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GOVERNMENT SUPPORTS AND TECHNOLOGY ADOPTION: EVIDENCE FROM TUNISIA

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This study investigates the effect of Industrial Upgrading and Modernization Program (IUMP) on the information and communication technology (ICT) adoption in Tunisia. Based on the Industrial Upgrading Survey 2016, we use the matching estimators to estimate the effect of subsidies, granted in the framework of IUMP, on the adoption of three groups of ICT (Software, Hardware and Network communications). Our results show that although the IUMP has a positive impact on the intensity of ICT adoption, the level of adoption remained under that the transition to knowledge economy requires. We also find that investment incentive has reduced the digital gap between developed and backward regions in the adoption of Software and Network communications, by contrast to the case of Hardware, for which the gap has increased.

Keywords: ICT, Digital Divide, Regional Disparity, Subsidies, Average Treatment Effect, Matching Estimators
JEL Classification: O18, D21, C21

1. INTRODUCTION

The diffusion of ICT (information and communication technologies) in the economy has been the subject of a huge and extensive literature over the last decades. This interest is justified by the large use of ICT, which became the key determinant of increasing the competitiveness of firms (Bresnahan et al., 2002; Ben Khalifa, 2017), industries (Ben Khalifa, 2013b; Van Ark et al., 2003), regions (Karlsson et al., 2010; Ben Khalifa, 2013a) and nations (Van Ark et al., 2008; Oliner and Sichel, 2002). As a general purpose technology, ICT provide an indispensable infrastructure for information transmitting, innovation spawning, cost saving, productivity increasing and market development (Ben Khalifa, 2017; Gretton et al., 2004; Bresnahan and Trajtenberg, 1995). Within the PCAST Report (2011) and Europe 2020 strategy (the Smart Specialization Strategy or 3S), ICT constitute one of the main pillars of economic growth, innovation and job creation. The 3S approach recognizes the importance of applying the foreign general purpose technologies such as ICT in traditional activities to create new economic opportunities, increase the competitiveness of firms and accelerate the catching-up process of regions and countries lagging behind (European Commission 2014; OECD, 2013). Likewise, the PCAST (2011) points out that US industries have become vulnerable to international competition and remedy this situation needs to increase the diffusion of advanced ICT in all sectors of economy.

In Tunisia, aware of the importance of ICT in socio-economic development, policy-makers have proposed to organize the World Summit on the Information Society (WSIS), since 1998. Moreover, ICT constitute a principal component in the Industrial Upgrading and Modernization Program (IUMP) launched by Tunisia in 1996. This program includes a number of projects destined to firms to modernize and strengthen their organization in a globalized and increasingly competitive knowledge-based economy (KBE), (ONUDI, 2002; Baugault and Filipiak, 2005). The program supports, among others, the restructuring process providing subsidies to support investment in ICT and complementary assets and capabilities (such as reorganization, quality certification, training, purchase of patents and know-how, technical assistance, etc.), fixed investment (equipment, modernization of production process, etc.), and financial restructuring.

More recently, Tunisia launched, in 2014, a National Strategic Plan “NSP Tunisia Digital 2020, which defines as strategy’s vision of becoming an “international digital reference and makes ICT an important lever for socio-economic development”. One of the strategic axes of the “Tunisia 2020” is to improve the competitiveness of all firms and sectors, by investing in ICT and positioning in the digital economy.

As the Upgrade Program, by granting subsidies, constitute the most important instrument of Tunisian industrial policy intended to stimulate the investment in ICT, we will firstly attempt, in this study, to evaluate the effectiveness of this program on ICT diffusion in Tunisian economy as a whole. Given the great regional disparity between Coastal and Inland regions, we will, secondly, investigate the effectiveness of the Upgrade Program on the ICT adoption across regions and whether or not it reduced the regional digital divide. Although ICT is global in nature, public policy may play an important role locally (Iammarino et al., 2004). It should pinpoint any constraints that will hamper the ICT diffusion process (Salvatore, 2003; Atzeni and Carboni, 2008). In this perspective, incentives represent critical factors in the diffusion of ICT and their impacts on a faster productivity growth and reduction of digital divide (Feldstein, 2003; Atzeni and Carboni, 2008).

In terms of policy, by understanding the effect of Upgrade program on ICT diffusion in both national and regional levels, policy makers shall take the necessary measures to stimulate and accelerate the diffusion of these technologies and reduce the regional disparities. Furthermore, although there is a vast literature on the importance of public supports in reducing territorial disparities (see for example, Harris and Trainor, 2005; Gabe and Kraybill, 2002) there is no agreement on the effectiveness of investment incentives (Atzeni and Carboni, 2008). This question is therefore still open, since several support programs are implemented in many countries such as the Upgrade programs in developing countries and the "Europe 2020" for European countries. We emphasize here, that by contrast to the growing literature around the impact of public aid on R&D investment, there are no studies, excepting the Atzeni and Carboni (2008)'s work, regarding the impact of subsidies on ICT investment. This work attempts to advance our knowledge in this subject.

The paper is structured as follows: Section 2 presents the dataset and the descriptive analyses. Section 3 describes the methodology. Section 4 investigates the determinants of ICT adoption. Sections 5 and 6 present the results. Section 7 concludes.

2. DATA COLLECTION AND ICT ADOPTION

The data we use for this study come from the Industrial Upgrading Survey. This was carried out in Tunisia in 2016 by the Ministry of Industry and Trade (Bureau of Industry Upgrading) and the Ministry of Development, Investment and International cooperation (Tunisian Institute of Competitiveness and Quantitative Studies). It is a cross section data. The general goal of this survey is to evaluate the impact of subsidies according in the framework of Industrial Upgrading and Modernization Program (IUMP) on the competitive and innovative performances of Tunisian firms over two subsamples, which covers IUMP- recipients and the non-recipients. The IUMP-recipient sample was stratified by 7 manufacturing industries (according to the classification of the Tunisian Agency of Promotion of Industry and Innovation, APII), three industry-firm size classes and four geographic localizations (according to the Tunisian National Land Use Plan, SNAT 1985 and the Regional Development Index 2015): Grand Tunis, the capital and more developed region; Center-East, the second industrial area; the North-East, close neighbour of Grand Tunis; and the Inland region, the backward region with regard to these three coastal regions (see Appendix 1 for more information). The second subsample (control subsample) was modeled on that of the IUMP-recipients, in order to respect the same proportions of firms in each of the above strata to ensure a rational and scientifically valid comparative assessment.

The dataset provided us with a current firm-level information (as of March-May 2016) on: ICT adoption (Software, Hardware and Network communications), structural variables (size, sectors, age, group membership, etc); organizational and cognitive variables (human capital, new organizational practices, R-D, innovation and partnerships), spatial variable (firm localization) and so on. We got valid information from 140 IUMP-recipients from Bureau of Industry Upgrading database that contain 2375 IUMP recipients (in the 2004-2014 period) and 98 non-recipients from non-IUMP recipients from 1676 firms. The total dataset for this study contains 238 observations. By size, medium firms (50 to 199 employees) had the largest share of 47. 5%; small (< 50), 38% and large (> 199 employees), 14%. Appendix 2 presents more detailed information on the characteristics of the surveyed firms for the whole sample and various subsamples.

