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Analysing the Occupational Skills Productivity of South Africa's Non-Agricultural Jobs: An ARDL Approach

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Abstract:

This study showed that South Africa's employment of different occupational groups or broad skills dubbed as highly either skilled, semi-skilled, and low- or unskilled labour, and explained variations in non-agricultural labor productivity in their respective capacities. The Autoregressive Distributed Lag Model (ARDL) was employed to gauge the long- and short-run cointegration between the regressand (non-agricultural labor productivity) and employment trends of broad skills for different occupational groups, i.e., clerks, crafts and trades, elementary, management, plant and machinery, professionals, sales and services, technicians and domestic workers, as explanatory or regressor series. The tests for variance decomposition and Granger causality were also estimated. Findings showed that different highly skilled occupations had different productivity effects. Evidence of positive short-run co-integration was established for highly skilled managers and technicians; however, in the long run, the results were non-significant for the technicians, whereas they were statistically significant but negative for managers. However, results for highly skilled professional occupations were statistically nonsignificant. Subsequently, semi-skilled craft and trade occupations and sales and services occupations exhibited statistically significant and positive long- and short-run cointegration with non-agricultural labor productivity. However, the results of semi-skilled occupations for clerks and plant operators were statistically non-significant. Lastly, positive long- and short-run co-integrating relationships were established for unskilled domestic work occupations and non-agricultural labor productivity, albeit negative but statistically significant co-integration was revealed between unskilled elementary occupations and the regressand.

Keywords: labour productivity, occupational groups, autoregressive distributed lag, skilled labour, unskilled labour.

分析南非非农业工作的职业技能生产率：一种自回归分布式滞后模型方法

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摘要：
这项研究表明，南非雇用不同的职业群体或广泛技能被称为高技能、半技能和低技能或非技能劳动力，并解释了他们各自能力的非农业劳动生产率的差异。自回归分布滞后模型被用来衡量回归变量（非农业劳动生产率）与不同职业群体广泛技能的就业趋势之间的长期和短期协整关系，即文员、手工业和贸易、初级、管理、工厂和机械、专业人员、销售和服务、技术人员和家庭工人，作为解释或回归序列。还估计了方差分解和格兰杰因果关系的检验。调查结果表明，不同的高技能职业对生产率的影响不同。为高技能的管理人员和技术人员建立了积极的短期协整证据；然而，从长远来看，结果对技术人员来说并不显着，而在统计上却很显着，但对管理人员来说是负面的。然而，高技能专业职业的结果在统计上不显着。随后，半熟练手工业和贸易职业以及销售和服务职业与非农业劳动生产率表现出统计上显着的正长期和短期协整关系。然而，文员和工厂操作员的半熟练职业的结果在统计上不显着。最后，非熟练家政工作和非农劳动生产率建立了正的长期和短期协整关系，尽管在非熟练初级职业和回归变量之间显示出负但统计上显着的协整关系.

关键词：劳动生产率、职业群体、自回归分布滞后、熟练劳动力、非熟练劳动力。

1. Introduction

Labor productivity is presented as the relationship between output and input, where output is measured per unit input (Abdel-Wahab et al., 2005). Most studies on labor market productivity have sought to gauge labor productivity effects of firm-level features and employee behavioral characteristics such as training, job security, work-life programs, employee happiness and satisfaction, and the work environment (such as Ichino & Riphahn, 2005; Dearden et al., 2006; Leung, 2009; Horst et al., 2014; Oswald et al., 2015; Alromaihi et al., 2017; Dialoke & Nkechi, 2017). In contrast to such a focus, this study seeks to understand how trends in different occupations contribute to productivity over time. Magwentshu et al. (2019) stress that South Africa has been incapable of cultivating the skills required by companies to advance and compete within a progressively technology-driven global environment. Overwhelmed by stagnating productivity, high unemployment, increased inequality, and depressed wage growth. Thus, the study focused on Statistics South Africa's occupational groups in analysing the macro- and cross-occupational labor productivity effects of South Africa's nonagricultural occupations. Amongst the considered occupational groups were clerks, crafts and trade occupations, elementary jobs, managers, plant and machinery occupations, professional occupations, sales and services, technicians, and domestic workers. These occupations detail a diverse portfolio of skills representing different skills content and are crucial in establishing diverse occupational contributions toward the collective macro-productivity of labor over time.

