Estimating effects of ICT intensity on productivity, employment and output in South Africa: an industry-level analysis

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Abstract

This article aims to estimate the effects of ICT intensity on labor productivity, employment and output of agro-processing industries. To achieve this, the ICT intensity index is applied to rank industries into 'more ICT-intensive' and 'less ICT-intensive' groups. Thereafter, the annual growth rates of labor productivity, employment and output were calculated. Ultimately, the effects of ICT intensity were examined using Pooled Mean Group estimation, the Toda and Yamamoto Granger Non-Causality Test, and the Impulse Response Function and Variance Decomposition analyses. The findings suggest that ICT intensity yields higher positive and significant effects on the growth of the more ICT-intensive industries. Evidence of a causal relationship was detected for the more ICT-intensive industries. The findings further proved that ICT intensity contributed more to the forecast error variance in the growth of the more ICT-intensive industries. Overall, this article provides evidence of ICT-led growth for industries that use ICT most intensively.

Keywords: ICT intensity; productivity; employment; output

1. Introduction

In today's epoch of technological developments, the key international organizations, such as the United Nations (UN) and the World Bank, view investment in ICT as one of the prerequisites for developing countries to implement in order to attain growth and development.[1] In particular, the UN posits supporting the innovation and technology development and increasing access to ICT as some of the strategies for boosting growth and development in developing countries (United Nations Development Programme [UNDP], 2016). In the same way, the World Bank holds an optimistic view that ICT has great potential to create jobs and enhance the economic growth of the developing countries (World Bank, 2012; World Bank, 2017).

Despite the above optimistic viewpoints, aggregate-level studies found either a negative or no significant effect of ICT investment on countries' growth (Edquist & Henrekson, 2017; Jorgenson & Stiroh, 1995, 1999; Mačiulytė-Šniukienėa & Gaile-Sarkane, 2014; Oliner &

Sichel, 1994). These aggregate-level findings are attributable to four main reasons. Firstly, ICT accounted for a small share of investment as a proportion of the total capital stock, such that it had small effects on aggregate output (Sichel, 1997, pp. 120–123; Stiroh, 2002). Second, the types of econometric models typically used do not account for variations in ICT intensity among industries (Stiroh, 2002). In other words, industries that use ICT most intensively are aggregated with those that use ICT the least in the analysis. According to Stiroh (2002), by aggregating industries in the analysis, studies miss out on the sources of ICT-led growth as, in reality, the degree of ICT use, and thus ICT-led growth, varies immensely across industries. Third, studies often analyse the causal relationship between ICT investment and measures of growth, such as Gross Domestic Product (GDP) and productivity in a bivariate setting, but neglect other factors that affect aggregate GDP and productivity (Chakraborty & Nandi, 2011; Hong, 2017; Lee et al., 2005; Masood, 2012; Yousefi, 2015). The consequence of analyzing the effects of ICT in a bivariate setting is that it gives rise to the econometric problem of omitted variable bias, casting doubt on the validity of the statistical inferences of a causal relation (Payne, 2010). Fourth, the use of econometric approaches that do not account for the lag effects of technology. According to Brynjolfsson and Hitt (1996) and Lee and Barua (1996), neglecting the lag effects of technology gives rise to a 'productivity paradox.'[2] The aforementioned serve as the reasons why aggregate-level studies have found either a negative or zero impact of ICT.

By contrast, industry-level studies have found positive and significant results for those industries that are either producing or using ICT most intensively (Abri & Mahmoudzadeh, 2015; Corrado et al., 2017; Moshiri, 2016). However, it is noted that no empirical findings have been reported on the contribution of ICT investment at the industry level on the performance of South Africa's economy. This article, therefore, examines the extent to which ICT investment contributes to the growth of labor productivity, employment and output of the agro-processing subsector.[3] The focus is on the agro-processing industries for both the economic and technical reasons.

Economically, the agro-processing sector has been earmarked in various policy plans as a catalyst to create jobs and spur economic growth and development, given its strong backward and forward linkages with other economic sectors.[4] However, it appears that efforts to develop the subsector have been ineffective in driving the required growth and development at the national level. This is evident through the statistics for GDP growth, the unemployment rate, and other measures of development at the national level (Statistics South Africa [Stats SA], 2017; World Bank, 2018; Stats SA, 2019a; Stats SA, 2019b). Hence, it is imperative for this article to unlock the potential gains that might accrue through investment in ICT in the agro-processing subsector. The findings provide an insight into how investment in ICT in the agro-processing subsector could contribute towards driving the subsector's growth.

Technically, focusing on the agro-processing subsector provides an insight into the network effects of ICT, that is, productivity effects from the use of ICT in the non-ICT sectors (Stiroh, 2002; van Ark, 2014). Based on Szewczyk (2009), it is presumed that developments in ICT at the national level would spill over to the industries, depending on their levels of ICT investment (expenditure). Consequently, higher ICT-led growth would arise in those industries that had invested highly in ICT. This assumption is supported by the empirical findings which have validated the point that industries that had invested more in ICT experienced higher growth rates than those that had invested less (Kuppusamy et al., 2009; Moshiri, 2016; Vu, 2013).

Against the above backdrop, and to avoid problems associated with aggregate-level studies, the agro-processing industries are ranked into 'more ICT-intensive' and 'less ICT-intensive' industry groups, by using the ICT intensity index. The disaggregation of industries is important for this article, as the agro-processing subsector comprises various industries, with varying requirements for ICT-intermediate inputs, and thus varying levels of ICT use. In consequence, the effects of ICT on growth performance would vary across industries. By disaggregating industries according to their ICT intensity, this article gives an insight into which group of industries would be receptive to, and benefit from, the exploitation of ICT investment. After calculating the ICT intensity of industries, the annual growth rates of labor productivity, employment and output were calculated. Ultimately, this article examines the effects of ICT intensity on the growth of labor productivity, employment and output. Again, to avoid problems associated with bivariate analysis, the causal relationship between ICT intensity and productivity, employment and output is examined in a multivariate setting. By doing so, this article avoids the econometric problem of omitted variable bias, while unlocking multiple causality channels that are undetectable under the bivariate setting.

The overarching aim of this article is to estimate the effects of ICT intensity on the labor productivity, employment and output of agro-processing industries. The specific objectives are:

1. To estimate short-and long-run effects of ICT intensity on the growth of labor productivity, employment and output;
2. To examine the causal relationship between ICT intensity and the growth of labor productivity, employment and output; and
3. To forecast the potential effects of ICT intensity on the growth of labor productivity, employment and output.

The succeeding sections of the article are ordered as follows. Section 2 discusses the literature on the effects of ICT on GDP/output, labor productivity and employment. Section 3 describes the data, variables and econometric approaches used in this article. Section 4 presents both the descriptive and empirical results. Section 5 highlights the key findings and presents concluding remarks.

2. Review of related literature

A broad range of studies have investigated the effects of ICT investment on economic growth and other measures of development through using varied data sources and analytical approaches, over diverse time periods. For the purpose of this article, the literature review focuses on the causal relationship between ICT and GDP growth, productivity and employment. Further to this, special attention is given to cross-country studies and studies at both the aggregate and industrial levels. The review starts with the discussion of how ICT contributes to productivity, GDP and employment, followed by a review of previous studies on the causal effects of ICT. The review ends with a focus on South Africa in order to highlight the gap in the literature that this article intends to fill.

In the empirical analysis, ICT contributes to productivity and economic growth in three ways. First, it increases labor and capital productivity (i.e. multi-factor productivity (MFP)) in the ICT-producing sector. Second, it contributes to capital deepening through productivity gains generated from the use of ICT as a capital input in the non-ICT sectors. Third, the greater use of ICT throughout the economy contributes to economy-wide total factor productivity (TFP) (Mefteh & Benhassen, 2015; Piatkowski, 2004; van Ark, 2003). Ultimately, TFP drives economic growth. Consequently, various studies have evaluated the causal effects of ICT and productivity and GDP (i.e. a measure of economic growth) at both the aggregate and industrial levels.

In summation, aggregate-level studies have found a bidirectional causal relationship between ICT investment and GDP for the developed countries, and unidirectional causality for the developing countries (Pradhan et al., 2014; Shiu & Lam, 2008). The divergence in the direction of causality is attributed to higher levels of investment in ICT in the developed countries, relative to developing countries. The divergence is further attributable to the fact that, in the developing countries, ICT has not reached the maturity level; hence, unidirectional causality is detectable. In a similar way, aggregate level-studies with a focus on productivity have proved that, in general, causality is detectable for developed countries, which suggests that developed countries are yet to experience productivity gains from ICT investment (Lee et al., 2005). Thus, aggregate-level studies have detected a causal relationship between ICT and both productivity and GDP for developed countries due to the higher level of investment in ICT, relative to the developing countries.

Similar to aggregate-level studies, industry-level studies have detected a causal relationship between ICT and productivity for industries with higher levels of investment. For example, Vu (2013) found a strong positive correlation between ICT investment and labor productivity growth for Singapore's sectors with higher ICT intensity. In a similar study, but with a focus on GDP, Kuppusamy et al. (2009) found that GDP growth in Malaysia is driven by those sectors that are investing highly in ICT (i.e. manufacturing and wholesale, relative to agriculture). Overall, the industry-level studies have found higher ICT-led growth (labor productivity and GDP) for the industries that have invested more in ICT.