Based on our dataset, we define, for empirical purpose, 14 ICT tools, which can be structured in three groups of ICT as defined by Baldwin and Sabourain (2001), Parhi (2005) and Gunawardana (2006):

- Software (8 software tools): CAD / Computer Aided Design; CAD / Computer Aided Drafting; CAPM / Computer Aided Production Management; CAMM / Computer Assisted Maintenance Management; ERP / Enterprise Resource Planning; CRM / Customer Relationship Management; SCM / Supply Chain Management; KMS / Knowledge Management System
- Hardware (3 hardware tools): Computer Numerically Controlled Machines; FPC / Flexible Production Cells; Robots
- Network Communications (3 NC): Intranet; Extranet; Website

Table 1 provides us with information on the adoption level of each of three ICT groups according to the IUMP participation and geographic area criterions. It shows that the intensity of Software adoption is higher than that of the Hardware and NETCOM adoption in the sample as a whole and in all subsamples related to the participation or not in the IUMP and to the geographic area. Regarding the IUMP participation, lines (4-5) show that subsidised firms are more likely than non-subsidised ones to intensively adopt each of the three ICT groups.

Table 1. ICT Adoption by Subsidised and Non-subsidised Firms

				Software		Hardware		NETCOM	
			Obs.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Whole economy	Whole sample	-	238	1.689	1.874	0.672	0.791	1.176	1.076
	Received Subsidies	Yes	140	2.192	1.896	0.857	0.809	1.457	1.082
		No	98	0.969	1.595	0.408	0.686	0.775	0.936
GTUNIS	Whole sample	-	78	1.705	1.921	0.679	0.764	1.230	1.030
	Received Subsidies	Yes	47	2.212	1.932	0.872	0.824	1.702	0.953
		No	31	0.935	1.651	0.387	0.558	0.516	0.677
NEAST	Whole sample	-	40	1.625	1.821	0.625	0.806	1.275	1.109
	Received Subsidies	Yes	21	2.380	1.746	0.857	0.910	1.381	1.160
		No	19	0.789	1.548	0.368	0.597	1.158	1.068
CEAST	Whole sample	-	74	2.108	1.962	0.810	0.839	1.324	1.111
	Received Subsidies	Yes	48	2.416	1.933	1.000	0.799	1.500	1.110
		No	26	1.538	1.923	0.461	0.811	1.000	1.058
IREG	Whole sample	-	74	1.043	1.534	0.478	0.722	0.760	0.992
	Received Subsidies	Yes	24	1.541	1.841	0.541	0.658	0.958	1.082
		No	22	0.500	0.859	0.409	0.796	0.545	0.858

Table 1 shows an intra-national comparison of the diffusion of ICT. According to the 1985 National Scheme for Territory Development (*Schéma National d'Aménagement du Territoire*, *SNAT*) and the Regional Development Index (2015),, we divide the national territory on four regions by virtue of their development level: Grand Tunis, the capital and more developed region; Center-East, the second industrial area; the North-East, close neighbour of Grand Tunis; and the Inland region, the backward region.

Lines (6; 9; 12 and 15) show that ICT diffusion process is not symmetric. The second economic power (Centre East) is the most user of ICT, contrary to the leading region (Grand Tunis), which comes in the second rank, and even in the third rank behind its neighbor North-East in the case of Network communications. Not surprisingly, the Inland region, the poorest region in the Tunisian economy, is the lowest user of ICT, with intensity of use close to half that of the Center-East. This result strongly supports two key ideas regarding the features of ICT diffusion process. The first is that the diffusion process of ICT is not purely hierarchical but it depends on the capacities of firms and regions to innovate and to transform (Rallet and Rochelandet, 2003; Cornford et al., 2006; Ben khalifa, 2013). The leading regions (the case of Grand Tunis in this study) are not necessarily the most able to invest in ICT and to enter the knowledge economy. On the contrary, they may be penalized by their previous success, which is a source of inertia and resistance to innovation (Abramovitz, 1986). As emphasis by Haudeville "in some cases there is a dynamic process, sometimes called a whirlpool, of mutual reinforcement of the different aspects of the knowledge economy, while in other cases nothing or almost nothing happens and scarce resources, which could have been used otherwise, are finally wasted" Haudeville (2009). So the hierarchical effect can be counterbalanced by a territorial effect which allows less developed regions to benefit more from the so-called ICT-based knowledge economy. This is the case for the eastern and northern regions, where the former has the higher level of adoption and the latter is almost similar to that of the leading region (Grand Tunis).

The second idea is that the territorial effect can be determinant in the diffusion of ICT and the move to the knowledge economy only if the region has a "critical mass" of materiel resources (ICT-Infrastructure, ICT suppliers, training centers, support centers, technology centers, universities, financial institutions, etc.) and immaterial resources (social capital, skills, institutional density, culture and sprit of innovation, etc.) on which the firms and the local development actors have to rely (Storper, 1996; Florida, 1995; Cornford et al., 2006; Karlsson et al., 2010; Ben Khalifa, 2013). Therefore, the Inland region is lagging behind in term of ICT adoption, because it is poor in key resources for global socio-economic development. If the situation persists might result further marginalization of the poor spaces, thus adding a digital dimension to the existing social and economic inequalities in and among Tunisian regions.

3. THE ANALYTICAL FRAMWORK

3.1. The Rational for Promoting the ICT Adoption through Investment Subsidies

The rational for public intervention in supporting innovative activities and equipment investments is largely based on the existence of two mainly forms of market failures. Firstly, imperfection in capital market exist, leading to financial constraints and credit rationing. The strong information asymmetries between borrowers and lenders lead to a higher cost of credit preventing often certain firms (particularly small and medium firms) with no internal funds to invest in innovation projects (Leland and Pyle, 1977; Hall, 1992). Secondly, knowledge is a non rival good; innovators cannot appropriate all the benefit arising from innovation and equipment investment making social marginal returns of new knowledge higher than private ones (Arrow, 1962; Griliches, 1992; De Long and Summers, 1991; Himmelberg and Petersen, 1994). The government intervention is therefore needed to compensate for this under-investment in innovation and equipment.

In addition to the classical argument justifying government support, several other options have been put forward, such as, protecting "infant industries", competitive edge of firms engaged in international markets and catching up with global productivity (List, 1841; Furtado, 1964; Mazzoleni and Nelson, 2007; Cunnigham et al., 2013). With the rapid globalization and the opening-up of developing countries, these arguments are more relevant for justifying the subsidies granted in the framework of Industrial Upgrading and Modernization programs (IUMP). Thus, in developing countries, firms are generally of small and medium size, which often lack managerial and organizational capacities and have limited financial and technological resources. The institutional environment and infrastructure are also other challenges that impact the capacity of firms to carry out business and industrial activities. All this leads in creating obstacles and barriers to firms to compete on both domestic and international markets (ONUDI, 2002; Baugault and Filipiak, 2005). The IUMP aims to take up these challenges in a holistic way in order to increase the competitiveness and innovation capacities of firms and facilitate the integration of developing countries in the global economy. According to Cunningham et al. (2012), the government should implement policies with respect to the social optimum by overcoming the appropriability problem, substitute failing markets by reducing uncertainty and by decreasing costs and risks.

