was the following:

$$IndiceTIC_i = \lambda_1 P\_ORD_i + \lambda_2 Int\_TIC_i + \beta_1 X_i + \beta_2 Z_i + \mu_i \tag{5}$$

Where: P_ORD_i is the sub-regional (city/town) number of firms that had at least one computer in use and Int_TIC_i is the intensity of digital technology adoption in each sector of activity. μ_i is the error term that was identically distributed. The second step of our specification was the following:

$$Ln\Delta(EMP_i) = \alpha + \beta_1 \overline{IndiceTIC}_i + \beta_2 X_i + \beta_3 Z_i + \varepsilon_i \tag{6}$$

with $\overline{IndiceTIC}_i$ being estimated from the first step. Equation 6 produced a causal effect of digital technology adoption on employment dynamics using the intensity of ICT use in the sector of activity and in the sub-region to account for the overall degree of variability in the instrument.

In the end, the present study tested the robustness of its results by using the money invested in technology as a measure of digital technology adoption. This alternative measure enabled us to rigorously establish the relationship between digital technology adoption and productivity and employment dynamics within firms operating in the manufacturing and service sectors in Senegal.

4.0 Profile of jobseekers using digital technologies

Table 1 provides a profile of jobseekers according to whether they were digital technology adopters or not. Overall, the results indicate the adopters were more likely to benefit from public employment programmes than the non-adopters. A disaggregated analysis by type of programme shows that the adopters benefitted more from solidarity contract programmes than the non-adopters. However, they were less likely to benefit from adaptation internship programmes than the non-adopters. We also found that there was no significant difference between the adopters and the non-adopters in terms of their participation in internship and apprenticeship, incubation internship, and spin-off contract programmes. On the other hand, the adopters were more likely to be found among the labour force than among the unemployed (10.6% of the labour force compared to 8.5% of the unemployed). Moreover, they were less likely to give up job search (2.6% of them compared to 5.2% of the discouraged) and were less likely to remain unemployed for a long time than the non-adopters (5.9 months compared to 7.1 months).

In relation to other variables, the digital technology adopters were also found to be different from the non-adopters in many respects (see Table A1 in the appendix for the full individual characteristics): first, female jobseekers constituted 37% of the adopters, while they constituted 44.1% of the non-adopters; second, on average, the adopters were slightly younger than the non-adopters (31.68 years of age compared to 30.89 years); third, the adopters were also better educated than the non-adopters: 87.2% of the adopters had attained a higher education level compared to 73.4% of the non-adopters. Indeed, we found that jobseekers with a higher education level were more likely to adopt digital technologies in their job search than those with a primary school or a secondary school education level. In terms of languages, we found that the adopters were likely to be more proficient in languages (Wolof, Arabic, French, and English) than the non-adopters. This suggests that a mastery of one of these languages facilitates the use of digital technologies for job searching in Senegal.

Table 1: Characteristics of the digital technology adopters vs. those of the non-adopters

Variables	(1) Adopters (N=1,082)	(2) Non-adopters (N=1,664)	Test of difference (1)-(2)
Outcome variables			
Participation in public employment programmes	0.345	0.282	0.063***
	[0.014]	[0.011]	
Participation in solidarity contract programmes	0.085	0.037	0.048***
	[0.010]	[0.006]	
Participation in spin-off contract programmes	0.004	0.007	-0.003 (ns)
	[0.002]	[0.003]	
Participation in adaptation internship programmes	0.039	0.080	-0.041***
	[0.007]	[0.009]	
Participation in apprenticeship internship programmes	0.351	0.355	-0.005 (ns)
	[0.017]	[0.015]	
Participation in incubation internship programmes	0.010	0.006	-0.004 (ns)
	[0.002]	[0.003]	
The unemployed	0.106	0.085	0.022*
	[0.009]	[0.007]	
The discouraged	0.026	0.052	-0.026***
	[0.005]	[0.005]	
Unemployment duration	5.933	7.130	-1.197*
	[0.496]	[0.469]	

Notes: - The values shown for the tests of difference are the tests of difference for group means.
- The values in brackets are standard deviations.
- ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.
- ns means 'not significant'.

Source: Compiled by the authors based on the EPAE (2018) survey.

Overall, most of the socioeconomic and demographic characteristics observed in the analysis can be correlated with each other. A multivariate analysis, which is discussed below, allows for a better isolation of the effect of each variable.

The present study adopted an empirical framework using a binary logit model, with the treatment variable described above being the dependent variable. As pointed out earlier, this is a dichotomous variable that was assigned the value 1 for jobseekers who adopted digital technologies in their job search and 0 for those who did not. Table 2 presents the results of the study's estimations.

Table 2 shows that, gender, age, education level, and knowledge of language were the main factors in adopting digital technologies for job-searching purposes: men were more likely to adopt digital technologies than women, while being female reduced the likelihood of using digital technologies for job searching by 6.7 percentage points. This suggests that there is need for gender-specific policies to promote digital technology adoption. The likelihood of a jobseeker adopting digital technologies increased with age. With those aged 20-24 years being taken as the reference, it transpires from Table 2 that the likelihood of using digital technologies increased by 12.9 percentage points for those aged 25-29 years, by 16.7 percentage points for those aged 30-34 years, by 23.9 percentage points for those aged 35-39, and by 24.5 percentage points for those aged 40-44. These results clearly indicate that adult jobseekers were more likely to use digital technologies than younger ones. Education level also had a positive and significant impact on digital technology adoption: having a secondary or higher education level significantly increased the likelihood of using digital technologies than just having a primary education level. This likelihood was highest for jobseekers with a higher education level. Further, proficiency in Wolof, Arabic, or English significantly increased this likelihood: jobseekers with skills in Wolof, Arabic, or English were more likely to use digital technologies than those without. In summary, it transpires from Table 2 that male jobseekers, adult ones, and those with a high level of education and good language skills were more likely to use digital technologies for job-searching purposes.

Table 2: Factors influencing jobseekers' adoption of digital technologies

Variables	Marginal effects	Std. deviations	P-value
Being female	-0.067***	0.0193	0.000
Being married	0.0204	0.0206	0.322
Age: from 20 to 24 years	Ref.	Ref.	Ref.
Age: from 25 to 29 years	0.129***	0.0327	0.000
Age: from 30 to 34 years	0.1670***	0.0333	0.000
Age: from 35 to 39 years	0.239***	0.0392	0.000
Age: from 40 to 44 years	0.245***	0.0582	0.000
Primary school education level	Ref.	Ref.	Ref.
Lower secondary school level	0.136**	0.0541	0.012
Secondary school in general	0.097*	0.0518	0.061
Higher education level	0.236***	0.0432	0.000
Very little knowledge of Wolof	Ref.	Ref.	Ref.
Little knowledge of Wolof	0.242***	0.0588	0.000
Good knowledge of Wolof	0.279***	0.0581	0.000
Very little knowledge of Arabic	Ref.	Ref.	Ref.
Little knowledge of Arabic	0.056**	0.019	0.004
Good knowledge of Arabic	-0.010	0.049	0.837
Very little knowledge of French	Ref.	Ref.	Ref.
Little knowledge of French	-0.027	0.212	0.897
Good knowledge of French	0.115	0.213	0.588
Very little knowledge of English	Ref.	Ref.	Ref.
Little knowledge of English	0.119**	0.048	0.014
Good knowledge of English	0.157**	0.052	0.002
Being a political party activist	0.013	0.030	0.647
Area of residence (district)	Yes	Yes	Yes
Number of observations	2606		
Prob>chi2	0.0000		
Pseudo R2	0.0593		
Wald chi2(21)	170.77		

Notes: The symbols *, **, and *** represent statistical significance levels at 10%, 5%, and 1% respectively. Standard deviations were corrected for heteroscedasticity.
Source: Compiled by the authors based on the EPAE (2018) survey.

5.0 Analysis of the impact of jobseekers' digital technology adoption on their participation in public employment programmes and on their job search

The present study followed a two-step approach to estimating the impact of jobseekers' digital technology adoption on their participation in public employment programmes and their job search: firstly, we used a simple probit model to measure the impact before the matching; secondly, we used the PSM and IPWRA methods to determine the impact after the matching on propensity scores (see Table 3).

Table 3: Estimation of the impact of digital technology adoption

	Before the matching	After the matching	
	PROBIT/OLS	PSM	IPWRA
Participation in public employment programmes	0.009	0.001	0.012
	(0.0173)	(0.019)	(0.017)
Participation in solidarity contract programmes	0.043***	0.031**	0.040***
	(0.0120)	(0.012)	(0.0117)
Participation in spin-off contract programmes	-0.005	0.003	0.004
	(0.004)	(0.003)	(0.003)
Participation in adaptation internship programmes	-0.049***	-0.045***	-0.045***
	(0.0122)	(0.012)	(0.010)
Participation in apprenticeship internship programmes	-0.025	-0.021	-0.029
	(0.021)	(0.024)	(0.021)
Participation in incubation internship programmes	0.002	0.004	0.002
	(0.005)	(0.004)	(0.003)
The unemployed	0.023**	0.023*	0.023*

	(0.011)	(0.012)	(0.012)
The discouraged	-0.014*	-0.019**	-0.016**
	(0.008)	(0.008)	(0.007)
Unemployment duration	-0.404	-0.233	-0.068
	(0.730)	(0.926)	(1.087)

Notes: The symbols *, **, and *** represent statistical significance levels at 10%, 5%, and 1%, respectively. The values in parentheses are standard deviations.
Source: Compiled by the authors based on the EPAE (2018) survey.

The results in Table 3 indicate that both before and after the matching, the jobseekers' digital technology adoption did not significantly influence their participation in public employment programmes. Before the matching, the jobseekers' digital technology adoption increased their chances of benefiting from solidarity contract programmes by 4.3% but reduced their chances of benefiting from adaptation internship programmes by 4.9%. After the matching, that is after controlling for the selection bias on observable characteristics using the PSM and IPWRA methods, digital technology adoption increased the jobseekers' chances of benefiting from solidarity contract programmes by 3.1-4% but reduced their chances of benefiting from adaptation internship programmes by 4.5%. Analysis of the results for before and after the matching also indicates that digital technology adoption did not significantly increase the jobseekers' chances of participating in incubation internship, apprenticeship internship, and spin-off contract programmes.

In sum, while the digital technology adopters were more likely to benefit from solidarity contract programmes, their chances of benefitting from incubation internship, apprenticeship internship, and spin-off contract programmes were the same as those of the non-adopters.

