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## **Exploring the nexus between ICT intensity, productivity, employment and output in South Africa: An industry-level analysis**

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### **Abstract**

This paper aims to estimate the effects of ICT intensity on labour 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 of industries. After calculating the ICT intensity of industries, we calculate the annual growth rates of labour productivity, employment and output. Ultimately, we examine the effects of ICT intensity on growth of labour productivity, employment and output using the Pooled Mean Group (PMG) estimations and the Toda and Yamamoto (TY) Granger Non-Causality Tests. The PMG findings suggest that ICT intensity yields higher positive significant effects on output growth of the more ICT intensive industries. The TY tests detected evidence of a causal relationship between ICT intensity and employment growth of the more ICT intensive industries. These findings are in conformity with the general findings that the causal effects of ICT are detectable for industries that use ICT most intensively.

Keywords: ICT intensity, productivity, employment, output

## 1. INTRODUCTION

South Africa is faced with severe economic challenges, the key of which are declining total factor productivity, sluggish growth and one of the highest jobless rates globally. Yet, investment in information and communication technology (ICT) has been proven to boost productivity and resuscitate growth in other countries. Specifically, the resurgence in productivity performance and growth in the US and other OECD countries in the 1990s has been attributed to both the expansion in the production of ICT and use by other economic sectors (Stiroh, 2002; Strauss and Samkharadze, 2011; Bloom, Sadun, and Van Reenen, 2012). It is on this premise that the World Bank holds an optimistic view that ICTs have great promise to create jobs, reduce poverty and inequalities, enhance productivity and boost the economic growth of developing countries (World Bank, 2012; World Bank, 2017).

Despite the above optimistic view, empirical findings have been less supportive tending to unravel negative or even zero significant effects of ICT for developing countries but positive effects for the developed countries. The negative or insignificant findings for the developing countries are attributable to numerous factors which are namely, the late adoption of ICT, low levels of ICT investment, limited complementary factors such as human capacity and skills, and lack high-quality data and the quality of the analytical approaches used (Wu and Liang, 2017; Niebel, 2018).

Empirically, ICT is modelled as a general-purpose technology, that is, technology with the potential to alter an entire industry, sector, or economy (Landes, 1976; Rosenberg, 1982). Consequently, various studies have evaluated the effects of ICT at both the aggregate and industrial levels. Overall, early aggregate studies found either negative or no significant effects of ICT investment on countries' growth (Oliner and Sichel, 1996; Jorgenson and Stiroh, 1995, 1999). By contrast, industry-level studies found positive significant results for those industries that are either producing or using ICT most intensively (Abri and Mahmoudzadeh, 2015; Moshiri, 2016; Corrado, Haskel and Jona-Lasinio, 2017).

The aggregate-level findings are attributable to three main reasons. First, ICT accounted for the small share of investment as a proportion of the total capital stock such that it had small effects on aggregate output (Sichel, 1997; Stiroh, 2002). Second, the use of econometric models which does not account for variations in ICT intensity among industries (Stiroh, 2002). In other words, aggregation of the industries that use ICT most intensively (i.e. more ICT intensive) with those that use ICT the least (i.e. less ICT intensive) in the analysis. As per Stiroh (2002a), 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 hence ICT-led growth varies immensely across industries. Third, analysing the causal relationship between ICT investment and measures of growth such as GDP and productivity in a bivariate setting, neglecting other factors affecting aggregate GDP and productivity (Lee, Gholami and Tong, 2005; Yousefi, 2011; Chakraborty and Nandi, 2011; Masood, 2012; Hong, 2017). The consequence of analyzing 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).

While, in general, studies found the positive significant effects of ICT when industries are disaggregated, there are no empirical findings on the contribution of ICT investment at the industry level on the performance of South Africa's economy. This study, therefore, attempts to examine the extent to which ICT investment contributes to the growth of labour productivity, employment and output of the agro-processing subsector. 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, spur economic growth and development given its strong backward and forward linkages with other economic sectors.<sup>1</sup> From this perspective, this study contributes to literature by examining the extent to which ICT investment in the sector contributed to productivity, GDP and employment. The findings will inform policymakers on how ICT investment in the agro-processing industries could contribute towards driving the desired growth and development.

