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The Information and Communication Technologies-Economic Growth Nexus in Tunisia: A Cross-Section Dynamic Panel Approach

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ABSTRACT

The rapid diffusion of information and communication technologies (ICT) is becoming an important determinant of national economic growth. This paper examines the relationship between development of ICT and economic growth in Tunisia based on a sector analysis. We employ the common correlated effect mean group (CCEMG) and augmented mean group (AMG) methods and annual panel data for 1997 to 2017, to explore the relationship between ICT diffusion and economic growth in Tunisia. Our sector analysis shows that the effect of ICT on value added is heterogenous depending on the sector of activity and provides three main findings. First, in some sectors such as financial services, transport, building and civil engineering, hotel and restaurant services and other market services ICT have a positive and significant impact on value added. These sectors benefit from use of ICT. Second, in some sectors such as trade and various manufacturing industries, ICT has a negative and significant impact on value added. These sectors need to be well organized and well managed to avoid domination by informalities. Third, in some sectors such as public administration there is a productivity paradox and despite huge investment in ICT they have no impact on value added due to the absence of a deep organizational change.

INTRODUCTION

Use of information and communication technologies (ICTs) has been growing since the late 1990s but it is only since around 2010 that they achieved massive adoption by companies and users in both developed and developing countries. In parallel with these developments, research analyzing the impacts of ICT adoption focusing on different countries and different economic activities has proliferated. These studies examine adoption of ICT in a range of economic fields and companies', governments', economic cooperation organizations' and universities' efforts to try to understand the magnitude of their impacts conclude that use of ICT can promote changes in the productive efficiency. While governments are interested in the effects of ICT use in general, their focus is mainly on the use of these technologies in projects. Since 2010, among the Internet, computers and related digital applications, ICT have been identified as the main promoter of social change, growth and innovation.

Increasing the wealth and living standards of their residents are the primary goals of all nations. Increased productivity and sustainable economic growth depend heavily on the realization of profitable and competitive domestic economic activities. The spread of new technologies to multiple sectors enabled by more effective use of human capital and knowledge has led to productivity increases; thus, technological developments are associated with both productivity and higher value added in economic activities. At the same time, new technological products and services often have high value-added and greater economic welfare.

Due to their contribution to economic growth, productivity and employment, ICT are becoming the main determinants of countries' social and economic development by contributing. Several studies point to their positive impact on national economic growth (Jorgenson and Vu, 2016). According to the neoclassical view, ICT increase economic growth through capital deepening based on reductions to the prices of ICT (van Ark et al., 2008). From a non-traditional perspective, ICT foster innovation by facilitating business-to-business transactions, production spillovers and network externalities (Paunov and Rollo, 2016). According to the World Economic Forum (2013), if countries' levels of digitalization were to increase by 10% this result in an increase of 0.75% in GDP per capita, and a 1.02% drop in the unemployment rate. Thus, digitalization matters for reducing poverty, creating new jobs and incomes, and providing access to health and education services (OECD, 2010).

Since the early 1980s, Tunisia has been using ICT and formulating strategies for their implementation in its economic and social development plans (Kamoun et al., 2010). Tunisia is considered to have the most sophisticated telecommunications and broadband infrastructures in North Africa and has some of the highest Internet penetration rates in the region. However, few works adopt a macroeconomic perspective to calculation of the contribution of ICT to economic growth. Ben Youssef and Mhenni (2004) estimate that at the time of their analysis, a specific strategy was needed to realize the full potential of digital technologies. Despite a consensus that ICT increase economic growth and productivity, only a few studies have extended Ben Youssef and Mhenni's work (Naanaa and Sellaouti, 2017; Saidi and Mongi, 2018; Kallal et al., 2021), due mostly to lack of data.

Despite good connectivity and early adoption of digital technologies, Tunisia does not seem to benefit from the full potential and opportunities they provide. Although adoption of ICTs has grown considerably, economic growth has not only no advanced at the same pace, it has worsened in some business sectors. This has been particular evident during the COVID-19 pandemic; many key sectors in Tunisia were unable to shift to online activity during the spring 2020 lockdown (ITES, 2020) and the pandemic crisis exposed the countries real digital inequality. It has emphasized the need to identify gaps and unmet prerequisites in order to unlock the full potential of digital technologies and the new opportunities for economic growth in Tunisia.