The second part of the table highlights the impact of digital technology adoption on job search before and after the matching. It shows that digital technology adoption significantly influenced job search: before the matching, the use of digital technologies increased the probability that an unemployed person would continue to actively search for a job by 2.3% while it reduced the probability that he/she would withdraw from the labour market by 1.4%. However, the use of digital technologies had no impact on unemployment duration.

Table 3 also shows that, after the matching, the use of digital technologies increased the probability that an unemployed person would remain in the labour force by 2.3% and reduced the probability that he/she would give up looking for a job by 1.6% to 2.3%. These results corroborate those of Beard et al. (2012) who found that the use of digital technologies provided information about job prospects that reduced the probability that an unemployed person thought that there were no jobs available or that there were no jobs for which he/she was qualified. The present study's results are also in line with those of Autor (2001) and Stevenson (2009) who found that the use of digital technologies appeared to reduce the costs associated with job search, thus keeping the unemployed in the labour force. Finally, our results indicate that the use of digital technologies reduced the time the jobseeker remained unemployed before getting a job. However, the impact was not found to be significant. This finding is consistent with those obtained by Kuhn and Skuterud (2004) and Fountain (2005) who too found that the Internet had little or no significant impact on unemployment duration. In a nutshell, the present study's results suggest that digital technology adoption helps the unemployed to continue their active job search efforts but does not reduce their unemployment duration.

6.0 Analysis of the effect of digital technology adoption on employment dynamics in the manufacturing and service sector firms

The debate on the relationship between ICT and employment remains a passionate one. One of its facets, which relates to the rapid diffusion of ICT, is the idea that digital technologies may replace some jobs and thus make some workers redundant. At the same time, it is assumed that ICT diffusion is likely to increase the productivity of firms and thus generate more employment. It is against this backdrop that the present study used primary survey data from 711 manufacturing and service sector firms in Senegal to examine the effect of ICT adoption on employment demand. While some previous studies have examined the impact of autonomic computing, complex software, the Internet, and the website on the use of routine tasks done by little equipped workers and highly educated workers (Almeida et al., 2017), in the present study, we constructed a synthetic ICT use index based on a set of components such as the Internet, the intranet, the website, and fixed and mobile phones.

Measurement of variables

The present study used the number of permanent jobs to approximate a firm's total labour force, consisting of both highly skilled and less skilled workers. While the fact that the existing literature used education level as a basis for establishing socio-professional categories, the present study grouped into two categories: that of highly skilled workers, comprising senior managers, senior technicians, and that of less skilled workers, comprising blue-collar workers and their supervisors. This way of characterizing the labour force is similar to that used by Locovone (2018) who categorized workers into skilled and unskilled workers in the case of Mexican firms. Categorizing workers in this way enabled us to control for the bias of valuing the quality of labour using educational attainment, given that the high unemployment rate in Senegal pushes graduates to take up any type of job that comes their way when they are looking for a job. We controlled for sector of activity and gender in employment in order to better account for the heterogeneities related to these two variables and which could simultaneously have an impact on ICT adoption and on labour demand.

To assess the effect of ICT on economic development, the literature has used several measures. Lacovone & Pereira-López (2018) used three alternative measures of ICT use, namely, the proportion of the workers who used computers, the Internet, and the amount of fixed assets that was related to computer equipment. For their part, Bloom et al. (2015) and Brambilla and Tortarrolo (2018) used a binary variable to measure investment in ICT. While these authors reported solid results, their ICT indicator did not account for situations in which ICT investment stocks had declined. The present study measured digital technology adoption using a composite ICT index constructed on three components: availability ICT tools, ICT use, and ICT infrastructure (see Table A2 in the appendix for details). We used the multiple component analysis (MCA) method, which makes it possible to reconcile nominal and ordinal variables, on the one hand, and to describe the associations between these variables and individuals (in this case firms), on the other hand. The MCA makes it possible to assign a weight to a given variable and to each of its modalities (Asselin, 2002).To normalize the indicators into an index, we borrowed the following equation from PNUD [UNDP] (2014), one which the UNDP uses to calculate its human development index:

$$ICTindex = \frac{Value\ of\ the\ ICT\ index - Min\ Value}{Max\ value - Min\ value} \quad (6)$$

While this specification has no fundamental effect on the value of the index, it does change the order of magnitude of the different values which the indicator can take and has the advantage of being able to set the minimum and maximum values in the MCA.

One of the variables constructed using the ACM is a firm's managerial ability. This type of ability creates a fertile environment for the adoption of digital technologies that are vital for the firm. It encompasses several dimensions such as human resource management, financial management, management of the socioeconomic environment, and ethics management, all of which are described in Table A3 (in the appendix). The rest of the variables are presented in Table A4 (in the appendix).

Statistical analysis

Table 4 presents descriptive statistics by sector of activity. Overall, the average level of digital technology adoption was 30%. In relation to specific sectors of activity, the average level of adoption was 24.66% in the industrial sector, 25.7% in the trade sector, and 39.65% in the services sector. Despite the large heterogeneity between sectors of activity, it is clear that the level of digital technology adoption was higher in the service sectors than in the manufacturing and trade sectors. With the use of digital technologies becoming increasingly indispensable for economic activity, irrespective of their sectors of activity, firms are equally increasingly adopting ICT tools and infrastructure to optimize their operations. Although the different firms were not created in the same year, the evolution of their use of technology enables their employees to work faster and more efficiently; it also enables an optimization of routine tasks, thanks to fluid communication between stakeholders.

Between 2010 and 2012, an increase was recorded in the number of workers for firms that used computers and had a service phone. There was an 85% increase in the case of highly skilled workers, and an 85.71% increase in the case of the less-skilled ones. This increase in both the number of workers and that of computers automatically suggests that there could be a relationship between the use of computers and the demand for labour in firms in Senegal. Even though the literature has reported a relationship between ICT and the labour market in developed countries (Autor, 2015), it would be more appropriate to test this relationship in a low-income country like Senegal. Computer-using firms had on average six highly skilled employees and 12 less skilled ones, with a 44.58% propensity to adopt product and process innovations and a 42.2% propensity to adopt non-technological innovations.

Although the rate of adoption of digital technologies varies from one firm to another, their use allows any firm to redefine its objectives, to easily make decisions according to the expectations of all its stakeholders, to easily manage information and to remotely track the delivery of products and services. While it is true that workers greatly benefit from the use of ICT in the sense that it gives them greater autonomy from their hierarchical authorities, it is equally true that ICT use can, not only accomplish routine tasks for workers, but it can also help the highly skilled workers to carry out non-routine cognitive tasks as well. Thus, digital technology adoption may affect the demand for labour, as shown in the literature (Autor & Dorn, 2013; Michaels et al., 2014; Brambilla & Tortarolo, 2018).

The present study further found that 67.23% of the employees who reached the position of manager had had experience in strategic business management, except for those who had created their own firm. Their managerial ability was no doubt correlated with their low level of education, to the extent that managers in the manufacturing sector had an average education level of just primary school (Grade 7), while the managers of the service and trade sector firms had a lower secondary certificate (Grade 10). For their part, on average, the managers of firms in the service sector had a lower secondary school certificate. This relatively low level of education is inconsistent with the education policies which Senegal has implemented since the 2000s, after the country achieved the completion point of the Heavily Indebted Poor Countries Initiative.

Table 4: Descriptive Statistics

	Industrial Sector	Trade Sector	Service Sector	Overall
Productivity	3.97e+08 (3.79e+09)	9383606 (5.68e+07)	4.51e+08 (4.82e+09)	2.57e+08 (3.31e+09)
Capital	1.74e+09 (1.70e+10)	7.43e+07 (6.23e+08)	1.97e+09 (1.20e+10)	1.14e+09 (91.17e+10)
Highly skilled jobs	5.720 (23.83)	2.285 (3.608)	10.919 (44.70)	5.702 (26.987)
Less skilled jobs	18.57 (65.41)	4.196 (18.29)	15.05 (58.80)	11.925 (50.279)
Size of the firm	25.33 (92.913)	6.480 (21.378)	30.211 (117.76)	19.088 (82.617)
ICT index	.2466 (.3686)	.257 (.3239)	.3965 (.3858)	.2904 (.3612)
Managerial ability	.4843 (.2525)	.4350 (.2375)	.5186 (.2674)	.4739 (.2524)
Technological innovation	.5103 (.5009)	.3665 (.4827)	.4757 (.5008)	.4458 (.4974)
Non-technological innovation	.4279 (.4958)	.3629 (.4817)	.4973 (.5013)	.4219 (.4942)
Inter-firm cooperation	.0823 (.2754)	.096 (.2952)	.1405 (.3485)	.1027 (.3037)
Manager's social capital	.2922 (.4557)	.3060 (.4617)	.4054 (.4923)	.3277 (.4697)
Manager's experience	.6831 (.4662)	.6406 (.4807)	.7027 (.4583)	.6723 (.4697)
Male gender	.9341 (.2485)	.8612 (.3463)	.8919 (.3113)	.8945 (.3074)
Management training for managers	.6831 (.4662)	.4767 (.5003)	.6486 (.4787)	.5921 (.4918)
Age of the firm	12.925 (12.87)	9.00 (8.237)	9.989 (11.29)	10.59 (10.924)
Manager's age	39.56 (14.28)	37.53 (15.015)	38.37 (15.77)	38.44 (14.96)
Education level	7.251 (6.429)	9.277 (6.769)	10.027 (6.874)	8.782 (6.778)
Industrial sector				.3418 (.4746)
Trade sector				.3952 (.4892)
Services sector				.2602 (.439)

Source: Compiled by the authors based on data from the DPEASF survey (2014).

Effect of digital technologies on employment

Table A5 and Table A7 (in the appendix) present the OLS estimations of Equation 4 and Equation 5. All specifications include, as control variables, the characteristics of the firm (size, age, sector of activity), the manager's characteristics (age, experience, social capital, managerial ability, education level, training in management) and the socioeconomic characteristics (innovation, inter-firm cooperation, the firm's capital). A positive and significant correlation was found between digital technology adoption and the number of firms using computers in their operation. A similar correlation was also found between the intensity of ICT use and the firm's sector of activity. A correlation between digital technology adoption and the ICT tools used was found to be strongly positive and significant regardless of sector of activity. This finding suggests that digital technology adoption increased significantly in firms operating in high growth ICT sectors. For example, it was found that a one-percentage-point increase in the number of computer-using firms at the regional level and in the intensity of ICT use across sectors of activity led to an increase in digital technology adoption of 2.0 percentage points on average.

