ECONOMIC DEVELOPMENT
AND WELL-BEING
RESEARCH GROUP

EDWRG Working Paper Series
January 2020

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Working Paper Number 05-2020

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Cite this paper: van Zyl., G. (2020). The impact of new production technology on employee productivity in the South African workplace. *EDWRG Working Paper Number 05-2020.*

The impact of new production technology on employee productivity in the South African workplace

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1. Introduction

The aim of this article is to determine the firm-based employee productivity impacts due to the acquisition and implementation of new production technologies in the South African workplace.

The rapid change in the technology base of firm activities and the impact that it has on employee productivity is an important aspect of the debate on employee productivity. No published firm-based research findings on the technology-employee productivity link for the South African workplace are available. This study specifically focusses on generating firm-based estimation results of the technology-employee productivity relationship when new machine and equipment technologies and employee diversity aggregates such as age and skill levels are included in the estimations.

The article is part of an on-going research project on various aspects of employee productivity in the South African workplace. Research thus far covers various aspects of firm-based employee productivity. These are i) remuneration dispersion (Van Zyl 2010) ii) different age-skill categories (Van Zyl 2013) iii) qualifications (Van Zyl 2013) iv) employee diversity (Van Zyl 2014) v) incentive schemes (Van Zyl 2015) vi) non-unionised participation platforms (Van Zyl 2016) vii) in-house training (Van Zyl 2017) and viii) employee migration to smaller firms (Van Zyl 2019).

2. Literature study

The impact of technological innovations on employee productivity, at the industry level, has been well researched internationally. (Allmon, Haas, Borcherding and Goodrum 2000; Altamirano and de Beers 2017; Antonioli, Mazzanti and Pini 2010; Brynjolfsen and Hitt 2003; Conti 2005; Filippetti and Peyrache 2015; Goodrum and Haas 2004; Jahangard 2008; Kunt and Kunt 2014; Lim and Sanidas 2011; Mačiulyte-Sniukiene and Gail-Sakane 2014; Mamum and Wickremasinghe 2014; Oliner and Sichel 2008; Papakonstantinou 2014; Romer 2006; Sharp and Qiao 2006; Techolz 2001). The estimation results of these studies (on the technology-employee productivity relationship) are in the main based on published data sets and estimation results based on firm-based data are limited. The literature indicates that, in general, technological innovations (in whatever format) have a positive impact on employee productivity. There are three main streams of literature on the impact of technology innovation on employee productivity.

The first stream of literature focuses specifically on the impact of information and communication technological innovations (hereafter referred to as ITC innovation) on employee productivity. Aspects that are generally covered include the diffusion of ITC innovations (transmission mechanisms), the removal of workplace inefficiencies and intensity levels of ITC technologies. Kunt et al. (2014) conclude that ITC innovation impacts on employee productivity via a transmission mechanism (accelerated workflow → increased efficiency of production processes → employee productivity) and that higher-skilled employees create higher levels of productivity when ITC innovation is introduced in the workplace. The study by Mačiulyte-Sniukiene et al. (2014) argues that ITC innovation creates effective dissemination of information, and via improved administrative and human resource strategies impacts positively on employee productivity. Romer (2006) is of the opinion that ICT technology innovations are responsible for the removal of inefficiencies in the workplace, thus contributing to higher levels of employee productivity. Mamum et al. (2014) are of the opinion that ICT innovation removes information asymmetry in the workplace, thus allowing employees to perform their duties more productively. Short-run diffusion of ICT innovation is faster than long-run diffusion. The argument is that workplace imperfections are removed more quickly and could translate sooner into higher employee productivity levels. The studies of Oliner et al. (2008) and Jahangard (2008) conclude that low levels of ITC innovation result in sub-optimal capital-to-labour ratios (and ultimately in weaker employee productivity levels) and that the employee productivity effect of ITC innovations is smaller for developing economies compared to developed economies.