Given that it is the use if and not adoption of ICT which determines their impact on economic growth, we are interested in the link between diffusion of ICT and evolution of added value in Tunisia, based on an analysis of the effects of ICT use at sector level. Our study provides three main contributions. First, it adds to the empirical literature on the effect of economic growth and should be informative for all developing countries but especially Tunisia. Second, we show that there is a positive relationship between ICT and economic growth in Tunisia, meaning that digitalization of the economy and society should contribute to economic growth. Third, we address the question of whether diffusion of ICT has the same impact on all sectors of activity. Our findings shows that there is an important heterogeneity in the digitalization of sectors in Tunisia and that some benefit from their rapid diffusion but others are lagging.

The paper is structured as follows. Section 2 provides a brief literature review, section 3 describes the methodology and data used for the analysis, section 4 discusses the results and main findings, and section 5 offers some conclusions and policy implications.

1. LITERATURE REVIEW

The ICT-economic growth nexus has been the focus of both applied and theoretical studies in recent years in order to support claims about the claimed effects of the knowledge economy on growth and productivity with empirical results. The first studies emerged in the 1990s, when the United States was showing high levels of economic performance thanks to past investment in ICT, and there were sufficient data to enable estimations. Since these investments and knowledge economy developments tend to be located in the industrialized countries, the first studies referred to developed countries. However, globalization saw the diffusion of ICT and increased international economic activities, investments and ICT adoption extending to include the developing countries and research began to focus also on emerging countries. Although the results of these studies vary based on different factors, they generally point to a positive effect of ICT on economic growth.

The earliest works on the effect of ICT on economic growth were mostly inconclusive, exemplified by the well-known productivity paradox proposed by Solow (1987) in the late 1980s who commented that "*you can see the computer age everywhere but in the productivity statistics*". The lack of correlation between ICT and productivity was due mostly to the inability to accurately measure the quality and prices of this capital.

Most macroeconomic and sectoral studies are based on a growth accounting approach in which intermediates, and capital input are given by the product of their share in total costs and their growth rates. Thus, an increase in inputs or an improvement in technology increases output and provides growth. In other words, growth accounting refers to determination of the contribution of labor and capital factors which affect growth, related to changes in output. Within the framework of Jorgenson and Griliches's (1967) standard growth accounting approach, three main factors increase labor productivity and economic growth: that is, increased capital intensity, changes to labor quality, and total factor productivity gains. We can identify the specific contribution provided mostly by ICT capital.

In the context of Tunisia, Saidi et al. (2015) investigate the effects of ICT on economic growth and find evidence of a positive relationship between rate of growth of GDP and the ICT index. Naanaa and Sellaouti (2017) investigate the effect of technological change on growth in an analysis of technology spillovers and their transmission channels, in five manufacturing sectors in Tunisia, and suggest that Tunisia should reinforce its ICT infrastructure. They found that the manufacturing sectors benefit from foreign direct investment only after a certain threshold of ICT development. Saidi and Mongi (2018) use a vector error correction model and show that ICT is driven by economic growth and vice versa while Kallal et al. (2021) use a panel pooled mean group form of the autoregressive distributed lag model for the period 1997-2015 and show that ICT diffusion has a positive long-term effect on economic growth but a negative short-term effect.

2. METHODOLOGY

2.1 Model specification

To assess the effects of ICT diffusion on economic growth in Tunisia in the short and long terms we build on the Solow's (1956) basic model and the augmented Solow model proposed by Mankiw et al. (1992). We include ICT in a Cobb-Douglas type production function. The general form of this relationship can be written as:

$$V_{it} = AK_{it}^{\alpha_1} L_{it}^{\alpha_2} ICT_{it}^{\alpha_3} \tag{1}$$

where V_{it} is aggregate value added, K is physical capital, L is labor and A is technology level. α_1, α_2 and α_3 are the respective output elasticities of capital, labor force and ICT.

By taking natural logarithms of the equation (Eq. 1),

$$LogV_{it} = LogA + \alpha_1 LogK_{it} + \alpha_2 LogL_{it} + \alpha_3 LogICT_{it} \tag{2}$$

we assume that ICT investments proxied by the ICT diffusion index (IDI), enhance technological progress by facilitating R&D and innovation and increasing the stock of knowledge which yields future returns. Thus, equation (Eq. 2) can be estimated as follows:

$$LogV_{it} = LogA + \alpha_1 LogK_{it} + \alpha_2 LogL_{it} + \alpha_3 LogIDI_{it} \tag{3}$$

2.2 Data and Variable Description

The data were collected from the national accounts provided by the Tunisia National Institute of Statistics (INS) and the Tunisia Institute of Competitiveness and Quantitative Studies (ITCEQ). The sample includes 17 economic sectors which are presented in table 1 and follow the international standard industrial classification (ISIC) of economic activities which ensures clear and relevant industry classification. All data are annual and cover the period 1997-2017.