To validate the instruments used, several tests were performed to assess the relevance of the variables used. A test of under-identification and weak identification showed that the regressions were not negatively affected by the identification problem, since the F-statistics were above or close to the critical value of 10% in all the models (Staiger & Stock, 1997). In addition, the reported value for the Sanderson and Windmeijer (2016) under-identification test suggests that the instrument was valid. The coefficients for the variable of interest obtained using the two-Stage least squares (2SLS) method were higher than those obtained using the ordinary least squares (OLS), which again shows that the instruments were valid.

Table 5 presents the two-Stage least squares (2SLS) estimations of Equation 6 in relation to digital technology adoption by Senegalese firms and to employment dynamics. The table shows that, digital technology adoption by Senegalese firms had a positive and significant impact on both the number of people they employed and the number of both their highly skilled and less skilled employees. Specifically, digital technology adoption by a firm increased the number of its highly skilled employees by 2.12% and that of its less skilled ones by 2.64%. This corresponds to a 0.52% greater impact for the less skilled jobs than for the highly skilled ones. This effect on highly skilled employment was 2.43 percentage points for the manufacturing firms, 1.83 percentage points for the trade sector firms, and 2.5 percentage points for the services sector ones. The effect on less skilled employment was 6.33 percentage points for the manufacturing firms, 1.56 percentage points for the trade sector firms, and 1.47 percentage points for the services sector ones. The adoption of these digital technologies, which enable the exchange of information between different stakeholders as well as the structuring of the production and marketing system, makes it possible to optimize employee potential and to increase the demand for highly qualified employment in service sector firms.

It thus transpires that digital technology adoption had a greater effect on the demand for the less skilled labour in Senegalese manufacturing firms. Regarding the demand for highly skilled labour, this effect was greater in the tertiary sector (trade and services). This means that digital technology adoption was an important source of change in skill boundaries and created a new competitive advantage for Senegalese firms. It affected and modified the cycle of a product and changed its distribution mode, which modified the firm's power relations with its stakeholders (competitors, suppliers, customers). This modification generated different gains in the execution of the chain of production of goods and services which was associated with the demand for both highly skilled and less skilled labour. These findings are consistent with the theoretical view that digital technology adoption is related to job quality improvement (Brambilla & Tortarolo, 2018). The only difference is that the present study found a bigger improvement in the less skilled jobs than in the highly skilled ones in the case of manufacturing firms. This difference was due to the fact that Senegalese firms are mostly small- and medium-sized enterprises, and therefore prefers to recruit a not-highly skilled workforce (senior technicians) and offer them retraining in ICT tools, which in the end is less costly for the firms in terms of payroll.

The Senegalese firms' use of digital technologies, that is technologies that automate their information exchange, their production system, their organizational system, and their marketing system, has caused those firms to change their occupational structure by increasing the number of both their highly skilled and less skilled labour force. Digital technologies affect the Senegalese labour market through information and automation of tasks performed by highly skilled and less skilled workers. An increase in the number of less skilled workers (manual and technical workers) in the firms' total workforce is potentially linked to their expansion of production and employment. However, a higher demand for less skilled workers than that for highly skilled ones was observed in the manufacturing firms, while the opposite was observed in the service sector firms, where the demand for highly skilled workers outstripped the demand for labour because of the complex adoption of digital technologies.

An increase in the number of highly skilled workers as a result of digital technology adoption was observed in the manufacturing sector. This increase was larger for the less educated workers in the same sector of activity, while for the firms in the trade and service sectors, the effect of digital technology adoption was smaller for the less skilled workers than for the highly skilled ones. For most of the highly skilled and the less skilled workers, a significant differential effect between sectors was observed (see Table 5).

Table 5: Two-stage least squares estimation

VARIABLES	Highly Skilled Jobs				Less Skilled Jobs				Total employment			
	Industrial Sector	Trade Sector	Services Sector	Overall	Industrial Sector	Trade Sector	Services Sector	Overall	Industrial sector	Trade sector	Service sector	Overall
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
ICT index	2.430*	1.829***	2.494**	2.116***	6.329**	1.556**	1.467	2.642***	6.720**	2.222***	1.665*	3.249***
	(1.381)	(0.562)	(1.073)	(0.540)	(2.641)	(0.687)	(1.091)	(0.653)	(2.784)	(0.651)	(1.063)	(0.666)
Firm's capital	0.00598	-0.00735	0.0150	0.00485	-0.0636	-0.00222	-0.00599	-0.00316	-0.0614	-0.00499	0.0236	0.00133
	(0.0294)	(0.00655)	(0.0153)	(0.00734)	(0.0562)	(0.00800)	(0.0156)	(0.00888)	(0.0592)	(0.00758)	(0.0152)	(0.00906)
Managerial ability	-0.398	-0.231	0.0652	-0.170	-0.480	0.706**	0.647	0.247	-0.371	0.447	1.000**	0.265
	(0.307)	(0.277)	(0.438)	(0.200)	(0.586)	(0.338)	(0.445)	(0.242)	(0.618)	(0.320)	(0.434)	(0.246)
Technological innovation in production	0.0797	-0.0966	-0.316*	-0.109	0.0406	-0.0284	-0.188	-0.117	0.0398	-0.0689	-0.357**	-0.148*
	(0.103)	(0.0965)	(0.172)	(0.0684)	(0.197)	(0.118)	(0.175)	(0.0828)	(0.208)	(0.112)	(0.171)	(0.0844)
Non-technological innovation	0.0996	0.0430	-0.0259	0.0247	-0.100	0.104	0.141	0.0739	0.0369	0.178	0.182	0.117
	(0.134)	(0.0977)	(0.188)	(0.0814)	(0.256)	(0.119)	(0.191)	(0.0985)	(0.270)	(0.113)	(0.186)	(0.100)
Inter-firm cooperation	0.684***	-0.0616	0.131	0.221*	-0.215	-0.361*	0.803***	0.121	-0.250	-0.235	0.847***	0.111
	(0.249)	(0.162)	(0.286)	(0.133)	(0.476)	(0.198)	(0.290)	(0.160)	(0.502)	(0.187)	(0.283)	(0.164)
Computer-to-employee ratio	-0.304***	-0.342***	-0.324***	-0.327***	-0.733***	-0.584***	-0.640***	-0.649***	-0.770***	-0.676***	-0.680***	-0.714***
	(0.0491)	(0.0521)	(0.0774)	(0.0315)	(0.0938)	(0.0637)	(0.0787)	(0.0381)	(0.0989)	(0.0604)	(0.0766)	(0.0389)
Firm's age	-0.0778	-0.0186	-0.359	-0.146*	-0.566**	-0.405***	-0.271	-0.392***	-0.417	-0.251*	-0.390*	-0.283***
	(0.142)	(0.119)	(0.230)	(0.0849)	(0.271)	(0.146)	(0.233)	(0.103)	(0.286)	(0.138)	(0.227)	(0.105)
Firm's age squared	0.0235	0.0123	0.178***	0.0659***	0.152**	0.120***	0.137**	0.141***	0.106	0.0851**	0.156**	0.108***
	(0.0358)	(0.0371)	(0.0643)	(0.0248)	(0.0685)	(0.0453)	(0.0654)	(0.0300)	(0.0722)	(0.0429)	(0.0637)	(0.0306)
Manager's social network	-0.0833	0.0924	0.0127	0.0412	-0.643**	-0.0844	0.111	-0.136*	-0.599*	-0.0342	-0.0378	-0.114
	(0.152)	(0.0815)	(0.186)	(0.0701)	(0.290)	(0.0996)	(0.189)	(0.0848)	(0.306)	(0.0943)	(0.184)	(0.0864)

Table 5: Two-stage least squares estimation continued

Manager's experience	0.0200	0.0347	-0.0445	-0.00935	0.276	-0.0206	-0.225	0.0373	0.307	-0.0146	-0.176	0.0417
	(0.114)	(0.0778)	(0.174)	(0.0653)	(0.219)	(0.0950)	(0.176)	(0.0790)	(0.231)	(0.0900)	(0.172)	(0.0805)
Gender	-0.146	-0.0115	0.120	-0.0170	0.195	0.111	0.172	0.153	-0.0215	0.0973	0.0527	0.0313
	(0.190)	(0.0995)	(0.243)	(0.0914)	(0.364)	(0.122)	(0.247)	(0.111)	(0.384)	(0.115)	(0.241)	(0.113)
Manager's training in management	0.00292	-0.0166	0.363**	0.0894	-0.314	0.0336	0.0211	-0.172**	-0.183	-0.00189	0.180	-0.0830
	(0.104)	(0.0750)	(0.160)	(0.0605)	(0.198)	(0.0916)	(0.163)	(0.0732)	(0.209)	(0.0868)	(0.158)	(0.0746)
Manager's age	-1.593	-2.344*	0.726	-1.725	3.414	-1.170	-5.395*	-1.855	3.370	-1.572	-3.088	-1.214
	(2.617)	(1.300)	(3.186)	(1.214)	(5.002)	(1.588)	(3.240)	(1.469)	(5.273)	(1.504)	(3.155)	(1.498)
Manager's age squared	0.226	0.365*	-0.163	0.239	-0.463	0.182	0.720	0.261	-0.459	0.267	0.390	0.181
	(0.375)	(0.187)	(0.458)	(0.173)	(0.716)	(0.228)	(0.465)	(0.210)	(0.755)	(0.216)	(0.453)	(0.214)
Education level	0.428	0.00441	-0.184	0.0408	0.775	0.334*	0.293	0.339**	0.972*	0.122	-0.103	0.249
	(0.290)	(0.146)	(0.331)	(0.134)	(0.553)	(0.178)	(0.336)	(0.163)	(0.583)	(0.169)	(0.327)	(0.166)
Education level squared	-0.215	-0.0172	0.00867	-0.0466	-0.424	-0.170**	-0.157	-0.187**	-0.511*	-0.0667	0.0121	-0.150*
	(0.141)	(0.0626)	(0.148)	(0.0619)	(0.270)	(0.0764)	(0.151)	(0.0749)	(0.284)	(0.0724)	(0.147)	(0.0763)
Industrial sector				0.128*				0.363***				0.275***
				(0.0671)				(0.0812)				(0.0828)
Services sector				0.0719				0.176*				0.139
				(0.0791)				(0.0956)				(0.0975)
Constant	2.988	3.720*	-0.923	2.985	-5.595	1.808	9.879*	3.134	-5.496	2.147	5.903	1.941
	(4.457)	(2.243)	(5.557)	(2.097)	(8.519)	(2.740)	(5.649)	(2.536)	(8.981)	(2.596)	(5.502)	(2.586)
	24.24	16.72	11.44	40.62	15.23	18.59	14.04	51.07	16.36	37.90	23.35	71.64
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
No. of obs.	243	281	185	711	243	281	185	711	243	281	185	711
R-squared	0.630	0.468	0.511	0.512	0.363	0.569	0.613	0.591	0.376	0.707	0.719	0.651

Notes: Standard deviations are given in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Source: Compiled by the authors based on the DPEASF (2014) survey.