Despite the aforementioned, another set of studies proved that ICT-led growth (GDP and productivity) depends on whether the analyses are undertaken in a bivariate or a multivariate setting. To give an example, studies that have investigated the effects of ICT in a multivariate setting (both aggregate and sectoral/industrial studies) found evidence of causality (Kuppusamy et al., 2009; Pradhan et al., 2014; Shahiduzzaman et al., 2015; Vu, 2013). On the contrary, bivariate studies found no evidence of a causal relationship between ICT and variables of interest (Beil et al., 2005; Chakraborty & Nandi, 2011; Hong, 2017; Lee et al., 2005; Masood, 2012; Rei, 2004; Yousefi, 2015). The rationale for conducting such analysis in a bivariate setting is data availability and/or scope of the analysis. Notwithstanding this, Payne (2010) notes that using a bivariate framework gives rise to the econometric problem of omitted variable bias, which casts doubt on the validity of the statistical inferences of a causal relation. Contrarily and according to Zachariadis (2007), using a multivariate model allows one to detect multiple causality channels deep-rooted under a bivariate setting, while avoiding omitted variable bias.

It is notable that while ICT is generally promoted due to its proven record of enhancing productivity and boosting GDP growth, contrary arguments have emerged with respect to employment. The key argument is that the use of ICT increases labor productivity, enabling the production of more output with less labor, giving rise to jobless growth (Organisation for Economic Co-operation and Development [OECD], 2016). Hence, it is fundamental for this article to review empirical findings on the relationship between ICT and employment. In general, despite the pessimistic views regarding the effects that ICT would have on employment, empirical findings have tended to find a positive correlation between ICT and employment (Atasoy, 2013; Etro, 2009; Khan et al., 2017; Kolko, 2012; Pantea et al., 2014).

In the case of South Africa, limited empirical studies have been done on the potential gains that could be accrued through investment in ICT at both the aggregate and industrial levels. At the aggregate level, the 2015 report by the Global Connectivity Index predicted that a 20% increase in ICT investment would lead to a 1% increase in GDP of 50 selected countries, including South Africa.[5] In another case, Salahuddin and Gow (2016) detected a positive and significant long-run relationship between internet usage and economic growth over the period 1991–2013. With respect to the industrial level, Fredderke and Bogetic (2009) found that telecommunication measures had a positive and significant effect on the labor productivity of the manufacturing sector over the period 1970–2000.[6] Further to this, Khan et al. (2017) found positive effects between ICT and employment for 12 Sub-Saharan African countries, including South Africa. Overall, the review of the literature highlights the point that studies on the role of ICT on South Africa's economy are yet to explore its impact on the agro-processing subsector. In particular, there are two gaps in the literature in relation to ICT and agro-processing that this article attempts to fill.

1. There is no available information base on ICT intensity of agro-processing industries that might be used to evaluate the effects of ICT.

A number of studies have used various indexes to rank industries according to the extent to which they use ICT (Abri & Mahmoudzadeh, 2015; Engelbrecht & Xayavong, 2006; Niebel et al., 2016; Stiroh, 2002; van Ark et al., 2002). An important point of note is that these studies did not explicitly focus on agro-processing industries due to the scope of their analyses. To give an example, the study by Niebel et al. (2016) did not provide an understanding of which of the agro-processing industries are more ICT intensive, and which are not. This is because the agro-processing industries under study were embedded in the manufacturing sector group. While earlier studies have included agro-processing industries in the analyses, it is notable that not all the agro-processing industries were included in the analyses and that some of the industries were bundled together (Abri & Mahmoudzadeh, 2015; Engelbrecht & Xayavong, 2006; Stiroh, 2002; van Ark et al., 2002). For instance, the Food, Beverages and Tobacco industries were bundled as one industry group, and as a consequence, these studies were inconclusive regarding which parts of this industry group are ranked as more or less ICT intensive. In summation, questions remain in the literature regarding which of the agro-processing industries are more, and which are less, ICT intensive.

- (2) There is no empirical evidence on how long it would take for ICT to yield a positive and significant effect on the growth of the agro-processing industries.

The most conclusive point derived from the disaggregated studies is that ICT investment (intensity) has a positive and significant effect for industries that are more ICT intensive, but insignificant for industries that are less ICT intensive (Abri & Mahmoudzadeh, 2015; Corrado et al., 2017; Moshiri, 2016; Stiroh, 2002). However, it is notable that these studies have not explicitly focused on agro-processing industries. This is with the exception of the study by Kuppusamy et al. (2009) that showed the insignificant effect of ICT investment on the GDP growth of the agricultural sector, which suggest that the agriculture sector is yet to gain from its technological investments.[7] The delimitation of this study is that it focused solely on the aggregated agricultural industries. Further to this, the study did not take into account the point that the economic performance gains from ICT investment manifest only after a certain time (Becchetti et al., 2003). This is attributed to the use of econometric approaches that do not account for the future potential effects of ICT on industries over a long period. Accounting for the future effects of ICT is imperative, as the impact of ICT on the economy follows a

Schumpeterian trend that begins with a negative or zero impact, followed by acceleration, and then a petering out (Moshiri, 2016). The reason for this trend is that the ICT investments might be counter-productive at the start due to the training of labor and redesign of job practices, as well as the realignment of work structures and scope; hence, returns only become notable over a longer period (Lee et al., 2005). However, previous studies have not explored how long it would take for ICT to yield a positive and significant impact on the agro-processing industries.

Against the above backdrop, this article intends to fill the identified knowledge gap by: (1) disaggregating the agro-processing industries into 'more ICT-intensive' and 'less ICT-intensive' industry groups by using the ICT intensity index; (2) calculating the annual growth rates of labor productivity, employment and output of industries; (3) estimating the effects of ICT intensity on growth of labor productivity, employment and output; (4) examining the causal relationship between ICT intensity and growth of labor productivity, employment and output; and (5) forecasting the future potential effects of ICT intensity on growth of labor productivity, employment and output.

3. Research methods

3.1. Description of data sources

To calculate ICT intensity, input-output (I-O) time-series data for 10 agro-processing industries were sourced from Stats SA. However, Stats SA only began to publish the I-O data on an annual basis from 2009, with 2014 being the latest year of publication (K. Parry, personal communication, October 9, 2018). Given this, I-O data from the South African Standardised Industry Indicator Database, which is collected, managed and owned by Quantec, is used for the missing years (Quantec, 2018a). The database is based on estimates and on the last full release of the underlying dataset by the Stats SA. In addition, data on productivity, employment and output were also sourced from the Trend Tables of the South African Standardised Industry Indicator Database due to the lack of comprehensive and up-to-date data available from the Stats SA. The methodology used to compile the overall data can be obtained from the Quantec website (Quantec, 2018b).

3.2. Description of variables

In this article, we adopt the method used by Engelbrecht and Xayavong (2006) for categorizing industries into 'more ICT-intensive' and 'less ICT-intensive,' based on their direct requirements for ICT inputs, using I-O data. The index developed by Engelbrecht and Xayavong (2006) is preferable over other indexes that are based on ICT capital stock (Abri & Mahmoudzadeh, 2015; Stiroh, 2002), and which are unavailable for the current analysis.[8] Accordingly, in terms of classifying industries, for all the indexes, the industries with values of less than the median value of the index are classified as 'less ICT-intensive,' while those with values above the median are 'more ICT-intensive.'

Based on Engelbrecht and Xayavong (2006), the ICT intensity index for industry j's (I_j) is defined as industry j's requirements for ICT intermediate inputs relative to total requirements by all the agro-processing industries for ICT inputs, expressed as follows:

$$I_j = \left(\frac{\sum_{j=1}^{n} ict^{*}\, j}{Tj} \right) X\, 100 \tag{1}$$

Given this, the ICT intensity of an industry is defined as the share of its purchase of, or expenditure on, ICT intermediate goods and services, relative to the total share by all the agro-processing industries.[9] To compute the ICT intensity of industries, we used the I-O data for the industries from 1994 to 2017.[10] The definition and classification of ICT and agro-processing industries is based on the United Nations' International Standard Industrial Classification of Economic Activities (ISIC, Rev. 4), which is used by both Stats SA and Quantec.

The other variables are defined as follows: labor productivity is the gross output per hours worked; employment is the total number of employees in an industry, including formal and informal employment (taking into account both casual and permanent employees); and real output is the value of goods or services produced in a particular industry, measured in millions of rands (Quantec, 2018c). Akin to previous studies, we transformed the raw data for labor productivity, employment and real output into mean growth rates (i.e. annual growth rates) (Engelbrecht & Xayavong, 2006; Lovrić, 2012; Vu, 2013).

In summation, the type of data used in this article comprises panel data, that is, time series on ICT intensity, labor productivity, employment and output over the period 1994–2017 for cross-sections of 10 agro-processing industries.[11] There are three justifications for using the panel approach in this article. Firstly, the article focuses on estimating the effects of ICT intensity with respect to groups in the sample (i.e. more ICT-intensive and less ICT-intensive industries), with heterogeneities with respect to labor productivity, employment and output. According to Lee et al. (2005), using the panel approach allows us to take into account heterogeneity across groups in the sample, which improves the accuracy of the findings. Second, panel data analyses allow researchers to obtain a detailed understanding of the impact of ICT along the continuum of ICT investment (Lucas, 1993; as quoted by Lee et al., 2005). Third, the use of panel data allows researchers to account for the lag effects of technology and avoid the 'productivity paradox' phenomenon (Brynjolfsson & Hitt, 1996; Devaraj & Kohli, 2000; Lee & Barua, 1996; Peffers & Dos Sontos, 1996; as quoted by Lee et al., 2005).