However, the potential problem for the effectiveness of certain government supports, particularly direct subsidies programs, is that all firms have an interest in applying for financial supports for the reason that, the marginal cost of public subsidies is lower than for internal and external sources of finance (Hall and Maffioli, 2008; Hussinger, 2008; Colombo et al., 2011). As a consequence, for financially constrained firms, receipt public subsidy will help to alleviate part of the cost of capital and therefore ought to increase their investment, creating a "crowding-in" effect. In contrast, if recipient firms are not financially constrained, they will simply substitute the public subsidies for internal funds or credits and will not increase their investment (the so-called "crowding-out" effect), which is sometimes considered rent-seeking behavior (Hall and Maffioli, 2008).

In the empirical side, there are plenty of studies evaluating the impact of public subsidies in promoting investment and innovation capabilities. In a literature review by David et al. (2000), two third of 33 studies show no crowding-out effects of private innovation investment through public subsidies. Thus, in the majority of the studies reviewed, public aid is shown to have additional effects on the innovation investment. Garcia-Quevedo (2004)'s review found that almost the half of 74 studies reports crowding-in effects, seventeen crowding-out and the rest were insignificant. More recently, Zunigia-Vicent et al. (2014) and Petrin (2018) report the summary of 77 and 226 studies respectively testing the crowding-in and crowding-out hypotheses. They found that the majority (62% and 54%, respectively) of the studies shows crowding-in effect, 20% crowding-out and the rest are insignificant or with mixed results. Beker (2015) indicated that empirical results before 2000 are inconclusive with respect to the effect of public supports on private investment. More recent research rejects the crowding-out hypothesis and tends to find additionality effect. Another finding of these studies is that the effects of public subsidies are bigger on small and medium enterprises (SMEs), firms in low-tech sectors and firms located in less advanced regions.

For the case of ICT investment, in our knowledge, there are no studies regarding the evaluation of the impact of public support on the ICT adoption. The Atzeni and Carboni (2008)'s study is an exception. Using a sample of Italian manufacturing firms, the authors have investigated the effect of public subsidies on ICT investment. They found that the global effect of public aid is positive, implying that firms would have invested less had they not received subsidies. However, the subsidy effect is more relevant for the small firms than for the medium and large firms and for the south than for the north of the country.

As noted in the introduction, Tunisian government, already within the past half of 1990s up to the present, direct a large sum of public funds towards assisting firms in expanding ICT investment to remedy the market failure by sharing the risks and costs, to devise ways to overcome innappropriability, and to promote competitiveness and long-term success of firms in ever more contested and internationalized markets. Consequently, Tunisia is a litmus paper for testing the effectiveness of public subsidies on ICT adoption across regions and in the country as a whole. We want to address three main issues when evaluating the efficiency of the subsidy program: (1) how much does public subsidy affect the intensity of ICT adoption? (2) Do subsidies crowed out or incentivize firms to increase their ICT investment? (3) Are there any regional differences in the effect of public subsidies?

From a methodological perspective, until 2000 the standard regressions are the most used models in the evaluation of the impact of public supports (Petrin, 2018). Such a method has been criticized, most notably by David et al. (2000), Cerulli (2010) and Blasio et al. (2014). They emphasized that the effect of investment subsidies cannot be effectively separated from unrelated effect and they stated that counterfactual evidence is required for more robust analysis. For this reason, in the last years, scholars increasingly have used the matching method to evaluate the impact of government subsidies (Petrin, 2018).

3.2. The Matching Estimation Procedure

The evaluation of the treatment effect is essentially a problem of missing data and selection bias. Missing data occur because we cannot observe both outcomes, with and without treatment, of the same individual at the same time. Selection bias arise because we cannot consider the mean outcome of non-treated individual as a proxy, since treated and non-treated individual usually differ even in the absence of treatment. The literature on the econometrics of evaluation offers different econometric evaluation techniques (see Wooldredege, 2010; Khandker et al., 2010 for a survey) such as Difference in-Difference (DD) estimator, IV estimation, selection models and nonparametric matching. The DD method requires data on treated and non-treated before and after treatment (program intervention). As our dataset consists of a cross-section, we cannot use the DD estimator. Likewise, we cannot apply the IV estimators and selection models because we have not valid instruments for the treatment variable in our dataset. Hence, the matching method is an appropriate solution for our case (Heckman et al., 1998; Dehejia and Wahba, 1999; Blasio et al., 2014). The advantage of the matching method over the methods we have just quoted is that for estimating the treated effect, we need neither a functional form for the outcome equation nor a distributional assumption on the error terms of the selection and outcome equations. The drawback of this method is that it only controls for observed heterogeneity among treated and non-treated individuals.

Matching estimators has become a popular non-experimental method of evaluation to estimate the average effect of a treatment or program intervention (see e.g. Dehejia and Wahba, 1999; Jaffe and Le, 2015; Radicic et al., 2016). The method compares the outcomes of treated individuals with those of matched nontreated, where matches are chosen on the basis of similarity in observed characteristics. In our case, matching method responds to the question "What the outcome of a treated firm with given characteristics have been in absence of the treatment? A treatment here is the granting of a subsidy following the participation in Industrial Upgrading and Modernization Program. The outcome (Y_i) is the adoption intensity of our three ICT groups: Software, Hardware and NETCOM. The evaluation parameter that responds to our question is the Average Effect of Treatment on the Treated (ATT), which gives us response about how much a treated firm (i.e. receiving the subsidy: $T = 1$) benefits compared to how much it would have done if not treated (i.e. not receiving a subsidy: $T = 0$). The parameter is given by the following equation (Rubin, 1974; Rosenbaum and Rubin, 1983):

$$ATT = E(Y_i(1) - Y_i(0)|X, T = 1) = E(\Delta|X, T = 1).$$

The difference, $\Delta = Y_1 - Y_0$, measures the effect of subsidy on ICT adoption, if we observe the two outcomes for the same firm with and without treatment at the same time. Yet, we can observe only one of the potential outcomes for each firm i: $Y_i(1)$ and $Y_i(0)$ are observed only for treated and nontreated firms, respectively. There is a problem of missing data. The unobserved outcome is called counterfactual outcome. As the counterfactual outcomes $Y(0)$ of the treated firms is not observed, the One has to find a proper substitute for it in order to estimate the ATT. We cannot use the average outcome of nontreated firms, because it is most likely that factors which determine the participation in IUMP also determine the ICT adoption. In other words, the ICT adoption of treated and control groups would differ even in absence of treatment leading to a 'self-selection bias'. One possible strategy is to assume that conditional on a set of observable covariates X, the potential outcomes are independent of treatment assignment (Rosenbaum and Rubin, 1983).

$$(Unconfoundedness)\ Y(1), Y(0) \perp T|X,\ \forall X.$$

Under the assumption of conditional independence, the selection is slowly based on observable characteristics and the choice of participants is "purely random" for a set of similar individuals. Moreover, the sampling method and the set of covariates, discussed above, allow us to assume that selection on unobserved covariates is unlikely. We add that a number of studies show that for high quality of data, rich in covariates related to treatment and outcome, matching on observable variables represents a good choice over propensity score technique (Angrist and Hahan, 2004), Kernel and local linear matching and DD matching (Smith and Todd, 2005).

Conditioning on X, the outcomes of one or more nontreated firms can be used as proxies of a counterfactual outcome of similar treated firm, if it has not been treated.