It transpires from Table 5 that a high computer-to-employee ratio had a negative impact on the demand for employment within firms. The firm's age was found to have an inverted U-shaped relationship, whether in relation to the demand for highly skilled labour or to that for the less skilled.

7.0 Robustness of the results and gender heterogeneity

Robustness of the results

Following Almeida et al. (2017), in the present study, we tested the robustness of the results concerning the relative proportions of workers in a firm using an alternative measure to digital technology adoption, such as investment in ICT. Using this measure enabled us to assess whether changing the indicator to define digital technology adoption within the firm led to a different effect on the demand for labour. Table 6 presents the results of the effect of ICT investment on the demand for highly skilled and less skilled labour in all the three sectors under consideration: the manufacturing, the trade, and the service sectors. These results show that there was an increase in highly skilled and less skilled jobs as a result of increased ICT investment or digital technology adoption. These results mirror those already reported above. This means that, overall, they are robust in the face of a change in the measurement of digital technologies. The increase observed in total employment reflects the adjustments in the composition of labour demand, where highly skilled jobs were related to routine and cognitive tasks performed by ICT tools and less skilled jobs that required ICT training.

The increasing use of computers by firms in a given region may change the structure of labour demand, since the workers sought by these firms will have advanced skills in ICT use. Such a change in the structure of labour demand could influence the quality of the labour sought. Indeed, the increasing use of computers by workers will improve their skills in handling the digital technologies which the firms they work for might adopt.

While the temporal trends specific to a given region could control for the potential changes in the region's labour quality over time, firms may relocate along the economic agglomeration to take advantage of better prices for digital technologies. However, this temporal effect was not taken account in the present study given the quality of the data used.

.

Table 6: Test of the robustness of the effect of ICT investment on employment

VARIABLES	Quality of Employment				Less Skilled Jobs				Total Employment			
	Industrial Sector	Trade Sector	Service Sector	Overall	Industrial Sector	Trade Sector	Service Sector	Overall	Industrial Sector	Trade Sector	Service Sector	Overall
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
ICT index	0.0254**	0.00776	-0.00192	0.0125**	0.041***	0.043***	-0.00479	0.030***	0.043***	0.0263**	0.000145	0.026***
	(0.0107)	(0.00967)	(0.0137)	(0.00636)	(0.0138)	(0.0127)	(0.0168)	(0.00811)	(0.0147)	(0.0119)	(0.0160)	(0.00776)
Firm's capital	0.060***	-0.00336	0.066***	0.045***	0.071***	-0.00037	0.0306	0.036***	0.072***	-0.00744	0.060***	0.043***
	(0.00975)	(0.00873)	(0.0159)	(0.00626)	(0.0126)	(0.0115)	(0.0195)	(0.00798)	(0.0134)	(0.0107)	(0.0186)	(0.00764)
Managerial ability	-0.314	0.396*	0.0459	0.129	0.0830	1.189***	0.937*	0.784***	0.289	1.215***	0.909*	0.882***
	(0.245)	(0.245)	(0.450)	(0.172)	(0.316)	(0.323)	(0.553)	(0.219)	(0.337)	(0.301)	(0.527)	(0.210)
Technological innovation in production	0.0980	0.00990	-0.196	-0.0231	-0.0291	0.0240	-0.0733	-0.0731	-0.00931	0.106	-0.174	-0.0621
	(0.0883)	(0.117)	(0.176)	(0.0712)	(0.114)	(0.154)	(0.216)	(0.0908)	(0.121)	(0.144)	(0.206)	(0.0869)
Non-technological innovation	0.110	0.0997	0.152	0.149*	0.125	0.0950	0.516**	0.266***	0.278*	0.167	0.404*	0.337***
	(0.115)	(0.115)	(0.197)	(0.0804)	(0.149)	(0.151)	(0.242)	(0.103)	(0.158)	(0.141)	(0.230)	(0.0982)
Inter-firm cooperation	1.428***	0.887***	0.480*	0.979***	0.565**	0.254	1.136***	0.899***	0.775***	0.861***	0.937***	1.010***
	(0.200)	(0.189)	(0.292)	(0.126)	(0.258)	(0.248)	(0.359)	(0.161)	(0.274)	(0.232)	(0.342)	(0.154)
Computer-to-employee ratio	-0.153***	-0.360***	-0.282***	-0.291***	-0.771***	-0.531***	-0.588***	-0.642***	-0.766***	-0.685***	-0.606***	-0.685***
	(0.0569)	(0.0731)	(0.0806)	(0.0388)	(0.0734)	(0.0962)	(0.0991)	(0.0495)	(0.0781)	(0.0898)	(0.0944)	(0.0473)
Firm's age	0.153	-0.303**	-0.549**	-0.197**	-0.101	-0.435**	-0.123	-0.37***	0.00770	-0.53***	-0.487*	-0.40***
	(0.143)	(0.129)	(0.241)	(0.0941)	(0.184)	(0.169)	(0.296)	(0.120)	(0.196)	(0.158)	(0.282)	(0.115)
Firm's age squared	-0.0209	0.0911**	0.221***	0.073***	0.0877*	0.137***	0.0962	0.146***	0.0645	0.171***	0.187**	0.153***
	(0.0362)	(0.0391)	(0.0671)	(0.0259)	(0.0466)	(0.0515)	(0.0825)	(0.0330)	(0.0496)	(0.0480)	(0.0785)	(0.0316)
Manager's social network	0.0586	0.198*	-0.133	0.0942	-0.164	0.0422	0.0295	-0.0197	-0.135	0.0821	0.108	0.0622
	(0.126)	(0.115)	(0.254)	(0.0877)	(0.163)	(0.151)	(0.312)	(0.112)	(0.173)	(0.141)	(0.297)	(0.107)
Manager's experience	0.0366	-0.0269	0.0642	0.0256	0.109	-0.0624	-0.450*	-0.0254	0.141	-0.0566	-0.276	0.0106
	(0.0964)	(0.0870)	(0.202)	(0.0687)	(0.124)	(0.115)	(0.248)	(0.0876)	(0.132)	(0.107)	(0.236)	(0.0839)
Gender	-0.0895	0.0672	0.109	0.0422	0.0776	0.215	-0.124	0.143	-0.0573	0.165	-0.134	0.0298
	(0.168)	(0.120)	(0.303)	(0.104)	(0.217)	(0.158)	(0.373)	(0.133)	(0.230)	(0.147)	(0.355)	(0.127)

Table 6: Test of the robustness of the effect of ICT investment on employment

Manager's training in management	-0.0935	0.00578	0.0551	0.00977	-0.30***	-0.104	0.0285	-0.171**	-0.261**	-0.0558	0.0479	-0.130*
	(0.0882)	(0.0840)	(0.170)	(0.0630)	(0.114)	(0.111)	(0.209)	(0.0804)	(0.121)	(0.103)	(0.200)	(0.0769)
Manager's age	-5.84***	-4.59***	-7.077*	-5.64***	-6.63***	-3.519*	-8.676*	-5.11***	-5.96***	-2.603	-8.907**	-4.88***
	(1.649)	(1.536)	(3.714)	(1.176)	(2.126)	(2.021)	(4.566)	(1.499)	(2.261)	(1.887)	(4.349)	(1.435)
Manager's age squared	0.797***	0.689***	0.984*	0.801***	0.889***	0.532*	1.170*	0.695***	0.796**	0.406	1.223*	0.674***
	(0.237)	(0.226)	(0.544)	(0.171)	(0.305)	(0.297)	(0.669)	(0.218)	(0.325)	(0.278)	(0.637)	(0.209)
Education level	-0.128	-0.176	-0.324	-0.130	-0.508**	0.295	0.203	0.0657	-0.346	-0.106	-0.0904	-0.118
	(0.167)	(0.138)	(0.297)	(0.112)	(0.216)	(0.182)	(0.365)	(0.142)	(0.230)	(0.169)	(0.347)	(0.136)
Education level squared	0.0507	0.0783	0.140	0.0496	0.223**	-0.140*	-0.0697	-0.0345	0.151	0.0551	0.0555	0.0501
	(0.0711)	(0.0553)	(0.116)	(0.0449)	(0.0917)	(0.0728)	(0.142)	(0.0572)	(0.0975)	(0.0680)	(0.135)	(0.0548)
Industrial sector				0.0468				0.314***				0.226***
				(0.0686)				(0.0876)				(0.0838)
Service sector				0.203***				0.280***				0.275***
				(0.0748)				(0.0955)				(0.0914)
Constant	10.48***	7.578***	12.61**	9.666***	12.12***	5.560	15.85**	8.920***	10.86***	4.017	16.26**	8.502***
	(2.861)	(2.595)	(6.275)	(2.008)	(3.690)	(3.415)	(7.714)	(2.561)	(3.925)	(3.188)	(7.348)	(2.452)
F-test	33.00	14.93	14.47	43.54	47.48	13.49	12.98	50.16	47.02	26.67	20.63	73.67
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00	0.000	0.000
No. of Obs.	0.800	0.640	0.732	429	158	161	108	429	158	161	108	429
R-squared	158	161	108	0.669	0.852	0.616	0.710	0.700	0.851	0.760	0.796	0.774

Notes: Standard deviations are given in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: Compiled by the authors based on the DPEASF (2014) survey.