Technically, focusing on the agro-processing subsector provides an explanation of the network effects of ICT (i.e. productivity effects from the use of ICT in the non-ICT sectors) (Stiroh, 2002; van Ark, 2014)). Following Szewczyk (2009), it is assumed that developments in ICT at the national level will spill over to the industries, depending on their levels of ICT investment (expenditure) such that industries investing highly in ICT benefit the most. In other words, an industry's share of ICT investment is used to measure its ability to utilise advancement in ICT at the national level. It is further assumed that higher ICT-led growth would arise in those industries that are investing more highly in ICT. This assumption is supported by empirical findings which validated that industries that invest more in ICT have higher growth rates than those that invest the least (Kuppusamy, Raman and Lee, 2009; Vu, 2013; Moshiri, 2016).

Against the above backdrop, to avoid problems associated with aggregate studies, agro-processing industries are ranked according to their ICT intensity (i.e. more ICT-intensive and less ICT intensive) using the ICT intensity index. The disaggregation of industries is important for this study for various reasons. As for an example, agro-processing comprises of various industries, with varying requirements for ICT intermediate inputs and hence varying levels of ICT use. In consequence, the effects of ICT on growth performance will vary across industries. By disaggregating industries according to their ICT intensity, this study informs policy on which group of industries is most conducive to the exploitation of ICT investment. After calculating the ICT intensity of industries, the annual growth rates of labour productivity, employment and output are calculated. Ultimately, we examine the effects of ICT intensity on growth of labour productivity, employment and output. Again, to avoid problems associated with bivariate analysis, we examine the causal relationship between ICT intensity and productivity, employment and output. By doing so, this study evades the econometric problem of omitted variable bias, while unlocking multiple causality channels which are undetectable under the bivariate setting.

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

- (i) To estimate short-and long-run effects of ICT intensity on growth of labour productivity, employment and output; and
- (ii) To test for the causal relationship between ICT intensity and growth of labour productivity, employment and output.

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

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<sup>1</sup> The policy plans include the New Growth Path, the National Development Plan, the Nine-Point Plan and the Agricultural Policy Action Plan.

## 2. REVIEW OF RELATED LITERATURE

A broad range of studies investigated the effects of ICT investment on economic growth and other measures of development using varied data sources, analytical approaches, and diverse time periods. For the purpose of this study, the review focuses on the causal relationship between ICT and GDP growth, productivity and employment. Further to this, special attention is given to cross-country analysis studies and studies at both the aggregate and industry levels.

In summation, aggregate studies found a bidirectional causal relationship between ICT investment and GDP for the developed countries and unidirectional causality for the developing countries (Shiu and Lam, 2008; Pradhan et al., 2014). 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 studies with a focus on productivity proved that, in general, causality is detectable for developed countries, which suggest that developed countries are yet to experience productivity gains from ICT investment (Lee et al., 2005).

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

In terms of employment 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 labour productivity, enabling the production of more output with less labour, giving rise to jobless growth (OECD, 2016). Hence, it is fundamental for this study to review empirical findings on the relationship between ICT and employment. In general, despite the pessimistic viewpoint regarding the effects that ICT will have on employment, empirical findings have tended to find a positive correlation between ICT and employment (Etro, 2009; Crandall and Singer, 2010; Kolko, 2012; Atasoy, 2013; Pantea, Biagi and Sabadash, 2014; Khan, Lilenstein, Oosthuizen and Rooney, 2017).

In the case of South Africa, there are limited empirical studies on the potential gains that could be accrued through investment in ICT. To quote a few, 2015 report by Global Connectivity Index (GCI) predicted that a 20% increase in ICT investment would lead to a 1% increase in GDP of 50 selected countries including South Africa. The report further positions South Africa as one of the top three developing countries, along Chile and China, with the potential to boost their economic growth through investment in ICT. In another case, Salahuddin and Gow (2016) detected a positive and significant long-run relationship between internet usage and South Africa's economic growth over the period 1991 to 2013. Thus, 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 four gaps in the literature in relation to ICT and agro-processing that this study attempts to fill:

- (i) Which of the agro-processing industries are more or less ICT intensive?
- (ii) What are the effects of ICT intensity on growth of employment, labour productivity and output of agro-processing industries?
- (iii) What is the causal relationship between ICT intensity and growth of employment, labour productivity and output?