We add an identification assumption to ensure that for each treated firm there is a set of firms with similar characteristics that choose to not participate in the program (Abadie and Imbens, 2002),. Formally:

$$c < Pr(T = 1|X = x) < 1 - c \text{ for some } c > 0.$$

In this study, we use the routine developed by Abadie et al. (2004), which employs the specific bias-corrected matching estimator provided by Abadie and Imbens (2002). The estimation of ATT is based on "nearest neighbor matching" using the mean outcomes for firms with similar values for the covariates. This provides a more homogenous distribution of ICT efforts among treated and nontreated firms, since firms are matched only with similar ones in terms of ICT determinants (Atzeni and Carboni, 2008). Using this matching technique, we do not need to estimate the determinant factors of treatment as in the case of propensity score techniques. We consider only the set of covariates that explain the intensity of ICT adoption.

3.3. The Choice of the Matching Covariates

Before matching, it is necessary to choose covariates on witch close matches are desired. The investigator should include those covariates expected to influence both the choice of treatment and the outcome of interest or only the outcome of interest (Brookhart et al., 2006; Rubin 1974). In these cases, the average treatment effect can be estimated parametrically with matching estimators in a way that each treated individual is compared to untreated one having identical or similar characteristics (values for covariate).

Covariates can be identified by either theoretical and/or empirical strategies (Budtz-Jørgensen et al., 2007; Lee and Burstyn, 2016). Theoretical strategies select the covariates from the founding of previous studies, i.e. ICT diffusion literature in our case. Empirical covariate identification strategies select covariates through use of objective criteria in the current working database. The most popular strategy include backward regression (backward elimination) based on stepwise testing of the relationship between covariates and the outcome (Walter and Tiemeier, 2009).

With backward regression technique, covariates are selected as those variables with a regression β on the outcome at a level of significance below a pre-specified. The backward selection model starts with all candidate covariates in the model. At each step, the covariate that is the least significant is removed. This process continues until no nonsignificant variables remain. The investigator sets the pre-specified level of significance at which variables can be removed from the model. The conventional selection criteria of 5% were show to be poorly suited for covariate selection. With these criteria, a risk for elimination of important covariates is high and estimation uncertainty will be undetermined (Lee and Burstyn, 2016; Budtz-Jørgensen et al., 2007; Cochran, 1968; Mickey and Greenland, 1989; Dales and Ury, 1978). Backward elimination with significance level of 20 and 25% is a popular choice and seems to provide a better estimation (Dales and Ury, 1978; Cochran, 1968; Mickey and Greenland, 1989; Budtz-Jørgensen et al., 2007; Lee and Burstyn, 2016).

In covariate selection, some investigators have relied on empirical strategy only when theoretical evidence is not available, but other investigators have identified a need for combining empirical and theoretical criteria (Hernan et al., 2002; Evans et al., 2012). Thus, a covariate with no effect on the outcome may show empirical evidence in a particular dataset due to random error. In contrary, a true determinant variable may show no empirical evidence. Most investigators have recommended first listing all theoretically possible covariates identified by the literature and then selecting those that should be adjusted for by empirical methods (Evan et al., 2012; Weng et al., 2009).

Here, we use a mixed approach for covariate selection. We start by a brief review of the ICT determinants identifying by the theoretical and empirical literature. Next, we use backward regression techniques with selection criteria of 25% to select, from the identified list of ICT determinants, the relevant covariates that influence the ICT diffusion in our dataset. With backward regression, concern is not the parameter estimates of the model but rather with the resulting balance of the covariates that can influence the ICT diffusion in the treated and control groups (Augurzky and Schmidt, 2001). Because of this standard concerns about collinearity and significance level of 5% do not apply.

4. DETERMINANTS OF ICT ADOPTION

Based on the ICT diffusion literature (Ben Khalifa, 2016a; Battisti et al., 2009; Atzeni and Carboni, 2008; Hollenstein, 2004), we formulate an equation that explains the determinant factors of ICT adoption. As we emphasize above, this is an important instrumental step in identifying the set of covariates which will be needed for the matching estimation. According to the literature of ICT diffusion, four groups of variables have been considered as vital to determining the intensity of ICT adoption ($ICTINT$):

$$ICTINT = F(Structural\ Characteristics, Absorptive\ Capacity,\\ Reorganization, Environment).$$

We assume following Battisti and Stoneman (2003) that the spillover effects, contrary to the case of inter-firm diffusion, are not a key determinant of the intensity of ICT adoption (i.e. intra-firm diffusion).

Using equation above, we identify and estimate three models that explain the intensity of ICT adoption. We thus get three dependent variables (outcomes of interest) as measures of ICT: Software, Hardware and Network communications (NETCOM). To specify the explanatory part of the model, we draw on the theoretical and empirical literature on technology diffusion, particularly ICT diffusion. As the purpose of this study is not to examine the determinant factors of ICT adoption, but rather to test the effectiveness of investment subsidy policies in this subject, we will briefly outline the covariates influencing the diffusion process of ICT, which will subsequently be used in the matching estimation. Appendix 3 presents an overview on the variables relating to the various groups of factors presumed to affect the ICT adoption.

The first group is related to the structural characteristics of the firm. It includes the size of the firm (Schumpeter, 1934; Mansfield, 1961; Davies, 1979; Gallego et al., 2011; Arduin et al., 2010; Ben Khalifa, 2016a), the age (Haller and Siedschlag, 2008; Ben Youssef et al., 2010; Ben Khalifa, 2016a, b), the affiliation to a group and to a multi-unit firm (Galliani and Roux, 2003; Bayo-Moriones and Lera-Lopez, 2007; Bocquet and Brossard, 2007; Gallego et al., 2011).

The second group of variables refers to the absorptive capacity of the firm, measured by four categories of variables: human capital, knowledge sources, ICT experience and innovation capabilities. These measures are based on the theoretical literature that strongly suggesting that the capacity of firm to adopt a new technology depend on the human capital level (Becker, 1964; Nelson and Phelps, 1966; Cohen and Levinthal, 1990), RD intensity (Cohen and Levinthal, 1989), the technology and innovation capabilities (Stoneman, 1981; Hollenstein, 2004; Battisti et al., 2009) and the networks alliance developed by the firm (Martin et al., 2006; Haller and Siedschlag, 2008; Schilling and Phelps, 2007).