Gender heterogeneity and the impact of technology on the firm's other variables

This section examines whether the digital technology adoption index had differential effects on employment in Senegalese firms according to their employees' gender. Table 7 presents the results of estimations of the effect of the digital technology adoption index by gender. These results indicate that the demand for employment for both male and female employees was tied to their digital technology adoption behaviour. A comparative analysis of the results shows that an increase in the digital technology index had a greater effect on the demand for highly skilled and less skilled male labour than for female labour. Although the effect on highly skilled employment for female employees was found to be non-significant, it was still smaller than the effect on highly skilled employment for male employees; similarly, the effect on less skilled employment was larger for male employees than for female ones. This is consistent with the theoretical view that digital technologies go hand in hand with an increasing demand for skilled labour. And this is evidence that an increased use of digital technologies by firms increases the demand for both the highly skilled and the less skilled labour, as found by Ndubuisi et al. (2021).

Table 7 also shows that digital technology adoption led the firms concerned to invest in training their employees in ICT. So, besides increasing the demand for highly skilled and less skilled labour, it led them to change their decision to train their employees on ICT use. The study found that, by adopting digital technologies, the Senegalese firms changed their behaviour with respect to the training provided to their employees; they increased the probability of providing ICT-specific training by an average of 3.27 percentage points. The effect of digital technology adoption for the firms that provided ICT-related training was found to be larger for less skilled workers (3.27 percentage points) than for the highly skilled ones (2.06 percentage points). This result is consistent with that found by Almeida et al. (2017) for firms in Chile, and which showed that digital technology adoption led those firms to invest in employee training.

Table 7: Heterogeneity in the effect of digital technology adoption on employment

VARIABLES	Female			Male			Training in ICT		
	Highly skilled employment	Less skilled employment	Overall	Highly skilled employment	Less skilled employment	Overall	Highly skilled employment	Less skilled employment	Overall
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
ICT index	2.981	2.062*	2.237**	4.535*	3.090***	2.358***	2.062*	3.270**	3.266***
	(1.889)	(1.091)	(0.960)	(2.488)	(1.009)	(0.840)	(1.091)	(1.308)	(1.214)
Firm's capital	-0.00969	-0.0155	-0.0101	-0.0113	-2.49e-05	0.00192	-0.0155	-0.0151	0.00442
	(0.0170)	(0.0171)	(0.0141)	(0.0215)	(0.0162)	(0.0103)	(0.0171)	(0.0213)	(0.0197)
Managerial ability	-1.119	0.524	0.466	-1.103	0.321	-0.0767	0.524	-0.144	0.0740
	(0.916)	(0.543)	(0.444)	(1.214)	(0.512)	(0.286)	(0.543)	(0.862)	(0.800)
Technological innovation in production	-0.293	-0.195	-0.160	-0.304	0.119	0.131	-0.195	-0.657*	-0.661*
	(0.329)	(0.194)	(0.153)	(0.340)	(0.174)	(0.0934)	(0.194)	(0.392)	(0.364)
Non-technological innovation	0.141	-0.0361	-0.0759	-0.0832	-0.205	-0.0918	-0.0361	-0.304	-0.0620
	(0.264)	(0.214)	(0.169)	(0.296)	(0.207)	(0.127)	(0.214)	(0.412)	(0.382)
Inter-firm cooperation	0.112	0.422*	0.0906	0.209	0.340	0.372*	0.422*	0.748**	0.716**
	(0.323)	(0.253)	(0.213)	(0.373)	(0.229)	(0.191)	(0.253)	(0.336)	(0.312)
Computer-to-employee ratio	-0.148	-0.120	-0.0602	0.00492	-0.260***	-0.331***	-0.120	-0.663***	-0.755***
	(0.137)	(0.0945)	(0.0699)	(0.116)	(0.0873)	(0.0554)	(0.0945)	(0.0968)	(0.0899)
Firm's age	-0.0136	-0.132	-0.370**	-0.113	-0.804***	-0.644***	-0.132	-0.364	-0.285
	(0.330)	(0.231)	(0.181)	(0.358)	(0.209)	(0.125)	(0.231)	(0.330)	(0.306)
Firm's age squared	0.0260	0.0890	0.157***	0.0441	0.231***	0.215***	0.0890	0.184**	0.146*
	(0.0892)	(0.0627)	(0.0513)	(0.107)	(0.0584)	(0.0347)	(0.0627)	(0.0889)	(0.0826)
Manager's social network	0.142	0.0586	-0.0485	0.171	0.0623	-0.0357	0.0586	-0.0343	-0.173
	(0.281)	(0.197)	(0.147)	(0.253)	(0.172)	(0.101)	(0.197)	(0.338)	(0.314)
Manager's experience	0.0704	-0.0280	0.0327	-0.279	0.0727	-0.0987	-0.0280	-0.120	-0.0618
	(0.241)	(0.206)	(0.146)	(0.272)	(0.190)	(0.0911)	(0.206)	(0.335)	(0.311)
Gender	-0.0140	0.00251	-0.262	-0.131	0.374	0.487***	0.00251	0.524	0.515
	(0.295)	(0.252)	(0.172)	(0.371)	(0.256)	(0.141)	(0.252)	(0.445)	(0.413)
Manager's training in management	0.0728	-0.0141	-0.146	0.142	-0.171	-0.104	-0.0141	-0.481	-0.136

Table 7: Heterogeneity in the effect of digital technology adoption on employment continued .

	(0.218)	(0.188)	(0.139)	(0.280)	(0.172)	(0.0848)	(0.188)	(0.316)	(0.293)
Manager's age	-7.779**	-6.596	-4.169*	-4.790	-5.604*	-3.032*	-6.596	-9.100*	-6.070
	(3.779)	(4.687)	(2.380)	(4.903)	(3.193)	(1.730)	(4.687)	(5.408)	(5.020)
Manager's age squared	1.098**	0.887	0.547*	0.689	0.752*	0.404	0.887	1.345*	0.901
	(0.543)	(0.654)	(0.340)	(0.681)	(0.449)	(0.247)	(0.654)	(0.785)	(0.729)
Education level	0.180	0.184	0.213	0.886	0.672*	0.212	0.184	0.245	-0.190
	(0.865)	(0.429)	(0.295)	(0.952)	(0.345)	(0.193)	(0.429)	(0.898)	(0.834)
Education level squared	-0.00988	-0.103	-0.119	-0.324	-0.341**	-0.131	-0.103	-0.123	0.0303
	(0.246)	(0.144)	(0.114)	(0.333)	(0.133)	(0.0907)	(0.144)	(0.297)	(0.276)
Industrial sector	-0.302	0.285	0.137	0.433	0.911***	0.684***	0.285	0.862**	0.681*
	(0.305)	(0.223)	(0.155)	(0.269)	(0.190)	(0.0925)	(0.223)	(0.404)	(0.375)
Service sector	0.352	0.693***	0.368**	0.163	0.172	0.273**	0.693***	0.679*	0.924***
	(0.271)	(0.218)	(0.179)	(0.332)	(0.191)	(0.110)	(0.218)	(0.344)	(0.319)
Constant	12.33*	11.44	7.931*	7.593	10.33*	6.000**	11.44	14.50	9.203
	(6.392)	(8.435)	(4.114)	(9.034)	(5.635)	(2.981)	(8.435)	(9.431)	(8.755)
No of Obs.	129	161	277	206	247	552	161	118	118
R-squared	0.750	0.417	0.308	0.479	0.503	0.579	0.417	0.604	0.655

Notes: Standard deviations are given in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: Compiled by the authors based on the *DPEASF* (2014) survey.

8.0 Conclusion and policy implications

The objective of this work was to examine the effect of digital technology adoption on labour market outcomes and employment dynamics in the manufacturing, trade, and services sector firms in Senegal. On the one hand, in order to assess the effect of digital technologies on young people's awareness of public employment programmes and their access to employment, the study applied the propensity score matching method to data obtained from a survey labelled “Improving Employment Policies” (Améliorer les Politiques d’Emploi, EAPE), which was conducted in 2018 among 2,746 individuals in Senegal. On the other hand, in order to measure the effect of digital technology adoption on employment dynamics in the manufacturing, trade and service sectors, it applied the instrumental variables method to data obtained from a survey called “Determinants of performance of firms in Francophone Sub-Saharan Africa: The Case of Senegal” (Déterminants de la Performance des Entreprises en Afrique Subsaharienne Francophone : Cas du Sénégal), which was conducted in 2014 among 723 firms.

The study found that, male and adult employees and those with a high level of education and good language skills were more likely to use digital technologies for job-searching purposes. It also found that digital technology adoption helped the unemployed youth to participate in solidarity contract programmes and to continue their active job-searching efforts, although it did not reduce the duration of their unemployment. It further found that the adoption of digital technologies by Senegalese firms had a statistically positive impact on both the proportions of highly skilled and less skilled employees in total employment in Senegal. In this regard, digital technology adoption by a firm increased the number of its highly skilled employees by 2.12% and that of its less skilled ones by 2.64%. This corresponds to a 0.52% greater impact for the less skilled employees than for the highly skilled ones.

It transpires from the present study that digital technology adoption plays an important role on the labour market and in job creation..To date, there are three official telecommunications operators: Sonatel, Free, and Expresso. Access to a broadband Internet connection is still limited because connectivity rates are still high in the country. The reduction in these rates in recent years has proved to be insufficient, as the cost of mobile Internet represents 12% of the gross monthly per capita income in Senegal, compared to 6% in Kenya (Banque Mondiale [World Bank], 2019). Thus, implementing reforms aimed at stimulating competition in service provision and investing in digital infrastructure can help reduce the cost of mobile Internet services, especially for young people seeking employment. Policies could also be aimed at reducing the operators' operational costs, for example, by reducing taxes and charges.

However, such policies may not be enough to facilitate digital technology adoption. As the present study found out, there are other barriers to this adoption. These include low levels of education and language skills, both of which underscore the importance of adopting human capital development policies. Indeed, low levels of education and/ or of language skills are likely to impede ICT use and even fuel misconception about the potential benefits of ICT.

Furthermore, the present study's results show that there is a gender gap in digital technology adoption. This is a pointer to the need for gender-specific policies for promoting this adoption. Such policies can include the provision of digital literacy training and initiatives designed to promote sustainable programmes for financing mobile devices and services destined for women and the youth.

Given the positive impact of digital technology adoption on employment dynamics in the manufacturing, trade, and services sector firms, policy makers should set up vibrant local digital ecosystems and, thus, reduce the cost of digital technology adoption within firms. The measures required to achieve such changes go far beyond the mobile phone industry and require action from all stakeholders, namely, the government, the local digital sector, and civil society.

