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Industry and geographic dynamics of employee productivity levels for different major job code and age categories in the South African workplace

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Orientation: This study was part of an ongoing research project on various aspects of employee productivity in the South African workplace.

Research purpose: The aim of this study was to determine the impact of industry and geographic dynamics on the employee productivity levels of different major job code and age categories.

Motivation for the study: None of the South African publications in this particular field exist, and it was deemed to be important to close this gap in the employee productivity literature.

Research approach/design and method: This study adopted a marginal productivity model to estimate marginal employee productivity levels, employee remuneration cost levels and net marginal productivity levels for different major job code and age categories within different industries and geographical areas.

Main findings: The age categories 30–45 and 45–55 years presented, in general, higher net marginal productivity levels in relation to the other age groups. Marginal employee productivity levels per major job code differ between different geographical areas and industries.

Practical/managerial implications: The estimations indicated the importance of focusing on the diffusion of new technologies and innovations at important major job code and age categories to maximise net employee productivity levels within firms and industries.

Contribution/value-added: The study contributed to policy debates on the attainment of higher levels of employee productivity when industry and geographic dynamics on the net productivity levels of different major job code and age categories are considered.

Keywords: marginal productivity model; marginal employee remuneration costs; fixed-effect panel data estimation; net marginal productivity.

Introduction

The aim of this research study was to contribute to the South African employee productivity literature when industry and geographic dynamics of different major job code and age categories are considered.

This research study is part of a broader study on various aspects of employee productivity when firm-based data sets are applied. No specific firm-based data research has yet been conducted in South Africa on the impact of industry and geographic dynamics on different major job code and age category employee productivity levels. It is generally hypothesised that there are industry and geographic differences when employee productivity levels for different major job codes and different age categories are considered. It is argued in this article that it is important to research on the possible link between industry and geographic dynamics and employee productivity impacts of different major job code and age category combinations in order to enable employee productivity practitioners to apply an estimation technique to determine the most effective major job code and age category focus when new technologies, innovations and learning effects are deployed to maximise employee productivity levels.

Various international studies have been performed on the employee–productivity relationship for different industries and occupations. These include those by Crépon, Deniau and Pérez-Duarte (2003) on the French manufacturing and non-manufacturing industries, Aubert and Crépon (2006) on the French trading and services sectors, Daveri and Maliranta (2007) on the Finnish electronics sector, forest industry and the services sector, and Vandenberghe and Waltenberg (2010) on the Belgian manufacturing and services sectors. The findings of most of these studies are mixed in terms of age–productivity contribution and industry age–productivity dynamics. In some industries, the 'younger' age category produced greater productivity levels, while in other industries, 'middle' and 'older' age categories are more productive.

The structure of the article is as follows: in the literature overview, the focus is exclusively on the two major empirical estimation regimes that are reported in published research on the employee productivity levels of different major job code and age categories. The literature overview is followed by the research design in which (1) the different hypotheses to be tested are listed, (2) the empirical research approach is explained, (3) the research participants and data requirements are discussed, and (4) the marginal employee productivity estimation results are discussed and explained in detail. The article concludes with a summary and recommendations for further research in this field.

Literature overview

The majority of published research on the age–employee productivity debate applies a Cobb–Douglas production function in which the heterogeneity and the simultaneity of the different employee age categories are taken into consideration (Cardosa, Guimaroes & Varejao 2011; Crépon et al. 2003; Daveri et al. 2007; Göbel & Zwick 2012; Lallemand & Rycx 2009; Skirbekk 2008; Tipper 2012; Vandenberghe & Waltenberg 2010). These models used published data sets, and a pooled ordinary least squared (OLS) estimation is normally performed to capture employee productivity–age dynamics that are essentially driven by cross-sectional variation in the data sets. It is normally estimated in a log-linear format where the dependent variables are not lagged. The studies indicated that it is sometimes difficult to control for all industry or firm characteristics and OLS estimates are then likely to be biased (heterogeneity). To accommodate for heterogeneity (time invariant), generalised methods of moments (GMM) estimations are performed in which lagged values of explanatory variables are included in the estimation. The availability of longitudinal data is viewed as essential for the estimation of employee productivity–age profiles. A longitudinal 'within firm' approach is specifically applied to enable the capturing of changes in employee productivity-age category dynamics over time within the data sets. The 'within firm' approach caters for endogeneity, where any other factors that might impact the employee productivity–age relationship are catered for. The results of OLS and GMM estimations are compared to establish the validity off the different specifications. An unconstrained relationship between employee productivity and the different age categories is incorporated into the estimations. To avoid biased results most of the log-linear Cobb–Douglas estimation formats incorporate variables such as net sales (dependent variable), the tenure of employees, the skill levels of employees, the age structure of employees, a broad range of industry/firm characteristics, capital expenditure and the total number of employees per firm in the data sets. The log-linear Cobb–Douglas format assumes perfect substitution amongst employees of different age groups. To determine the correctness of the dynamic specification a test for serial correlation in the disturbance term is performed.

Hellerstein, David and Troske (1999); Roger and Wasmer (2009); and Van Ours and Stoeldraijer (2010) applied a marginal productivity approach to estimate the employee productivity–age dynamics of data sets. In the Hellerstein et al. (1999) and Van Ours and Stoeldraijer (2010) models, a log-linear estimation format of the Cobb–Douglas production function is applied; however, the concept of marginal productivity (defined as the addition to employee productivity) is incorporated into the estimation approach. The basic premise is that different age categories have different marginal productivities in relation to each other. This approach assumes perfect substitution between the different age categories and assumes constant relative employee cost across firms in the data sets. In the estimation process, pooled cross-section estimations ('as between' estimations) are performed to remove bias (e.g. it can be argued that a firm with a significant share of an employee age category, i.e., more productive than other age categories produce, on average, more than a firm that has a lower share of the same age category). The approach then includes fixed-effect estimations (referred to as 'within firm variation') to remove potential spurious correlation effects between employee productivity–age category dynamics (e.g. it can be argued that an age category can be more productive than another age category in comparable firms when the production output share of the more productive employee age category increases more in relation to the production output share of the other employee age categories). As is the case with the Cobb–Douglas approach, in general, potential endogeneity bias is cleared by the application of GMM in which the age category variables are lagged with two periods and finally by three periods as additional instrumental variables. The variables of the log-linear specification are real sales value or real production added (dependent variable) and independent variables are normally capital expenditure, the number of employees in the different age categories, average total number of employees in the data set and industry/firm characteristics. The Roger and Wasmer (2009) model applied a unique production function approach in which a nested constant-elasticity-of-substitution (CES) specification is applied. It is not a log-linear format. In this approach imperfect substitution between different categories of employees is possible and employee productivity–age category dynamics might differ between different major occupations. This approach allows for (1) the determination of marginal productivities across different age categories, (2) employee remuneration cost comparison between different employee age categories and net productivity levels of the different age categories, within data sets.