Labor market productivity is an essential means of combating poverty, establishing a competitive workforce, and realizing quality jobs via increased wages, sound operating conditions, and increased human resource investment (Khan et al., 2009:478). According to Sahabuddin (2020), the study of worker productivity is fueled toward the utilization of labor in achieving effectiveness and efficiency. Coinciding with prepositions for high school and higher education attainment to induce skills quality even during low demand for skilled workers (Asik et al., 2020:1). Occupation types span high- and low-paying jobs, routine and nonroutine jobs, and sophisticated and nonsophisticated jobs (Marcolin et al., 2016). However, they may also be categorized as either high-skilled jobs (i.e., managerial and professional), mid-skilled jobs (i.e., manufacturing and routine office jobs), and low-skilled jobs (personal services) (Goos et al., 2009:58). Table 1 lists the various types of occupations within different occupational groups according to the International Standard Classification of Occupations (ISCO).

Table 1. International Standard Classification of Occupations (ISCO) (International Labour Organisation, 2022)

Occupational groups	Types	
Managers	●	Chief Executives, Senior Officials and Legislators
	●	Administrative and Commercial Managers
	●	Production and Specialized Services Managers
	●	Hospitality, Retail and Other Services Managers
Professionals	●	Science and Engineering Professionals
	●	Health Professionals
	●	Teaching Professionals
	●	Business and Administration Professionals
	●	Information and Communications Technology Professionals
	●	Legal, Social and Cultural Professionals
Technicians and Associate Professionals	●	Science and Engineering Associate Professionals

	● Health Associate Professionals
	● Business and Administration Associate Professionals
	● Legal, Social, Cultural and Related Associate Professionals
	● Information and Communications Technicians
Clerical Support Workers	● General and Keyboard Clerks
	● Customer Services Clerks
	● Numerical and Material Recording Clerks
	● Other Clerical Support Workers
Services and Sales Workers	● Personal Services Workers
	● Sales Workers
	● Personal Care Workers
	● Protective Services Workers
	● Models, Salespersons and Demonstrators
Craft and Related Trades Workers	● Building and Related Trades Workers (excluding Electricians)
	● Metal, Machinery and Related Trades Workers
	● Precision, Handicraft, and Printing Workers
	● Electrical and Electronic Trades Workers
	● Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers
Plant and Machine Operators and Assemblers	● Stationary Plant and Machine Operators
	● Assemblers
	● Drivers and Mobile Plant Operators
Elementary Occupations	● Cleaners and Helpers
	● Agricultural, Forestry and Fishery Labourers
	● Labourers in Mining, Construction, Manufacturing and Transport
	● Food Preparation Assistants
	● Street and Related Sales and Services Workers
	● Refuse Workers and Other Elementary Workers

Occupations' routine content and intensity and their relative skills tend to differ accordingly. Autor et al. (2003) classifies aggregates of occupation routine intensities based on their task routine task intensity, where tasks are classified as either non-routine cognitive (requires analytical skills), non-routine manual (requires coordination of eye-hand-foot), routine cognitive (requiring ability to observe standards, tolerances or limits), and routine manual (requiring "finger dexterity" in using fingers to handle small objects with speed and precision). Marcolin et al. (2016) presented the following routine intensity of occupations based on the routine intensity index (RII), as illustrated in Table 2. The RII was said to capture the routine content and a dimension of the skill content of occupations. It proposed that complex occupations that are less likely to be routinized have lower RII in terms of their mean and median values, with P95 illustrating the index value for the most to the least frequently routinised, which suggested that elementary occupations and plant operators were the most frequently routinized occupations.