The capital variable is measured as capital stock at constant 2010 prices, and the labor variable is measured as the active population. The IDI is constructed to capture the level of diffusion of ICT throughout the economy and determines the share of ICT in the added value of a particular sector. This index provides a useful tool to allow policymakers to benchmark and assess diffusion of ICT and promote ICT investment which improve economic growth. Technically, the IDI is built based on an input-output analysis (Suh and Lee, 2017). According to Leontief (1986), input-output tables record intersectoral transactions related to a production of a good/service in a national economy over a certain period, and consuming goods/services from other industries that is intermediate consumption. The rows in the table present the values of total intermediate supply for each sector and represent the horizontal demand-side of the Leontief model. The columns present the supply-side and describe the composition of inputs required by a particular industry to produce its output.

The IDI is obtained by dividing the intermediate input of sector *j* from ICT sector by the total input of sector *i*. The IDI is based on a demand-side or supply-driven model (Suh and Lee, 2017), and is specified as follows:

$$IDI = \left(\frac{x_{ij}}{x_{i\bullet}} \right)$$

where *i* and *j* = 17 economic sectors.

The ICT sector is classified according to the definition in OECD (2009), the ISIC activities (UN, 2008) and the INS. OECD (2009) defines ICT as combining "*all economic activities that contribute to the visualization, processing, storage and transmission of information electronically*". This definition is based on ISIC Rev. 3.1 (UN, 2008). In Tunisia, the Post and Telecommunication sector is the ICT official sector of the formal statistical system. This sector includes several industries such as computer hardware and software, telecommunications, Internet-based content, applications and services and can be grouped into :

- ICT manufacturing sector producing electronics, computers, and peripheral components, telecommunications devices, consumer electronics, instruments and appliances for measuring, checking, testing and navigating;
- ICT services sector including wholesaling of computers, electronics, components, software applications, software services, telecommunications services, postal services, information processing services, computers and telecommunications equipment repair services and other information services; and
- ICT media and content sector which includes publishing, film, broadcasting, recording and other information activities.

Table 1. The diffusion of ICT in Tunisian economic sectors

	1997-2000	*2001-2005*	*2006-2010*	*2011-2017*
Agriculture and fishing	0.22%	0.35%	0.50%	0.31%
Agriculture, food and tobacco industries	0.82%	1.11%	2.45%	1.66%
Construction materials, ceramics and glass	0.60%	0.73%	1.62%	1.03%
Mechanical and electrical industries	5.71%	7.23%	9.87%	13.60%
Chemical industries	1.57%	1.83%	1.18%	0.64%
Textile, clothing and leather	0.23%	0.35%	9.83%	10.20%
Various manufacturing industries	2.67%	3.79%	0.82%	0.99%
Mines and hydrocarbons	0.16%	0.22%	5.34%	2.43%
Electricity, gas and water	0.59%	1.15%	0.38%	0.23%
Building and civil engineering	1.67%	2.24%	6.03%	4.10%
Trade	22.37%	25.21%	15.39%	19.09%
Transport	3.35%	5.30%	2.45%	1.36%
Post and telecommunications	42.91%	28.10%	5.61%	4.59%
Hotel and restaurant services	1.26%	2.07%	1.37%	0.42%
Financial services	4.77%	6.02%	7.57%	6.36%
Other market services	3.16%	4.34%	13.64%	17.19%
Public administration	7.95%	9.97%	15.94%	15.81%

Note: Author's calculations, based on National Institute of Statistics of Tunisia (INS) and Tunisian Institute of Competitiveness and Quantitative Studies (ITCEQ) data.

2.3. Preliminary tests

2.3.1 Slope homogeneity test

In the dynamic panel data analysis, the assumption of slope homogeneity must be checked. Whether the variables are homogeneous or heterogeneous determines the form of the cointegration tests to be applied. The first studies on the homogeneity test were conducted by Swamy (1970). The next equation shows the Swamy test ($\hat{S}$).

$$\hat{S} = \sum_{i=1}^{N}\left(\hat{\beta}_i - \tilde{\beta}_{WFE}\right)' \frac{X_i' M_\tau X_i}{\tilde{\sigma}_i^2}\left(\hat{\beta}_i - \tilde{\beta}_{WFE}\right)$$

Pesaran and Yamagata (2008) proposed the delta (Δ) test as an improved version of Swamy's test of slope homogeneity. According to this test, in a cointegration equation such as $Y_{it} = \alpha + \beta_{it} + \varepsilon_{it}$, it expresses a slope coefficient such as β_{it} and the hypotheses about the Δ test are as follows.