The estimation approach adopted in this article is a log-linear marginal productivity approach, and it applies certain methodologies from the Van Ours and Stoeldraijer (2010) and Roger and Wasmer (2009) models. The data sets used in this study are not published data sets but exclusively sample data sets. This necessitated the adoption of a different variation and methodology for the productivity model specification for the firm-based data sets drawn from a South African sample.

Research design

The research design comprises the hypothesis to be tested, research participants (sample sets) and data requirements, and an outline of the research approach. This is followed by a step-by-step description of the estimation model specification.

Hypotheses

Four hypotheses and null hypotheses were tested in the article, which are as follows:

H1: For the firm-based data sets, the employee productivity levels per major job-age category, within the same industry, differ between the three different geographical areas.

H1$_o$: For the firm-based data sets, the employee productivity levels per major job-age category, within the same industry, do not differ between the three different geographical areas.

H2: For the firm-based data sets, the employee productivity contributions per major job-age category differ between industries and between geographical areas.

H2$_o$: For the firm-based data sets, the employee productivity contributions per major job-age category do not differ between industries and between geographic areas.

H3: For the firm-based data sets, net employee productivity contribution per major job-age category is affected by the impact of remuneration cost levels (within different industries and between the different geographical areas).

H3$_o$: For the firm-based data sets, net employee productivity contribution per major job-age category is not affected by the impact of the remuneration cost levels (within different industries and between the different geographical areas).

H4: For the firm-based data sets, net employee productivity levels per major job-category, industry and geographical area differ and the net productivity levels in the lower gross geographic product (GGP) area are not consistently and significantly lower when compared with higher GGP geographical areas.

H4$_o$: For the firm-based data sets, net employee productivity levels per major job-category, industry and geographical area differ and the net productivity levels in the lower GGP area are consistently and significantly lower when compared with higher GGP geographical areas.

Research approach

A marginal productivity approach was applied to estimate the productivity levels of different major job code and age categories in different industries and geographical areas. Firm-based time-series were employed and applied in the estimation processes. The aim of the marginal productivity approach was to determine the marginal productivity contributions, the marginal employee remuneration cost efficiencies and, finally the net marginal productivities of all the major job code – age categories (per industry and geographical area).

For the marginal productivity approach, the general assumption was adopted that the marginal productivity contribution of employees in different major job code and age categories are more effectively captured when the ratios of the marginal productivities in the different major job code and age categories are estimated and compared. In the model specification the marginal productivity distribution and remuneration cost estimates for the different major job code and age categories were first estimated. Then, the estimates of the first log-linear model were applied in a second log-linear estimation where the different marginal productivity ratios, employee remuneration cost ratios and the net marginal productivity ratios (between different major job code and age categories) were estimated. In this article the construction and manufacturing industries are used as proxy industries (based on their importance in the GGP of any geographic area in South Africa). The Gauteng, Western Cape and the Eastern Cape provinces were proxy geographical areas (with the aim of reflecting provinces with varying GGP levels). The Gauteng province represented the high GGP geographic area, the Western Cape province represented the middle-to-high GGP geographical area, while the Eastern Cape province represented the low-to-middle GGP geographical area.

The study applied International Standard Classification of Occupations (ISCO)-88 major job codes 72 (721, 722, 723) and 73 (731, 732) for the manufacturing industry and major job code 71 (711, 712, 713) for the construction industry. The different major job and sub-codes are listed in Table 1.

The introduction of the three major job codes in the article was carried out to capture job-related estimation differentials. Four age categories were included in the study (younger than 30 years age category, 30–45 years age category, 45–55 years age category and the 55 years and older age category). The age categories were constructed to cater for possible international comparisons and for data availability.

TABLE 1: Different International Standard Classification of Occupations-88 major job codes.

Industry	Major job code	Description of occupation
Construction	Code 71	Building and related-trade workers
	Sub-code 711	Building frame and related-trade workers
	Sub-code 712	Building finishers and related-trade workers
	Sub-code 713	Painters, building structurer cleaners and related-trade workers
Manufacturing	Code 72	Metal, machinery and related-trades workers
	Sub-code 721	Sheet and structural metal workers, moulders and welders
	Sub-code 722	Blacksmiths, toolmakers and related trades workers
	Sub-code 723	Machinery, mechanics and repairers
	Code 73	Handicraft and printing workers
	Sub-code 731	Handicraft workers
	Sub-code 732	Printing trades workers

Source: ILO ISCO-88.

Research participants and data requirements

The quarterly sample period was 2013Q1–2018Q4. Rich firm-based sample data sets were established by the author over a period of 15 years in the manufacturing and construction industries for various geographical areas in South Africa. The sampling of firms was performed in such a manner that the firms cover a variety of sub-sectors in the two industries. The sample sets were deemed to be statistically significant. The sample data sets for the different manufacturing industries in the three geographical areas were supplied by 68 firms in the Gauteng province, 58 firms in the Western Cape province and 36 firms in the Eastern Cape province. The sample data sets for the different construction industries in the three geographical areas were supplied by 45 firms in the Gauteng province, 32 firms in the Western Cape province and 22 firms in the Eastern Cape province. All the data sets collected from the firms in the two industries were secondary data. Ethical clearance (ethical clearance code 21SECO035) was obtained to use the sample firm-based data sets.

For the marginal productivity model estimations, the following time-series for the average of each sample data set were constructed:

- Average quarterly data series for total real sales for the two industries in the three different geographical areas.
- Average quarterly data series on the changes in real sales for the two industries in the three different geographical areas.
- Average quarterly data series on changes in real capital stock per industry.
- Average quarterly data series on firm-based dynamics for the two industries such as the level of the introduction of new technology (0 if no new technology was used, 1 if low levels of new technology were used and 2 if higher levels of new technology were used), changes in industry dynamics (0 if slow adaptation to changing industry dynamics was experienced and 1 if the adaptation to changing industry dynamics was satisfactory) and firm profitability for the full firm-based data sets per industry and geographical area.
- Average quarterly data series on the number of employees in the different major job code and age categories for each industry in the three geographical areas.
- Average quarterly data series of the percentage change in the number of employees per major job code category for the two industries in the three different geographical areas.
- Quarterly data series for the ratio of the average percentage change in the number of employees per major job code – age category and the average percentage change in real sales.
- Quarterly data series of the total employee remuneration cost per major job code and age category per industry and geographical area.
- Quarterly data series for the percentage change in employee remuneration costs per major job code and age category per industry and geographical area.
- Quarterly data series for the ratio of the percentage change in real sales and the percentage change in employee remuneration costs per major job code and age category per industry and geographical area.

Presentation of the marginal employee productivity estimation model

In order to estimate the marginal productivity ratios, marginal employee remuneration cost ratios and net marginal productivity ratios, distribution and substitution estimates and the employee remuneration estimates for the major job code and age categories (for the two industries in the three geographical areas) had to be estimated. Distribution estimates refer to the spread of marginal productivity levels between the different age categories within the same major job category, while substitution estimates refer to the substitution of marginal productivity levels between different major job codes. Both distribution and substitution estimates were incorporated into the second log-linear estimation model when the marginal productivity ratios of the different major job code and age categories for the two industries in the three geographical areas were estimated. Average data series for marginal employee remuneration costs were constructed as the average percentage change in real remuneration levels per major job code and age category divided by the percentage change in the average real total remuneration cost per major job code (per industry and geographical area).