This paper intends to fill the identified knowledge gap by (1) disaggregating the agro-processing industries into more ICT intensive and less ICT intensive using the ICT intensity index; (2) calculate the annual growth rates of labour productivity, employment and output of industries; (3) estimate effects of ICT intensity on growth of labour productivity, employment and output; and (4) examine the causal relationship between ICT intensity and growth of labour 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 are sourced from the Statistics South Africa (Stats SA). However, the Stats SA only began to publish the I-O data on an annual basis from 2009 to 2014, with 2014 being the latest year of publication (Parry, 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 data is based on estimates and on the last full release of the underlying dataset by the Stats SA. In addition, data on labour productivity, employment and output for 10 industries were also sourced from Trend Tables of the South African Standardised Industry Indicator Database due to lack of comprehensive and up-to-date data from the Stats SA (Quantec, 2018b). The methodology used to compile the I-O data and data on economic performance variables can be obtained from Quantec website (Quantec Research, 2018c).

#### 3.2 Description of variables

In this study, we adapt Engelbrecht and Xayavong's (2006) method of ranking industries into "more ICT-intensive" and "less ICT-intensive" based on their direct requirements for ICT inputs using Input-Output (I-O) data. The index by Engelbrecht and Xayavong (2006) is preferable over other indexes which are based on ICT capital stock (Stiroh, 2002; Abri and Mahmoudzadeh, 2015), which is unavailable for the current analysis. However, 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".

Following, 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 to total requirements by all the agro-processing industries for ICT inputs expressed as follows:

$$I_j = \frac{(\sum_{j=1}^n I^{ict}_j^*)}{T_j} \times 100 \quad (1)$$

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 to the total share by all the agro-processing

industries. To compute the ICT intensity of industries, we used the I-O data for the industries from 1994 to 2017. 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: labour productivity is the gross output per hours worked; employment is the total number of employees in an industry, including formal, informal as well as casual and permanent employment; and real output is the quantity of goods or services produced in a particular industry. (Quantec, 2018c). Akin to previous studies, we transformed the raw data for the labour productivity, employment and real output into mean growth rates (i.e. annual growth rates) (Engelbrecht and Xayavong, 2006; Lovrić, 2012; Vu, 2013).

In summation, the type of data used in this study is a panel; time series on ICT intensity, labour productivity, employment and output over the period 1994 to 2017 for cross-sections of 10 agro-processing industries. The choice of the time period is based on data availability. The justification for using the panel approach is that special attention is given to groups in the sample (i.e. more ICT intensive and less ICT intensive industries), with heterogeneities with respect to labour productivity, employment and output. Thus, using the panel approach allows us to take into account heterogeneity across groups in the sample as well as across individual. Over and above, the time period, from 1994 to 2017, is very short to conduct the analysis; hence, conducting the analysis using panel data allows us to have more degrees of freedom than using time-series or cross-sectional data. Further to this, the use of panel data enables us to control for omitted variable bias and to reduce the problem of multicollinearity among variables. Within this vein, more accurate and efficient estimation results can be obtained.

### 3.3 The model

The autoregressive distributed lag (ARDL) framework developed by Pesaran and Shin (1995, 1999), Pesaran, Shin and Smith (1996) and Pesaran (1997) is applied to estimate the effect of ICT intensity on the economic performance of industries for the period 1994 to 2017. The ARDL is preferable in this study for two reasons. First, unlike techniques such as 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., and Lee, 2009). The basic ARDL (p, q) model is as follows:

$$Y_t = \alpha_0 + \sum_{i=1}^p \beta_j Y_{t-i} + \sum_{i=0}^q \delta' j X_{t-i} + \varepsilon_{jt} \quad (2)$$