The second stream of literature focuses in addition to ITC innovation on the impact of both organisational innovations (hereafter referred to as OI) and technological innovations (hereafter referred to as TI) on employee productivity. Two major aspects covered in this literature stream include the importance of complementary innovations to ICT and different OI channels. Brynjolfsson et al. (2003) and Antonioli et al. (2010) argue that organisational innovations such as supply chain management improvements, innovative training practices, and improved human resource management, and product innovations for both products and services should complement ICT innovation in the workplace and result in greater levels of employee productivity. The study by Papakonstantinou (2014) concludes that complementary innovations to ICT innovation create a greater level of skilled employees with a resultant positive impact on employee productivity. Conti (2005) is of the opinion that the generation and accumulation of skill levels are complementary to technology innovations and that only under these circumstances can OI and TI diffusion occur to impact positively on employee productivity.

The third stream of literature deals in depth with the impact of production technology innovation (new machinery and equipment) on employee productivity. This stream of research covers aspects such as the different driving factors of technological innovations in machinery and equipment, the cost of new production technologies, the different types of technology and the creation of competitive advantages due to investment in new production technologies. Lim et al. (2011) argue that the impact of technical production innovations on employee productivity differs between firms and industries. This study indicates the importance of the capital-to-employee ratio to capture the capital intensity of new production technologies. The study by Altamirano et al. (2017) concludes that technological innovations in production capital stock significantly improves employee productivity and that new production technology innovations achieve competitive advantages for firms and industries. Increased employee productivity is an important channel for the attainment of a competitive edge in the market. Sharp et al. (2006) consider the cost of investing in new production technologies. The high real cost of new production technologies could dampen investment in new machinery and equipment, with a resultant limited impact on the improvement of employee productivity. The study by Goodrum et al. (2004) is a major contribution to understanding the impact of technological innovation in machinery and equipment in the workplace on employee productivity. The study argues that the acquisition and implementation of new machine and equipment technologies will result in relative increases in capital-to-employee ratios and thus ultimately affect employee productivity positively. There are five distinct driving factors for the relative increase in the capital-to-employee ratio namely, the level of amplification of human energy, the level of control, the fundamental range, ergonomics and information processing. All of these driving forces must be included in determining the impact of production technology innovations on employee productivity.

It is important to note that new technologies (in whatever form) will partly explain improvements in employee productivity and that there are other factors, such as the improvement in human capital and learning-by-doing effects, that will also impact on employee productivity. This study focuses in the main on the impact of new production technology innovations on employee productivity in the South African workplace.

3. Research design

3.1. Research approach and method

The research design comprises the

- specification of the technology – employee productivity estimation model,
- identification of firm-based technology index factors, the construction of a firm-based technology index and firm-based technology-employee ratios,
- identification of the age and skill level attributes to be included in the technology – employee productivity estimation model,
- compilation of firm-based data sets,
- different estimation processes and
- interpretation of the estimation results.

3.2. Data requirements

The manufacturing industry of Gauteng Province is used as a case study to capture the employee productivity effects due to the acquisition and implementation of new production technologies (given the importance of this industry in the gross geographical product of Gauteng Province and the availability of firm-based data). Individual firms in the sample group supplied firm-based data. The sample-set of 74 firms covers a variety of sub-sectors in the manufacturing industry. The sample set of firms is statistically significant.

The sample period is 2009-2016 and the collation of the required data covers bi-annual time-periods (2009-2010; 2011-2012; 2013-2014; 2015-2016). For each firm in the sample, the following required data sets apply for each year in the sample period:

- Real production monetary values;
- Real employee remuneration values;
- Real spending on machinery and equipment;
- Real expenditure on new ICT infrastructure;
- Real spending on new machinery and equipment;
- Lists to rate the importance of the technology driving factors (in order to calculate technology index scores);
- Total of employees according to the three age groups and the two skill levels. In order to maintain continuity in the broader research agenda on various aspects of firm-based employee productivity in the South African workplace, the same descriptors for age and skill levels are used. The following three age groups are used: younger than 35 years, between 35 and 55 years of age, and older than 55 years of age. To distinguish between skilled occupations (Category A) and less skilled occupations (Category B), the International Standard Classification of Occupations (IOCO-88) is used. (Van Zyl, 2017).