3.3. The model

The autoregressive distributed lag (ARDL) framework, developed by Pesaran and Shin (1999, pp. 371–413), is applied to estimate the effect of ICT intensity for the period 1994–2017. The ARDL is preferable in this article for two reasons. Firstly, unlike techniques such as those used by Engle and Granger (1987), Johansen and Juselius (1990), Johansen (1988, 1991) and Phillips and Ouliaris (1990), the ARDL can be applied in the presence of mixed order of integration. Second, the framework produces consistent and efficient estimates, even in the case of small sample studies (as is the case in this study), implying that cointegration can be conducted for 30 or more observations (Kuppusamy et al., 2009). The basic ARDL (p, q) model is as follows:

$$Y_t = a_0 + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{i=1}^{q} \delta_i X_{t-i+\epsilon it} \tag{2}$$

For the purpose of this study, we consider the four-variable vector autoregressive (VAR) model, composed of ICT intensity (ICT), labor productivity (LP), employment (EMP) and real output (RO). Thus, the analyses are conducted in a multivariate setting. Consequently, the basic

ARDL (p, q) model is transformed into specific ARDL (p, q, r, s) model, as follows:

$$\Delta ICT_t = \alpha 01 + \sum_{i=1}^{p} \alpha 1i \Delta ICT_{t-i} + \sum_{i=1}^{q} \alpha 2i \Delta LP_{t-i} + \sum_{i=1}^{r} \alpha 3i \Delta \mathrm{EMP}_{t-i} + \sum_{i=1}^{s} \alpha 4i \Delta RO_{t-i} + \lambda_1 ICT_{t-1} + \lambda_2 LP_{t-1} + \lambda_3 \mathrm{EMP}_{t-1} + \lambda_4 RO_{t-1} + \epsilon_{1it} \quad (3)$$

$$\Delta LP_t = \alpha 02 + \sum_{i=1}^{q} \alpha 1i \Delta LP_{t-i} + \sum_{i=1}^{p} \alpha 2i \Delta ICT_{t-i} + \sum_{i=1}^{r} \alpha 3i \Delta \mathrm{EMP}_{t-i} + \sum_{i=1}^{s} \alpha 4i \Delta RO_{t-i} + \lambda_1 ICT_{t-1} + \lambda_2 LP_{t-1} + \lambda_3 \mathrm{EMP}_{t-1} + \lambda_4 RO_{t-1} + \epsilon_{2it} \quad (4)$$

$$\Delta \mathrm{EMP}_t = \alpha 03 + \sum_{i=1}^{r} \alpha 1i \Delta \mathrm{EMP}_{t-i} + \sum_{i=1}^{p} \alpha 2i \Delta ICT_{t-i} + \sum_{i=1}^{q} \alpha 3i \Delta LP_{t-i} + \sum_{i=1}^{s} \alpha 4i \Delta RO_{t-i} + \lambda_1 ICT_{t-1} + \lambda_2 LP_{t-1} + \lambda_3 \mathrm{EMP}_{t-1} + \lambda_4 RO_{t-1} + \epsilon_{3it} \quad (5)$$

$$\Delta RO_t = \alpha 04 + \sum_{i=1}^{s} \alpha 1i \Delta RO_{t-i} + \sum_{i=1}^{p} \alpha 2i \Delta ICT_{t-i} + \sum_{i=1}^{q} \alpha 3i \Delta LP_{t-i} + \sum_{i=1}^{s} \alpha 4i \Delta \mathrm{EMP}_{t-i} + \lambda_1 ICT_{t-1} + \lambda_2 LP_{t-1} + \lambda_3 \mathrm{EMP}_{t-1} + \lambda_4 RO_{t-1} + \epsilon_{4it} \quad (6)$$

where ICT = ICT intensity (%); EMPt, LPt and ROt are growth rates of employment (%), labor productivity (%) and output (%), respectively. All the variables are in percentage form; hence the equations are not in log forms. ϵ_{ts} are stochastic error terms, often called impulses or innovations. Each dependent variable is a function of its lagged values and the lagged values of other variables in the model.

3.3.1. Determining the optimal lags

The ARDL framework allows each variable to have its own optimal lag. In view of this, two criteria are used to determine the orders of the lags in the ARDL model: The Akaike Information Criterion (AIC) and the Schwartz Bayesian criterion (SBC) (Kuppusamy et al., 2009). The lag order that gives the lowest value of either the AIC or the SBC is chosen as the optimal lag. For annual data, as is the case in this study, Pesaran and Shin (1999) recommended 1–2 lags. By using lags, this article avoids the 'productivity paradox' problem.

3.3.2. Diagnostic testing

The next step after determining the optimal ARDL model involves conducting diagnostic testing to examine the robustness of the model (Kuppusamy et al., 2009). Specifically, the diagnostics tests for normality of error terms, the functional form of the model, serial correlation and heteroscedasticity are performed to prove the robustness of the ARDL model. The Jarque-Bera test is performed to examine whether the error terms are normally distributed. The Ramsey Regression Specification Error Test (RESET) test is conducted to test for the functional form of the model. The Autoregressive Conditional Heteroscedastic (ARCH) test is undertaken for the purpose of testing for heteroscedasticity. The Lagrange multiplier (LM) test is performed to test for the existence of serial correlation.

3.3.3. Panel unit root testing

The Im-Pesaran-Shin (IPS) unit root test, developed by Im et al. (2003), is applied to verify the order of integration among variables. Alternative unit root tests to the IPS test include the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979), the ADF-GLS test (or DF-GLS test) (Elliott et al., 1996), the Phillips and Perron (PP) test (Phillips & Perron, 1988), and the Ng-Perron test (Ng & Perron, 1995, 2001). The IPS is preferable over these tests as it tests for stationarity in panels that combine information from the cross-section dimension with that from the time-series dimension, so that fewer time observations are required for the test to have power (Im et al., 2003). The IPS tests are applied by averaging individual ADF t-statistics across cross-section units. A separate ADF regression is, therefore, specified for each cross-section with individual effects and no time trend, as follows (Im et al., 2003):

$$\Delta Yit = \alpha i + \rho iyi, t1 + \sum_{j=1}^{\rho i} \beta_i j \Delta yi, tj + \epsilon it \tag{7}$$

Y_{it} is the series for industry i in the panel over period t; p_i is the number of lags chosen for the ADF regression; Δ is the first difference filter (I_L), and ϵ_{it} refers to independently and normally distributed random variables for all i and t with zero means and finite heterogeneous variances. After estimating the separate ADF regressions, the average of the t-statistics for the individual ADF regressions is as follows:

$$\bar{t}NT = \frac{1}{N}\sum_{i=1}^{N} tiT(\rho i\beta i\Big) \tag{8}$$

It has been proven that the standardized t-bar statistic converges to the standard normal distribution as N ∞ T. As stated in Im et al. (2003), the t-bar test has better performance when N and T are small, which confirms that the test has sufficient power to test for stationarity (Hassan et al., 2014). The rationale for unit root testing is to ensure that variables are stationary, with the purpose of avoiding spurious regression and generating results that are applicable in other periods. This validates forecasting of the future potential effects of ICT intensity.

3.3.4. Panel cointegration testing

After testing for stationarity, the Bounds Cointegration Test, developed by Pesaran et al. (2001), is applied to examine if a long-run relationship exists among ICT intensity, labor productivity, employment and output. This test is preferable over other tests (Engle & Granger, 1987; Johansen, 1988; Johansen & Juselius, 1990; Pedroni, 1999; Phillips & Ouliaris, 1990) as it is capable of testing for cointegration among variables, irrespective of the order of integration. Also, the Test can be applied to studies with small sample sizes (as is the case with this study). The Bounds Cointegration Test is composed of two sets of critical values for a given significance level: the upper bound I (1) and the lower bound I (0). The decision criteria for cointegration are as follows: (1) H_0 is rejected if the value of the F-statistic exceeds the critical value for the upper bound I (1), which means that cointegration exists (i.e. there is long-run relationship among variables); (2) H_0 cannot be rejected if the F-statistic is less than the critical value for the lower bound I (0), which means that cointegration does not exist (i.e. no long-run relationship among variables); and (3) the Test is considered inconclusive if the F-statistic falls between the upper bound I (1) and the lower bound I (0) (Pesaran et al., 2001).

Overall, if a long-run relationship exists among variables, it implies that such variables are related and can be modeled in a linear fashion. In other terms, even if there are shocks in the short run, which may affect movement in the individual variables, they would converge with time (in the long run).

In line with Belloum (2014), the bounds test is conducted by estimating Equations (3) to (6) by ordinary least squares (OLS). This is followed by conducting an F-test for the joint significance of the coefficients of the lagged levels of the variables, H_0: $a_{1i} = b_{1i} = d_{1i} = p_{1i} = 0$ against H_1: $a_{1i} \neq b_{1i} \neq d_{1i} \neq p_{1i} \neq 0$ for i = 1, 2, 3, 4. The F-statistic is conducted on level forms and when each of the variables is the dependent variable, as specified in Equations (3) to (6).