The first log-linear specification was applied to estimate the marginal productivities of the different major job code and age categories (in the two industries and the three geographical areas). The specification assumed that the different employee age categories were treated heterogeneously for different major job code and age groupings but homogeneously within the same major job code and age categories. The log-linear specification allowed for the estimation of the distribution and the substitution estimates that will determine marginal productivity differentials per major job code and age category and the marginal remuneration cost estimates (in the two industries and three geographical areas). The distribution estimates indicated the marginal productivity gains within a major job code for different age categories, while the substitution estimates indicated the marginal productivity gains between the different job code and age categories. The first log-linear estimation is specified as follows:

$$\mathit{ln}\mathrm{RS}_{ij} = a + \alpha \mathit{ln}\mathrm{K}_{ij} + \psi \mathit{ln}\mathrm{FC}_{ij} + \beta \mathit{ln}\mathrm{L}_{ij} + \delta_{aij} \mathit{ln}\mathrm{JC}^{sp-1} + \gamma \mathit{ln}\mathrm{ERC}_{ijl} + \varepsilon, \qquad \text{[Eqn 1]}$$

where $\mathit{ln}\mathrm{RS}_{ij}$ is the average quarterly changes in real sales and serves as the proxy for marginal productivity changes; $\alpha \mathit{ln}\mathrm{K}_{ij}$ is the estimate of the marginal efficiency of the real capital stock per industry and geographical area, $\psi \mathit{ln}\mathrm{FC}_{ij}$ estimates other firm-level controls per industry and geographical area; $\beta \mathit{ln}\mathrm{L}_{ij}$ estimates the marginal productivity of the total number of employees in different industries and geographical areas; $\delta \mathit{ln}_j\mathrm{JC}_{aij}^{\ sp-1}$ estimates the distribution parameters of marginal productivity within the same major job code for the different age categories and *sp* is the substitution parameters of marginal productivity between the different job code and age categories; $\gamma \mathit{ln}\mathrm{ERC}_{aij}$ is the estimate for the employee remuneration costs per major job code and age category in the two industries and three geographical areas; and ε is the error term.

The signs of the estimates for $\alpha ln K_{ij}$ (marginal efficiency of capital stock) and $\psi ln FC_{ij}$ (other firm-based characteristics) were important to understand and explain the magnitudes of marginal productivity estimates. The marginal efficiency of capital stock refers to the acquisition and diffusion of new technologies and innovations. Studies such as Altamirano and De Beers (2017), Brynjolfsson and Hitt (2003) and Goodrum and Haas (2004), strongly proposed the integration of the acquisition and diffusion of new technologies and innovations in econometric estimations when employee productivity spill-over effects are measured. A positive sign for $\alpha ln K_{ij}$ indicated that the efficiency of capital (more specifically greater levels of the acquisition and diffusion of new technologies and innovations) for the sample data sets has a positive impact on marginal productivity. The reverse argument is true for a negative sign. A positive sign for $\psi ln FC_{ij}$ indicated that changes in other firm-based characteristics such as higher levels of new technology acquisition and innovation, adaptation to dynamic industry changes and higher profitability levels will have a positive impact on marginal productivity. The reverse argument is true for a negative sign.

A comparison of marginal productivities for the different major job code and age categories required the estimation of the ratios between the different marginal productivities of the different major job code and age categories. In essence the marginal productivity levels of the different age categories can be established (in real terms) only if they are viewed in relation to the marginal productivity levels of other age categories per the same major job code (thus the use of a ratio approach). The ratio of different distribution parameters represents the ratio of the marginal productivity levels of the different major job code and age categories (Roger and Wasmer 2009):

$$ME_{J1\text{-}A1}/ME_{J1\text{-}A2} = \partial L/\partial L_{J\text{-}A1} \div \partial L/\partial L_{J\text{-}A2} = \lambda = \delta_{J1\text{-}A1}/\delta_{J1\text{-}A2}(L_{J\text{-}A1}/L_{J\text{-}A2})^{sp\text{-}1}. \quad \text{[Eqn 2]}$$

In Equation 2, the ratio of the marginal productivities for different age categories within the same major job code is defined as the marginal productivity of age group 1 divided by the marginal productivity of age group 2 ($ME_{J1\text{-}A1}/ME_{J1\text{-}A2}$). This ratio is equal to λ, which is equal to the ratio of the two estimated distribution parameters for the different age categories but for the same major job code ($\delta_{J1\text{-}A1} / \delta_{J1\text{-}A2}$), given the ratio of the average total number of employees for the same major job code but for different age categories (for a specific substitution parameter sp^{-1}). Series for the different λ-ratios of all the different age categories per major job code for the two industries and three geographical areas were constructed.

The specifications for the different marginal productivity distribution parameter ratios (λ), the employee remuneration cost ratios (γ) and the net marginal productivity parameter ratios (Ŋ) are listed in Table 2.

The λ-ratio estimates enabled a comparison of the marginal productivities between different age categories per major job code and between the two industries in the three geographical areas. Higher λ-ratio estimates indicated higher comparable marginal productivity ratios, while lower λ-ratio estimates indicated lower comparable marginal productivity ratios. As an example, assume that the λ_4 estimate for major code 72 is 1.75. An estimate of 1.75 for λ_4 (representing the ratio of the marginal productivities for the age category 30–45 years and the age category younger than 30 years) is an indication that the marginal productivity of the age category 30–45 years is (in relation) higher than the marginal productivity of the age category younger than 30 years.

TABLE 2: Specification of the marginal productivity distribution parameter ratios, employee remuneration cost parameter ratios and the net marginal productivity parameter ratios.

Parameters	Parameter ratio specification
λ_1-γ_1-Ŋ$_1$	Ratio of age group younger than 30 years and age group between 30 and 45 years
λ_2-γ_2-Ŋ$_2$	Ratio of age group younger than 30 years and age group between 45 and 55 years
λ_3-γ_3-Ŋ$_3$	Ratio of age group younger than 30 years and age group older than 55
λ_4-γ_4-Ŋ$_4$	Ratio of age group between 30 and 45 years and age group younger than 30 years
λ_5-γ_5-Ŋ$_5$	Ratio of age group between 30 and 45 years and age group between 45 and 55 years
λ_6-γ_6-Ŋ$_6$	Ratio of age group between 30 and 45 years and age group older than 55 years
λ_7-γ_7-Ŋ$_7$	Ratio of age group between 45 and 55 years and age group younger than 30 years
λ_8-γ_8-Ŋ$_8$	Ratio of age group between 45 and 55 years and age group between 30 and 45 years
λ_9-γ_9-Ŋ$_9$	Ratio of age group between 45 and 55 years and age group older than 55 years
λ_{10}-γ_{10}-Ŋ$_{10}$	Ratio of age group older than 55 years and age group younger than 30 years
λ_{11}-γ_{11}-Ŋ$_{11}$	Ratio of age group older than 55 years and age group between 30 and 45 years
λ_{12}-γ_{12}-Ŋ$_{12}$	Ratio of age group older than 55 years and age group between 45 and 55 years