3.3. Model specification

The estimation of the change in employee productivity is on a bi-annual basis (2009 & 2010; 2011 & 2012; 2013 & 2014; 2015 & 2016).

Distinct estimation processes are applied in this article. For the first set of estimations, an adapted version of the Goodrum et al. (2004) model is applied. The aim of these estimations is to construct a technology index and construct technology-to-employee ratios. This is done for each firm over the bi-annual time-period to estimate percentage changes in employee productivity.

In the model, the real average expenditure on machinery and equipment is the proxy for technology. Real average remuneration levels of employees are the proxy for the employee component in the technology-to-employee ratio. Estimating changes in employee productivity requires the construction of a technology index. The technology index is the sum of index score changes of the impact factors of technology divided by the number of observations.

$$\textbf{Technology index} = \Sigma^{N}_{i,t} \; (\Delta FR + \Delta EE + \Delta ER + \Delta EC + \Delta IP) / N$$

(equation 1)

In the equation:

- ΔFR is changes in the index scores of the functional range of equipment and machinery for firm *i* and for period $_t$;
- ΔEE is the changes in the index scores of employee effort in the workplace for firm *i* and for period $_t$;
- ΔER is the changes in the index scores of ergonomic characteristics of equipment and machinery for firm *i* and for period $_t$;
- ΔEC is the changes in the index scores of physical employee control over machinery and equipment for firm *i* and for period $_t$;
- ΔIP is the changes in index scores of information processing in the workplace for firm *i* and for period $_t$;
- N is the number of observations.

The quantification of the level of change in each of these technology impact factors (due to real changes in machinery and equipment spending) is done in the following manner:

For no changes a value of 0 is awarded; for limited changes, a value of 1 is awarded; for medium-level changes, a value of 2 is awarded and for high-level changes, a value of 3 is awarded. A technology index score for each firm in the sample for the bi-annual time-periods is determined. In this model, employee productivity is the real production value divided by total real employee remuneration.

The percentage change in employee productivity (for each firm over the bi-annual time-period) is defined as:

$$\textbf{\% change in EP = EP year}_{\mathbf{x}} \textbf{ – EP year}_{\mathbf{x-1}} \div \textbf{EP}_{\mathbf{x-1}}$$

(equation 2)

In the equation:

- EP is employee productivity;
- Year $_x$ is the current year;
- Year $_{x-1}$ is the previous year.

A bi-annual employee-productivity-compound-rate for each firm in the sample is calculated.

The existence of collinearity between the different technology impact factors is considered once the technology index is constructed.

The next step is to construct changes to the technology-to-employee ratios (for each firm over the bi-annual time-periods). Changes in the technology-to-employee ratio is defined as:

$$\boldsymbol{\Delta} \textbf{ technology-to-employee ratio} = (\mathbf{TE_x/EM_x}) - (\mathbf{TE_{x-1}/EM_{x-1}})$$

(equation 3)

In the equation:

- TE_x is the current real average expenditure on technology;
- EM_x is the current real average employee remuneration level;
- TE_{x-1} is the real average expenditure on technology in the previous period;
- EM_{x-1} is the real average employee-remuneration level in the previous period.

A higher technology-to-employee ratio is indicative of greater technology intensity levels.

The next step is to perform a simplified regression for the relationship between changes in the technology-to-employee ratio and employee productivity for the sample group of firms over the bi-annual time-period. Positive estimates are indicative of positive relationships between the real expenditure on production technology and employee productivity. Increases in employee productivity are thus linked to increases in the technology-to-employee ratio (improvement in production technology facilitates real increases in employee productivity). The magnitude of the estimates is also considered. Higher positive estimate values are indicative of greater positive impacts on employee productivity, while lower positive estimate values are indicative of smaller impacts on employee productivity.