H_0: $\beta_i = \beta$, the slope coefficients are homogeneous.

H_1: $\beta_i \neq \beta_j$, the slope coefficients are heterogeneous.

Pesaran and Yamagata (2008) proposed two test statistics: $\tilde{\Delta}$ (for large samples) and $\tilde{\Delta}_{adj}$ (for small samples) to check these hypotheses.

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right)$$

$$\tilde{\Delta}_{adj} = \sqrt{\frac{N(T+1)}{T-k-1}}\left(\frac{N^{-1}\tilde{S}-k}{\sqrt{2k}}\right)$$

where *N* is the cross-section dimension, *T* is the time series dimension, *S* is the Swamy test statistic, and *k* is the number of explanatory variables. Table 2 presents the homogeneity test results.

Table 2. Slope Homogeneity Test (Pesaran and Yamagata, 2008)

Slope Homogeneity Tests	Δ statistic	p value
$\tilde{\Delta}$ test	19.262***	0.000
$\tilde{\Delta}_{adj}$ test	22.067***	0.000

Notes: The null hypothesis for slope heterogeneity test is slope coefficients are homogenous. (***) denotes significant at 1% level.

Since the p-values of the Δ tests calculated in table 2 are less than the 1% significance level we reject the null hypothesis and conclude that heterogeneity exists across sample sectors and we should use heterogeneous panel techniques.

2.3.2 Cross-section dependence test

Our sample consists of a panel of institutional sectors in the same national economy. We assume possible dependence among sectors which is confirmed by the weak cross-sectional dependency test (Pesaran, 2015). This test verifies the existence of potential common correlation effects in our data. Ignoring cross-sectional dependence (CD) in the data can lead to biased estimates. This test is given by the following equation:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho_{ij}\right)$$

Table 3 presents the results of the Pesaran (2015) test.

Table 3. Pesaran (2015) test for weak cross-sectional dependence

Pesaran (2015) test for weak cross-sectional dependence		
Variables (in Ln)	*CD-Statistic*	*P-value*
Value added (VA)	53.376***	0.000
Capital (K)	53.413***	0.000
Labor (L)	53.431***	0.000
ICT Diffusion Index (IDI)	50.932***	0.000

Notes: The CD statistic is normally distributed under the null hypothesis of weak CD. (***) denotes significant at 1% level.

According to the results in the table 3, the null hypothesis of cross-section weak dependence is strongly rejected since p-values are less than 1% significant for all the variables and we can conclude there is significant evidence of cross-section dependency between variables. This suggests that a positive or negative shock in any sector in the panel can be transmitted to other sectors.

2.3.3 Panel unit-root test

Since the CD test reveals cross-section dependence among the variables, first-generation unit root tests may provide biased results and second-generation unit root tests must be applied to account for this CD of errors and for slope heterogeneity. We use Pesaran's (2003) CADF test and Pesaran's (2007) CIPS test to test the order of integration of the different variables. The CADF is given by the following equation:

$$\Delta Z_{it} = \phi_i + \varsigma_i Z_{i,t-1} + \sigma_i \bar{Z}_{t-1} + \sum_{j=0}^{p} \sigma_{ij} \Delta \bar{Z}_{t-1} + \sum_{j=1}^{p} \lambda_{ij} \Delta Z_{i,t-1} + \varepsilon_{it}$$

where, $\bar{Z}_{t-1}$ and $\Delta\bar{Z}_{t-1}$ are averages for lagged and first difference of each cross-section series.
CIPS statistics are obtained from CADF as follows:

$$CIPS = \frac{1}{N}\sum_{i=1}^{n} CADF_i$$

In both tests, the null hypothesis indicates the existence of a unit root. Table 4 presents the test results which show that value added (LnVA) and capital (LnK) are stationary at first difference (I(1)), and labor and IDI (LnIDI) are stationary at level (I(0)). The fact that all the series are not stationary at level is important for the panel cointegration test; it was decided that the cointegration relationship between these series could be analyzed.