Table 2. Determinants of ICT Adoption (Multiple-imputation Estimates)

	SOFTWARE	HARDWARE	NETCOM
SIZE	ns	//	0.237 (0.084)
AGE	ns	0.295 (0.187)	//
GROUP	//	-0.456 (0.25)	1.043 (0.003)
MULT-UNIT	//	0.699 (0.053)	0.454 (0.142)
EDUCATION	1.225 (0.165)	1.008 (0.135)	1.58 (0.061)
TRAINING	0.641 (0.032)	//	//
SOFTWARE	na	0.615 (0.000)	0.41 (0.000)
HARDWARE	1.201 (0.000)	na	//
NETCOM	0.642 (0.000)	//	na
RD	0.952 (0.018)	ns	//
COOPERATION	//	//	0.621 (0.056)
PDINNOV	ns	//	0.573 (0.066)
PCINNOV	ns	0.873 (0.004)	//
MINNOV	//	//	//
REORG	0.749 (0.021)	//	//
X	-0.618 (0.227)	ns	//
X2	//	2.577 (0.238)	//
IREG	reference	reference	reference
GTUNIS	ns	ns	0.568 (0.124)
NEST	ns	ns	1.137 (0.016)
CEST	(0.566 (0.222)	ns	0.855 (0.030)
MEI	reference	reference	reference
FPI	-1.391 (0.027)	-0.797 (0.165)	0.187 (0.670)
BMCGI	-1.302 (0.064)	ns	ns
CI	-1.560 (0.027)	ns	ns
TCI	ns	0.669 (0.176)	ns
LSI	ns	ns	ns
DI	ns	0.773 (0.168)	-0.132 (0.785)
N	238	238	238
F	7.54	5.18	6.03
Imputation	20	20	20
Prob>F	0.000	0.000	0.000

Note: All variables presented in the table are significant at least at 25 percent level (p-value=0.25) as recommended by Cochran (1968), Mickey and Greenland (1989), Dales and Ury (1978), Budtz-Jørgensen et al., 2007, Lee and Burstyn 2016, and estimated coefficients and p-values in parentheses. //: variable removed by the backward selection; Statistics are adjusted for heteroscedasticity using the Huber-White method. ns: means not significant. na: not applicable

The firm’s ability to introduce organizational innovations is another major determinant of ICT adoption. The role of organizational innovations on ICT adoption is well argued by the Milgrom and Roberts’ super-modularity theory (1990; 1995). According to this theory, firms that introduced organizational innovations are more able to exploit ICT due to the ‘system effect’ generated by the association of both technological and organizational innovations. Several empirical studies confirm this theoretical affirmation and find a positive link between ICT use and adoption of new organizational practices (Ben Khalifa, 2014; Battisti et al., 2009; Bocquet et al., 2007;

Fabiani et al., 2005; Bresnahan et al., 2002).

The fourth group refers to the environment in which the firm operates such as pressure on the international market (Gallego et al., 2011; Haller and Siedschlag, 2008; Fabiani et al., 2005; Hollenstein, 2004). The industry (Hollenstein and Woerter, 2008) and region (Atzeni and Carboni, 2008) within which the firm performs its activities are also used to control for unobserved heterogeneity and omitted bias.

Table 2 shows that education, training, adoption of Hardware and Network communications, R&D and reorganization are good predictors of Software adoption. Interestingly, for our analysis, environment factors have some impacts on the Software adoption. The probability of a firm being an intensive user of Software is determined by the market, the region and the industry sector in which the firm operates. The Hardware adoption is significantly influenced (positively or negatively) by the firm structural characteristics (size, age, affiliation to a group or multi-establishment firm), the share of educated employees, the Software adoption, the introduction of process innovation, the market area and the industry sector. Finally, the main determinant factors of the adoption of the Network communications are the size, the affiliation to group and multi-establishment firm, the education, the Software adoption and the introduction of product and process innovation. With regard to the environment factors, the results emphasize a significant difference across regions in NETCOM adoption.

5. EFFECT OF SUBSIDIES ON ICT ADOPTION

This section aims to explore the impact of the subsidies by comparing the intensity of ICT adoption in subsidised firms (treated firms) and non-subsidised firms (untreated firms). To this end we use matching with replacement. This method consists in matching a given untreated subject to more than one treated one. Matching with replacement involves a trade-off between bias and variance where reducing the former and increasing the later (Smith and Todd, 2005). We estimate the average treatment effect for the treated firms (ATT) using as outcome variables the three ICT sub-indicators: Software, Hardware and Network communications adoption in the firm. The treatment is a dummy $T_i = 1$ if the firm received a subsidy and $T_i = 0$ otherwise. As subsidy is provided to invest in the tangible and intangible capital (see Section 1) and not necessary in ICT capital alone, this study aims to investigate whether the Industrial Upgrading and Modernization Program by reducing the financial cost of global investment has a significant effect on the ICT adoption.

For each outcome indicator, the matching covariates come from the logistic regressions discussed above. We impose the dummy regions to be constrained as an exact match, so that firm can only be matched to firms belonging to the same region. This allows a less random distribution of ICT effort among the untreated and treated group, since matching is done based only on ICT specific dimensions (Atzeni and Carboni, 2008). Thus, as shown in Appendix 2, the random treatment hypothesis cannot be supported. Treated firms are larger, older, are more likely to belong to groups and multi-establishment firms, invest more in human capital and R&D, more innovative and so on. Furthermore, treated and untreated firms may also differ in their unobservable characteristics which need to be taken in consideration in interpreting the comparative results. However, subsidised firms may be close to their untreated counterparts, making it possible the evaluation exercise.

Table 3. Average Treatment Effect (ATT) Estimation Results

	ATT	Std. Err.	P-values
SOFTWARE	1.116	0.217	0.000
Matching covariates: EDUCATION, FORMATION, RD, HARDWARE, NETCOM, X, Sector and Region dummies. Regions are constrained to be an exact match.			
HARDWARE	0.400	0.103	0.000
Matching covariates: AGE, GROUP, MULTI-UNIT, EDUCATION, PCINNOV, X, X2, Sector and Region dummies. Regions are constrained to be an exact match.			
NETCOM	0.484	1.223	0.000
Matching covariates: SIZE, GROUP, MULTI-UNIT, EDUCATION, PDINNOV, COOPERATION, SOFTWARE, Sector and Region dummies. Regions are constrained to be an exact match.			

Note: ATT obtained with nearest neighbour matching estimator, with bias correction and controlling for heteroskedasticity (Abadie et al., 2004).

Table 3 provides the results of the average treatment effect of the treated (ATT). Receiving the subsidies has positive and significant effects on the treated firms for all ICT groups. Thanks to the subsidies they received, granted firms increase their adoption by, on average, 1.116 technologies for the Software, 0.400 for the Hardware and 0.484 for the Network communications. Dividing the ATT by the Mean of ICT adoption of non-treated firms, the subsidies increase the adoption of Software by 115%, the Hardware by 98% and the Network communications by 62%.

Given the weak ICT adoption by Tunisian firms (see Section 2), we can conclude that the IUMP although it has boosted investment in ICT, there is still insufficient, by its own, to build ICT- based knowledge economy in Tunisia. Thus, as shown in this paper the technology diffusion process in Tunisian firms is determined not only by the ICT costs but also by the absorptive capacity and organizational innovations. Such implementations are costly and investment specifics. So, it may be that many firms have insufficient resources of their own and having difficulty obtaining additional funds and credits to invest in ICT and in complementary assets. This becomes even more likely for the small and medium sized firms and those operating in a backward area. The government has a critical role to play in correcting the market failure in financial sector to facilitate the access of firms to external funds and stimulate the ICT investment. Moreover, the subsidy policies must be coupled by accompanying policies to support firms in the definition and implementation of their ICT strategies and complementary assets.

The low investment in ICT can be also explained by socio-cultural factors rooted in history. Historical analysis shows weaknesses in innovation and entrepreneurial culture in Tunisia (Ben Khalifa, 2013). In this regard, Cohen and Levinthal, (1990), Florida, (1995) and Rallet and Rochelandet (2003) argue that the ICT appropriation and therefore their benefits and diffusion level are governed by the capacities of firms, regions and countries to learn, innovate and transform and not by the free interplay of market forces (decrease of the ICT costs with time). To promote the technological and organizational change, the government must have awareness of the historical feature of the week innovation capacity of Tunisian economy, a political will, a strategic vision and time to foster the modernization of the economy and all forms of innovation.