References

Acemoglu, D. and P. Restrepo. 2019. "Automation and new tasks: How technology displaces and reinstates labor". *Journal of Economic Perspectives*, 33(2): 3–30.

Almeida, R.,A.M. Fernandes, M. Viollaz and R.K. Almeida. 2017. "Does the adoption of complex software impact employment composition and the skill content of occupations? Evidence from Chilean firms". World Bank Policy Research Working Paper No. 8110. The World Bank, Washington, D.C., June.

ANSD. 2016. Rapport annuel de l'Agence nationale de la Statistique et de Démographie (ANSD). Statistique de l'économie sociale du Sénégal en 2013, Février 2016. https://www.ansd.sn

Asselin, L. M. 2002. Composite indicator of multidimensional poverty. Multidimensional Poverty Theory. CECI, June 2002, 34p.

Autor, D. H., Dorn, D., & Hanson, G. H. 2015. Untangling trade and technology: Evidence from local labour markets. *The Economic Journal*, *125*(584), 621-646.

Autor David, & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, *103*(5), 1553-97.

Autor, D.H. (2001). Wiring the labor market. Journal of Economic Perspectives 15 (1), 25–40.

Banque Mondiale (World Bank). 2019. *Digital Economy for Africa (DE4A): Country Diagnostic of Senegal. http://documents1.worldbank.org/curated/en/814111559645179494/pdf/Country-Diagnostic-of-Senegal.pdf*

Beard, T. R., Ford, G. S., Saba, R. P., & Seals, Jr., R. A. 2012. Internet use and job search. Telecommunications Policy, 36(4), 260–273.

Bloom, N., Draca, M., and Van Reenen, J.2015. Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity. Technical report, Review of Economic Studies, 102(1):167-201.

Brambilla, I. and D. Tortarolo. 2018. *Investment in ICT, Productivity, and Labor Demand*. Washington, D.C.: The World Bank.

Brenzel, H., Czepek, J., Kubis, A., Moczall, A., Rebien, M., R¨ottger, C., Szameitat, J., Warning, A. and Weber, E. 2016. 'Neueinstellungen im Jahr 2015: Stellen werden h¨aufig ¨uber pers¨onliche Kontakte besetzt', IAB-Kurzbericht

Brynjolfsson, E., T. Mitchell and D. Rock. 2018. “What can machines learn, and what does it mean for occupations and the economy?” *AEA Papers and Proceedings,* 108: 43–47.

Cardona, M., T. Kretschmer and T. Strobel. 2013. “ICT and productivity: Conclusions from the empirical literature”. *Information Economics and Policy*, 25(3): 109–125.

Chinoracký, R. and T. Čorejová. 2019. “Impact of digital technologies on labor market and the transport sector”. *Transportation Research Procedia*, 40: 994–1001.

Crandall, R., W. Lehr and R. Litan. 2007. “The effects of broadband deployment on output and employment: A cross-sectional analysis of U.S. data”.. Issues in Economic Policy Series. The Brookings Institution, June.

Cusolito, A.P. and W.F. Maloney. 2018. *Productivity Revisited: Shifting Paradigms in Analysis and Policy*. Washington, D.C.: The World Bank.

De Stefano, T., R. Kneller and J. Timmis. 2014.*The (Fuzzy) Digital Divide: The effect of Broadband Internet Use on UK Firm Performance*. University of Nottingham Discussion Papers in Economics, Discussion Paper 14/06.

Diene, M., S.A. Dieng, K. Drame and M. Fall. 2015. Analyse des déterminants de la performance des entreprises en Afrique Subsaharienne francophone: cas du Sénégal. Final Report.

Fabritz, N. 2013. “The impact of broadband on economic activity in rural areas: Evidence from German municipalities”. Ifo Working Paper No. 166. Ifo Institute for Economic Research, July.

Fernandez-Portillo, A., M. Almodovar-Gonzalez and R. Hernandez-Mogollon. 2020. “Impact of ICT development on economic growth. A study of OECD European Union countries”. *Technology in Society*, 63: 101420.

Fountain, C. 2005. Finding a job in the Internet age. Social Forces, 83(3), 1235–1262.

Freeman, C. and L. Soete. 1997. *The Economics of Industrial Innovation*. Psychology Press.

Gillett, S.., W.H. Lehr, C.A. Osorio and M.A. Sirbu. 2006. “Measuring the economic impact of broadband deployment”. Final Report, National Technical Assistance, Training, Research, and Evaluation Project No. 99-07-13829.

Goldfarb, A. and C. Tucker. 2019. “Digital economics”. *Journal of Economic Literature*, 57(1): 3–43.

Gürtzgen, N., and A. Diegmann, L. Pohlan and G.J. van den Berg. 2021. “Do digital information technologies help unemployed job seekers find a job? Evidence from the broadband Internet expansion in Germany”. *European Economic Review,* 132: 103657.

Hasbi, M. 2017. “Impact of very high-speed broadband on local economic growth: Empirical evidence”. 14th International Telecommunications Society (ITS) Asia Pacific Regional Conference, ‘Mapping ICT into Transformation for the Next Information Society’. International Telecommunications Society, Kyoto, Japan, 24–27 June.

Heckman, J. J. Ichimura, H. and Todd, P.1998. Matching as an econometric evaluation estimator. Review of Economic Studies, 65, 261–294.

International Telecommunication Union (ITU). 2017. *Measuring the Information Society Report.* Volume 2. ICT Country profiles. International Telecommunication Union.

Ivus, O. and M. Boland. 2015. "The employment and wage impact of broadband deployment in Canada". Canadian Journal of Economics, 48(5): 1803–30.

Kandilov, A.M.G., I.T. Kandilov, X. Liu and M. Renkow. 2011. "The impact of broadband on U.S. Agriculture: An evaluation of the USDA broadband loan program". Selected paper prepared for presentation at the Agricultural and Applied Economics Association's 2011 AAEA & NAREA Joint Annual Meeting. Pittsburgh, Pennsylvania, 24–26 July.

Kim, Y. and P. Orazem. 2012. "Broadband Internet and firm entry: Evidence from rural Iowa". Iowa State University Working Paper No. 12026. Iowa State University, December.

Kroft, K. and D.G. Pope. 2014. "Does online search crowd out traditional search and improve matching efficiency? Evidence from Craigslist". Journal of Labor Economics, 32(2): 259–303.

Kuhn, P. and H. Mansour. 2013. "Is Internet job search still ineffective?" The Economic Journal, 124(581): 1213–33.

Kuhn, P., & Skuterud, M. 2004. Internet job search and unemployment durations. American Economiic Review, 94(1), 218–232.

Lacovone, L. and M. Pereira-López. 2018. ICT Adoption and Wage Inequality: Evidence from Mexican Firms. Washington, D.C.: The World Bank.

Lacovone, L., Pereira, M and Schiffbauer, M. 2016. ICT Use, Competitive Pressures and Firm Performance in Mexico (April 11, 2016). World Bank Policy Research Working Paper No. 7629, Available at SSRN: https://ssrn.com/abstract=2763310

Maliranta, M. and P. Rouvinen. 2004. "ICT and business productivity: Finnish microlevel evidence". In OCDE, The Economic Impact of ICT – Measurement, Evidence and Implications, pp. 213–39. Paris: Organisation for Economic Co-operation and Development.

Mang, C. 2012. "Online job search and matching quality". Ifo Working Paper No. 147. Ifo Institute for Economic Research, November.

Michaels, G., Natraj, A., and Van Reenen, J. 2014. Has ICT polarized skill demand? evidence from eleven countries over twenty-five years. Review of Economics and Statistics, 96(1):60-77.

MINPOST. 2016. Stratégie "Sénégal numérique 2025". Ministère des Postes et des Télécommunications République du Sénégal.

Myovella, G., M. Karacuka and J. Haucap. 2020. "Digitalisation and economic growth: A comparative analysis of sub-Saharan Africa and OECD economies". Telecommunications Policy, 44(2): 101856.

Ndubuisi, G., C. Otioma and G.K. Tetteh. 2021. "Digital infrastructure and employment in services: Evidence from sub-Saharan African countries". Telecommunications Policy, 45(8): 102153.

Pilat, D. and A. Wölfl. 2004. ICT Production and ICT Use: What Role in Aggregate Productivity Growth? Paris: Organisation for Economic Co-operation and Development. http://eprints.uanl.mx/5481/1/ 1020149995.PDF.

O'Mahony, M. and B. Van Ark. 2003. EU Productivity and Competitiveness: An Industry Perspective: Can Europe Resume the Catching-up Process? 273p. Luxembourg: Office for Official Publications of the European Communities.

République du Sénégal. 2019. Rapport d'avancement de la mise en œuvre du programme d'action d'Istanbul en faveur des PMA pour la période 2011-2018. Ministère de l'Economie, du Plan et de la Coopération.

République du Sénégal. 2014. Plan Sénégal Emergent. Available at https://www.un-page.org/files/public/plan_senegal_emergent.pdf

Rubin, D. 1980. Discussion of Randomization Analysis of Experimental Data: The Fisher Randomization Test by D. Basu. Journal of the American Statistical Association, 75, 591-593

Solow, R.M. 1987. "We'd better watch out". New York Time Book Review, 36.

Sanderson, E. and F. Windmeijer. 2016. "A weak instrument F-test in linear IV models with multiple endogenous variables". Journal of Econometrics, 190(2): 212–21.

Staiger, D. and J. Stock. 1997. "Instrumental variables regression with weak instruments". Econometrica, 65(3): 557–86.

Stanley, T.D., H. Doucouliagos and P. Steel. 2018. "Does ICT generate economic growth? A meta-regression analysis". Journal of Economic Surveys, 32(3): 705–26.

Stevenson, B., 2009, "The Internet and Job Search", in Studies of labor market intermediation, University of Chicago Press, p. 67-86.

UNDP. 2020. Latest Human Development Index Ranking. New York. Available at http://hdr.undp.org/en/content/ latest-human-development-index-ranking

UNDP (2014), Human Development Report 2014, Sustaining Human Progress: Reducing Vulnerabilities and Building Resilience, Posted on: January 01, 2014

World Economic Forum (WEF). 2017. The Global Human Capital Report 2017. Preparing people for the future of work.