3.3.5. Pooled mean group (PMG) estimation

One of the delimitations of the Cointegration Tests is that they cannot estimate the short-run and long-run effects together with the speed of adjustment towards long-run equilibrium. To address this delimitation, the PMG estimation is undertaken to estimate short-run and long-run relationship among variables, as well as the error correction adjustment speed. The PMG is chosen because it allows for convergence speeds and short-term adjustments to vary across industries, thereby allowing cross-industry heterogeneity. Furthermore, PMG provides consistent and efficient estimates, irrespective of the order of integration (Pesaran et al., 1999). To apply PMG, the specific ARDL (p, q, r, s), as specified by Equations (3) – (6), is re-formulated in an error correction form as follows:

$$\Delta ICTt = \alpha 01 + \sum_{i=1}^{p-1} \alpha 1i \Delta ICTt - i + \sum_{i=1}^{q-1} \alpha 2i \Delta LPt - i + \sum_{i=1}^{r-1} \alpha 3i \Delta \mathrm{EMP}t - i + \sum_{i=1}^{s-1} \alpha 4i \Delta ROt - i + \lambda 1 ICTt - 1 + \lambda 2 LPt - 1 + \lambda 3 \mathrm{EMP}t - 1 + \lambda 4 ROt - 1 + \Phi ECTt\text{-}1 + \epsilon 1it \tag{9}$$

$$\Delta LPt = \alpha 02 + \sum_{i=1}^{p-1} \alpha 1i \Delta ICTt - i + \sum_{i=1}^{q-1} \alpha 2i \Delta LPt - i + \sum_{i=1}^{r-1} \alpha 3i \Delta \mathrm{EMP}t - i + \sum_{i=1}^{s-1} \alpha 4i \Delta ROt - i + \lambda 1 ICTt - 1 + \lambda 2 LPt - 1 + \lambda 3 \mathrm{EMP}t - 1 + \lambda 4 ROt - 1 + \Phi ECTt\text{-}1 + \epsilon 2it \tag{10}$$

$$\Delta EMPt = \alpha 03 + \sum_{i=1}^{p-1} \alpha 1i \Delta ICTt - i + \sum_{i=1}^{q-1} \alpha 2i \Delta LPt - i + \sum_{i=1}^{r-1} \alpha 3i \Delta \mathrm{EMP}t - i + \sum_{i=1}^{s-1} \alpha 4i \Delta ROt - i + \lambda 1 ICTt - 1 + \lambda 2 LPt - 1 + \lambda 3 \mathrm{EMP}t - 1 + \lambda 4 ROt - 1 + \Phi ECTt - 1 \tag{11}$$

$$\Delta ROt = \alpha 04 + \sum_{i=1}^{p-1} \alpha 1i \Delta ICTt - i + \sum_{i=1}^{q-1} \alpha 2i \Delta LPt - i + \sum_{i=1}^{r-1} \alpha 3i \Delta \mathrm{EMP}t - i + \sum_{i=1}^{s-1} \alpha 4i \Delta ROt - i + \lambda 1 ICTt - 1 + \lambda 2 LPt - 1 + \lambda 3 \mathrm{EMP}t - 1 + \lambda 4 ROt - 1 + \Phi ECTt\text{-}1 + \epsilon 4it \tag{12}$$

In summation, the PMG estimations, as described by Equations (9) – (12), are applied to estimate short-and long-run effects of ICT intensity on the growth of labor productivity, employment and output.

3.3.6. Panel Granger causality test

While previous techniques have examined the presence of a relationship among variables (Bounds Test) and the effects thereof (PMG), Lee et al. (2005) expressed the view that an existence of a strong association between ICT and variables of interest does not prove a causal relationship. In other words, these techniques do not test for the direction of the causal relationship among variables. Therefore, to test for the causal relationship between ICT intensity and growth of labor productivity, employment and output, a modified version of the Granger causality test, developed by Toda and Yamamoto (1995), TY hereafter, is applied. The TY Granger non-causality test is preferred over the renowned Engle and Granger (1987) test because it can be applied when variables are integrated of different orders. By so doing, the TY overcomes pre-test bias and size distortion associated with unit root and cointegration tests (Caragata & Giles, 2000, pp. 221–240; Clark & Mirza, 2006; Yamada & Toda, 1998). To apply the TY test, the specific ARDL (p, q, r, s) models, as specified by Equations (3) – (6), are modified by augmenting an additional lag order to the optimal lag (Caporale & Pittis, 1999).

3.3.7. Impulse response function (IRF) and variance decomposition (VDC) analyses

One of the drawbacks of cointegration and causality techniques is that one cannot predict the future potential causal relationship beyond the sample size (Salahuddin & Gow, 2016). To avoid this drawback, two out of the sample causality techniques, namely IRFs and VDCs, are applied to predict the potential effects of ICT intensity beyond the sample. The IRFs determine the length of time and extent to which the endogenous variable responds to a shock arising from the exogenous variables (Shahbaz et al., 2016). On the other hand, the VDCs calculate how the behavior of one variable is affected by its own shocks, relative to other variables (Lütkepohl, 2007). In brief, after determining causality, the IRFs and VDCs techniques are applied to examine the degree or magnitude of causality among variables and the extent of exogeneity among the variables, over and above the sample period (Shahbaz et al., 2016).

4. Descriptive and empirical results

4.1. Descriptive results

Table 1 provides a summary of the statistics to provide a description of the nature of the data. The statistics describe the maximum, minimum, mean and median values of the variables ICT, LP, EMP and RO. The statistics further include the standard deviation, skewness and kurtosis.

Table 1. Summary statistics of the variables.

Variable	Max	Min	Mean	Med	Std	Skew	Kur
Panel A: All industries							
ICT	51.90	0.44	10.00	7.34	10.48	2.33	13.13
LP	132.43	−27.75	3.21	1.42	15.04	4.35	35.27
EMP	29.25	−22.94	−0.79	−0.72	6.70	0.15	4.98
RO	45.51	−11.75	2.20	1.36	6.29	1.91	8.25
Panel B: More ICT-intensive industries							
ICT	51.90	4.15	15.67	10.66	12.16	1.66	4.60
LP	25.60	−27.75	1.80	1.26	8.91	8.91	3.53
EMP	17.39	−22.94	−0.52	−0.79	6.07	−0.01	4.34
RO	18.95	−11.75	1.69	1.22	5.19	0.53	4.31
Panel C: Less ICT-intensive industries							
ICT	14.32	0.44	4.34	4.15	2.82	0.92	4.23
LP	132.43	−24.28	4.59	1.41	19.18	4.03	25.28
EMP	29.25	−22.31	−1.05	−0.51	7.27	0.27	5.14
RO	45.51	−10.32	2.69	1.75	7.19	2.26	13.66

Note 1: ICT is the ICT intensity (%); LP is the labor productivity growth; EMP is employment; RO is the real output growth. Note 2: Max = Maximum; Min = Minimum; Med = Median; Std = Standard Deviation; Skew = Skewness; Kur = Kurtosis.

Table 2 presents the results from the Variance Inflation Factor (VIF) analyses. The VIF analyses were undertaken in advance of the empirical analyses to determine the extent of multicollinearity among the regressors. Overall, the results clearly illustrate that all VIF values are less than 5, which implies that there is no multicollinearity problem.[12]

Table 2. Variance inflation factors results.

Dependent variable	Independent variable			
	Panel A (All industries)			
	ICT	EMP	LP	RO
ICT	–	1.59	1.77	1.24
EMP	1.00	–	1.12	1.11
LP	1.00	1.00	–	1.00
RO	1.00	1.43	1.43	–
	Panel B (More ICT-intensive industries)			
	ICT	EMP	LP	RO
ICT	–	1.94	2.26	1.48
EMP	1.00	–	1.17	1.17
LP	1.00	1.01	–	1.01
RO	1.00	1.54	1.54	–
	Panel C (Less ICT-intensive industries)			
	ICT	EMP	LP	RO
ICT	–	1.58	2.20	1.75
EMP	2.46	–	1.43	1.5
LP	2.42	1.02	–	1.15
RO	2.49	1.39	1.48	–

Note: ICT is the ICT intensity (%); LP is the labor productivity growth rate (%); EMP is the growth rate of employment (%); RO is the real output growth rate (%).

4.1.1. ICT intensity of industries

Using an ICT intensity index, defined as the industries' direct requirements for ICT intermediate inputs, we distinguish industries into two categories (i.e. more ICT-intensive industries and less ICT-intensive industries). Akin to previous studies, we use the median value of the index as the point of reference for ranking industries into the two categories (Chen et al., 2016; Engelbrecht & Xayavong, 2006; Stiroh, 2002). The ICT intensity index (I_j) results indicate that the median value is 7.37%. Within this vein, industries with an ICT intensity index of greater than the median of 7.37% are ranked as more ICT-intensive, and vice versa for the less ICT-intensive industries. Table 3 shows the ICT intensities of the industries.

Table 3. ICT intensity of industries.

Industry	ICT intensity index (%)
Food	37.20
Beverages	11.02
Tobacco	0.84
Textile	8.12
Wearing Apparel	6.62
Leather	3.96
Wood	5.86
Paper	11.16
Rubber	10.08
Furniture	5.12
Total	**100**
More ICT-intensive industries	**78**
Less ICT-intensive industries	**22**
Total	**100**

Source: Authors' calculations.

The findings indicate that the Food, Beverages, Textile, Paper and Rubber industries are ranked as more ICT intensive. Inversely, the less ICT-intensive industries are Tobacco (0.84%), Wearing Apparel (6.62%), Leather (3.96%), Wood (5.86%) and Furniture (5.12%). Thus, five industries are more ICT intensive, while the remaining five are less ICT intensive. The results further show that the more ICT-intensive industries account for 78% of the share of the direct requirements for ICT intermediate inputs, while the less ICT-intensive industries account for the remaining 22%. Overall, these results provide an information base on the ICT intensity of the comprehensive agro-processing industries, which can be used to evaluate the effects of ICT on the growth of labor productivity, employment and output.

4.1.2. Annual growth rates

After calculating the ICT intensity of the industries, we calculated the weighted annual average growth rate of employment, labor productivity and output for the industries of interest over the period 1994–2017. The detailed results are presented in Table 4.

Table 4. Weighted annual average growth rate, 1994–2017.

Industry	Employment (%)	Labor productivity (%)	Output (%)
More ICT intensive	−3.6	7.0	7.7
Less ICT intensive	−6.7	16.5	13.1

Source: Authors' calculations.

The weighted annual growth rate results indicate that the less ICT-intensive industries are surpassing their counterparts with respect to the growth of both labor productivity and output. In terms of employment, both groups of industries experienced a decline in growth. However, the more ICT-intensive group experienced the least decline in employment growth.