For the same major job code, a greater employee remuneration cost ratio estimate (γ) is indicative of higher real marginal remuneration costs per age category, while a smaller employee remuneration cost ratio estimate is indicative of lower real marginal remuneration cost per age category. The marginal employee remuneration cost ratios can be explained in the following manner: assume that the parameter estimate γ_1 for major job category 71 (ratio between age categories younger than 30 years and 30–45 years) is equal to 0.60. The fact that the γ_1 estimate for major job code 71 is less than 1 indicates that the marginal employee remuneration cost estimate for the younger than 30 years age group is (in relation) lower than the marginal employee remuneration cost estimate of the 30–45 years age category.

The net marginal productivity ratios (Ŋ) of all the different age categories, per major job code, were computed as the marginal productivity ratio of two major job code and age categories (λ) divided by the marginal employee remuneration cost ratio of the same two major job code and age categories (γ). Greater net marginal productivity ratio estimates are indicative of a greater net marginal productivity level for a major job code and age category. Assume that the Ŋ$_1$ (net marginal productivity ratio for the younger than 30 years age category in relation to the 30–45 years age category) estimate for major job code 71 is equal to 1.20. The estimate for the net marginal productivity parameter ratio of 1.20 is a clear indication that the net marginal productivity ratio for the younger than 30 years age category in relation to the 30–45 years age category is superior.

The next step in estimation was to construct different series for λ, γ and Ŋ ratios per major job code in the two industries and the three geographical areas (the different estimates of the first log-linear estimation were applied). A second log-linear estimation was performed where the weighted series for the average percentage change in real sales was the dependent variable and the different λ, γ and Ŋ ratios (per major job code in the two industries in the three different geographical industries) the independent variables. The estimates (per major job code, industry and geographical area) indicated the different marginal productivity, marginal remuneration costs and net marginal productivity contributions of the different age categories in relation to the other age categories:

$$ln\%\Delta \mathrm{RS}_{ij} = \mathrm{a} + \lambda ln\mathrm{MPC}_{aij} + \gamma ln\mathrm{MRC}_{aij} + \text{Ŋ} ln\mathrm{NMB}_{aij} + \varepsilon \qquad \text{[Eqn 3]}$$

where $ln\%\Delta \mathrm{RS}_{ij}$ is the percentage change in real sales; $\lambda ln\mathrm{MPC}_{aij}$ represents the marginal productivity ratio estimates for all the major job code and age categories in the two industries and the three geographical areas; $\gamma ln\mathrm{MRC}_{aij}$ represents the marginal remuneration cost ratio estimates for all the major job code and age categories in the two industries and the three geographical areas; $\text{Ŋ} ln\mathrm{NMB}_{aij}$ represents the net marginal productivity ratio estimates for all the major job codes and age categories in the two industries and the three geographical areas.

Estimation results

The final estimation results (after possible heterogeneity, simultaneity and correlation effects were catered for) are presented in Tables 3, 4.

Presentation and discussion of the final estimation results for the construction industry (major job code 71)

The final efficiency of the capital estimate, firm-based control estimate, the marginal productivity distribution ratio estimates, the employee remuneration cost ratio estimates and the net marginal productivity ratio estimates for the construction industries (major job code 71) are displayed in Table 3.

For the construction industry, efficiency estimates for the capital outlay (α) are positive, indicating a positive relationship between the efficiency of capital stock (the acquisition and diffusion of new technologies and innovations) and marginal employee productivity. The estimations for firm-based characteristics (ψ) are significantly positive. The estimations are indicative of a strong impact of greater levels of investment in new technology and innovation, faster adaptation to changing industry dynamics and higher levels of profitability on employee productivity levels.

The marginal productivity distribution ratio estimates of the younger than 30 years age category (all three geographical areas) were consistently less than (in relation to) those of the other three age groupings (λ_1; λ_2; λ_3). For both the Gauteng and Western Cape provinces, the estimated marginal productivity distribution ratios for the two 45–55 age categories are greater than (in relation to) the 30–45 age categories (λ_7; λ_8; λ_9). For the Eastern Cape province, the estimates for the marginal productivity distribution ratios for the 30–45 years age category were greater in relation to the 45–55 years age category (λ_4; λ_5; λ_6). In general, the magnitude of the marginal productivity distribution ratios differs between the three geographical areas.

The marginal remuneration cost ratio estimates indicated the lowest relative marginal remuneration cost levels for the younger than 30 years age category in relation to the other age categories in all three geographical areas (γ_1; γ_2; γ_3). In relation to the other age categories, the estimates indicate that the 30–45 years age category has the highest marginal remuneration cost levels (γ_4; γ_5; γ_6), except for the Eastern Cape province, where the 45–55 years age category had the highest marginal remuneration cost estimates (γ_7; γ_8; γ_9).

The net marginal productivity ratio estimates for the 45–55 years age category for both the Gauteng and Western Cape provinces were greater than 1, indicating superior net marginal productivity levels for the 45–55 years age group in relation to the other age categories (Ŋ_7; Ŋ_8; Ŋ_9). For the Eastern Cape province, the net marginal productivity estimates for the 45–55 years age category were all less than 1(Ŋ_7; Ŋ_8; Ŋ_9), indicating inferior net marginal productivity levels in relation to all the other age groups. The net marginal productivity estimates for the 30–45 years age category in the Eastern Cape province were greater than 1(Ŋ_4; Ŋ_5; Ŋ_6), indicating superior net marginal productivity levels in relation to the other age categories. In the Western Cape province, the net marginal productivity estimates for the older than 55 years age group in relation to all the other age categories were all less than 1(Ŋ_{10}; Ŋ_{11}; Ŋ_{12}) but the estimates were mixed (either greater or less than 1) for both the Gauteng and Eastern Cape provinces. The net marginal productivity estimates for the younger than 30 years age category were also mixed (either greater or less than 1) for the three geographical areas.

Table 4 displays the final efficiency of capital estimate, the firm-based control estimate, the marginal productivity distribution ratio estimates, the employee remuneration cost ratio estimates and the net marginal productivity ratio estimates for the manufacturing industries (major job codes 72 and 73).

According to the final model estimates of the manufacturing industries for major job codes 72 and 73 as presented in Table 4, the industry efficiency estimates for the capital

TABLE 3: Capital efficiency, firm-based characteristics and estimates of the marginal productivity model for the construction industries.