Appendixes

Appendix A: Descriptive statistics and results of the study's estimations

Table A1: Characteristics of digital technology adopters and non-adopters

Variables	(1) Adopters (N= 1,082)	(2) Non-adopters (N= 1,664)	Test of difference (1)-(2)
Outcome variables			
Participation in public employment programmes	0.345	0.282	0.063***
	[0.014]	[0.011]	
Participation in solidarity contract programmes	0.085	0.037	0.048***
	[0.010]	[0.006]	
Participation in spin-off contract programmes	0.004	0.007	-0.003 (ns)
	[0.002]	[0.003]	
Participation in adaptation and retraining programmes	0.039	0.080	-0.041***
	[0.007]	[0.009]	
Participation in internship training and apprenticeship programmes	0.351	0.355	-0.005 (ns)
	[0.017]	[0.015]	
Participation in incubation internship programmes	0.010	0.006	-0.004 (ns)
	[0.002]	[0.003]	
The unemployed	0.106	0.085	0.022*
	[0.009]	[0.007]	
The discouraged	0.026	0.052	-0.026***
	[0.005]	[0.005]	
Unemployment duration	5.933	7.130	-1.197*
	[0.496]	[0.469]	
Individual characteristics			
Female	0.370	0.441	-0.071***
	[0.015]	[0.012]	
Married	0.604	0.625	-0.021 (ns)
	[0.015]	[0.012]	
Age	31.684	30.898	0.786***
	[0.189]	[0.163]	
Education level			
Primary school	0.033	0.113	-0.080***
	[0.005]	[0.008]	
Lower secondary school	0.045	0.072	-0.026***
	[0.006]	[0.006]	

General secondary school	0.050	0.082	-0.032***
	[0.007]	[0.007]	
Higher education	0.872	0.734	0.138***
	[0.010]	[0.011]	
Knowledge of French			
Very little	0.002	0.003	-0.001(ns)
	[0.001]	[0.001]	
Little	0.031	0.106	-0.075***
	[0.005]	[0.008]	
Good	0.967	0.891	0.076***
	[0.005]	[0.008]	
Knowledge of English			
Very little	0.029	0.089	-0.060***
	[0.005]	[0.007]	
Little	0.687	0.707	-0.020(ns)
	[0.014]	[0.011]	
Good	0.284	0.205	0.080***
	[0.014]	[0.010]	
Knowledge of Arabic			
Very little	0.439	0.531	-0.093***
	[0.015]	[0.012]	
Little	0.527	0.433	0.093***
	[0.015]	[0.012]	
Good	0.035	0.035	0.001
	[0.006]	[0.005]	
Knowledge of Wolof			
Very little	0.005	0.022	-0.018***
	[0.002]	[0.004]	
Little	0.305	0.348	-0.043***
	[0.014]	[0.012]	
Good	0.690	0.630	0.060***
	[0.014]	[0.012]	
Political party activist	0.098	0.108	-0.010(ns)
	[0.009]	[0.008]	

Notes: The values shown for the tests of difference are the tests of difference for group means.
Values in brackets are standard deviations.
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.
ns means not significant.
Source: Compiled by the authors based on the EPAE survey data.

Table A2: Components of the composite ICT index

Dimension	Designation	Item No .on the questionnaire
Dimension 1: possession of ICT tools	Having a computer	p6q101_01
	Having an internet network	p6q101_04
	Having a mobile phone	p6q101_03
	Having a fixed telephone	p6q101_02
	Having a fax	p6q101_05
	Having a printer	p6q101_07
	Having a scanner	p6q101_06
	Having a photocopier	p6q101_08
Dimension 2: ICT use	Use of Skype for exchanges	p6q203
	Use of a website	p6q205
	Use of an intranet	p6q203
	Use of a WIFI connection	p6q104
	Use of specialized software for production	p6q207
	Use of a computerized exchange system for exchanges	
	Use of a computerized trading system for the production chain	p6q206
	Use of the Internet for business	p6q210
Dimension 3: ICT infrastructure	Number of computers	p6q102_4

Source: Compiled by the authors based on the EPAE survey data.

Table A3: Components of the managerial ability index

Dimension	Designation	Question Item No .
Human resource management	- Employees are rewarded - Autonomy granted for the management of day-to-day activities - Autonomy to invest - Autonomy in recruiting and firing - Delegation of certain responsibilities to employees - Performance-based criteria for promoting employees - Involvement of employees in decision-making in the firm	m3q304_1 m3q3071 m3q3072 m3q3073 m3q306 m3q301 m3q305
Financial management	Having a business plan	m4q106
Management of the socioeconomic environment	- Affiliation of most of the company's employees - Having a staff representative in the company - Sharing the employee's concerns with the manager - Social dialogue as a key component of the company's performance	m4q401 m4q402 m4q403 m4q407
Ethics management	- Having a company culture (socio-cultural habits, quality cult, transparency cult, dress code, work method, sense of moral values, collective belief) - Having a written code of ethics in your company (dress code, graphic codes, modes of expression) - Having undertaken steps to improve the company's image	m4q501 m3q201 m4q602

Source: Compiled by the author based on the EPAE survey data

Table A4: Description of variables

Variables	Description
Characteristics of the firm's manager	
Manager's education level (in number of years of study)	No formal education = 1; Primary school certificate (CEP)= 6; Lower Secondary School Certificate (BEPC)= 10; Probatoire (certificate for the two years before the final year of secondary school)= 12; Secondary School-Leaving Certificate (Bacc)= 13 ; vocational training certificate (BTS)= 15; Bachelor’s degree (Licence)= 16; Master’s degree/PhD= 19
Manager's age	The manager's age in number of years
Manager’s experience	1= The manager has professional experience in business management and 0 if not
Manager's gender	1 = Male; 0 = Female
Manager's training in management	1= Yes: has received management training; 0= No
Managerial ability	Indicator constructed through an MCA of variables related to human resources, financial management, management of the socioeconomic environment, and ethics management
Characteristics of the firm	
The firm’s age	Computed from the year the firm was set up to the date of the survey
The firm’s sector of activity	1= primary sector, 2= industrial sector, 3= tertiary sector (trade and services). From the present study were excluded companies from the primary sector which were quite under-represented in the database (only 12 firms).
Employment variables	
Total employment (calculated)	Sum of permanent skilled and unskilled jobs.
Skilled employment	Number of highly skilled jobs
Unskilled employment	Number of less skilled jobs
ICT-related variables	
Employee ICT-related training	1= If there was ICT training for employees and 0 if not
ICT index	Composite index based on the MCA
Inter-firm cooperation	Did your firm cooperate with other firms or organizations between 2011 and 2013?
Technological innovation in products and processes	Whether or not new products and processes were introduced between 2011 and 2013
Non-technological innovation	Whether or not the firm introduced new ways of working, new organizational methods, new promotion and distribution techniques between 2011 and 2013
Intensity of ICT use	Cluster variables by survey department

Source: Compiled by the authors based on the EPAE survey data.

Table A5: OLS estimations of digital technology

VARIABLES	Industrial Sector	Trade Sector	Service Sector	Overall
	Coef.	Coef.	Coef.	Coef.
Number of firms having a computer	0.00133	0.00341***	0.00178	0.00234***
	(0.000925)	(0.000973)	(0.00140)	(0.000600)
Intensity of ICT use	0.0188*	0.0179***	0.0495***	0.0232***
	(0.0110)	(0.00676)	(0.0162)	(0.00549)
Capital	0.0199***	0.00213	0.00746**	0.00917***
	(0.00261)	(0.00261)	(0.00343)	(0.00158)
Managerial ability	0.0988	0.286***	0.203*	0.198***
	(0.0789)	(0.0822)	(0.110)	(0.0497)
Technological innovation	0.00585	0.0615*	0.0397	0.0316
	(0.0316)	(0.0364)	(0.0480)	(0.0212)
Non-technological innovation	0.0506	0.0582	0.0450	0.0711***
	(0.0360)	(0.0373)	(0.0502)	(0.0227)
Inter-firm cooperation	0.112**	0.139***	0.121*	0.138***
Computer-to-employee ratio	(0.0569)	(0.0529)	(0.0689)	(0.0326)
	0.00281	-0.00457	0.0360*	0.0147
Firm's age	(0.0151)	(0.0213)	(0.0192)	(0.00996)
	0.0299	-0.0979**	-0.116**	-0.0520**
Firm's age squared	(0.0410)	(0.0429)	(0.0586)	(0.0259)
	-0.00191	0.0272**	0.0279	0.0155**
Manager's social network	(0.0109)	(0.0136)	(0.0169)	(0.00748)
	0.0743*	0.00750	-0.0156	0.0244
Manager's experience	(0.0380)	(0.0335)	(0.0524)	(0.0223)
	-0.0474	-0.0482	-0.0553	-0.0523**
Gender	(0.0335)	(0.0310)	(0.0483)	(0.0206)
	-0.0109	0.0154	-0.0118	0.0141
Manager's training in management	(0.0576)	(0.0406)	(0.0683)	(0.0294)
	-0.0130	-0.00296	0.000893	-0.00908
Manager's age	(0.0307)	(0.0308)	(0.0452)	(0.0194)
	-1.289**	-0.320	-1.482*	-0.939***
Manager's age squared	(0.568)	(0.520)	(0.805)	(0.342)
	0.185**	0.0400	0.207*	0.129***
Education level	(0.0815)	(0.0749)	(0.116)	(0.0493)
	-0.151***	-0.120**	-0.127	-0.141***
Education level squared	(0.0538)	(0.0508)	(0.0811)	(0.0334)

	0.0820***	0.0678***	0.0887***	0.0824***
Industrial sector	(0.0217)	(0.0192)	(0.0297)	(0.0127)
	1.870*	0.411	1.991	-0.0228
Service sector	(0.993)	(0.910)	(1.382)	(0.0224)
				0.0425*
Constant				(0.0231)
				1.334**
				(0.598)
F-test	29.62	18.23	12.60	51.00
Prob > F	0.000	0.000	0.000	0.000
R-squared	0.704	0.556	0.577	0.596
No. of observations	243	281	185	711

Notes: Standard deviations are given in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: Compiled by the authors based on the DPEASF (2014) survey.

Table A6: Instrument validation test

Statistical test	Industrial Sector	Trade Sector	Service Sector	Overall
F-test for the excluded instruments	2.81 0.0062	9.42 0.000	5.47 0.005	16.61 0.000
Under-identification test	15.95 0.005	18.845 0.000	11.435 0.0033	32.66 0.000
Weak-identification test	10.23	9.417	15.468	19.93

Source: Compiled by the authors based on the EPAE survey data.