Table 4. Results of panel unit-root

Variables (in log)	*Level*		*First-difference*		*Order*
	Without trend	*With trend*	*Without trend*	*With trend*	
	Cross-Sectionally Augmented IPS (CIPS)				
LnVA	-2.637***	-2.399	-3.895***	-4.185***	I(1)
LnK	-2.044	-1.980	-2.888***	-3.279***	I(1)
LnL	-2.714***	-3.339***	-4.882***	-4.873***	I(0)
LnIDI	-3.239***	-3.838***	-4.962***	-5.012***	I(0)
	Cross-Sectionally Augmented Dicky-Fuller (CADF)				
LnVA	-2.052*	-2.231	-2.981***	-3.330***	I(1)
LnK	-1.888	-1.862	-3.034***	-3.365***	I(1)
LnL	-2.061*	-2.712**	-3.031***	-3.210***	I(0)
LnIDI	-2.149**	-2.684**	-2.845***	-2.832***	I(0)

Notes: The panel unit-root test was performed under the null hypothesis wherein the variables are homogeneous non-stationary. (***), (**), and (*) denote statistical significance level at 1%, 5%, and 10%, respectively.

2.3.4 Panel cointegration test

After performing the stationarity test we examine whether there is a long-term relationship between the variables used in the model. We assume CD among our variables and heterogeneous slope coefficients. Therefore, tests that consider CD in a cointegration analysis will be more efficient in terms of results. There are several cointegration analysis methods but the Westerlund (2007) is the most recent and has more power compared to other residual-based panel cointegration tests.

The Westerlund (2007) test is based on structural rather than residual dynamics and, considering the error correction model. There are four different cointegration test. Two of these test techniques provide panel statistics and are designed to test the alternative hypothesis that the panel as a whole is cointegrated, the other two tests provide group statistics and consider that at least one unit is cointegrated. In addition, since Westerlund (2007) assumes that there is no dependency between the cross-section units that make up the panel, Chang (2004) suggests comparing the cointegration statistics with the critical values by considering bootstrap values. To calculate the panel test statistics in the Westerlund (2007) cointegration test, we first estimate the following error-correction framework:

$$\Delta V_{it} = \delta_i' d_t + \alpha_i \left(V_{i,t-1} - \beta_i' X_{i,t-1} \right) + \sum_{j=1}^{pi} \alpha_{ij} \Delta V_{i,t-1} + \sum_{j=0}^{pi} \gamma_{ij} \Delta X_{i,t-j} + e_{it}$$

where $t = 1, \cdots, T$ and $i = 1, . \cdots, N$ are the time-series and cross-section units, respectively, *d* is the deterministic components, *X* is the vector of the explanatory variables (capital, labor and IDI), *p* is the lag order and α is the error-correction term.

To test for a cointegration relationship in the panel data set, the following group-mean cointegration statistics (Ga, Gt) are estimated.

$$G_t = \frac{1}{N} \sum_{i=1}^{N} \frac{\hat{\alpha}_i}{se(\hat{\alpha}_i)} \sim N(0,1)$$

$$G_a = \frac{1}{N} \sum_{i=1}^{N} \frac{T\hat{\alpha}_i}{se(1)} \sim N(0,1)$$

where $se(\hat{\alpha}_i)$ is the conventional standard error of $\hat{\alpha}_i$.

Null and alternative hypotheses for group-mean cointegration statistics are defined as follows:

H_0: $\alpha_i = 0$; there is no cointegration for all the cross-sectional units.
H1: $\alpha_i < 0$; there is cointegration for at least one of the cross-sectional units.

Rejection of the null hypothesis shows that there is a cointegration relationship among the variables for at least one of the cross sections.

In the third stage, the error correction coefficient and its standard error are calculated for the entire panel as:

$$P_t = \frac{\hat{\alpha}}{se(\hat{\alpha})}$$

$$P_a = T\hat{\alpha}$$

Null and alternative hypotheses for the panel statistics are defined as follows:

H_0: $\alpha_i = 0$; there is no cointegration for the panel as a whole.
H_1: $\alpha_i = \alpha < 0$; there is cointegration for the panel as a whole.

Table 5 presents the results of the Westerlund (2007) panel cointegration tests which indicate that all the statistics are statistically significant, and consequently the null hypothesis of no cointegration can be rejected suggesting that there is a cointegration relationship among the variables in all sectors and the entire panel.

Table 5. Westerlund (2007) Panel cointegration tests

Statistic	*Value*	*Z-value*	*P-value*
G_t	-4.596***	-11.620	0.000
G_a	-10.937**	-2.063	0.019
P_t	-19.073***	-10.410	0.000
P_a	-13.433***	-5.983	0.000

Notes: The G_t and G_a statistics test co-integration for each cross-section, and P_t and P_a test cointegration in the panel under the null hypothesis of no cointegration. (***), (**) denote statistical significance level at 1% and 5%, respectively.