Table 2. Routine intensity of occupation (Marcolin et al. 2016)

	Mean	**Standard deviation**	**P5**	**Median**	**P95**
Managers	1.61	0.61	1	1.5	2.75
Professionals	1.87	0.71	1	1.75	3.25
Technicians	2.04	0.89	1	1.75	4
Clerks	2.33	1.04	1	2	4.5
Skilled agriculture workers	2.05	1.01	1	1.75	4.25
Crafts	2.44	1.11	1	2.25	4.75
Plant operators	2.99	1.23	1	3	5
Elementary occupations	2.93	1.23	1	2.75	5

Table 3 further highlights the diverse mix of skills in the workforce across occupations, having classified the skill content of occupations following the job's skills dimensions spanning routine or manual, analytical, and interpersonal content. The classification of skills as either high-skill, middle-skill, or low-skill jobs hinges on the specification of jobs based on training and education levels required (Holzer & Lerman, 2009:1-2) and adapted to South Africa's business and skills market following Statssa (2014), Capazario & Venter (2020:12), and BUSINESSTECH (2022). Holzer and Lerman (2009) note that middle-skill occupations typically require post-secondary education but less than a bachelor's degree requiring training from vocational certificates, diplomas or associate degrees, on-the-job training, etc. However, such classifications only reflect average skills of broad occupational groups as certain technical and managerial occupations may require less than a bachelor's degree, whereas certain middle-skill categories may solely require high school. Nevertheless, jobs such as managers and professionals tend to be highly analytical and interpersonal skills often with high-paying remuneration (Dicarlo et al., 2016).

Table 3. Occupational groups and skills mix adapted to South Africa's skills and business market. Authors' compilation with information obtained from Goos et al. (2009), Holzer and Lerman (2009), Statssa (2014), Foko (2015), Dicarlo et al. (2016), Capazario & Venter (2020), BUSINESSTECH (2022)

	Occupational groups	**Occupational skills mix**
Managers	High-skill	Analytical and interpersonal skills
Professionals	High-skill	
Technicians	High-skill	
Clerks	Semi- or middle-skill	Analytical, interpersonal, and routine-manual skills.
Sales and services	Semi- or middle-skill	The low level of specialization: low occupational skills mix
Craft and trade	Semi- or middle-skill	Highly intensive in manual and routine skills
Plant operators	Semi- or middle-skill	
Elementary occupations	Unskilled or low-skilled	
Domestic workers	Unskilled or low-skilled	

The modern economy has witnessed key disruptors in employment and occupational patterns in the form of globalization and technological changes or innovation. These factors affect the type and number of skills demanded, job composition, and availability of jobs (ILO, 2008; ILO, 2018). Globalization presents the offshorability of tasks where, i.e., a certain non-routine intensity and complex tasks can be offshored (Marcolin et al., 2016). Due to technological changes, literature on the biases of technological change suggests the polarization of employment patterns denoting the increases in the employment of high- and low-skilled jobs on the extreme ends of the occupational distribution, and the decline in mid- and middle-skilled jobs, mostly in advanced economies (Acemoglu, 2002; Author et al., 2006; Goos et al., 2009; Holzer & Lerman, 2009). It is said that computers or innovation often substitute occupations characterized by a well-defined routine task and complement occupations focused on conducting tasks with more abstract analytical skills (Dicarlo et al., 2016:4).

As a result, middle-skill jobs, which are mostly characterized by routine-intensive tasks, are replaced by systems of information communication technology (ICT). The latter complements non-routine and abstract tasks, which tend to be high- and low-skilled occupations (Autor et al., 2008; Goos et al., 2014). Goos et al. (2009) further iterate that the advent of technological progress has led to replacement effects of routine labor such as craft and clerical jobs often positioned in the middle of the wage distribution. Meanwhile, the increase in the share of income of the rich has witnessed an increase in their demand for low-skilled workers whose occupations mostly comprise the provision of services to the rich (Manning, 2004; Ragusa & Francesca, 2007). Evidence provided by MacCrory et al. (2014) suggests a demand decrease in substitutable skills that contest with machines and a demand increase for non-substitutable skills, i.e., interpersonal skills, where machines have limited capabilities, and a demand increase in complementary skills that encompass deductive reason and thus complements machines.