Table A7: OLS estimations

VARIABLES	Highly Skilled Employment				Less Skilled Employment				Total employment			
	Industrial Sector Model	Trade Sector Model	Service Sector Model	Overall Model	Industrial Sector Model	Trade Sector Model	Service Sector Model	Overall Model	Industrial sector Model	Trade sector Model	Service sector Model	Overall Model
ICT index	0.0358***	-0.00263	0.0282**	0.0168***	0.0353***	-0.00056	-0.0057	0.0088	0.0465***	-0.00051	0.0251**	0.0197***
	(0.00836)	(0.00537)	(0.0110)	(0.00456)	(0.0111)	(0.00745)	(0.0124)	(0.00567)	(0.0111)	(0.00653)	(0.0120)	(0.00536)
Firm's capital	0.968***	0.671***	1.037***	0.956***	1.481***	1.148***	1.434***	1.482***	1.430***	1.122***	1.504***	1.472***
	(0.193)	(0.127)	(0.242)	(0.107)	(0.257)	(0.176)	(0.271)	(0.133)	(0.255)	(0.154)	(0.264)	(0.126)
Managerial ability	-0.206	0.169	0.383	0.116	0.155	0.847***	0.654*	0.533***	0.322	0.826***	1.035***	0.702***
	(0.222)	(0.177)	(0.340)	(0.140)	(0.297)	(0.246)	(0.381)	(0.174)	(0.294)	(0.215)	(0.371)	(0.165)
Technological innovation in production	0.0904	-0.0185	-0.276*	-0.0702	0.0761	-0.000877	-0.187	-0.0786	0.0785	0.00540	-0.353**	-0.0884
	(0.0915)	(0.0778)	(0.154)	(0.0611)	(0.122)	(0.108)	(0.173)	(0.0759)	(0.121)	(0.0946)	(0.168)	(0.0718)
Non-technological innovation	0.171*	0.117	0.0567	0.113*	0.138	0.130	0.143	0.162**	0.297**	0.248**	0.191	0.252***
	(0.104)	(0.0796)	(0.161)	(0.0655)	(0.138)	(0.110)	(0.181)	(0.0814)	(0.137)	(0.0968)	(0.176)	(0.0770)
Inter-firm cooperation	0.859***	0.145	0.346	0.407***	0.366	-0.289*	0.808***	0.307***	0.384*	-0.0383	0.871***	0.397***
	(0.168)	(0.113)	(0.219)	(0.0943)	(0.224)	(0.157)	(0.245)	(0.117)	(0.222)	(0.137)	(0.239)	(0.111)
Computer-to-employee ratio	-0.304***	-0.353***	-0.272***	-0.313***	-0.732***	-0.588***	-0.639***	-0.635***	-0.769***	-0.687***	-0.674***	-0.693***
	(0.0438)	(0.0452)	(0.0617)	(0.0286)	(0.0584)	(0.0627)	(0.0692)	(0.0355)	(0.0580)	(0.0549)	(0.0673)	(0.0336)
Firm's age	-0.0288	-0.137	-0.497***	-0.204***	-0.404**	-0.447***	-0.274	-0.451***	-0.240	-0.363***	-0.406**	-0.373***
	(0.120)	(0.0921)	(0.188)	(0.0745)	(0.160)	(0.128)	(0.211)	(0.0926)	(0.159)	(0.112)	(0.205)	(0.0876)
Firm's age squared	0.0212	0.0462	0.211***	0.0846***	0.144***	0.132***	0.138**	0.159***	0.0978**	0.117***	0.159***	0.137***
	(0.0319)	(0.0292)	(0.0543)	(0.0215)	(0.0426)	(0.0405)	(0.0609)	(0.0268)	(0.0422)	(0.0355)	(0.0592)	(0.0253)
Manager's social network	0.0104	0.105	-0.0129	0.0641	-0.332**	-0.0798	0.111	-0.113	-0.259*	-0.0219	-0.0407	-0.0785
	(0.111)	(0.0708)	(0.168)	(0.0641)	(0.148)	(0.0983)	(0.188)	(0.0796)	(0.147)	(0.0861)	(0.183)	(0.0753)
Manager's experience	-0.0313	-0.00703	-0.105	-0.0504	0.106	-0.0353	-0.227	-0.00378	0.121	-0.0543	-0.183	-0.0211
	(0.0927)	(0.0656)	(0.152)	(0.0578)	(0.124)	(0.0910)	(0.171)	(0.0718)	(0.123)	(0.0797)	(0.166)	(0.0680)
Gender	-0.181	0.00756	0.0727	-0.00996	0.0812	0.117	0.171	0.160	-0.146	0.115	0.0474	0.0422
	(0.168)	(0.0863)	(0.218)	(0.0844)	(0.223)	(0.120)	(0.245)	(0.105)	(0.222)	(0.105)	(0.238)	(0.0992)
Manager's training in management	-0.0268	-0.0111	0.391***	0.0787	-0.412***	0.0356	0.0217	-0.183***	-0.290**	0.00335	0.183	-0.0994

Table A7: OLS estimations continued

	(0.218)	(0.188)	(0.139)	(0.280)	(0.172)	(0.0848)	(0.188)	(0.316)	(0.293)
Manager's age	-7.779**	-6.596	-4.169*	-4.790	-5.604*	-3.032*	-6.596	-9.100*	-6.070
	(3.779)	(4.687)	(2.380)	(4.903)	(3.193)	(1.730)	(4.687)	(5.408)	(5.020)
Manager's age squared	1.098**	0.887	0.547*	0.689	0.752*	0.404	0.887	1.345*	0.901
	(0.543)	(0.654)	(0.340)	(0.681)	(0.449)	(0.247)	(0.654)	(0.785)	(0.729)
Education level	0.180	0.184	0.213	0.886	0.672*	0.212	0.184	0.245	-0.190
	(0.865)	(0.429)	(0.295)	(0.952)	(0.345)	(0.193)	(0.429)	(0.898)	(0.834)
Education level squared	-0.00988	-0.103	-0.119	-0.324	-0.341**	-0.131	-0.103	-0.123	0.0303
	(0.246)	(0.144)	(0.114)	(0.333)	(0.133)	(0.0907)	(0.144)	(0.297)	(0.276)
Industrial sector	-0.302	0.285	0.137	0.433	0.911***	0.684***	0.285	0.862**	0.681*
	(0.305)	(0.223)	(0.155)	(0.269)	(0.190)	(0.0925)	(0.223)	(0.404)	(0.375)
Service sector	0.352	0.693***	0.368**	0.163	0.172	0.273**	0.693***	0.679*	0.924***
	(0.271)	(0.218)	(0.179)	(0.332)	(0.191)	(0.110)	(0.218)	(0.344)	(0.319)
Constant	12.33*	11.44	7.931*	7.593	10.33*	6.000**	11.44	14.50	9.203
	(6.392)	(8.435)	(4.114)	(9.034)	(5.635)	(2.981)	(8.435)	(9.431)	(8.755)
No of Obs.	129	161	277	206	247	552	161	118	118
R-squared	0.750	0.417	0.308	0.479	0.503	0.579	0.417	0.604	0.655

Note: Standard deviations are given in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: Compiled by the authors based on the DPEASF (2014) survey.

Appendix B: Description of the different programmes under in the National State-Employer Agreement

As part of its policy of promoting youth employment, in 1987, the Government of Senegal signed the National State-Employer Agreement (Convention Nationale État-Employeur, CNEE), which was renewed in 2000 and again in 2009. This Agreement is an effective public-private partnership framework designed to ensure active and regular promotion of youth employment. It was signed between the government, represented by the Minister of Economy and Finance, the Minister of National Education, the Minister of Public Service, Labour and Employment, and private partners represented by the Chairman of the National Council of Employers (Conseil National du Patronat, CNP) and the Chairman of the National Confederation of Employers in Senegal (Confédération Nationale des Employeurs du Sénégal, CNES). Through this agreement, the Government of Senegal has made the fight against youth unemployment a national priority for poverty eradication. The agreement provides for several measures aimed at promoting employment as essential components of the national employment policy, in view of the following considerations: the fact that vocational training, apprenticeship, and the preparation of young graduates for employment are effective means of improving their professional skills and of facilitating their integration into production circuits; the important role that company managers could play in the training of young graduates through internships in order to adjust their profile to market needs; the opportunities for job creation on the labour market and the important role that employers could play in helping qualified employees to set up their own businesses and to establish synergy with their company of origin.

The measures taken consist of the following programmes: the internship and apprenticeship programmes (apprenticeship training, incubation internships, adaptation or retraining internships), the "solidarity contract" programme, the "spin-off contract" programme, and the "SME human resources financing" programme. The present study examined the following five programmes: the internship and apprenticeship programme, the solidarity contract programme, the spin-off contract programme, the adaptation or retraining internship programme, and the incubation internship programme.

a) The internship and apprenticeship programme is one which aims to promote the integration of young people into the labour market by enabling them to benefit from training, apprenticeship, or continuous training which will equip them with a qualification that meets the requirements of the labour market.

b) The solidarity contract is a programme that enables young graduates to get a teaching practice opportunity with a private educational institution.

c) The spin-off contract programme is one that enables a skilled employee aspiring to self-employment to start his/her own business or to take over one, with financial support from the government and/or a company.

d) The adaptation or retraining internship is a programme intended for young graduates of technical and vocational training institutions and those of higher education ones. It is aimed at enabling the graduates to gain practical experience and, thus, to increase their chances of getting paid employment.

e) The incubation internship is a programme designed for young graduates of higher education and technical and vocational training institutions, as well as for young people with a minimum of five years' experience in a managerial position. It is aimed at preparing future entrepreneurs through appropriate training based on coaching, assistance, and mentoring.

Mission

To strengthen local capacity for conducting independent, rigorous inquiry into the problems facing the management of economies in sub-Saharan Africa.

The mission rests on two basic premises: that development is more likely to occur where there is sustained sound management of the economy, and that such management is more likely to happen where there is an active, well-informed group of locally based professional economists to conduct policy-relevant research.

www.aercafrica.org

Learn More

www.facebook.com/aercafrica

www.instagram.com/aercafrica_official/

twitter.com/aercafrica

www.linkedin.com/school/aercafrica/

Contact Us
African Economic Research Consortium
Consortium pour la Recherche Economique en Afrique
Middle East Bank Towers,
3rd Floor, Jakaya Kikwete Road
Nairobi 00200, Kenya
Tel: +254 (0) 20 273 4150
communications@aercafrica.org