2.4 Panel model Estimation

Recent studies analyzing the impact of new technologies on productivity and economic growth use panel data approaches. However, these studies underestimate issues related to coefficient slope heterogeneity and especially CD which can bias their results. Recent developments particularly in long panels, have enabled the construction of estimators (common correlated effects mean group - CCEMG and augmented mean group - AMG) which take account of endogeneity, slope heterogeneity and CD problems. These estimators also consider structural breaks and shocks.

The method used in this study is appropriate for panels whose time dimension exceeds the individual dimension, as is the case in our study. Consider the following equations where $i = 1, \cdots, N$ is the individual dimension and $t = 1, \cdots, T$ is the time dimension.

$$V_{it} = \alpha_i X_{it} + e_{it} \quad (4)$$

$$e_{it} = \varphi_{1i} + \theta_{1i} f_t + \varepsilon_{it} \quad (5)$$

$$X_{it} = \varphi_{2i} + \theta_{2i} f_t + \eta_i g_t + u_{it} \quad (6)$$

where X_{it} and V_{it} are observable, α_i is the coefficient of observable regressors specific to individuals, e_{it} includes the unobservable factors and ε_{it} is the error term. The unobservables in equation (5) include the fixed effect which captures individual heterogeneity not dependent on time and also unobserved common factors f_t and the coefficient of heterogeneity θ_i which capture time-dependent heterogeneity and CD. ε_{it} and u_{it} are assumed to be white noise. Although the terms f_t and g_t induce CD of both errors and regressors, f_t accounts for possible interindividual dependencies between errors and regressors. Thus, the presence of f_t in (5) and (6) induces endogeneity biases in the equation to be estimated, and therefore problems related to identification of α_i.

The CCEMG estimator solves the problem of interindividual dependence by including as additional regressors the individual means of the independent ($\overline{X}$) and dependent ($\overline{V}$) variables. Pesaran (2006) shows that these averages consider unobserved common factors f_t. The differentiated impact of the common factors (θ_i) is solved by estimating the equation for each individual and then calculating the unweighted average of the coefficients over the whole panel which is a mean group (MG) procedure. According to Chudik and Pesaran (2015), the CCEMG estimator is robust to the presence of the effects of a global shock and externalities. We can express the estimated coefficient CCEMG as follows:

$$\widehat{\alpha}_{CCEMG} = N^{-1} \sum_{i=1}^{N} \widehat{\alpha}_i \quad (7)$$

However, Eberhardt (2012) points out that the CCEMG estimator treats common factors as nuisance parameters which is of no interest in some empirical analyses since the means are difficult to interpret. Therefore, Eberhardt the AMG estimator which unlike CCEMG does not treat common factors as nuisance parameters but assumes that these factors represent a common dynamic process (CDP) which can be estimated. Thus, the AMG estimator solves the identification problem based on a three-step procedure:

First step: a pooled difference OLS model (eq. 8) is estimated with $T-1$ dummy time variables for which the coefficients are collected and renamed CDP.

$$\Delta V_{it} = b' \Delta X_{it} + \sum_{t=2}^{T} c_t \Delta DUMMY_t + \upsilon_{it} \quad (8)$$

Second step: the CDP is added to the model as an explicit variable or by subtracting from the dependent variable in each group in order to augment the group specific model.

$$\tilde{V}_{it} = V_{it} - CDP \tag{9}$$

Third step: the model is estimated for each individual in the panel and then the average of the estimated coefficients is calculated as in the case of Pesaran and Smith's (1995) Mean Group (MG) model.

$$\widehat{\alpha}_{AMG} = N^{-1}\sum_{i=1}^{N}\widehat{\alpha}_i \tag{10}$$

This study uses the above estimators which consider both coefficient slope heterogeneity and the presence of CD to analyze the nexus between ICT diffusion and economic growth. Before performing the various estimates indicated above, we conducted various tests for slope homogeneity, interindividual dependence, stationarity and cointegration. Tables 6 and 7 provide the outcomes of these estimations.

3. EMPIRICAL RESULTS

The goodness of fit of the models is measured by the root mean squared error (RMSE). The estimated RMSE for the CCEMG model is 0.0377 and for the AMG model is 0.0446, both of which are relatively low pointing to satisfactory goodness of fit. The estimated CD (statistics reported in table 6) imply that the issue of CD is resolved.