The next step is the estimation of the relationship between the technology index, the technology-to-employee ratio and changes in employee productivity for the sample of firms:

% Δ in employee productivity = f (technology index, technology-to-employee ratio)

(equation 4)

A quadratic regression for this particular relationship is done for the different bi-annual time-periods. Of importance for this study is the sign and magnitude of the estimations and the average variance of the changes in employee productivity. The regression estimates indicate what percentage change in employee productivity is attributed to changes in the technology index and the technology-to-employee ratio. Greater technology index-values and technology-to-employee ratios should result in a greater positive percentage change in employee productivity. The opposite is also true.

The next step is to cater for the impact of the individual technology factors on employee productivity. To perform the estimations a series of dummy variables are included (a value of 1 if a change in technology is experienced and a value of 0 if no change in technology is experienced). This is done for the sample of firms for the bi-annual time-periods. The aim of these estimations is to determine the magnitude of the impact that each technology component has on changes in employee productivity.

For the second set of estimations, fixed-panel data estimations are performed when employee diversity attributes of age and skill levels are included (for the entire sample of firms over the bi-annual time period). Fixed-panel data estimations are performed to determine the percentage change in employee productivity based on the technology-to-employee ratio, the technology index, the different technology components, the different age groups, and the different skill levels. These fixed-panel estimations are done for the different bi-annual time-periods. In the fixed-panel data estimations employee productivity is defined as the percentage change in real average production divided by average real employee remuneration. The percentage change in employee productivity is:

$$\mathbf{\%\Delta EP_{i,t,t-1} = \alpha\Delta TE\text{-}EM_{i,t,t-1} + \beta TI_{i,t,t-1} + \lambda ICT_{i,t,t-1} + \theta\Sigma^{n}_{i,t,t-1} (\Delta FR_{a,s} + \Delta EE_{a,s} + \Delta ER_{a,s} + \Delta EC_{a,s} + \Delta IP_{a,s}) + \varepsilon}$$

(equation 5)

In the equation:

- $\%\Delta EP_{i,t,t-1}$ is the percentage change in employee productivity for firm *i* for the period *t-(t-1)*; $\alpha\Delta TE\text{-}EM_{i,t,t-1}$ is the real technology-employee ratio for firm *i* for the period *t-(t-1)*;
- $\beta TI_{i,t,t-1}$ is the technology index for firm *i* for the period *t-(t-1)*;
- $\lambda ICT_{i,t,t-1}$ is real ICT spending for firm *i* for the period *t-(t-1)*;
- $\theta\Sigma^{n}_{i,t,t-1}$ is the sum of the technology factors for the different age groups and the different skill levels for firm *i* for the period *t-(t-1)*;
- $\Delta FR_{a,s}$ is the change in the functional range for the different age groups and skill levels;
- $\Delta EE_{a,s}$ is the change in employee effort due to the improvement in technology for the different age groups and skill levels;
- $\Delta ER_{a,s}$ is the change in ergonomic characteristics for the different age groups and skill levels; $\Delta EC_{a,s}$ is the change in physical employee control over equipment and machinery for the different age groups and skill levels;
- $\Delta IP_{a,s}$ is the change in information processing in the workplace for the different age groups and skill levels and **ε** the error term)

The fixed-panel data estimates are indicative of the percentage impact of each technology component on employee productivity for each age group and skill level over the bi-annual time-periods for the sample group of firms. A positive estimate relates to an increase in employee productivity, while a negative estimate indicates a decrease in employee productivity.

4. Estimation results.

The first estimation concerns the percentage annual growth in employee productivity (defined as percentage growth in real production values divided by the percentage increase in real employee remuneration) due to real spending on new technology for the full sample of firms over the 2009-2016 time-period.

The estimation results indicate that employee productivity grew by 16.2% over this period and at an average bi-annual rate of 4.05%. These results are indicative of the positive impact that growth in real spending on new machinery and equipment has on employee productivity. The results also confirm greater percentage growth rates for employee productivity during the bi-annual time-periods in which real spending on new production technologies accelerated.

The second estimation results concern the possible existence of collinearity between the different technology impact factors. The aim is to make sure that standard errors will not increase in the panel data estimations (for the sample group of firms). A correlation matrix for the technology components is constructed.