4.2. Empirical results

This section provides the empirical results derived from the determination of the optimal lag, unit root testing, cointegration testing, PMG estimation, TY Granger Non-Causality testing and IRF and VDC analyses. The reporting of the results covers Panel A (i.e. All industries), Panel B (i.e. More ICT-intensive industries), and Panel C (i.e. Less ICT-intensive industries).

4.2.1. Optimal lag results

The findings from the determination of the optimal lags show that, in all cases, the optimal lags are either 1 or 2, which is in conformity with the recommendations by Pesaran and Shin (1999) for annual data. The detailed results are presented in Table 5.

Table 5. Optimal lag results.

Variable	Optimal lag
Panel A (All industries)	
ICT	2
EMP	1
LP	2
RO	2
Panel B (More ICT-intensive industries)	
ICT	2
EMP	2
LP	1
RO	1
Panel C (Less ICT-intensive industries)	
ICT	1
EMP	1
LP	1
RO	2

Note: ICT = ICT intensity (%); LP = labor productivity growth rate (%); EMP = growth rate of employment (%); RO = real output growth rate (%).

4.2.2. Diagnostic test results

The diagnostic tests for normality, functional form, heteroskedasticity and serial correlation have been performed to test for the robustness of the ARDL model. Table 6 presents the diagnostic test results.

Table 6. Diagnostic test results.

Variables	Diagnostic test			
	J-B test	Ramsey RESET	ARCH test	LM test
Panel A (All industries)				
ICT	493.28 (0.000)***	0.00(0.953)	1.77(0.197)	1.10(0.306)
EMP	0.53(0.521)	1.31 (0.997)	1.08(0.309)	0.13(0.84)
LP	0.47(0.640)	1.16 (0.106)	5.16(0.036)	1.49(0.365)
RO	1.22(0.682)	0.00 (0.958)	0.83(0.371)	0.03(0.878)
Panel B (More ICT-intensive industries)				
ICT	68.32 (0.000)***	0.06 (0.923)	0.11 (0.754)	0.13 (0.876)
EMP	0.57(0.751)	0.46 (0.495)	0.03 (0.956)	2.01 (0.183)
LP	0.34 (0.432)	0.04 (0.172)	0.74(0.841)	0.05 (0.702)
RO	1.63 (0.277)	0.07 (0.923)	0.34 (0.911)	0.44 (0.822)
Panel C (Less ICT-intensive industries)				
ICT	22.27 (0.000)***	40.00 (0.000)***	13.58 (0.000)***	0.24(0.623)
EMP	2.41 (0.956)	1.75 (0.357)	0.32(0.570)	0.24(0.623)
LP	1.89 (0.140)	1.20(0.274)	0.34(0.557)	0.34(0.557)
RO	2.02 (0.157)	1.43(0.109)	1.54 (0.216)	1.99(0.141)

Note 1: ICT is the ICT intensity (%); LP is the labor productivity growth rate (%); EMP is growth rate of employment (%); RO is the real output growth rate (%). *Note 2*: J-B = Jarque-Bera; RESET = Ramsey Regression Specification Error Test; ARCH = Autoregressive Conditional Heteroskedastic; LM = Lagrange multiplier. *Note 3*: Figures in parenthesis are the *P*-values. *Note 4*: ** significant at 5% level; *** significant at 1% level.

Overall, the results clearly demonstrate that, when EMP, LP and RO are endogenous and the error terms are normally distributed, the model is correctly specified, and that there is no autoregressive conditional heteroskedasticity and serial correlation. At the same time, there is evidence of non-normality of error terms for all the Panels when ICT is endogenous, and of misspecification errors and heteroskedasticity for Panel C industries when ICT is endogenous. To remedy the identified problems, the empirical analyses were conducted by setting EMP, LP and RO as endogenous to avoid the non-normality, misspecification and heteroskedasticity problems evident when ICT is endogenous.[13]

4.2.3. Unit root test results

The results of the IPS unit root test are presented in Table 7.

Table 7. Panel unit root test results.

Variable	IPS-statistic	*P*-values	Order of integration
Panel A: All industries			
ICT	−2.41152***	0.0079	I(0)
LP	−5.76321***	0.0000	I(0)
EMP	−5.55652***	0.0000	I(0)
RO	−6.54138***	0.0000	I(0)
Panel B: More ICT-intensive industries			
ICT	−0.60147	0.2738	I(1)
ΔICT	−5.115***	0.0000	
LP	−3.51433***	0.0002	I(0)
EMP	−3.78996***	0.0001	I(0)
RO	−3.78873***	0.0001	I(0)
Panel C: Less ICT-intensive industries			
ICT	−2.94489	0.0016	I(0)
LP	−7.04130	0.0000	I(0)
EMP	−6.86551	0.0000	I(0)
RO	−8.91867	0.0000	I(0)

Note: IPS-statistic = Im, Pesaran and Shin W-stat; *** indicates significance at 1% level; the test equation is the intercept.

The findings illustrate that all the variables in Panels A and C are stationary in their level forms, and therefore require no differencing. In the same way, for Panel B, the variables EMP, LP and RO require no differencing as they are stationary in their level forms (i.e. integrated of order I (0)). At the same time, the variable ICT became stationary after first differencing, which implies that it is integrated of order I (1). Overall, the IPS test results show that variables in Panels A and C are integrated of order I (0), while those in Panel B are integrated of different orders (i.e. a combination of orders I (1) and I (0)). Therefore, the findings generated in this article can be applied in other periods, which validates the forecasting of the future potential effects of ICT intensity.

4.2.4. Panel cointegration test results

The unit root test results proved that the variables are integrated of different orders, which justifies the use of the Bounds Cointegration Test, which is applicable regardless of whether variables are I (1) or I (0). This section, therefore, reports on the empirical results of the Bounds Test which is applied to prove if a long-run relationship exists among variables. The Bounds Test results are presented in Table 8.

Table 8. Bound test cointegration results.

Dependent variable	AIC lags	Computed F-statistic	Is there cointegration?	ARDL or ECM?
Panel A: All industries				
EMP	1	4.95	Yes	ECM
LP	2	5.73	Yes	ECM
RO	2	8.75	Yes	ECM
Panel B: More ICT-intensive industries				
EMP	2	18.90	Yes	ECM
LP	1	15.70	Yes	ECM
RO	1	10.07	Yes	ECM
Panel C: Less ICT-intensive industries				
EMP	1	32.86	Yes	ECM
LP	1	38.25	Yes	ECM
RO	2	30.79	Yes	ECM
Critical values		I(0)	I(1)	
10%		2.37	3.2	
5%		2.79	3.67	
1%		3.65	4.66	

Note 1: ICT is the ICT intensity (%); LP is the labor productivity growth rate (%); EMP is the growth rate of employment (%); RO is the real output growth rate (%). *Note 2*: The critical values are available from Pesaran et al. (1999).

The general finding is that, for all the Panels, the null hypothesis of no cointegration is rejected when the variables EMP, LP and RO are specified as endogenous. This is so on the grounds that the F-statistic values are higher than all the critical values for both the I (0) and I (1). The findings, therefore, validate the existence of a long-run relationship amongst the variables. This implies that the variables are related and can be modeled in a linear fashion. In other terms, even if there are shocks in the short run, which may affect movement in the individual variables, they would converge with time (in the long run).

4.2.5. PMG results

The Bounds Test results show whether cointegration exists among variables. However, the Test (as is the case with other Cointegration Tests) is only limited to the nature of cointegration (i.e. whether cointegration exists or not). The Test, therefore, does not provide evidence of short-run or long-run causal effects among variables. To address this delimitation, we estimated both the short-run and long-run effects. Since this study focuses on assessing ICT-led growth, the discussion is limited to the effects of ICT intensity on the growth of employment, labor productivity and output. The results from the PMG estimates are presented in Table 9.

- Effects on employment

The PMG findings show that ICT intensity has no significant effect on the employment growth of Panel A (i.e. aggregated industries) in both the short run and the long run. These findings are in conformity with aggregate-level studies that found zero significant effects of ICT when industries were aggregated (Edquist & Henrekson, 2017; Jorgenson & Stiroh, 1995, 1999; Jorgenson & Stiroh, 1995, 1999; Mačiulytė-Šniukienėa & Gaile-Sarkane, 2014; Oliner & Sichel, 1994; Oliner & Sichel, 1994). In spite of the effect being insignificant, it is positive, which dispels the pessimistic views regarding the effects of ICT on employment. With reference to disaggregated industries, positive and significant effects are notable only in the short run for both the more and less ICT-intensive industry groups (i.e. Panels B and C). However, while it is noted that, in the short run, the effect is higher for the less ICT-intensive industries, in the long run, it is positive for the more ICT-intensive group, but negative for the less ICT-intensive industries.

Table 9. Short-run and long-run effects results.