Table 6. Panel model estimation results - CCEMG and AMG approaches

	CCEMG		AMG	
	Coefficient	Std. Err.	Coefficient	Std. Err.
Capital	0.291***	0.113	0.298**	0.129
Labor	0.320***	0.112	0.212**	0.107
ICT Diffusion Index	0.056**	0.024	0.040***	0.015
Constant	-0.678	3.036	2.535*	1.526
Common dynamic process			0.596*	0.326
CD statistics	-1.18		-1.51	
Root Mean Squared Error (sigma)	0.0377		0.0446	

Notes: The CD test was performed under the null hypothesis of cross-section independence. (***), (**), and (*) denote statistical significance level at 1%, 5%, and 10%, respectively.

The panel model estimation results (CCEMG and AMG approaches) show that all the coefficients are statistically significant. Capital and labor are positive and statistically significant at the 1% level in CCEMG model and 5% in the AMG model, and the IDI is positive and statistically significant at the 1% level in the AMG model and at 5% in the CCEMG model. Overall, our results indicate that labor and capital explain around 60% of growth in the CCEMG model and around 50% of growth in the of AMG model. ICT explains only some 5% of economic growth.

Although investment in ICT has increased significantly, most economic growth is explained by the traditional factors of physical capital and labor. Indeed, average annual growth in the Tunisian economy reached 3.59% in the period 1997-2017, with the most important contributions provided by labor (32%) and the stock of capital (29%).

The variable for availability and diffusion of ICT is statistically significant at the 5% and 1% levels for the CCEMG and AMG specifications respectively, suggesting that availability and diffusion of ICT may promote value added growth through several transmission channels. First, the outputs of the ICT sector are acquired by firms as capital goods and / or as intermediate consumption goods, and also, as final consumption goods. The high investment in equipment and ICT-derived goods by firms and consumers has resulted in an increase in overall economic growth. Also, as the stock of capital produced by the ICT sector and used in other sectors of the economy grows, labor productivity increases in ICT goods producing sector. The main mechanism resembles a Keynesian ICT investment multiplier greater than the non-ICT investment multiplier. Given their generic nature, ICTs appear to exert greater economic effects on the rest of the economy.

Second, there is a deflator effect of lower ICT prices on the rest of the economy. The continual fall in the prices of ICT hardware and software, increased storage and better operation and communication have led companies to increase their investment in ICT and in some cases to overinvest in ICT. Third, there has been a relative increase in the share of capital compared to labor in the use of inputs where ICTs are seen as biased technologies. This leads to the favoring of capital over labor and skilled labor over unskilled labor. In other words, the growth process favors the accumulation of capital which results in a decrease in the relative rate of employment, increased automation of processes and an increase in the relative share of the capital factor.

This makes it possible to change the organization of production, markets and companies, rethink business practices, simplify the supply chain and reduce transaction costs. However, unlike other forms of capital ICT capital subject to rapid obsolescence leading to rapid depreciation and demand for greater profitability from companies. Fourth, ICT can be associated with increases affecting the intangible components of outputs such as variety, convenience of consumers and associated services. The apparent effect is related to increased informational content of goods and services incorporating ICT which increase quality and promote differentiation among products and services.

These benefits make it possible to improve the utility effect for consumers without modifying either the price or the quantity of the products that incorporate ICT. Better product quality is required to be competitive, and increased competition encourages less productive firms to leave the market. Finally, there is an overall productivity effect of factors whose externalities linked to ICT have been widely diffused throughout the economy allowing increased productive efficiency and increased rates of technical progress. This results in an increase in the Solow residual (the part of growth not explained by the separate factors of production).

Our findings point to important heterogeneity of productivity and economic growth among sectors. Table 7 provides three main findings. First, in some sectors such as financial services, transport, building and civil engineering, hotel and restaurant services and other market services ICT have a positive and significant impact on value added. In the case of financial services sector, the elasticity is very high (38.7%) and it is also high in agriculture, food and tobacco, suggesting that the agribusiness sector benefits from use of ICT.

Second, in the trade and various manufacturing industries sectors ICT has a negative and significant impact on value added. The case of the trade can be explained by the increased adoption and use of ICT by firms which promotes use of e-commerce. However, e-commerce is not well organized in Tunisia and most transactions are related to the informal sector. This has resulted in a sector where people are buying and selling in the presence of no controls. In addition, formal sector firms are selling some products in an informal way. This explains the negative and significant impact of ICT in the trade sector.