Table 1: Correlation matrix for technology index components

	TI_{FR}	**TI_{EE}**	**TI_{ER}**	**TI_{EC}**	**T_{IP}**
TI_{FR}	1	0.36	0.35	0.17	0.22
TI_{EE}	0.36	1	0.40	0.41	0.33
TI_{ER}	0.35	0.40	1	0.01	0.35
TI_{EC}	0.17	0.41	0.01	1	0.05
T_{IP}	0.22	0.33	0.35	0.05	1

*All the correlations are significant at the 95% confidence level.

Source: Own estimations

The highest level of pairwise collinearity is between the change in employee effort and the change in the physical employee control over new machinery and equipment. The lowest level of pairwise collinearity is between the change in the physical control over new machinery and equipment and the change in the ergonomic characteristics of the new machinery & equipment. The matrix indicates no collinearity given the fact that no pairwise correlation exceeds a maximum benchmark of 0.70. This result confirms the significance of each of the technology components and the technology index per se.

The third estimation results consider the regression results of the effects of the technology index and the technology-to-employee ratio on the percentage change in employee productivity for the full sample group of firms.

Table 2: Percentage change in employee productivity (1)

Bi-annual time-period	**Constant**	**$(T/E)^2$**	**TI^2**	**R^2**
2009-2010	2.64	88.24 (3.14)	7.12 (4.02)	0.28
2010-2012	2.89	89.92 (2.88)	7.88 (3.78)	0.29
2013-2014	3.12	92.18	8.12	0.32

		(2.90)	(3.04)	
2015-2016	3.48	93.52 (3.08)	8.64 (4.16)	0.33

*The t-values are in parenthesis. N=74

Source: Own estimations

Of importance is the magnitude and expansion of the R^2. The results indicate that for the whole sample of firms, on average 31% of the increases in employee productivity are explained by changes in the technology index and the technology-to-employee ratio. It is also important to note that this trend has constantly increased over the bi-annual time-periods.

The fourth regression results on employee productivity also cater for a technology-change versus a no-technology-change scenario for the full sample of firms. A dummy variable series is included in the regression to cater for these scenarios. The aim of this particular regression is to estimate the percentage of the total variation in employee productivity as well as the employee productivity contribution of the different technology components due to the different driving factors of technology changes, the technology impact scenarios, and the technology-to-employee ratio. The regression results are listed in Table 3.

Table 3: Percentage change in employee productivity (2)

Constant	**T/E**	**TI**	**FR**	**EE**	**ER**	**EC**	**IP**	**R^2**
3.43 (0.12)	82.48 (3.44)	10.12 (2.14)	4.48 (1.88)	15.43 (4.62)	18.10 (3.88)	12.12 (3.25)	2.02 (1.08)	0.32

*The t-values are in parenthesis.

Source: Own estimations

The changes in the different components of technology, the technology index, the technology-to-employee ratio, and the different technology scenarios explain 32% of the increase in employee productivity. This result is similar to the previous regression result. In terms of the impact of the different technology components on employee productivity, the results indicate (for the full sample of firms) that changes in the ergonomic characteristics of the new machinery and equipment have the highest positive impact on employee productivity (they contribute 18% of the increase in employee productivity). The functional range of new equipment and machinery has the lowest positive impact on employee productivity (about 4.5%).

The results of the fixed-panel data estimations are listed in Tables 4-7.

Table 4: Summary panel data estimations: technology-employee ratio and the technology index

	2009-2010	**2011-2012**	**2013-2014**	**2015-2016**
$\alpha_{T/EM}$	5.11 (1.88)	5.78 (2.01)	6.03 (1.78)	6.08 (2.42)
β_{TI}	4.04	4.09	5.11	5.29

	(1.64)	(2.19)	(2.06)	(2.18)
λ_{ICT}	3.27 (1.13)	3.33 (1.09)	3.59 (1.23)	3.77 (1.31)

*The t-values are in parenthesis.

Source: Own estimations

$\alpha_{T/EM}$: The positive technology-employee estimates are an indication that the percentage growth in the real spending on new technology compared to the percentage growth in real employee remuneration (technology-employee ratio increases) had a continuously positive impact on employee productivity over the bi-annual time-periods.