Major job code	Industry	Descriptor	Parameter	Estimate (α and ψ)	G	WC	EC
71	Construction	-	α	1.92* (0.82)	-	-	-
-	-	-	ψ	2.61* (0.55)	-	-	-
		Marginal productivity ratio parameter estimates					
-	-	-	λ_1	-	0.75* (0.24)	0.71* (0.22)	0.69* (0.24)
-	-	-	λ_2	-	0.69* (0.16)	0.70* (0.12)	0.76* (0.21)
-	-	-	λ_3	-	0.81* (0.17)	0.92* (0.20)	0.85* (0.28)
-	-	-	λ_4	-	1.35* (0.41)	1.43* (0.48)	1.46* (0.36)
-	-	-	λ_5	-	0.93* (0.26)	0.99* (0.31)	1.11* (0.36)
-	-	-	λ_6	-	1.09* (0.33)	1.31* (0.51)	1.23* (0.39)
-	-	-	λ_7	-	1.46* (0.35)	1.45* (0.40)	1.32* (0.49)
-	-	-	λ_8	-	1.08* (0.39)	1.02* (0.25)	0.91* (0.30)
-	-	-	λ_9	-	1.18* (0.37)	1.33* (0.53)	1.12* (0.41)
-	-	-	λ_{10}	-	1.24* (0.43)	1.09* (0.33)	1.19* (0.29)
-	-	-	λ_{11}	-	0.92* (0.28)	0.77* (0.16)	0.82* (0.19)
-	-	-	λ_{12}	-	0.85* (0.21)	0.76* (0.18)	0.90* (0.20)
		Marginal remuneration cost ratio parameter estimates		-			
-	-	-	γ_1	-	0.75* (0.21)	0.80* (0.19)	0.78* (0.20)
-	-	-	γ_2	-	0.80* (0.32)	0.81* (0.22)	0.73* (0.27)
-	-	-	γ_3	-	0.87* (0.21)	0.89* (0.21)	0.82* (0.21)
-	-	-	γ_4	-	1.34* (0.41)	1.26* (0.31)	1.29* (0.25)
-	-	-	γ_5	-	1.07* (0.19)	1.02* (0.25)	0.94* (0.20)
-	-	-	γ_6	-	1.16* (0.31)	1.12* (0.29)	1.06* (0.17)
-	-	-	γ_7	-	1.26* (0.39)	1.24* (0.40)	1.38* (0.37)
-	-	-	γ_8	-	0.94* (0.28)	0.99* (0.30)	1.07* (0.19)
-	-	-	γ_9	-	1.09* (0.22)	1.10* (0.17)	1.13* (0.23)
-	-	-	γ_{10}	-	1.16* (0.23)	1.13* (0.36)	1.23* (0.27)
-	-	-	γ_{11}	-	0.87* (0.20)	0.90* (0.17)	0.96* (0.16)
-	-	-	γ_{12}	-	0.92* (0.20)	0.92* (0.19)	0.89* (0.17)
		Net marginal productivity ratio parameter estimates					
-	-	-	Ŋ_1	-	1.01* (0.20)	0.89* (0.15)	0.88* (0.19)
-	-	-	Ŋ_2	-	0.87* (0.21)	0.87* (0.17)	1.05* (0.22)
-	-	-	Ŋ_3	-	0.94* (0.16)	1.04* (0.21)	1.06* (0.17)
-	-	-	Ŋ_4	-	1.01* (0.14)	1.12* (0.21)	1.14* (0.23)
-	-	-	Ŋ_5	-	0.87* (0.15)	0.97* (0.21)	1.18* (0.25)
-	-	-	Ŋ_6	-	0.94* (0.19)	1.17* (0.25)	1.16* (0.21)
-	-	-	Ŋ_7	-	1.15* (0.33)	1.18* (0.29)	0.96* (0.17)
-	-	-	Ŋ_8	-	1.15* (0.21)	1.03* (0.19)	0.85* (0.20)
-	-	-	Ŋ_9	-	1.09* (0.21)	1.21* (0.31)	0.99* (0.22)

Table 3 continues on the next page →

TABLE 3 (Continues...): Capital efficiency, firm-based characteristics and estimates of the marginal productivity model for the construction industries.

Major job code	Industry	Descriptor	Parameter	Estimate (α and ψ)	G	WC	EC
-	-	-	$Ŋ_{10}$	-	1.07* (0.19)	0.97* (0.21)	0.97* (0.18)
-	-	-	$Ŋ_{11}$	-	1.06* (0.17)	0.86* (0.14)	0.86* (0.15)
-	-	-	$Ŋ_{12}$	-	0.93* (0.21)	0.83* (0.16)	1.02* (0.23)

*, $p < 0.05$; *t*-values are in parenthesis.
G, Gauteng; WC, Cape; EC, Eastern Cape.

outlay (the acquisition and diffusion of new technologies and innovations) (α) and for firm-based characteristics (ψ) are both significant and positive for the manufacturing industries. As was the case with the construction industry, the significant positive estimates are indicative of a strong impact of greater levels of the acquisition and diffusion of new technology and innovation, faster adaptation to changing industry dynamics and higher levels of profitability on employee productivity levels.

For both major job codes in the manufacturing industries, the marginal productivity distribution ratio estimates for both the younger than 30 years ($\lambda_{1;}\lambda_{2;}\lambda_{3}$) and older than 55 years ($\lambda_{10;}\lambda_{11;}\lambda_{12}$) age categories were less than (in relation to) the marginal productivity distribution estimates of the other two age categories. The marginal productivity distribution ratio parameter estimates for the 30–45 years ($\lambda_{4;}\ \lambda_{5;}\ \lambda_{6}$) and the 45–55 years ($\lambda_{7;}\ \lambda_{8;}\ \lambda_{9}$) age group were all greater than 1 (for all three geographical areas), indicating superior marginal productivity levels in relation to the other two age categories. It is important to note that the differentials of the distribution ratio estimates of the 30–45 years and 45–55 years age categories were relatively small.

The marginal employee remuneration cost ratio estimates for major job codes 72 and 73 indicated that the marginal remuneration cost levels of the 30–45 years age category were the highest in relation to the other three age categories ($\gamma_{4;}\gamma_{5;}\gamma_{6}$), followed by the 45–55 years age category ($\gamma_{7;}\gamma_{8;}\gamma_{9}$). The estimation differentials between the 30–45 years and 45–55 years age categories were relatively small. The marginal remuneration cost ratio estimates for the younger than 30 years ($\gamma_{1;}\ \gamma_{2;}\ \gamma_{3}$) were all less than 1 (for both codes and for all three geographical areas): a clear indication of the superior marginal remuneration cost levels of this age category in relation to the other age categories.

The net marginal productivity ratio estimation results were mixed and differ between the two major job codes and between the different geographical areas. For the Gauteng province, major job code 72, the estimations were all greater than 1 for the age categories younger than 30 years, 30–45 years and the 45–55 years in relation to each other. The net marginal productivity differentials between these three age categories are relatively small. The estimates for the older than 55 years age group were all smaller than 1, indicating inferior net marginal productivity levels in relation to the other age groups. A totally different picture emerged for major job code 73 estimates. The estimates for the older than 55 years age group in relation to the other three age categories were greater than 1, indicating superior net marginal productivity levels in relation to the other three age categories. The net marginal productivity estimation results for the 45–55 age group ($Ŋ_{7;}\ Ŋ_{8;}\ Ŋ_{9}$) are less than 1, indicating inferior net marginal productivity levels in relation to the other age categories.