6. REGIONAL DISPARITIES IN ICT ADOPTION AND SUBSIDY EFFECTS

The statistic and econometric analyses, viewed in the previous sections, show a regional disparity in the ICT diffusion in Tunisia. In this section we will explore how the subsidies can affect the ICT diffusion in sub-national levels and whether or not they have reduced the digital gap between Tunisian regions. We split the data into four sub-samples, corresponding to the firm's geographic localization: Grand Tunis, North-East, Center-East and Inland region. The results show that the subsidy effects differ from one region and technology to another and between technologies in the same region (Table 4).

With regard to the Software, the North-East has the highest average treatment effect, increasing Software adoption by 1.752 units, followed by Inland region (1.379), Center-East (1.236) and Grand Tunis (0.749). Dividing the ATT by the Mean of Software adoption of non-treated firms, the subsidies increase Software adoption by 222% in North-East, 270% in Inland region, 80% in Center-East and 80% in Grand Tunis. This result shows that public aid is far more important for firms located in the less developed regions, i.e. Inland region and North-East. Thus, the structural and financial weakness of these two regions makes firms more sensitive to the financial aid. This means that investment incentive although they did not boost enough ICT investment in the various regions, without public aid the regional digital divide and therefore the regional disparity would have been wider than it actually. This finding is similar to the result provided by Azteni and Carboni (2008) on Italian micro-data.

For the case of Hardware, the subsidies have no a significant effect on technology adoption in Inland region, contrary to Grand Tunis that have the most important average treatment effect (0.632 units), following by North-East (0.522) and Center-East (0.519). Incentives to investment increase the Hardware adoption by 163% in Grand Tunis, 142% in North-East and 113% in Center-East. Therefore, unlike the case of Software, the public policies rather than reducing the digital divide, they enlarge the gap between the three coastal regions and the Inland region.

Table 4. Average Treatment Effect (ATT) Estimation Results by Region

Outcome variable	Region	Obs.	ATT	Std. Err.	P-values
SOFTWARE	GTUNIS	78	0.749	0.404	0.064
	Matching covariates: SIZE, EDUCATION, RD, HARDWARE, NETCOM, PCINNOV, REORG and Sector dummies.				
	NEAST	40	1.752	0.404	0.000
	Matching covariates: AGE, MULTI-UNIT, RD, HARDWARE PCINNOV, REORG, X and Sector dummies.				
	CEAST	74	1.237	0.386	0.001
	Matching covariates: RD, HARDWARE, NETCOM,REORG, X, X2 and Sector dummies.				
	INLR	46	1.35	0.368	0.000
	Matching covariates: SIZE, AGE, GROUP, MULTI-UNIT, EDUCATION, HARDWARE, PDINNOV, PCINNOV, MINNOV, Sector dummies.				
HARDWARE	GTUNIS	78	0.633	0.147	0.000
	Matching covariates: GROUP, MULTI-UNIT, EDUCATION, TRAINNING, SOFTWARE, PDINNOV, PCINNOV, MINNOV, REORG, X, X2 and Secotr dummies.				
	NEAST	40	0.522	0.214	0.015
	Matching covariates: GROUP, MULTI-UNIT, EDUCATION, TRAINNING, PCINNOV, REORG, and secotr dummies.				
	CEAST	74	0.519	0.178	0.004
	Matching covariates: GROUP, MULTI-UNIT, RD, SOFTWARE, X, X2, and Secotr dummies.				
	INLR	46	0.169	0.195	0.387
	Matching covariates: GROUP, COOPERATION, SOFTWARE, NETCOM, PCINNOV, and Secotr dummies.				
NETCOM	GTUNIS	78	1.197	0.172	0.000
	Matching covariates: GROUP, RD, SOFTWARE, HARDWARE, PDINNOV, MINNOV, and Secotr dummies.				
	NEAST	40	-0.449	0.389	0.248
	Matching covariates: SIZE, AGE, MULTI-UNIT, EDUCATION, TRAINNING, COOPERATION, RD, SOFTWARE, X, X2 and Secotr dummies.				
	CEAST	74	0.747	0.229	0.001
	Matching covariates: GROUP, MULTI-UNIT, RD, SOFTWARE, X and Secotr dummies.				
	INLR	46	0.412	0.225	0.082
	Matching covariates: SIZE, MULTI-UNIT, EDUCATION, MINNOV, X, X2 and Secotr dummies.				

Note: ATT obtained with nearest neighbour matching estimator, with bias correction and controlling for heteroskedasticity (Abadie et al., 2004). Matching covariates: determined by econometric estimations in regional level (estimations results are presented in Appendix 4)

Regarding the Network communications, the public support has the highest average treatment effect in Grand Tunis (1.197) flowing by Center-East (0.747) and the Inland region (0.412). This means that subsidies increase the Network communications by 232% in Grand Tunis, 76% in Inland region and 75% in Center-East. In North-East, the ATT is not significant, yet its level of communication technology adoption is comparable to the other coastal regions. For the case of NETCOM, the result shows that public policies have reduced the digital divide adoption between Coastal regions.

However, the gap between Grand Tunis and Inland region is enlarged.

In Overall, we conclude that the most developed regions (Grand Tunis and Center-East) use subsidies to invest in the three technology groups, while the less developed ones prefer some technology groups to others (i.e. Software and Hardware for the North-East and Software and NETCOM for the Inland region). Thus, the structural and financial weakness of these regions prevents them from targeting all ICT groups. Given that, the three groups of ICT are complementary (Baldwin and Sabourain, 2001), we also underline that, despite incentives to investment, there is a risk that the digital divide will remain and may widen and the regional disparity in Tunisia is liable to grow deeper.

7. CONCLUSION AND POLICY IMPLICATIONS

Using new micro-data from the Industrial Upgrading Survey 2016, this paper evaluates the effect of incentive policies on the information technology investment in Tunisian manufacturing firms. More precisely, we estimate the effects of the subsidies granted in the framework of the Industrial Upgrading and Modernization Program (IUMP) on the adoption intensity of three ICT groups: Software, Hardware and Network communications.

Our results show that for all ICT groups, granted firms would have adopted less ICT, had they not received the financial aid. However, the effects of subsidies on the intensity of ICT adoption differ from one group of technology and region to another and between technologies in the same region. For the case of Software, the effects of subsidies are far more important in less developed regions (i.e. Inland region and North-East) than more developed ones (i.e. Center-East and Grand Tunis). Thanks to the Upgrade Program, subsidised firms located in North-East, third Tunisian region in terms of socio-economic development, is ranked second behind Center-East and in front of Grand Tunis, while non-subsidised firms adopt less ICT than their counterparts in these both more developed regions. Likewise, for the Inland region although the gap in technology adoption is still large, without public aid, the digital divide would have been wider than it actually.