For the purpose of this study, we consider the four-variable vector autoregressive (VAR) model composed of ICT intensity, labour 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:

$$ICT_t = a_1 + \sum_{i=1}^p a1iICT_{t-i} + \sum_{i=1}^q b1iLP_{t-i} + \sum_{i=1}^r d1iEMP_{t-i} + \sum_{i=1}^s \rho1iRO_{t-i} + \varepsilon_{1t} \quad (3)$$

$$EMP_t = a_3 + \sum_{i=1}^p a2iICT_{t-i} + \sum_{i=1}^q b2iLP_{t-i} + \sum_{i=1}^r d2iEMP_{t-i} + \sum_{i=1}^s \rho2iRO_{t-i} + \varepsilon_{2t} \quad (4)$$

$$LP_t = a_2 + \sum_{i=1}^p a3iICT_{t-i} + \sum_{i=1}^q b3iLP_{t-i} + \sum_{i=1}^r d3iEMP_{t-i} + \sum_{i=1}^s \rho3iRO_{t-i} + \varepsilon_{3t} \quad (5)$$



$$RO_t = a_4 + \sum_{i=1}^p a_{4i} ICT_{t-i} + \sum_{i=1}^q b_{4i} LP_{t-i} + \sum_{i=1}^r d_{4i} EMP_{t-i} + \sum_{i=1}^s \rho_{3i} RO_{t-i} + \varepsilon_{4t} \quad (6)$$

Where ICT= ICT intensity (%); EMP<sub>t</sub>, LP<sub>t</sub> and RO<sub>t</sub> are growth rates of employment (%), labour productivity (%) and output (%), respectively. All the variables are in percentage form hence the equations are not in log forms.  $\varepsilon_t$ s 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. By application, the VAR must be specified in levels since VAR in differences would be mis-specified (Cuthbertson, 2002).

### 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). 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 to 2 lags.

### 3.3.2 Panel Unit Root Testing

The Im-Pesaran-Shin (IPS) unit root test developed by Im, Pesaran and Shin (2003) is applied to verify the order of integration among variables. The rationale is to ensure that variables are stationary with the purpose of avoiding spurious regression and generate results that are applicable in other periods, which validates forecasting. Alternative unit root tests to the IPS entail, amongst others, the Augmented Dickey-fuller (ADF) test (Dickey and Fuller, 1979), ADF-GLS test (or DF-GLS test) (Elliott, Rothenberg and Stock, 1992), Phillips and Perron (PP) test (Phillips and Perron, 1988) and Ng-Perron test (Ng and Perron, 1995, 2001). The IPS is preferable over these tests given that 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 is 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):

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (7)$$

$Y_{it}$  is the series for industry  $i$  in the panel over period  $t$ ;  $p_i$  is the number of lags chosen for the ADF regression;  $\Delta$  is the first difference filter (I<sub>L</sub>), and  $\varepsilon_{it}$  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:

$$\bar{t}_{NT} = \frac{1}{N} \sum_{i=1}^N t_{iT} (p_i \beta_i) \quad (8)$$

It has been proven that the standardized t-bar statistic converges to the standard normal distribution as  $N \rightarrow \infty$ . As stated in Im et al., (1997), t-bar test has better performance when  $N$  and  $T$  are small, which confirms that test has enough power to test for stationarity (Sallahuddin, Abu and Hussin, 2014).

### 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 the long-run relationship exists among variables. The Test is preferable over other tests (Engle and Granger, 1987; Johansen, 1988; Johansen and Juselius, 1990; Phillips and Ouliaris 1990; Pedroni, 1999) 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 the long-run relationship exists among variables, it implies that such variables are related and can be modelled 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 (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 as well as the speed of adjustment towards long-run equilibrium. To address this delimitation, the PMG regression developed by Pesaran et al. (1999) is applied 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. Also, PMG provides consistent and efficient estimates irrespective of the order of integration (Pesaran and Smith, 1995; Pesaran, 1997; Pesaran et al. 1999). To apply PMG, the specific ARDL (p, q, r, s) is re-formulated in an error correction form as follows:

$$\Delta ICT_t = a_1 + \sum_{i=1}^{p-1} a_{1i} \Delta ICT_{t-i} + \sum_{i=1}^{q-1} b_{1i} \Delta LP_{t-i} + \sum_{i=1}^{r-1} d_{1i} \Delta EMP_{t-i} + \sum_{i=1}^{s-1} \rho_{1i} \Delta RO_{t-i} + \Phi ECT_{t-1} + \varepsilon_{1t} \quad (9)$$

$$\Delta EMP_t = a_3 + \sum_{i=1}^{p-1} a_{2i} \Delta ICT_{t-i} + \sum_{i=1}^{q-1} b_{21i} \Delta LP_{t-i} + \sum_{i=1}^{r-1} d_{2i} \Delta EMP_{t-i} + \sum_{i=1}^{s-1} \rho_{2i} \Delta RO_{t-i} + \Phi ECT_{t-1} + \varepsilon_{2t} \quad (10)$$