For the Western Cape province, the estimates for major job codes 72 and 73 were also relatively mixed. The estimates for major code 72 indicated that the net marginal productivity levels of the 45–55 years age group ($Ŋ_{7;}\ Ŋ_{8;}\ Ŋ_{9}$) were superior in relation to the other age groups but for major job code 73 the estimation results for the same age category indicated inferior net marginal productivity levels in relation to all the other age groups. For major job code 72 the estimates indicated that the net marginal productivity levels of the 30–45 years age category ($Ŋ_{4;}\ Ŋ_{5;}\ Ŋ_{6}$) were inferior in relation to all the other age groups but a mixed picture emerged for major job code 73. All the net marginal productivity estimates for the younger than 30 years age group for major job code 73 were greater than 1 ($Ŋ_{1;}\ Ŋ_{2;}\ Ŋ_{3}$), indicating superior net marginal productivity levels in relation to the other age groups (the estimates for job code 72 are mixed). The estimates for the older than 55 years age category were mixed for both major job codes.

As was the case with the other two geographical areas, the estimates for the Eastern Cape differ between the two major job codes. For major job code 72 the estimates for the 45–55 years age group ($Ŋ_{7;}\ Ŋ_{8;}\ Ŋ_{9}$) were greater than 1, indicating superior net marginal productivity levels in relation to the other age categories. For major job code 73 the estimates for the same age category were all less than 1, indicating inferior net marginal productivity levels in relation to the other age categories. A similar pattern emerged for the older than 55 years age category. The estimates for the older than 55 years age category for major job code 72 were less than 1 (indicating inferior net marginal productivity levels in relation to all the other age categories) but for major job code 73 the estimates were all greater than 1 (indicating superior net marginal productivity levels in relation to all the other age categories). The estimates for the 30–45 years age category were also mixed.

Discussion of the final estimation results in terms of the stated hypothesis

What can be derived from all the discussions of the estimation results? In terms of the different marginal productivity

TABLE 4: Capital efficiency, firm-based characteristics and the marginal productivity model estimates for the manufacturing industries.

Major job code	Industry	Descriptor	Parameter	Estimate (α and ψ)	G	WC	EC
72 and 73	Manufacturing	-	α	1.82* (0.45)	-	-	-
-	-	-	Ψ	2.35* (0.63)	-	-	-
		Marginal productivity ratio parameter estimates					
72	-	-	λ_1	-	0.84* (0.21)	0.83* (0.19)	0.75* (0.17)
73					0.73* (0.15)	0.83* (0.20)	0.82* (0.17)
72	-	-	λ_2	-	0.87* (0.22)	0.82* (0.15)	0.80* (0.18)
73					0.75* (0.13)	0.86* (0.23)	0.90* (0.20)
72	-	-	λ_3	-	0.98* (0.24)	0.94* (0.21)	0.98* (0.30)
73					0.89* (0.21)	0.89* (0.26)	0.94* (0.18)
72	-	-	λ_4	-	1.20* (0.39)	1.21* (0.34)	1.35* (0.29)
73					1.37* (0.43)	1.21* (0.20)	1.23* (0.22)
72	-	-	λ_5	-	1.04* (0.21)	1.01* (0.30)	1.07* (0.26)
73					1.02* (0.18)	1.03* (0.14)	1.10* (0.22)
72	-	-	λ_6	-	1.18* (0.23)	1.12* (0.31)	1.32* (0.40)
73					1.22* (0.31)	1.23* (0.27)	1.15* (0.21)
72	-	-	λ_7	-	1.16* (0.21)	1.23* (0.34)	1.26* (0.29)
73					1.35* (0.36)	1.18* (0.29)	1.12* (0.22)
72	-	-	λ_8	-	0.97* (0.23)	1.03* (0.18)	0.94* (0.24)
73					0.99* (0.17)	1.01* (0.23)	0.92* (0.19)
72	-	-	λ_9	-	1.14* (0.27)	1.15* (0.33)	1.24* (0.40)
73					1.20* (0.26)	1.21* (0.16)	1.05* (0.20)
72	-	-	λ_{10}	-	1.02* (0.23)	0.97* (0.18)	1.03* (0.15)
73					1.13* (0.21)	0.98* (0.13)	1.07* (0.17)
72	-	-	λ_{11}	-	0.86* (0.20)	0.90* (0.23)	0.76* (0.17)
73					0.83* (0.20)	0.82* (0.18)	0.88* (0.22)
72	-	-	λ_{12}	-	0.89* (0.23)	0.88* (0.24)	0.81* (0.17)
73					0.84* (0.21)	0.84* (0.18)	0.96* (0.25)
		Marginal remuneration cost ratio parameter estimates					
72	-	-	γ_1	-	0.84* (0.22)	0.83* (0.17)	0.80* (0.15)
73					0.79* (0.14)	0.78* (0.16)	0.76* (0.15)
72	-	-	γ_2	-	0.87* (0.21)	0.86* (0.24)	0.87* (0.22)
73					0.73* (0.16)	0.71* (0.13)	0.68* (0.20)
72	-	-	γ_3	-	0.97* (0.24)	0.96* (0.19)	0.90* (0.26)
73					0.98* (0.25)	0.97* (0.22)	0.94* (0.26)
72	-	-	γ_4	-	1.20* (0.31)	1.22* (0.35)	1.25* (0.29)
73					1.28* (0.33)	1.27* (0.29)	1.33* (0.41)
72	-	-	γ_5	-	1.04* (0.18)	1.13* (0.20)	1.08* (0.17)
73					0.92* (0.21)	1.18* (0.21)	0.91* (0.21)
72	-	-	γ_6	-	1.16* (0.24)	1.17* (0.21)	1.12* (0.19)
73					1.24* (0.25)	1.23* (0.20)	1.24* (0.23)
72	-	-	γ_7	-	1.15* (0.29)	1.15* (0.30)	1.18* (0.27)
73					1.39* (0.31)	1.22* (0.29)	1.48* (0.34)

Table 4 continues on the next page →

TABLE 4 (Continues...): Capital efficiency, firm-based characteristics and the marginal productivity model estimates for the manufacturing industries.