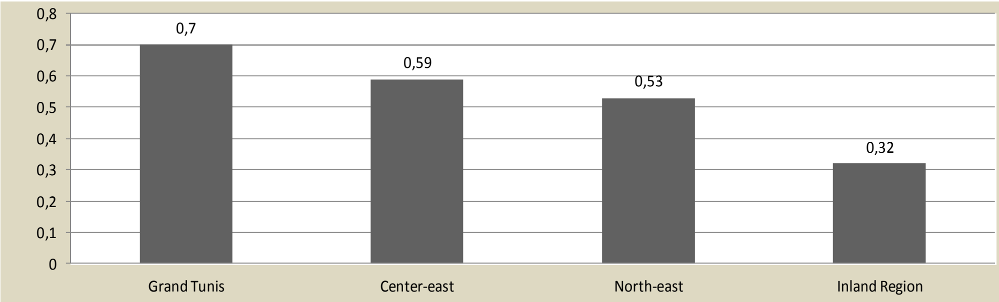
For the case of Hardware adoption, the Center-East is the most users followed successively by Grand Tunis, North-East and Inland region. In the later region, the subsidies show no effects by contrast to the Grand Tunis, where they have the greater impacts front of North-East and Center-East. It results that the digital gap between Inland region and Coastal region, contrary to the gab within the latter region, has been widening. Finally, the public aid has increased the adoption of Network communications in Centre-east and Inland region and in a greater measure in Grand Tunis. However, the subsidies did not have any effect in the intensity of NETCOM adoption in the North-East region. Despite this, the average adoption of NETCOM in the region is comparable to that of the Center-East and even higher than that of Grand Tunis, we can conclude that the Upgrade Program has reduced the digital gap between Coastal and Inland regions in the adoption of Software and Network communication, by contrast to the case of Hardware, for which the gap has increased.

However, we have to remember that the overall level of ICT adoption in surveyed firms is low and that even for the more developed regions and for the subsidised firms. This can be explained by the fact that ICT adoption is determined not only by the financial investment costs but also by the complementary assets such as organizational innovations, human capital and R&D. Moreover, the diffusion and appropriation of ICT goes beyond the individual strategies of firms (Cornford et al., 2006; Florida, 1995) and involve the endowment in the regional level of a critical mass of key resources (infrastructures, financial institutions, ICT suppliers, production and technology transfers centers, supports organisms, skilled labor, universities, training center, incubators, etc.), on which the firm must rely (Ben Khalifa, 2013, 2017; Karlsson et al., 2010; Cornford et al., 2006). From this point of view, the digital gap between Inland and Costal region appears as a consequence of pre-existing regional inequalities in resources distribution.

To reduce the digital gap and increase the overall level of ICT adoption, programs with a project-related incentive must involve partnerships of firms, local development actors and the civil society. The diffusion process of ICT is the result of a variety of structural forces that go beyond the firm's boundaries (Swanson and Ramiller, 1997). A broad inter-organizational community, made up of all the designers and managers of the technological system, managers involved in investment or use of ICT, scholars, adopters, suppliers, regulatory bodies, etc. reflects on the meaning to be assigned to the new tools They define an “Organizing Vision” (OV) which corresponds to a “focal community idea for the application of information technology in organization” (Vaujany, 1999). The Organizing Vision will constitute a “conceptual framework, a sensitive image of innovation, indicating for what uses it is adapted, how it works, under what conditions it can best be used, organizational changes implies, and how it should be implemented” (Vaujany, 1999).

In knowledge-based economy, we argue that the broad diffusion and appropriation of ICT implies that the development actors (publics and privates) understand ICT as a pervasive, interactive and cooperative working technology, enabling the exchange of information and knowledge, the enlargement of network-based working and the improvement of firm competitiveness in terms of innovation (products and processes) and conquest of international markets.

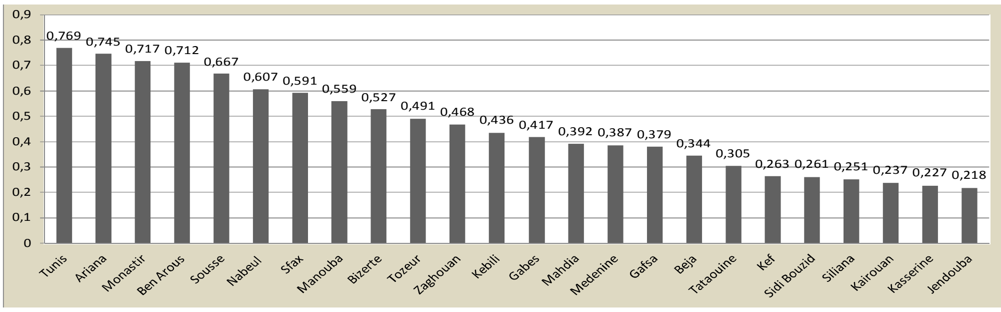
APPENDICES



Source: Our compilation based on information from regional development index from ITCEQ (2015).

Note: Grand Tunis (Ariana, Ben Arous, Manouba, Tunis); Nord-east (Bizerte, Nabeul, Zaghouan); Centre-east (Mahdia, Monastir, Sfax, Sousse), Inland Region (The other 13 Gouvernorates)

(a) Average of Regional Development Index (0-1)



Source: ITCEQ (2015).

(b) Regional Development Index (Tunisia)

Figure A1. Regional Development Index 2015, Tunisia

Table A2. Descriptive Statistics: Subsidised and Non-subsidised Firms

Variable	Total sample Received Subsidies			GT Received Subsidies		NEST Received Subsidies		CEST Received Subsidies		IREG Received Subsidies	
	Total	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
	Number of Observations										
	238	140	98	47	31	21	19	48	26	24	22
	Mean										
Size	4.147	4.42	3.75	4.336	3.671	4.719	4.134	4.277	3.574	4.640	3.736
<50	0.382	0.3	0.5	0.298	0.516	0.238	0.263	0.417	0.654	0.125	0.5
> 50 <199	0.475	0.486	0.459	0.510	0.451	0.476	0.684	0.375	0.308	0.667	0.455
>199	0.143	0.214	0.04	0.191	0.032	0.286	0.053	0.208	0.038	0.208	0.045
AGE	2.402	2.65	2.04	2.856	2.237	2.493	2.087	2.661	2.019	2.365	1.175
GROUP	0.289	3.78	1.63	0.45	0.225	0.385	0.052	0.410	0.153	0.166	0.181
MULT-UNIT	0.243	0.277	0.19	0.317	0.146	0.297	0.055	0.223	0.361	0.291	0.181
EDUCATION	0.180	0.198	0.153	0.228	0.193	0.173	0.144	0.211	0.145	0.138	0114
TRAINING	0.495	0.642	0.285	0.723	0.258	0.666	0.473	0.583	0.269	0.583	0.181
SOFTWARE	1.689	2.19	0.969	2.212	0.935	2.380	0.789	2.416	1.538	1.541	0.5
HARDWARE	0.672	0.857	0.408	0.872	0.387	0.857	0.368	1	0.461	0.541	0.40
NETCOM	1.176	1.46	0.775	1.702	0.516	1.380	1.157	1.5	1	0.958	0.545
RD	0.386	0.5	0.224	0.617	0.258	0.571	0.210	0.416	0.230	0.375	0.181
COOPERATION	0.336	0.435	0.193	0.510	0.193	0.38	0.105	0.416	0.269	0.375	0.181
PDINNOV	0.529	0.607	0.418	0.765	0.451	0.523	0.315	0.541	0.346	0.5	0.545
PCINNOV	0.340	0.435	0.204	0.489	0.129	0.476	0.105	0.416	0.307	0.333	0.272
MINNOV	0.235	0.292	0.153	0.319	0.129	0.238	0.052	0.291	0.230	0.291	0.181
REORG	0.546	0.621	0.438	0.787	0.516	0.619	0.210	0.583	0.461	0.375	0.5
X	0.55	0.549	0.55	0.483	0.626	0.695	0.585	0.504	0.379	0.643	0.617
GT	0.327	0.335	0.316								
NEST	0.168	0.15	0.193								
CEST	0.310	0.342	0.265								
IREG	0.193	0.171	0.224								
FPI	0.176	0.178	0.173	0.191	0.096	0.19	0.105	0.104	0.192	0.291	0.318
BMCGI	0.105	0.128	0.071	0.170	0.064	0.047	0.105	0.125	0.115	0.125	0
CI	0.109	0.092	0.132	0.106	0.129	0.142	0.210	0.083	0.115	0.041	0.09
MEI	0.130	0.135	0.122	0.191	0.161	0.19	0.052	0.104	0.192	0.041	0.045
TCI	0.235	0.242	0.224	0.148	0.161	0.19	0.315	0.104	0.192	0.333	0.272
LSI	0.084	0.064	0.112	0.042	0.161	0.095	0.105	0.083	0.076	0.041	0.09
DI	0.159	0.157	0.163	0.148	0.225	0.142	0.105	0.187	0.115	0.125	0.181