$$\Delta LP_t = a_2 + \sum_{i=1}^{p-1} a_{3i} \Delta ICT_{t-i} + \sum_{i=1}^{q-1} b_{31i} \Delta LP_{t-i} + \sum_{i=1}^{r-1} d_{3i} \Delta EMP_{t-i} + \sum_{i=1}^{s-1} \rho_{3i} \Delta RO_{t-i} + \Phi ECT_{t-1} + \varepsilon_{3t} \quad (11)$$

$$\Delta RO_t = a_4 + \sum_{i=1}^p a_{4i} \Delta ICT_{t-i} + \sum_{i=1}^q b_{41i} \Delta LP_{t-i} + \sum_{i=1}^r d_{4i} \Delta EMP_{t-i} + \sum_{i=1}^s \rho_{4i} \Delta RO_{t-i} + \Phi ECT_{t-1} + \varepsilon_{4t} \quad (12)$$

### 3.3.6 Panel Granger causality test

While previous techniques examine the presence of a relationship among variables (Bounds Test) and effects thereof (PMG), Masood (2012) expressed that the existence of a relationship between variables does not prove causality. Also, these techniques do not test for the direction of the causal relationship among variables. Therefore, to test for causality between variables, 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 (Yamada and Toda, 1998; Caragata and Giles, 2000; Clark and Mirza, 2006). To apply the TY test, the specific ARDL (p, q, r, s) models (i.e. equations (3) to (6)) are modified by augmenting an additional lag order to the optimal lag (Caporale and Pittis, 1997).

In the context of causality, this study assesses the ICT intensity-growth nexus involving three economic performance variables (i.e. labour productivity, employment and real output) that could be affected by ICT intensity and/or affect ICT intensity. Therefore, based on Engle and Granger (1987), the following hypotheses are tested:

- (i)  $H_{1a}$ : ICT intensity Granger-causes employment growth;
- (ii)  $H_{1b}$ : Employment growth Granger-causes ICT intensity;
- (iii)  $H_{2a}$ : ICT intensity Granger-causes labour productivity growth;
- (iv)  $H_{2b}$ : Labour productivity growth Granger-causes ICT intensity;
- (v)  $H_{3a}$ : ICT intensity Granger-causes real output growth; and
- (vi)  $H_{3b}$ : Real output growth Granger-causes ICT intensity.

## 4. DESCRIPTIVE AND EMPIRICAL RESULTS

### 4.1 Descriptive results

This section provides descriptive statistics to provide the nature of the data (variables) used in the paper. The descriptive statistics covers the results of the ICT intensity index for the purpose of classifying industries into more ICT intensive and less ICT intensive. Consequently, the reporting of the results entails three Panel of industries. Panel A is all the agro-processing industries. Panel B is composed of the more ICT intensive industries while Panel C comprises of the less ICT intensive industries. The annual growth rates of labour productivity, employment and output for Panel of industries also provided in this section. The aim is to shed light on the contribution of Panel of industries to the growth of labour productivity, employment and output of the agro-processing sub-sector.

#### 4.1.1 ICT intensity of industries

Using ICT intensity index defined as the industries' direct requirements for ICT intermediate inputs, we distinguish industries into two categories (i.e. more ICT-intensive 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 (Stiroh, 2002; Engelbrecht and Xayavong 2006; Chen et al., 2016). The ICT intensity index ( $I_j$ ) results indicate that the median value is 7.37%. Within this vein, industries with the ICT intensity index of greater than the median of 7.37% are ranked as more ICT-intensive and vice versa for less ICT-intensive industries. Table 1 shows the ICT intensity of the industries.