Major job code	Industry	Descriptor	Parameter	Estimate (α and ψ)	G	WC	EC
72	-	-	γ_8	-	0.97* (0.18)	0.96* (0.20)	0.94* (0.17)
73					1.09* (0.15)	1.12* (0.20)	1.13* (0.17)
72	-	-	γ_9	-	1.12* (0.21)	1.08* (0.14)	1.05* (0.11)
73					1.35* (0.31)	1.17* (0.35)	1.39* (0.28)
72	-	-	γ_{10}	-	1.04* (0.20)	1.05* (0.18)	1.12* (0.21)
73					1.03* (0.12)	1.04* (0171)	1.07* (0.13)
72	-	-	γ_{11}	-	0.87* (0.22)	0.86* (0.18)	0.90* (0.21)
73					0.81* (0.16)	0.82* (0.20)	0.81* (0.18)
72	-	-	γ_{12}	-	0.90* (0.21)	0.91* (0.17)	0.96* (0.19)
73					0.75* (0.14)	0.74* (0.11)	0.73* (0.15)
		Net marginal productivity ratio parameter estimates					
72	-	-	η_1	-	1.01* (0.17)	1.02* (0.19)	0.94* (0.15)
73					0.93* (0.21)	1.05* (0.17)	1.08* (0.19)
72	-	-	η_2	-	1.02* (0.18)	0.96* (0.20)	0.93* (0.20)
73					1.03* (0.14)	1.22* (0.22)	1.33* (0.25)
72	-	-	η_3	-	1.01* (0.16)	0.98* (0.20)	1.09* (0.15)
73					0.91* (0.21)	1.06* (0.18)	1.01* (0.12)
72	-	-	η_4	-	1.01* (0.14)	0.99* (0.24)	1.08* (0.21)
73					1.07* (0.11)	0.95* (0.18)	0.93* (0.18)
72	-	-	η_5	-	1.01* (0.23)	0.95* (0.22)	0.99* (0.22)
73					1.11* (0.25)	1.15* (0.35)	1.23* (0.26)
72	-	-	η_6	-	1.02* (0.20)	0.96* (0.21)	1.18* (0.24)
73					0.99* (0.18)	1.01* (0.17)	0.93* (0.17)
72	-	-	η_7	-	1.01* (0.23)	1.06* (0.23)	1.08* (0.21)
73					0.98* (0.18)	0.83* (0.17)	0.76* (0.18)
72	-	-	η_8	-	1.01* (0.22)	1.07* (0.14)	1.01* (0.21)
73					0.91* (0.18)	0.88* (0.12)	0.83* (0.13)
72	-	-	η_9	-	1.02* (0.16)	1.20* (0.34)	1.18* (0.24)
73					0.89* (0.13)	0.87* (0.17)	0.76* (0.11)
72	-	-	η_{10}	-	0.98* (0.17)	1.02* (0.23)	0.92* (0.20)
73					1.10* (0.21)	0.95* (0.13)	1.01* (0.17)
72	-	-	η_{11}	-	0.99* (0.15)	1.05* (0.15)	0.85* (0.19)
73					1.03* (0.18)	1.01* (0.13)	1.09* (0.21)
72	-	-	η_{12}	-	0.99* (0.23)	0.98* (0.22)	0.85* (0.20)
73					1.12* (0.25)	1.14* (0.26)	1.32* (0.23)

*, $p < 0.05$; t-values are provided in parenthesis.
G, Gauteng; WC, Cape; EC, Eastern Cape.

distribution ratios estimation results, it is evident that (1) the marginal employee productivity levels per major job-age category within an industry differ between the different geographical areas, and (2) the marginal employee productivity levels per major job category differ between industries and geographical areas. Hypotheses H1 and H2 are thus accepted, and the null hypotheses are rejected.

The net marginal productivity estimation results for both the construction and manufacturing industries indicate that for some major job code and age categories, the net marginal productivity levels can be greater than the marginal productivity levels. This is especially true in the case of major job code and age categories, where the marginal remuneration cost ratios are smaller in relation to the other major job code

TABLE 5: Final fixed-effect panel data estimation results for the full firm-based data sets.

Parameter	Construction	Manufacturing	Gauteng	Western Cape	Eastern Cape
α	0.79* (0.17)	0.63* (0.14)	-	-	-
Ψ	1.09* (0.31)	1.13* (0.33)	-	-	-
λ < 30/Cons/71/	-	-	0.47* (0.17)	0.40* (0.14)	0.37* (0.19)
λ30-45/Cons/71/	-	-	0.57* (0.13)	0.51* (0.11)	0.46* (0.13)
λ45-55/Cons/71/	-	-	0.64* (0.21)	0.67* (0.17)	0.59* (0.22)
λ > 55/Cons/71/	-	-	0.47* (0.18)	0.51* (0.13)	0.50* (0.11)
λ < 30/Man/72/	-	-	0.41* (0.13)	0.39* (0.10)	0.43* (0.15)
λ < 30/Man/73/	-	-	0.39* (0.11)	0.36* (0.13)	0.39* (0.12)
λ30-45/Man/72/	-	-	0.62* (0.19)	0.61* (0.17)	0.58* (0.21)
λ30-45/Man/73/	-	-	0.61* (0.14)	0.56* (0.15)	0.55* (0.13)
λ45-55/Man/72/	-	-	0.56* (0.22)	0.58* (0.17)	0.53* (0.14)
λ45-55/Man/73/	-	-	0.51* (0.11)	0.49* (0.13)	0.47* (0.16)
λ > 55/Man/72/	-	-	0.43* (0.20)	0.44* (0.17)	0.40* (0.15)
λ > 55/Man/73/	-	-	0.39* (0.10)	0.38* (0.12)	0.35* (0.15)
γ < 30/Con/71/	-	-	0.27* (0.09)	0.25* (0.10)	0.28* (0.12)
γ30-45/Con/71/	-	-	0.41* (0.17)	0.43* (0.15)	0.40* (0.19)
γ45-55/Con/71/	-	-	0.38* (0.09)	0.40* (0.17)	0.35* (0.13)
γ > 55/Con/71/	-	-	0.29* (0.10)	0.31* (0.11)	0.30* (0.08)
γ < 30/Man/72/	-	-	0.23* (0.10)	0.21* (0.08)	0.20* (0.07)
γ < 30/Man/73/	-	-	0.19* (0.07)	0.17* (0.05)	0.18* (0.04)
γ30-45/Man/72/	-	-	0.39* (0.11)	0.37* (0.12)	0.38* (0.10)
γ30-45/Man/73/	-	-	0.40* (0.17)	0.36* (0.12)	0.41* (0.14)
γ45-55/Man/72/	-	-	0.43* (0.15)	0.51* (0.17)	0.47* (0.13)
γ45-55/Man/73/	-	-	0.44* (0.20)	0.53* (0.19)	0.51* (0.17)
γ > 55/Man/72/	-	-	0.31* (0.11)	0.34* (0.09)	0.30* (0.13)
γ > 55/Man/73/	-	-	0.33* (0.09)	0.30* (0.12)	0.32* (0.08)
μ < 30/Con/71/	-	-	0.21* (0.08)	0.20* (0.11)	0.28* (0.10)
μ30-45/Con/71/	-	-	0.27* (0.09)	0.33* (0.07)	0.35* (0.11)
μ45-55/Con/71/	-	-	0.34* (0.11)	0.38* (0.13)	0.36* (0.10)
μ > 55/Con/71/	-	-	0.19* (0.07)	0.21* (0.10)	0.18* (0.08)
μ < 30/Man/72/	-	-	0.31* (0.20)	0.34* (0.22)	0.39* (0.19)
μ < 30/Man/73/	-	-	0.29* (0.19)	0.35* (0.18)	0.30* (0.18)
μ30-45/Man/72/	-	-	0.44* (0.21)	0.47* (0.19)	0.43* (0.15)
μ30-45/Man/73/	-	-	0.41* (0.17)	0.43* (0.19)	0.47* (0.18)
μ45-55/Man/72/	-	-	0.51* (0.19)	0.54* (0.21)	0.52* (0.16)
μ45-55/Man/73/	-	-	0.49* (0.15)	0.50* (0.17)	0.54* (0.12)
μ > 55/Man/72/	-	-	0.27* (0.18)	0.29* (0.14)	0.26* (0.19)
μ > 55/Man/73/	-	-	0.22* (0.13)	0.24* (0.17)	0.23* (0.11)