Table A3. Specification of the Explanatory Variables

Explanatory Variable	Description
	Firm Characteristics
	Firm Structural Characteristics
SIZE	Number of employees in the firm (in log)
AGE	Number of years the firm has been established (in log)
GROUP	Binary variable that take value "1" if firm belongs to a group, 0 otherwise
MULT-UNIT	Binary variable that take value "1" if firm affiliates to multi-unit firm, 0 otherwise
	Absorptive Capacity
	Human Capital
EDUCATION	Share of employees with tertiary degree (%)
TRAINING	Binary variable that take value of "1" if firm carried out staff training and zero otherwise.
	Knowledge Resources
R&D	Binary variable indicating whether or not the firm carried out internal R&D activity.
COOPERTION	Binary variable indicating whether or not the firm has partners.
	ICT Experience
SOFTWARE	Discrete variable reflecting the number of Software tools used by the firm (1 to 8).
HARDWARE	Discrete variable reflecting the number of Hardware tools used by firm (1 to 3).
NETCOM	Discrete variable reflecting the number of Network communications tools used by the firm (1 to 3).
	Innovation Capabilities
PRINNOV	Binary variable indicating whether or not the firm has introduced product innovation during the three years 2014-1016.
PCINNOV	Binary variable indicating whether or not the firm has introduced process innovation during the three years 2014- 2016.
MKINNOV	Binary variable indicating whether or not the firm has introduced marketing innovation during the three years 2014- 2016.
	Reorganization
REORG	Binary variable indicating whether or not the firm has introduced organizational innovations during the three years 2014- 2016
	Environment
Competition	Two continuous variables corresponding to the share of export sales (X) and its square (X2).
Industry	7 dummies corresponding to 7 manufacturing industries: FPI (Food Processing Industries); BMCGI (Building Materials, Ceramics and Glass Industries) ; CI (Chemical Industries) ; MEI (Mechanical and Metal Works Electric, Electronics and Electrical Appliances); TCI (Textile and Clothing industries); LSI (Leather and Shoes Industries); DI (Diverse Industries)
Localization	4 dummies corresponding to 4 regions: GTUNIS (Grand Tunis); NEAST (North-East); CEAST (Center-East); IREG (Inland Region)

Table A4. Determinants of ICT Adoption in Tunisian Firms (Multiple-imputation Estimates)

	SOFTWARE				HARDWARE				NETCOM			
	GTUNIS	NEST	CEST	IREG	GTUNIS	NEST	CEST	IREG	GTUNIS	NEST	CEST	IREG
SIZE	0.316			2.117						2.388		0.669
	(0.22)			(0.001)						(0.010)		(0.090)
AGE		-1.1		-1.157			0.675			-1.439		
		(0.113)		(0.091)			(0.14)			(0.118)		
GROUP				-2.059	-1.131	-1.383	-0.771	1.145	1.793		1.98	
				(0.244)	(0.16)	(0.053)	(0.255)	(0.119)	(0.001)		(0.003)	
MULTI-UNIT		-1.881	ns	1.346	1.049	1.923	1.281			-3.553	1.098	2.56
		(0.221)		(0.153)	(0.23)	(0.030)	(0.062)			(0.014)	(0.034)	(0.028)
EDUC	0.263			9.326	2.799	2.458				9.879		13.763
	(0.046)			(0.037)	(0.057)	(0.127)				(0.000)		(0.004)
TRAINING						1.767				-1.882		
						(0.100)				(0.031)		
SOFTWARE	na	na	na	na	0.623		0.773	0.682	0.512	0.757	0.407	
					(0.004)		(0.000)	(0.006)	(0.010)	(0.010)	(0.001)	
HARDWARE	1.37	0.942	0.942	1.226	na	na	na	na	0.516			
	(0.000)	(0.121)	(0.121)	(0.085)					(0.075)			
NETCOM	1.082		0.851					0.574	na	na	na	na
	(0.001)		(0.000)					(0.049)				
RD	0.845		0.806	-2.538	ns				0.708	-1.324	0.927	
	(0.117)		(0.153)	(0.09)					(0.139)	(0.201)	(0.071)	
COOPERATION								-1.416		2.675		
								(0.031)		(0.008)		
PDINNOV				-1.066	-0.944			ns	1.34			
				(0.178)	(0.200)				(0.009)			
PCINNOV	-0.730	1.816		1.144	2.047	1.758		0.771				
	(0.21)	(0.236)		(0.128)	(0.009)	(0.085)		(0.231)				
MINNOV		ns		1.531	-0.927				0.775			1.500
				(0.172)	(0.155)				(0.15)			(0.071)
REORG	1.459	3.445	0. 735		2.223	-1.617						
	(0.024)	(0.014)	(0.167)		(0.017)	(0.229)						
X		-1.243	-4.717	ns	-14.699		7.784			13.899	-1.201	10.113
		(0.158)	(0.237)		(0.005)		(0.106)			(0.053)	(0.048)	(0.060)
X2			5.160		15.052		-6.830			-13.446		-8.697
			(0.181)		(0.003)		(0.148)			(0.067)		(0.077)
SECTOR	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	78	74	40	46	78	74	40	46	78	74	40	46
F	8.10	3.63	4.95	5.27	3.46	2.25	5.02	2.41	5.46	2.41	5.83	7.51
Prob>F	0.000	0.000	0.000	0.000	0.000	0.035	(0.000)	(0.0248)	0.000	0.0075	0.000	0.000

Note: All variables presented in the table are significant at least at 25 percent level (p-value=0.25) as recommended by Cochran (1968), Mickey and Greenland (1989), Dales and Ury (1978), Budtz-Jørgensen et al., 2007, Lee and Burstyn 2016, and estimated coefficients and p value in parentheses. Empty squares: variable removed by the backward selection; Statistics are adjusted for heteroscedasticity using the Huber-White method. ns: means not significant. na: not applicable

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