**Table 1: ICT intensity of industries**

Industry	ICT intensity index (%)
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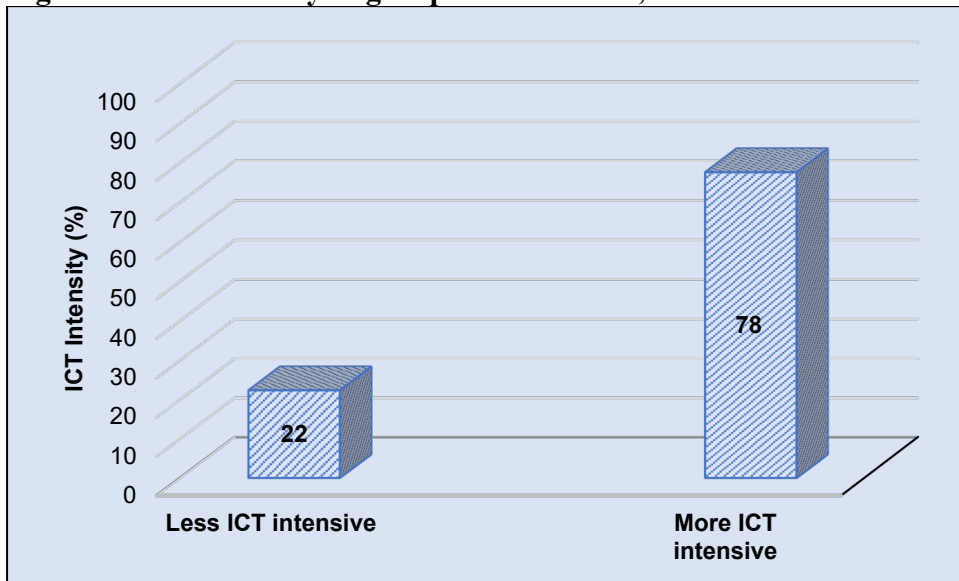
Food	37.20
Beverages	11.02
Tobacco	0.84
Textile	8.12
Wearing Apparel	6.62
Leather	3.96
Wood	5.86
Paper	11.16
Rubber	10.08
Furniture	5.12
<b>Total</b>	<b>100</b>

Source: Author' calculations based on Quantec (2018b) and Stats SA

The findings indicate that five industries which are namely Food, Beverages, Textile, Paper and Rubber 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 5 are less ICT intensive.

The results further show that the more ICT intensive industries account for 78% of the share of the direct requirement for ICT intermediate inputs as shown in Figure 1. The less ICT intensive industries account for the remaining 22%.

**Figure 1: ICT intensity of groups of industries, 1994-2017**



Source: Author based on Quantec (2018b) and Stats SA

#### 4.1.2 Annual Growth Rates

After calculating the ICT intensity of industries, we calculated the weighted annual average growth rate of employment, labour productivity and output for industries over the period 1994 to 2017. The detailed results are presented in Table 2.

**Table 2: Weighted annual average growth rate, 1994-2017**

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

Food	-0.3%	3.1	2.0
Beverages	-0.9%	-0.2	0.8
Tobacco	-0.9%	3.3	2.1
Textile	-2.3%	2.6	1.2
Wearing Apparel	-2.7%	4.5	1.0
Leather	-1.8%	4.9	3.8
Wood	0.9%	1.1	3.2
Paper	1.7%	0.1	2.4
Rubber	-1.8%	1.3	1.3
Furniture	-2.1%	2.8	2.2

Source: Authors' calculations based on Quantec (2018b) and Stats SA

The weighted annual growth rate results indicate that the less ICT intensive industries are surpassing their counterparts with respect to growth rates of both labour productivity and output. In terms of employment, both groups of industries experienced a decline in employment growth. However, the more ICT intensive group experienced the least decline in employment growth. For individual industries, the Leather industry exhibits the highest growth in both labour productivity and output. Contrarily, the Beverages industry has the lowest growth in both labour productivity and output. With reference to employment, all industries experienced a decline in employment growth. Comparatively, the Wearing Apparel industry experienced the highest decline in employment growth whereas the Food industry experienced the least decline in employment.

## 4.2 EMPIRICAL RESULTS

This section provides empirical results derived from the determination of optimal lag, the unit root testing, the cointegration testing, PMG estimation, TY Granger Non-Causality testing and IRF and VDC analyses. The reporting of the results covers Panel A (All industries), Panel B (More ICT intensive industries) and Panel C (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 3.