Dependent variable	Short-run effect ICT	EMP	LP	RO	Long-run effects ICT	EMP	LP	RO	ECT_{-1}
Panel A: All industries									
ICT	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
EMP	0.00	–	−0.00	0.00	0.81 (0.690)	–	−0.83***	1.01***	−0.62***
	(0.789)		(0.435)	(0.340)			(0.000)	(0.000)	(0.000)
LP	−0.03 ***	−0.42	–	0.16	−1.13***	1.40	–	1.20 ***	−0.48***
	(0.000)	(0.132)		(0.368)	(0.000)	(0.546)		(0.000)	(0.000)
RO	−0.14**	−0.09	−0.03	–	0.71***	−0.26	0.62***	–	−0.37***
	(0.032)	(0.368)	(0.259)		(0.000)	(0.874)	(0.000)		(0.000)
Panel B: More ICT-intensive industries									
ICT	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
EMP	0.25*	–	−0.01	−0.12	0.41 (0.290)	–	−0.62***	0.52***	−0.38***
	(0.072)		(0.822)	(0.375)			(0.000)	(0.000)	(0.000)
LP	−0.07	−0.00	–	−0.47***	0.48* (0.06)	−0.94	–	0.78**	−0.87***
	(0.725)	(0.994)		(0.005)		(0.334)		(0.014)	(0.000)
RO	0.09	0.15	0.14 **	–	0.39** (0.028)	−0.005	0.19***	–	−0.75***
	(0.407)	(0.156)	(0.03)			(0.874)	(0.000)		(0.000)
Panel C: Less ICT-intensive industries									
ICT	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
EMP	0.58*	–	−0.05	0.14	−0.181 (0.359)	–	−0.28***	0.31***	−0.98***
	(0.07)		(0.265)	(0.178)			(0.000)	(0.001)	(0.000)
LP	−0.02	−0.42	–	−0.493**	−1.52***	−0.49	–	0.74**	−0.97***
	(0.915)	(0.558)		(0.038)	(0.000)	(0.334)		(0.025)	(0.000)
RO	−0.22***	−0.27	−0.05	–	0.27*** (0.002)	−0.002	0.13***	–	−0.89***
	(0.007)	(0.263)	(0.150)			(0.88)	(0.002)		(0.000)

Note 1: ICT = ICT intensity (%); LP = labor productivity growth rate (%); EMP = growth rate of employment (%); RO = real output growth rate (%). Note 2: Figures in parenthesis are the *P*-values. Note 3: ***, **, * significant 1%, 5% and 10%, respectively.

- Effects on labor productivity

The PMG findings further show that ICT intensity yields a negative and significant effect on the labor productivity of the aggregated industries in both the short run and the long run. Again, these findings are in accordance with early aggregate-level studies that found negative and significant effects of ICT when industries were aggregated. In terms of the disaggregated industries, the findings show that, in the short run, ICT intensity yields negative but insignificant effects on both groups of industries. However, in the long run, it exhibits a positive and significant effect on labor productivity growth of the more ICT-intensive group, but a negative and significant effect for the less ICT-intensive group. The findings specifically illustrate that, in the long run, a 1 percentage point increase in ICT intensity would increase labor productivity growth of the more ICT-intensive group by a 0.48 percentage point. Contrarily, an increase in ICT intensity would decrease labor productivity growth of the less ICT-intensive group by a 1.52 percentage point.

- Effects on output growth

The PMG findings exhibit the fact that ICT intensity has no significant effect on the output growth of the aggregated industries in both the short run and the long run. Nonetheless, while, in the long run, ICT intensity yields positive and significant effects on output growth of both the less and more ICT-intensive groups, its effect is higher for the more ICT-intensive group.[14] To be exact, a 1 percentage point increase in ICT intensity would increase the output growth of the more ICT-intensive industries by a 0.39 percentage point, and that of the less ICT-intensive industries by a 0.27 percentage point. These findings are in line with those of previous studies which found that industries that invest more in ICT have higher growth rates than those that invest the least have (Kuppusamy et al., 2009; Moshiri, 2016; Vu, 2013).

4.2.6. Granger causality test results

While the PMG regression captured the effects of ICT intensity, it is said that the existence of a relationship between variables does not prove causality. Hence, the TY Non-Granger Causality Test is applied to test for the existence of causality and the direction of the causal relationship among variables. The multivariate Granger causality results are presented in Table 10.

Table 10. Multivariate TY Non-Granger Causality Test results.

Dependant Variable	Independent variables			
Panel A (All industries)				
	ICT	LP	EMP	RO
ICT	–	n/a	n/a	n/a
LP	2.104 (0.349)	–	0.422 (0.809)	16.49*** (0.000)
EMP	1.877 (0.391)	0.959 (0.6190)	–	1.145 (0.564)
RO	2.103 (0.349)	4.898* (0.086)	7.315** (0.025)	–
Panel B (More ICT-intensive industries)				
	ICT	LP	EMP	RO
ICT	–	n/a	n/a	n/a
LP	0.815 (0.665)	–	0.516 (0.772)	5.974* (0.050)
EMP	3.204* (0.073)	1.174 (0.555)	–	2.029 (0.362)
RO	2.922 (0.232)	2.879 (0.237)	2.055 (0.357)	–
Panel C (Less ICT-intensive industries)				
	ICT	LP	EMP	RO
ICT		n/a	n/a	n/a
LP	1.228 (0.267)	–	0.483 (0.486)	6.396** (0.011)
EMP	3.544 (0.169)	1.895 (0.168)	–	2.094 (0.147)
RO	0.272 (0.601)	0.113 (0.736)	0.019 (0.888)	–

Note 1: ICT = ICT intensity (%); LP = labor productivity growth rate (%); EMP = growth rate of employment (%); RO = real output growth rate (%). Note 2: Figures in parenthesis are the *p*-values. Note 3: ***, **, * significant 1%, 5% and 10%, respectively.

The TY Granger Causality Test findings signify that there is no causal relationship between ICT intensity and growth in labor productivity, employment and output of the aggregated industries. These results are in conformity with the general findings that the causal effects of ICT are undetectable when industries are aggregated. In the same vein, the Test found no evidence of a causal relationship for the less ICT-intensive group. On the other hand, evidence of a causal relationship is only observable between ICT intensity and employment growth for the more ICT-intensive group. These results are in conformity with the general findings that causal effects of ICT are detectable for industries that use ICT more, as compared with those that use ICT less.

4.2.7. IRF results

Figures 1, 2 and 3 depict the IRFs for Panels A, B and C, respectively.

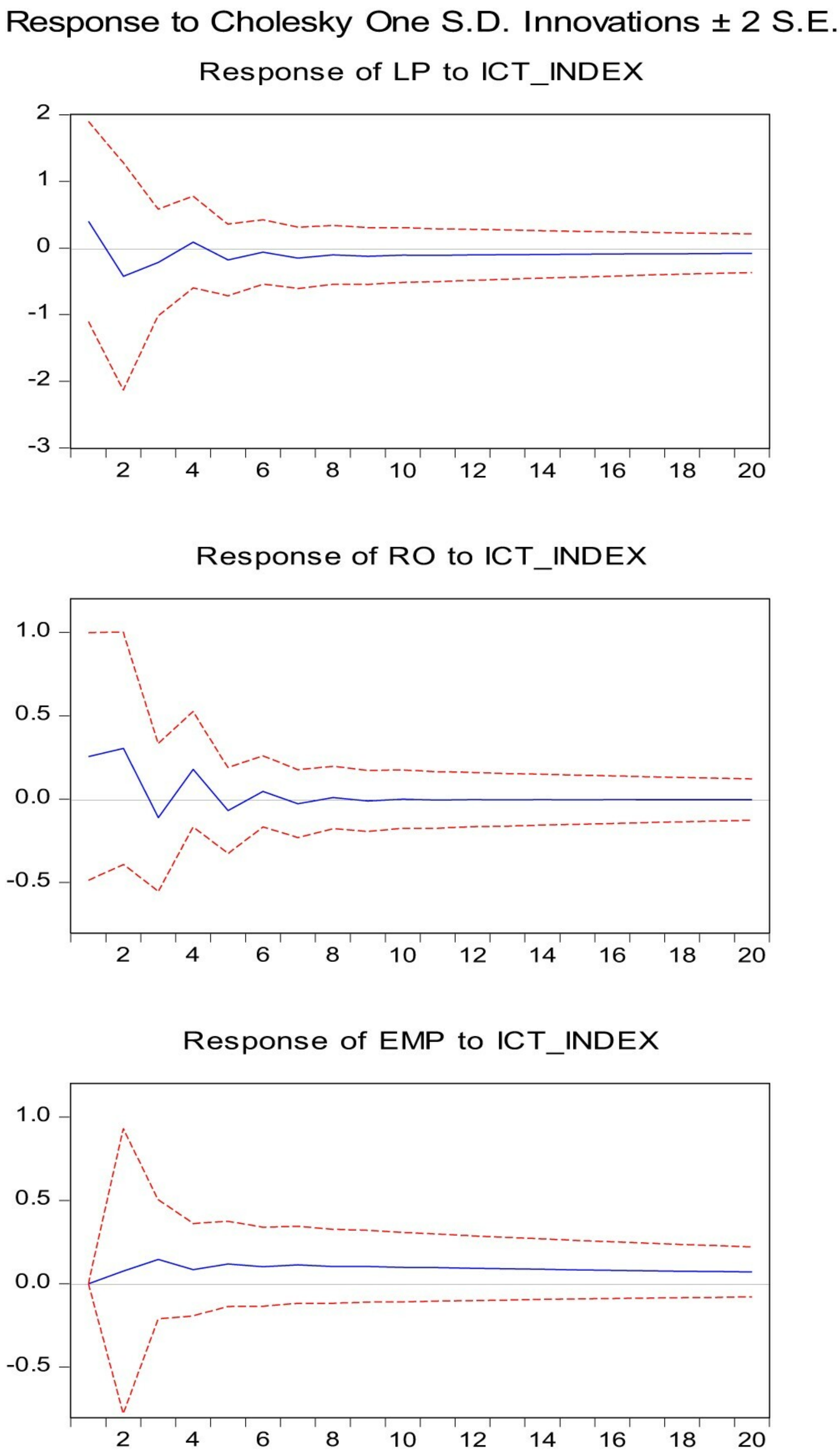

Figure 1. IRFs for Panels A.