Third, some sectors are subject to a productivity paradox. In several sectors the impact of ICT on value added is not significant. In the case of public administration, despite huge investment in ICT there is no impact on the value added. The insignificant impact of ICT in public administration is due to the absence of deep organizational change.

Table 7. Long-run elasticity of output with regard to ICT: individual sectors

	CCEMG		AMG	
	Elasticity	*Std. Err.*	*Elasticity*	*Std. Err.*
Agriculture and fishing	0.103	0.070	0.010	0.060
Agriculture, food and tobacco industries	0.101*	0.055	0.156***	0.025
Construction materials, ceramics and glass	0.015	0.058	-0.024	0.031
Mechanical and electrical industries	-0.008	0.012	-0.008	0.012
Chemical industries	-0.009	0.011	-0.003	0.013
Textile, clothing and leather	0.109	0.096	0.097	0.086
Various manufacturing industries	-0.041***	0.011	-0.019**	0.008
Mines and hydrocarbons	-0.014	0.050	0.009	0.047
Electricity, gas and water	0.017*	0.010	0.018*	0.009
Building and civil engineering	0.029***	0.011	0.034***	0.008
Trade	-0.025***	0.009	-0.012*	0.007
Transport	0.069*	0.041	0.085***	0.035
Post and telecommunications	0.026*	0.015	0.028**	0.013
Hotel and restaurant services	0.074*	0.041	0.044**	0.022
Financial services	0.387***	0.096	0.192***	0.063
Other market services	0.098***	0.039	0.080**	0.037
Public administration	0.011	0.038	-0.005	0.041

Notes: (***), (**), and (*) denote statistical significance level at 1%, 5%, and 10%, respectively.

The Dumitrescue-Hurlin Granger causality tests was employed as a robustness check to that of the CCEMG and AMG estimators, and their outcomes are shown in Table 8. They affirm that the results of the causality test are consistent with the results of the panel estimators.

Table 8. Dumitrescu and Hurlin Granger non-causality tests

Variables	*Value Added*	*Capital*	*Labor*	*ICT Index*
Value Added	–	13.5854*** (11.1940)	14.7529*** (12.7163)	19.4241*** (18.8067)
Capital	16.1751*** (14.5705)	–	15.4166*** (13.5816)	12.6951*** (10.0332)
Labor	16.1751*** (14.5705)	10.9950*** (7.8166)	–	3.6211*** (7.6418)
ICT Index	10.4074*** (7.0504)	16.9476*** (15.5778)	12.2166*** (9.4092)	–

Notes: The W-statistics marked with (***) are statistically significant at 1% level. Z-statistics are shown in parentheses.

CONCLUSIONS AND POLICY IMPLICATIONS

This study evaluated the relationship between ICT development and economic growth in Tunisia using a sector analysis. It shows that ICT plays an important role in the development of economic sectors. It contributes to empirical work on the effect of ICT diffusion on economic growth in a developing country context -Tunisia. We constructed an ICT Diffusion Index (IDI) for the Tunisian economy for 17 sectors in the period 1997-2017. We employed very advanced econometric methods to explain the relationship between ICT and economic growth in a sector context.

Using the CCEMG and AMG methods with annual panel data ranging from 1997 to 2017, we found a significant positive relationship between ICT and economic growth in Tunisia. We found that the effect of ICT on value added differs depending on the sector. Sectors benefiting from a positive and significant impact of ICT on value added are financial services, transport, building and civil engineering, hotel and restaurant services and other market services whereas there is a negative and significant impact on trade and various manufacturing industries. Public administration shows evidence of a productivity paradox in that despite huge investment in ICT there is no impact on value added.

We suggest that the ICT infrastructure should be strengthened to increase investment in ICT and support digitalization of different sectors of the economy. Three main policies should be implemented to increase the contribution of the ICT to economic growth. First, there is a need to strengthen the digital infrastructure, and improving network security and reducing the digital divide should be priorities for Tunisia. Investing in broadband provision for rural areas could reduce regional inequalities and the digital divide. Second, the workforce needs to be reskilled and trained to adopt new organizational practices in firms. Implementation of new technologies requires new skills to unlock the large economic and social opportunities that digitalization can offer. Business strategies should be formulated and proactive policy frameworks adopted to promote digital development and technological innovation in firms. Third, supporting sector digitalization is imperative. Many sectors failed to shift to online during COVID-19 crisis and strategies need to be implemented to benefit from the new opportunities provided by digitalization.

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