**Table 3: Optimal lag results**

Variable	Optimal lag
<b>Panel A (All Industries)</b>	
ICT	2
EMP	1
LP	2
RO	2
<b>Panel B (More ICT intensive Industries)</b>	
ICT	2
EMP	2
LP	1
RO	1
<b>Panel C (Less ICT intensive industries)</b>	
ICT	1
EMP	1
LP	1
RO	2

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

#### 4.2.2 Unit Root Test Results

The results of the IPS unit root test are presented in Table 4. Three varying outcomes were derived after performing the IPS stationarity test. The first outcome is that, for Panels A and C, IPS-statistics are statistically significant at 1% in the level forms of the variables ICT intensity, employment, labour productivity and output. This means that these variables are stationary in their level forms (i.e. integrated of order I (0)) and therefore requires no differencing.

**Table 4: Panel unit root test results**

Variable	IPS-statistic	P-values	Order of integration
<b>Panel A: All industries</b>			
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)
<b>Panel B: More ICT industries</b>			
ICT	-0.60147	0.2738	I(1)
$\Delta$ ICT	-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)
<b>Panel C: Less ICT industries</b>			
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)

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

The second outcome is that, for Panel B, three variables, labour productivity, employment and output are significant at 1% in their level forms while the ICT intensity variable is not. This means that the three variables are stationary in their level forms (i.e. integrated of order I (0)) and therefore requires no differencing. On one hand, the variable ICT intensity became stationary after first-differencing, which implies that it is integrated of order I (1). The third outcome, the overall finding, is that the 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 order I (1) and I (0)).

#### 4.2.3 Cointegration Test Results

The unit root test results proved that the variables are integrated of different orders which justifies the use of 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 Bound Test results are presented in Table 5.

**Table 5: Bound Test Cointegration Results**

Dependent variable	AIC lags	Computed F-statistic	Is there cointegration?	ARDL or ECM?
<b>Panel A: All industries</b>				
ICT	2	1.90	No	ARDL
EMP	1	4.95	Yes	ECM
LP	2	5.73	Yes	ECM
RO	2	8.75	Yes	ECM
<b>Panel B: More ICT intensive industries</b>				

ICT	2	2.1	No	ARDL
EMP	2	18.90	Yes	ECM
LP	1	15.70	Yes	ECM
RO	1	10.07	Yes	ECM
<b>Panel C: Less ICT intensive industries</b>				
ICT	1	6.87	Yes	ECM
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	

The findings for Panels A and B show that the null hypothesis of no cointegration cannot be rejected when ICT is set as the dependent the variable. This is because the F-statistic values are lower than the critical values for both the I (0) and I (1). This implies that there is no evidence of a long-run relationship among variables when ICT is the dependent variable. Contrariwise, the null hypothesis of no cointegration is rejected when the variables EMP, LP and RO are specified as the dependent variable. This is 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 when the variables EMP, LP and RO are taken as the dependent variables.

In terms of Panel C, the findings are that the null hypothesis of no cointegration is rejected when all the variables are specified as the dependent variables. This is because the F-statistics values (ICT (6.87), EMP (32.86), LP (38.25) and RO (30.79)) are greater than all the critical values for both I (0) and I (1) Bounds. The results, therefore, provide evidence of a long-run relationship amongst the variables regardless of which variable is the dependent variable.

#### 4.2.4 PMG Results

The Bound Test results showed 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, do not provide evidence of short-run and/or long-run causal effects among variables. To address this delimitation, we estimated the ARDL to determine the short-run effects (in cases where the long-run relationship does not exist) and both the short-run and long-run effects (in cases where a long-run relationship exists). Since the study focuses on assessing the ICT-led growth, the discussion is limited to the effects of ICT intensity on the growth of employment, labour productivity and output. The results from the ARDL and ECM estimates for Panels of industries are presented in Table 6.

**Table 6: Short-run and long-run effects for Panel of industries**

Dependent variable	Short-run effect				Long-run effects				ECT <sub>-1</sub>
	ICT	EMP	LP	RO	ICT	EMP	LP	RO	
<b>Panel A: All industries</b>									
ICT	-	0.01 (0.69)	0.00 (0.921)	0.00 (0.84)	-	N/A	N/A	N/A	N/A
EMP	0.00 (0.789)	-	-0.00 (0.435)	0.00 (0.340)	0.81 (0.690)	-	-0.83*** (0.000)	1.01*** (0.000)	-0.62*** (0.000)
LP	-0.03 *** (0.000)	-0.42 (0.132)	-	0.16 (0.368)	-1.13*** (0.000)	1.40 (0.546)	-	1.20 *** (0.000)	-0.48*** (0.000)