β_{TI} : An increase in the technology index has a continuously positive impact on employee productivity. Increased real spending on new machinery and equipment over the bi-annual time-periods created greater positive index values for the technology components and thus an increasingly positive impact on employee productivity.

λ_{CTI} : The positive estimation for ICT indicates a positive relationship between real spending on ICT and employee productivity. This is true for all the bi-annual time-periods.

Table 5: Summary panel data estimations: the functional range of new technology

	2009-2010	**2011-2012**	**2013-2014**	**2015-2016**
$\theta_{\Delta FRa\ below\ 35}$	5.14 (1.65)	5.37 (2.17)	5.54 (1.89)	5.63 (2.55)
$\theta_{\Delta FRa\ 35\text{-}55}$	6.05 (2.23)	6.19 (1.76)	6.27 (2.75)	6.51 (3.03)
$\theta_{\Delta FRa\ older\ 55}$	2.10 (1.76)	2.13 (1.21)	2.17 (1.74)	2.20 (1.82)
$\theta_{\Delta FRa\ category\ A}$	3.17 (1.88)	3.21 (1.65)	3.46 (1.68)	3.68 (1.08)
$\theta_{\Delta FRa\ category\ B}$	5.06 (2.07)	5.81 (1.99)	6.09 (2.69)	6.17 (2.32)

*The t-values are in parenthesis.

Source: Own estimations

Expansion in the functional range of new machinery and equipment has a positive percentage growth impact on employee productivity for all age groups and for the different skill levels. The positive percentage growth impact is more pertinent for the 35-55 age group and for the lower-skilled (category B) employee category. The least positive productivity growth impact is for employees in the older age bracket and for the higher-skilled employee grouping.

Table 6: Summary panel data estimations: employee effort of new technology

	2009-2010	**2011-2012**	**2013-2014**	**2015-2016**
$\theta_{\Delta EEa\ below\ 35}$	2.11 (1.01)	2.15 (1.03)	2.21 (1.08)	2.29 (1.05)
$\theta_{\Delta EEa\ 35\text{-}55}$	5.01 (2.16)	5.07 (2.05)	5.34 (1.88)	5.37 (2.17)

$\theta_{\Delta EEa\ older\ 55}$	4.13 (1.16)	4.17 (1.21)	4.51 (1.71)	4.77 (1.08)
$\theta_{\Delta EEa\ category\ A}$	3.04 (1.53)	3.14 (1.66)	3.23 (2.07)	3.31 (1.97)
$\theta_{\Delta EEa\ category\ B}$	4.11 (1.59)	4.19 (1.77)	4.53 (1.59)	4 (1.55)

*The t-values are in parenthesis.

Source: Own estimations

The employee effort impact of new technology has a positive impact on employee productivity for all age groups and skill levels. The positive impact is more pertinent for the 35-55 employee age grouping and for the lower-skilled category of employees. The employee effort impact of new technology is much lower for the youngest segment of employees and lower for the more-skilled employee category.

Table 7: Summary panel data estimations: ergonomic characteristics

	2009-2010	2011-2012	2013-2014	2015-2016
$\theta_{\Delta ERa\ below\ 35}$	3.11 (1.78)	3.21 (1.65)	3.27 (1.71)	3.51 (1.80)
$\theta_{\Delta ERa\ 35\text{-}55}$	5.71 (2.18)	5.83 (2.08)	6.04 (2.88)	6.12 (2.68)
$\theta_{\Delta ERa\ older\ 55}$	5.93 (1.98)	6.07 2.18)	6.19 (2.38)	6.37 (2.17)
$\theta_{\Delta ERa\ category\ A}$	4.04 (1.48)	4.17 (1.33)	4.23 (1.27)	4.31 (1.62)
$\theta_{\Delta ERa\ category\ B}$	3.27 (2.01)	3.31 (1.85)	3.41 (1.97)	3.53 (2.03)

*The t-values are in parenthesis.