*, $p < 0.05$; *t*-values are provided in parenthesis.

and age categories. For other major job code and age categories, the estimated net marginal productivity levels can be smaller than the estimated marginal productivity levels because of higher marginal remuneration cost levels. Hypothesis H3 is thus accepted, and the null hypothesis $H3_0$ is rejected.

It can be argued that the net marginal productivity estimation results differ between the major job codes, industries and geographical areas. The net marginal productivity estimation results are mixed for the three geographical areas, and there is no conclusive evidence that the lower GGP geographical area (the Eastern Cape province), in general, created net marginal productivity levels that are consistently lower compared with the higher GGP geographical areas. Hypothesis H4 is therefore accepted, and null hypothesis $H4_0$ is rejected.

Testing the robustness of the final marginal productivity model estimates

A fixed-effect panel data estimation was performed, which included the full firm-based data sets to determine the marginal productivity, marginal employee remuneration cost and the net marginal productivity estimates of all the individual age groupings per major job code in the two industries and three geographical areas. The robustness of the marginal productivity model can be determined when the fixed-effect panel data estimates are compared with the estimates of the marginal productivity model. Robustness of the marginal productivity model estimates should be confirmed if the fixed-effect panel data estimates are in relative terms similar.

Higher marginal productivity estimates (λ age group/industry/major job code/geographical area) are indicative of relatively high employee productivity levels, higher marginal employee remuneration cost estimates (γ age group/Industry/major job code/geographical area) are indicative of higher relative remuneration cost levels, while higher net marginal productivity estimates (μ age/industry/major job code/geographical area) are indicative of greater levels of cost efficient productivity levels.

The capital efficiency (acquisition and diffusion of new technologies and innovations) (α) and firm-based characteristic (ψ) estimates for both the construction and manufacturing industries were positive and significant. This is a clear indication that increases in the acquisition and diffusion of new technologies and innovations will have a positive impact on employee productivity levels. The significant estimations for (ψ) were indicative of a strong impact of greater levels of investment in new technology and innovation, faster adaptation to changing industry dynamics and higher levels of profitability on employee productivity levels. It can be argued that the significant estimations for firm-based characteristics (especially the quicker diffusion of new technology and innovation in the workplace) combined with learning effects could explain the higher employee productivity levels of the 30–45 years and the 45–55 years age categories.

For the construction industries (major job code 71) in all three provinces the highest employee productivity levels were indicated by the higher estimates for the 45–55 years age category (λ45–55/Cons/71/), followed by the 30–45 years age category (λ30–45/Cons/71/). The lowest employee remuneration cost changes for the construction industries in all three geographical areas were indicated by the significantly lower estimates of the younger than 30 years age category (γ < 30/Con/71/). The estimations of the employee remuneration cost levels for both the 30–45 years (γ30–45/Con/71/) and the 45–55 years age (γ45–55/Con/71/) categories were higher than the estimates of the other two age categories. For the construction industries in all three geographical areas, the estimations indicated the highest net employee productivity levels for both the 30–45 years (μ30–45/Con/71/) and 45–55 years (μ45–55/Con/71/) categories.

For the manufacturing industries, the estimations were in a similar range for both major job codes 72 and 73. The highest employee productivity estimates were for the 30–45 years age category (λ30–45/Man/72/; λ30–45/Man/73/) followed by the 45–55 years age category (λ45–55/Man/73/; λ45–55/Man/73/). As is the case with the construction industries, the employee remuneration cost change estimates for the manufacturing industries (both major job codes 72 and 73 in all three geographical areas) were the lowest for the younger than 30 years age category (γ < 30/Man/72/; γ < 30/Man/73/). The 45–55 years age category (γ45–55/Man/72/; γ45–55/Man/73/) had the highest employee remuneration cost level estimates followed by the 30–45 years age category (γ30–45/Man/72/; γ30–45/Man/73/). The older than 55 years age category obtained the lowest net employee productivity estimates (μ > 55/Man/72/; μ > 55/Man/73/) compared with the other three age groupings (for both major job codes 72 and 73 in all three geographical areas).

It is again important to note that for the manufacturing industries, in general, there is no conclusive indication that the higher GGP geographical areas (the Gauteng and Western Cape provinces) had consistently higher productivity estimates compared with the lower GGP geographical area (the Eastern Cape province).

The fixed-effect panel data estimates, in general, confirmed the robustness of the marginal employee productivity model estimates.

Conclusion

The aim of this study was to determine the impact of industry and geographic dynamics on employee productivity levels of different major job code and age categories.

A marginal productivity model was applied to estimate the relative marginal productivity levels, marginal employee remuneration cost levels and net marginal productivity levels for the different major job codes and age categories (per industry and geographical area). The results of the estimations are important for employee productivity practitioners to (1) identify the scale and focus of the diffusion of new technologies to groups of highly productive employees, (2) understand the productivity dimensions created by industry dynamics and geographical area differences and (3) express the importance of control over employee remuneration costs if net marginal productivity benefits are to be realised.

The estimation and computation results indicate that (1) the middle to older age categories (30–45 years and the 45–55 years) generated higher marginal productivity levels in relation to the other age categories (this was the case for both industries and all the geographical areas), which confirms the results of some international studies that 'older' employees are responsible for higher productivity gains in the workplace, (2) the magnitude of marginal employee remuneration costs is an important driving factor for net marginal productivity levels, (3) marginal employee productivity levels per major job code and age category within the same industry differ between geographical areas (which was the case of the majority of findings of international studies in this regard), (4) marginal employee productivity levels per major job code and age category differ between industries and geographical areas and (5) no conclusive evidence could be derived that the lower GGP geographical area created net marginal productivity levels that are consistently lower than those of the higher GGP geographical areas.

Further studies in this regard will include a greater spectrum of employee diversity aspects such as gender, race and skills development when the research on industry and geographic dynamics of employee productivity-age categories is expanded.

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Competing interests

The authors have declared that no competing interest exists.

Author's contributions

This is a single authored article, and it meets the criteria for authorship as outlined by the policy.

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