RO	-0.14** (0.032)	-0.09 (0.368)	-0.03 (0.259)	-	0.71*** (0.000)	-0.26 (0.874)	0.62*** (0.000)	-	-0.37*** (0.000)
<b>Panel B: More ICT intensive industries</b>									
ICT	-	-0.00 (0.998)	0.00 (0.894)	-0.00 (0.931)	-	N/A	N/A	N/A	N/A
EMP	0.25* (0.072)	-	-0.01 (0.822)	-0.12 (0.375)	0.41 (0.290)	-	-0.62*** (0.000)	0.52*** (0.000)	-0.38*** (0.000)
LP	-0.07 (0.725)	-0.00 (0.994)	-	-0.47*** (0.005)	0.48* (0.06)	-0.94 (0.334)	-	0.78** (0.014)	-0.87*** (0.000)
RO	0.09 (0.407)	0.15 (0.156)	0.14 ** (0.03)	-	0.39** (0.028)	-0.005 (0.874)	0.19*** (0.000)	-	-0.75*** (0.000)
<b>Panel C: Less ICT intensive industries</b>									
ICT	-	0.00 (0.799)	-0.02* (0.095)	0.06** (0.041)	-	-0.09 (0.28)	-0.04 (0.229)	-0.029 (0.745)	-0.42*** (0.000)
EMP	0.58 * (0.07)	-	-0.05 (0.265)	0.14 (0.178)	-0.181 (0.359)	-	-0.28*** (0.000)	0.31*** (0.001)	-0.98*** (0.000)
LP	-0.02 (0.915)	-0.42 (0.558)	-	-0.493** (0.038)	-1.52*** (0.000)	-0.49 (0.334)	-	0.74** (0.025)	-0.97*** (0.000)
RO	-0.22*** (0.007)	-0.27 (0.263)	-0.05 (0.150)	-	0.27*** (0.002)	-0.002 (0.88)	0.13*** (0.002)	-	-0.89*** (0.000)

Note 1: Figure in parenthesis are the P-values; Note 2: \*\*\*, \*\*, \* indicate significance at 1%, 5% and 10% respectively

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 and long-run. However, positive significant effects are notable only in the short-run for both Panels B and C (the less and more ICT intensive industry groups). Further to this, ICT yields a negative effect on labour productivity of the aggregated agro-processing industries and less ICT intensive industry group in both short-and long-run. Nonetheless, positive significant effects are notable only in the short-run for the more ICT intensive group. Also, while ICT intensity yields positive significant effects on output growth of both the less and more ICT intensive groups, its effect is higher for the more ICT intensive group.

#### 4.2.5 Granger Causality Test Results

While previous techniques examined the presence of a relationship among variables and effects thereof, 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 7.

**Table 7: Multivariate TY Non-Granger Causality Test results**

<b>Panel A (All industries)</b>				
Dependant Variable	Independent variables			
	ICT	LP	EMP	RO
ICT	-	1.843 (0.397)	0.751(0.686)	3.780 (0.151)
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)	-
<b>Panel B (More ICT intensive industries)</b>				
	ICT	LP	EMP	RO
ICT	-	0.886 (0.6419)	1.482 (0.476)	2.113 (0.347)
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)	-
<b>Panel C (Less ICT intensive industries)</b>				



	ICT	LP	EMP	RO
ICT		0.831(0.361)	0.042 (0.836)	0.006 (0.720)
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=labour 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 at 10 % level; \*\* Significant at 5% level; \*\*\* Significant at 1% level.

The TY Granger Causality Test findings signify that there is no causal relationship between ICT intensity and growth in labour productivity, employment and output of the agro-processing industries (i.e. Panel A). 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 contrary, 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, comparable to those that use ICT less.

## 5. Conclusion

This paper examined the extent to which ICT intensity contributes to the growth of labour productivity, employment and output of the more and less ICT intensive industries. The PMG results proved that ICT intensity yields higher positive significant effects on output growth of the more ICT intensive industries. On one hand, the TY tests detected evidence of a causal relationship between ICT intensity and employment growth of the more ICT intensive industries. These findings are in conformity with the general findings that the causal effects of ICT are detectable for industries that use ICT most intensively. Overall, this paper provides evidence of ICT-led growth for South Africa's agro-processing industries that use ICT most intensively.

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