Source: Own estimations

The improved ergonomic characteristics of new technology have a positive impact on employee productivity for all age groups and skill levels. Employees in the oldest age bracket and for the higher-skilled employee bracket experience the greatest employee productivity increase. Employees in the youngest age bracket and for the lower-skilled employee bracket experience the lowest employee productivity increase.

Table 8: Summary panel data estimations: change in employee physical control

	2009-2010	2011-2012	2013-2014	2015-2016
$\theta_{\Delta ECa\ below\ 35}$	2.91 (1.11)	3.01 (1.44)	3.11 (1.69)	3.16 (1.62)
$\theta_{\Delta ECa\ 35\text{-}55}$	4.91	5.08	5.16	5.22

	(1.99)	(2.11)	(2.13)	(2.17)
$\theta_{\Delta ECa\ older\ 55}$	4.72 (1.91)	4.84 2.06)	4.02 (1.89)	5.03 (2.29)
$\theta_{\Delta ECa\ category\ A}$	2.14 (1.31)	2.35 (1.18)	2.47 (1.19)	2.61 (1.61)
$\theta_{\Delta ECa\ category\ B}$	3.76 (1.09)	3.84 (1.05)	4.04 (1.07)	4.13 (1.16)

*The t-values are in parenthesis.

Source: Own estimations

Changes in the physical control over new machinery and equipment (less human control) have a positive impact on employee productivity for all employee age groups and skill levels. These higher employee productivity impacts are pertinent for the 35-55 employee age bracket and for lower-skilled employees. The employee productivity impacts are the lowest for the younger employee age bracket and for the higher-skilled employee segment.

Table 9: Summary panel data estimations: change in information processing

	2009-2010	2011-2012	2013-2014	2015-2016
$\theta_{\Delta IPa\ below\ 35}$	1.85 (0.81)	2.03 (0.76)	2.08 (0.49)	2.14 (0.62)
$\theta_{\Delta IPa\ 35-55}$	2.54 (1.02)	2.59 (0.99)	2.61 (1.05)	2.67 (1.01)
$\theta_{\Delta IPa\ older\ 55}$	3.02 (1.11)	3.07 (1.02)	3.14 (1.08)	3.20 (1.13)
$\theta_{\Delta IPa\ category\ A}$	2.34 (1.05)	2.41 (1.01)	2.49 (1.05)	2.51 (1.09)
$\theta_{\Delta IPa\ category\ B}$	1.67 (0.69)	1.76 (0.75)	1.79 (0.67)	1.83 (0.76)

*The t-values are in parenthesis.

Source: Own estimations

Changes in the information-processing capabilities of new machinery and equipment have a positive impact on employee productivity for all employee age groups and skill levels. These higher employee productivity impacts are pertinent for the older than 55 employee age bracket and for higher-skilled employees. The employee productivity impacts are the lowest for the younger employee age bracket and the lower-skilled employee bracket.

The estimation results, in general, indicate that the greatest positive employee productivity impact of the expansion in new technology is generated by the 35-55 age group (three of the five components of technology) and by the lower-skilled employee segment (four of the five components of technology).

5. Conclusion

The aim of this article was to determine the firm-based employee productivity impacts due to the acquisition and introduction of new production technology in the South African workplace.

The results of this study are, firstly, a confirmation of international research results that improvements in the technology base of firms have, in general, a positive impact on employee productivity. Secondly, the results of this study indicates variable positive employee productivity impacts that an improvement in production technology (via increases in the functional range of new technology, lower employee effort, improved ergonomic characteristics of new technology, less physical employee control over new technology and higher levels in information processing) has on different employee age groups and skill levels in the workplace. Thirdly, the estimation results again confirm in general the higher employee productivity levels generated by the 35-55 employee age group concluded in previous studies (Van Zyl, 2016; Van Zyl, 2017). In contrast with findings in previous studies on other aspects of firm-based employee productivity, the lower-skilled employee segment, in general, generated greater employee productivity levels due to the acquisition and implementation of new production technologies.

This study could be developed further by way of a comparative examination of the impact of technology on employee productivity between different industries. In addition, more employee diversity parameters, such as gender and race, could be included in these estimations.

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