Table 4. Descriptive statistics

	High-skilled occupations			**Middle-skilled occupations**	
	Manager	**Professional**	**Technical**	**Clerk**	**Craft and trade**
Mean	1272.889	858.8519	1507.259	1602.352	1840.056
Median	1286	863.5	1487	1600	1881.5
Maximum	1528	1072	1683	1783	2094
Minimum	1019	654	1213	1403	1521
Std. Dev.	133.7245	87.16898	104.3716	94.60886	152.4867
Skewness	-0.09298	-0.00879	-0.34514	-0.00199	-0.14591
Kurtosis	1.90961	2.704111	2.69157	1.982632	1.747619
Jarque-Bera	2.752945	0.197683	1.286124	2.328871	3.720629
	Middle-skilled occupations			**Low-skilled occupations**	
	Sales and Services	**Plant and Machine Operations**		**Elementary**	**Domestic workers**
Mean	2292.296	1276.593		3397.463	985.537
Median	2300	1276.5		3306	995.5
Maximum	2777	1394		3842	1100
Minimum	1828	1160		2939	745
Std. Dev.	284.591	65.25726		304.7642	57.25142
Skewness	-0.00972	0.077649		0.101358	-1.61708
Kurtosis	1.709	2.028416		1.480706	7.976898
Jarque-Bera	3.75088	2.17821		5.286036	79.26595

Table 4 illustrates the descriptive statistics of South Africa's occupational employment trends from the first quarter of 2008 to the first quarter of 2022. In the case of the South African economy, middle-skilled jobs have experienced an ongoing decline in employment patterns, as represented by the negatively skewed distribution in the descriptive statistics, except for plant and machine operators. This was assumed by Autor et al. (2008) and Goos et al. (2014) to be a result of progressive replacements of routine tasks in middle-

skilled jobs. Yet on average, these jobs were still higher than some high- and low-skill jobs, making the case that despite the advent of technological progress and globalization processes, middle- and low-skilled labor remains a crucial component of South Africa's labor force, with an average of about 1602 thousand clerks and 1840 thousand craft and trade occupations, 2292 thousand sales and services occupations and 1276 thousand plant and machine operators over time. Thereby, with all semi-skilled jobs but the plant and machinery occupations topping each South Africa's high-skilled average employed occupations for the period.

Moreover, the high unemployment rates of South African graduates denote the low job demand even for highly skilled individuals. Likewise, high-skilled occupations have also witnessed decreasing trends as shown by the negatively skewed patterns in such occupations, perhaps also echoing Marcolin et al. (2016) in sentiments of the threats in the transfer or the offshoring of skills in international markets with better incomes due to globalization opportunities. Particularly in developed markets with increased demand for labor, particularly professional, technical, and managerial services. However, Pritchett (2001) also cites that educational attainment may not always stimulate economic growth and productivity due to reduced education quality and mismatch in skills. Educational quality may be so low that it does not foster increased cognitive skills and may contribute to low or negative productivity.

Also, reduced structural change levels foster the absence of demand for high-skilled labour, especially across sectors of high value-added industries and services to basic manufacturing. This can also be explained by the lack of within-sector skills training and upgrading, which according to Hendricks (2010) is a more significant key player than structural change when explaining education variations between countries. Meanwhile, most development studies recognize the implications of structural change on income variations across countries (Restuccia et al., 2008). Moreover, globalisation-led participation in international value chains has amplified high-level skills demand vital for economies specializing in sophisticated business services and advanced technological systems within manufacturing processes (OECD, 2017; International Labour Organisation – World Trade Organisation, 2017). Subsequently, low-skilled elementary occupations were observed to have had some of the highest employment trends accounting for about 3397 thousand employed jobs on average. Domestic workers as a more specialized occupational group accounted for about 985 thousand employed occupations on average.

2. Literature Review

McGowan and Andrews (2015) assessed the implications of higher mismatches in skills and qualifications on labor productivity in 19 OECD countries. Results revealed that higher mismatches coincided with lower labor productivity due to inefficient resource allocation, with over-skilling and under-qualification being key contributors to such impacts. The Chartered Institute of Management Accountants (CIMA) (2021) also highlighted that adjustments in the quality of labor (skills) led to productivity growth of about 18 per cent for the period 1981 to 2007 in the United Kingdom (UK). Meanwhile, higher-skilled occupations were identified to have been the key driver of productivity growth and subsequently iterated the importance of skills development toward enhanced productivity. Okumu and Mawejje (2020) used firm-level data to analyse the interaction between firm productivity and labor skills. Findings revealed that university and high school education had large effects on young and small firms, while skills development and training had a positive association with labor productivity for larger and older firms. Coinciding with Dearden et al. (2000) assertion that increased training, research and development (R&D) and the employment of highly skilled workers have a likelihood of accounting for higher productivity. Marcolin et al. (2016) point out that developing economies have mostly focused on assembly and production-related tasks and skills, whereas developed countries largely specialize in high value-added activities. Meanwhile, most job losses are to be experienced among middle-skilled workers largely executing routine-focused tasks.