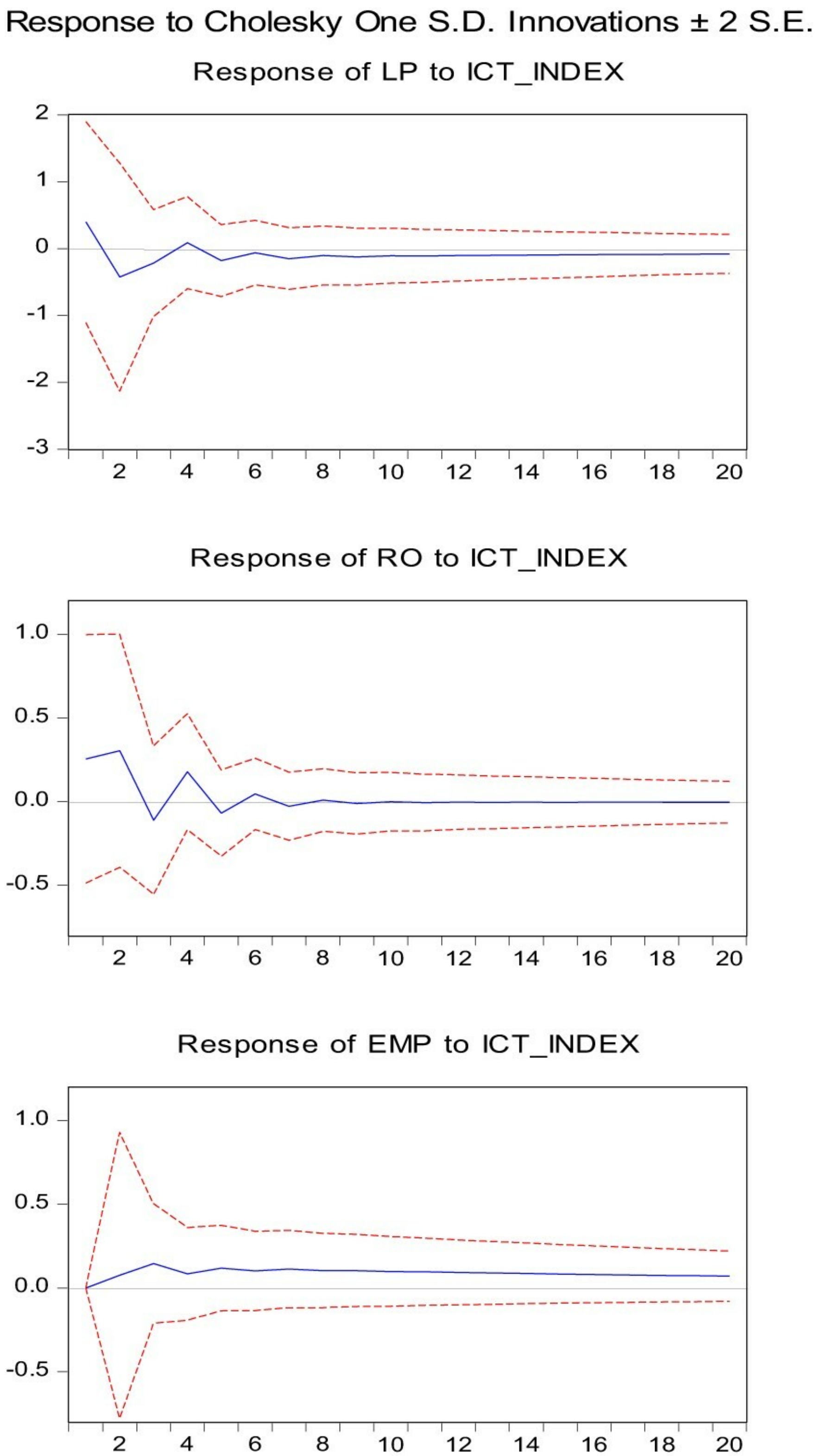

Figure 2. IRF for Panels B.

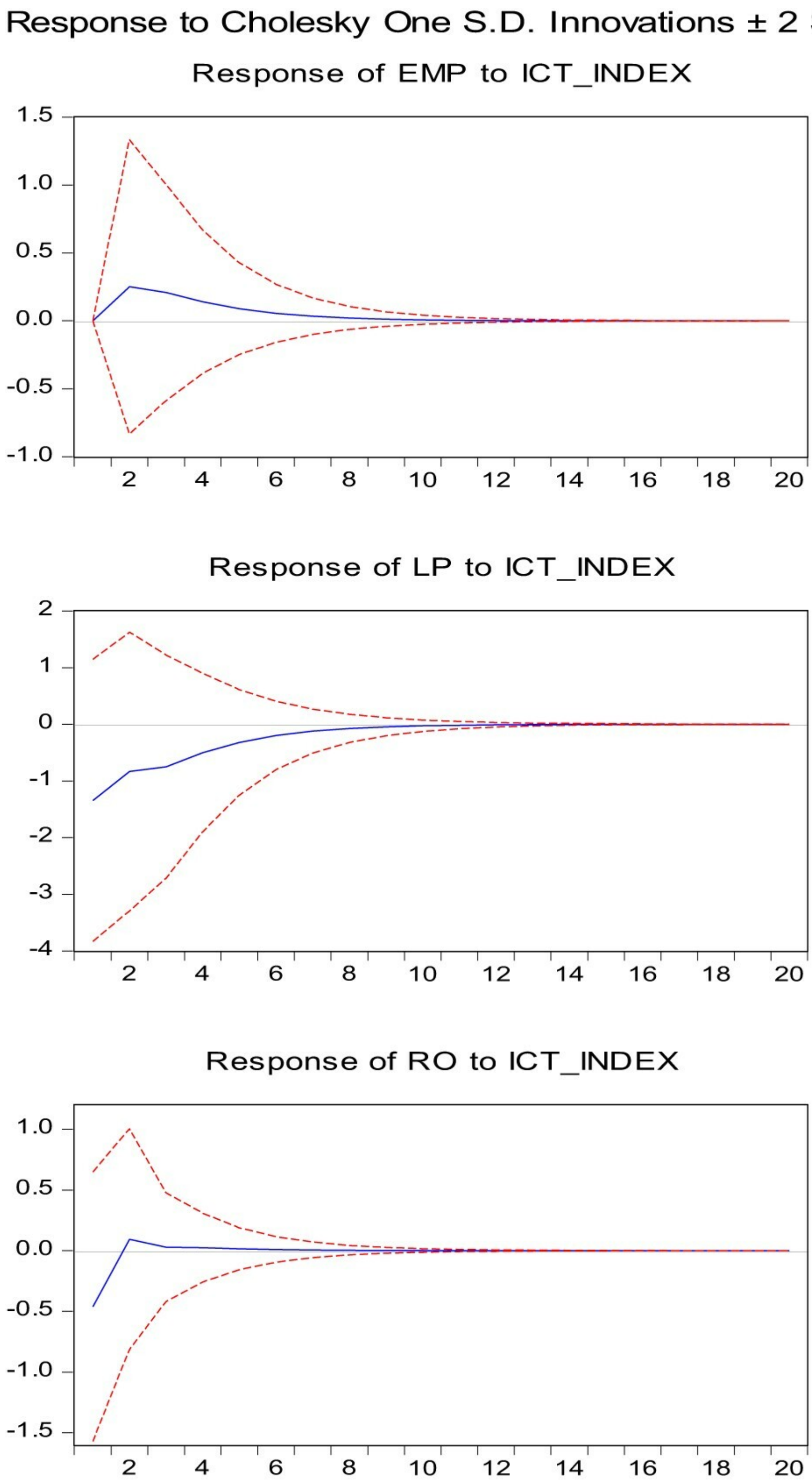

Figure 3. IRFs for Panels C.

The forecast period is segregated into two: short-run and long-run periods. In all cases, periods 1–5 are considered to comprise the short-run period, while periods 6 up to the 20th forecast period are regarded as comprising the long-run period. Table 11 provides a summary of the responses of the endogenous variables to shock in ICT intensity.

Table 11. Summary of the IRF of endogenous variables (Panel of industries).

Endogenous variables	Period 1–5 (Short-run)	>5–20 (Long-run)
Panel A (All industries)		
EMP	Positive	Positive
LP	Positive & Negative	Negative
RO	Positive & Negative	Positive
Panel B (More ICT intensive)		
EMP	Negative & positive	Positive
LP	Positive & negative	Positive
RO	Positive & negative	Positive
Panel C (Less ICT intensive)		
EMP	Positive	Positive
LP	Negative	Positive
RO	Negative & positive	Positive

Note: EMP = Employment growth rate (%); LP = Labour productivity growth rate (%); RO = real output growth rate (%).

From Table 11, 'Negative' implies that the response is negative throughout the period under consideration, and the contrary for 'Positive.' 'Negative and Positive' implies that the response of the endogenous variables to the shock in ICT intensity starts with a negative, followed by a positive, effect, and vice versa for 'Positive and Negative.' Overall, in the short run, four varying outcomes are observable. In particular, the various responses of the endogenous variables to shock in ICT intensity are as follows:

- Negative throughout the short-run period;
- Positive throughout the short-run period;
- Start with a negative followed by a positive effect; and
- Start with a positive followed by a negative effect.

The IRF findings exhibit that, in the short run, mixed effects ('Positive and Negative' and 'Negative and Positive') are detectable with respect to the response to shocks in ICT intensity. This is with the exception of Panels A and C, wherein positive effects with respect to employment growth are observable.

In the long run, regardless of which Panel, a one S.D shock in ICT intensity yields a positive effect on the growth of employment, labor productivity and output. This is apart from Panel A, which displays a negative effect of ICT intensity on labor productivity growth in the long run. In summation, in the long run, a one S.D shock in ICT intensity yields a positive effect on the growth of employment, labor productivity and output of both the more and less IC-intensive industry groups. These findings give an indication of how long it would take for ICT to yield a positive and significant effect on the growth of the agro-processing industries. More specifically, the results suggest that growth gains from ICT investment are notable over a long period.

4.2.8. VDC results

Although the IRF captures the length of time and the extent to which the endogenous variable responds to a shock resulting from the exogenous variables, it does not capture the magnitude of such effects (Salahuddin & Gow, 2016). Given this, the VDC analyses were undertaken to capture this magnitude. Over and above this, and given the multivariate setting under which the analysis was conducted, the VDC results allow us to unlock the influence of one variable on others. Table 12 demonstrates the VDC results.

Table 12. VDC results.

		ICT	EMP	LP	RO
Dependent variable: EMP					
Independent variables		ICT	EMP	LP	RO
Panel A	**1**	0.587730	99.41227	0.000000	0.000000
	5	0.669157	98.44007	0.440115	0.450654
	10	0.780586	98.32705	0.441747	0.450614
	15	0.864186	98.24353	0.442047	0.450235
	20	0.923376	98.18441	0.442250	0.449964
Panel B	**1**	0.979831	99.02017	0.000000	0.000000
	5	2.252189	93.91185	1.964057	1.871900
	10	2.555161	93.60804	1.959739	1.877064
	15	2.804365	93.36540	1.955799	1.874436
	20	2.978350	93.19613	1.953132	1.872387
Panel C	**1**	0.591109	99.40889	0.000000	0.000000
	5	0.728351	97.88947	0.566642	0.815538
	10	0.736782	97.87937	0.566981	0.816862
	15	0.736841	97.87931	0.566982	0.816869
	20	0.736841	97.87931	0.566982	0.816869
Dependent variable: LP					
Independent variables		ICT	EMP	LP	RO
Panel A	**1**	0.505490	28.34879	71.14572	0.000000
	5	0.510534	28.95456	64.78593	5.748968
	10	0.541516	28.94681	64.75773	5.753945
	15	0.567504	28.93920	64.74084	5.752451
	20	0.585832	28.93385	64.72894	5.751380
Panel B	**1**	3.835279	35.91509	60.24963	0.000000
	5	3.801509	33.61287	54.91920	7.666417
	10	3.909849	33.58048	54.84995	7.659724
	15	3.916523	33.57809	54.84608	7.659307
	20	3.921344	33.57639	54.84331	7.658956
Panel C	**1**	0.191810	27.57473	72.23346	0.000000
	5	0.552316	29.51432	66.17372	3.759640
	10	0.573108	29.50903	66.15576	3.762100
	15	0.573253	29.50899	66.15564	3.762111
	20	0.573254	29.50899	66.15564	3.762111
Dependent variable: RO					
Independent variables		ICT	EMP	LP	RO
Panel A	**1**	0.151119	0.947468	17.55970	81.34172
	5	0.552275	1.722754	16.59683	81.12814
	10	0.561038	1.724715	16.58973	81.12451
	15	0.561302	1.724716	16.58968	81.12430
	20	0.561460	1.724714	16.58965	81.12417
Panel B	**1**	1.188316	2.573352	28.25050	67.98783
	5	3.625216	3.903210	25.21064	67.26093
	10	3.729780	3.901393	25.18517	67.18366
	15	3.741574	3.900951	25.18210	67.17538
	20	3.750099	3.900601	25.17988	67.16942
Panel C	**1**	0.641616	0.298609	18.42137	80.63840
	5	0.656849	0.343231	18.91751	80.08241
	10	0.657214	0.343291	18.91744	80.08206
	15	0.657216	0.343291	18.91744	80.08206
	20	0.657217	0.343291	18.91744	80.08206

The VDC findings proved that, overall, ICT intensity contributed the more to the forecast error variance in growth rates of employment, labor productivity and output of the more ICT-intensive industries, as opposed to both the aggregated and less ICT-intensive industry groups. This does not negate the fact that each endogenous variable contributed the most to the forecast error variance in the growth of itself. Furthermore, employment contributed more than ICT intensity did to the forecast error variance in labor productivity growth. Further to this, labor productivity contributed more to output growth than ICT intensity did. The only case in which ICT contributed the most to forecast error variance is with respect to the employment growth of the more ICT-intensive industries. These findings, therefore, suggest that ICT intensity is a stronger predictor of employment growth of the more ICT-intensive industries.

5. Conclusion

This article has examined the extent to which investment in ICT contributes to the growth in labor productivity, employment and output of South Africa's agro-processing subsector. To achieve this, the ICT intensity index was applied to rank 10 agro-processing industries into two groups of industries, comprising the more ICT-intensive industries and the less ICT-intensive industries. The rationale for ranking the industries into two groups is that empirical studies have proved that industries that had invested more in ICT (i.e. more ICT-intensive industries) experienced higher growth rates than those that had invested less (i.e. less ICT-intensive industries). The results from the ICT intensity index proved that five agro-processing industries were more ICT intensive (i.e. Food, Beverages, Paper, Rubber and Textile), while the remaining five were less ICT intensive (i.e. Tobacco, Leather, Wearing Apparel, Wood and Furniture). The results serve as an information base on the ICT intensity of the comprehensive agro-processing industries.

After ranking the industries into the two industry subgroups, their respective annual growth rates of labor productivity, output and employment were calculated. Ultimately, PMG estimations were conducted to estimate the short- and long-run effects of ICT intensity on growth of labor productivity, employment and output (Objective 1). The TY tests were conducted to examine the causal relationship between ICT intensity and the growth of labor productivity, employment and output (Objective 2). The VDC and IRF analyses were conducted to forecast the potential effects of ICT intensity on growth of labor productivity, employment and output (Objective 3). The PMG findings showed that the effects of ICT intensity on growth were higher for the more ICT-intensive industry group. The findings, therefore, prove that higher ICT-led growth would arise in those agro-processing industries that are investing more highly in ICT. The TY tests detected evidence of a causal relationship between ICT intensity and the employment growth of the more ICT-intensive industries. This implies that ICT investment 'causes' employment growth in the agro-processing industries that invested more in ICT.

The IRF findings proved that, in the long run, ICT intensity would impact positively on the growth of labor productivity, output and employment of both the industry groups. This finding varies from the TY Test in which there was no causal relationship between ICT intensity and growth for the less ICT-intensive industry group. Therefore, the fact that positive effects for the less ICT-intensive industries were only detected in the long run implies that the returns to ICT investment for the less ICT-intensive industries would be notable over a long period.

However, VDC results, which show the magnitude of the impact, indicated that while ICT intensity would contribute to the growth of both the industry groups, its contribution would be higher for the more ICT-intensive industry group. The implication is that higher ICT-led growth would be realized by the agro-processing industries that invest more in ICT.

The overall findings of this article suggest that an increase in ICT investment would enhance the growth performance (i.e. labor productivity, output and employment) of the agro-processing subsector. Therefore, there is a need for the implementation of policy interventions aimed at increasing the level of ICT investment of agro-processing industries. This would enhance the growth performance of the agro-processing subsector and, ultimately, drive South Africa's growth.

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Notes

1 ICT is defined, in this article, as any technology used to process, communicate, transmit and display information through electronic means (Organisation for Economic Cooperation and Development [OECD], 2011; Statistics South Africa [Stats SA], 2015).

2 The term 'productivity paradox' was devised by Solow (1987) to clarify the limited or zero evidence on the contribution of ICT to productivity growth in the US in the 1970s and 1980s.

3 ICT investment is defined, in this article, as expenditure by the industry on ICT products, services and activities. Agro-processing is defined, in this article, as a subset of the manufacturing sector that processes raw materials and intermediate products derived from the agricultural sector (Food and Agricultural Organization [FAO], 1997).

4 The policy plans include the New Growth Path, the National Development Plan, the Nine-Point Plan and the Agricultural Policy Action Plan.

5 The report further positions South Africa as one of the top three developing countries, along with Chile and China, with the potential to boost their economic growth through investment in ICT.

6 The telecommunication measures include fixed lines and total telephone connections.

7 This is attributed to the low use of ICT by the agricultural industries. Moreover, most of the agricultural industries, albeit not all, are resource-based industries whose production activities are generally labor-intensive rather than information-intensive (Shyam, 2011).

8 The ICT intensity is used as a proxy for ICT investment.

9 We adapted the ICT intensity index by Engelbrecht and Xayavong (2006) in that our index considers only the ICT intermediate inputs, while that of Engelbrecht and Xayavong includes all the total inputs (i.e. both the ICT and non-ICT inputs). The ICT Intensity index is relative to industries embedded in the analysis. Therefore, it is acknowledged that some industries may be less or more ICT-intensive if other industries were to be included. Also, the Index is based on the period 1994 to 2017. Therefore, the index values for industries might change with changes in the time period.

10 The ICT intermediate inputs covered are Printing, Telecommunication, Radio, TV, Postal & Courier and Computer and Related Activities.

11 The choice of the time period is based on data availability. We acknowledge that the time period is very short for conducting the analysis; hence, conducting the analysis using panel data allows us to have more degrees of freedom, than using either time-series or cross-sectional data would.

12 The VIF values of less than 5 indicate that there is no collinearity, while those of more than 5 signify the presence of collinearity.

13 Since the study focuses on estimating effects of ICT intensity, by setting EMP, LP and RO as endogenous, the study is able to capture effects on the growth of employment, labor productivity and output, as ICT remains exogenous in all cases.

14 It should also be noted that while, in the long run, ICT intensity yields positive and significant effects on the output growths of both the less and more ICT-intensive groups, in the short-run, it yields no significant effect on the output of the more ICT-intensive group, and a negative and significant effect for the less ICT-intensive group.

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