Galindo-Rueda and Haskel (2005) further showed that firms that largely comprised college-educated, full-time and male employees accounted for increased productivity, yet substantial differences across sectors, particularly for part-time workers working for extremely low wages, have displayed productivity differences. Khan et al. (2009) illustrate that highly skilled jobs tend to attain a premium labor market wage level, whereas the wage rate increases of unskilled and skilled jobs significantly lag behind highly skilled occupation wage increases. Moreover, Rehman and Mughal (2013) revealed a positive relationship between Pakistani labor productivity and skilled labour and a negative relationship between unskilled labor and labor productivity. Kinyondo and Mabugu (2009) also showed that productivity was associated with increased earnings mostly among skilled workers, relative to other skill types. Additionally, a study by Baptist and Teal (2014) showed that technological changes accounted for variations in productivity in five African countries, specifically in South Africa, Nigeria, Ghana, Kenya, and Tanzania. Haskel et al. (2005) asserted that the hiring of skilled workers correlated with productive manufacturing firms. Thus, top decile plants on the total factor productivity (TFP) distribution largely employed workers with additional schooling on average, relative

to those in the bottom decile.

Using a variable regression, Asik et al. (2020) established that changes in highly educated workers corresponded to a causal effect on the productivity level. However, productivity growth was negatively associated with an upgrade in overall skills following the exclusion of the government sector from the equation, indicating a downward sloping return to the demand for educated labor over time. Further echoing Abdel-Wahab (2008) who showed that simple advancements in levels of qualifications or training participation rates lead to an unlikely improvement in the construction sector productivity for the United Kingdom over the period 1995 to 2006. Abdel-Wahab (2008) relayed such effects on the time taken by experienced workers in coaching new entrants, especially if there are many trainees onsite. However, such training may focus mostly on health and safety standards as opposed to productivity-driven efforts, while other factors such as better work organization and capital investment may be productivity-inducing factors as opposed to training. Keep et al. (2006) also underscored that skills are often taken as "scapegoats" in averting focus from addressing more serious shortcomings, such as the modus operandi of managing and motivating workers.

3. Methodology

The study employed a quantitative approach in meeting the focus objective of analysing the effects of occupational skills on aggregate labor productivity based on South Africa's quarterly nonagricultural occupational level data. This specifically involved data on nonagricultural labor productivity, the number of employed people in thousands as clerks, in crafts and trade occupations, elementary occupations, managers, plant and machinery occupations, professional occupations, sales and services jobs, technical jobs, and domestic work occupations. Nonagricultural labor productivity was considered to be the dependent variable, while employed personnel in the different forms of occupations served as the independent or explanatory variables. All data were retrieved from Statistics South Africa's (STATSSA) quarterly labor force survey (QLFS) with about 54 quarterly observations across the sample period 2008 quarter one to 2021 quarter two. Moreover, all time series were transformed according to each variable's natural logarithmic form before conducting the econometric analysis.

Estimations of short- and long-run relationships were conducted using Pesaran et al. (1999) and Pesaran et al. (2001) autoregressive distributed lag (ARDL) models. The ARDL model was estimated to reveal potential co-integrating vectors among the explanatory and dependent variables. The ARDL model is a dynamic tool with the capacity to deal with a changing economy's dynamic series and is also a superior model to traditional co-integration approaches and works with variables with either I(0) or I(1) orders of integration (Dube & Zhou, 2013). To verify the robustness of the estimated models, the study conducted normality tests, autocorrelations tests, and heteroscedasticity tests as means of diagnostic testing. Henceforth, Equation (1) below was estimated as a means of estimating the ARDL model's bounds test to co-integration in analysing co-integrating relationships between non-agricultural labor productivity and employment series in occupations covering clerks, crafts and trade occupations, elementary occupations, managers, plant and machinery occupations, professional occupations, sales and services jobs, technical jobs and domestic work occupations.

$$\Delta LLABPROD_t = \alpha_0 + \sum_{i=1}^{k} \beta_i \Delta LLABPROD_{t-i} + \sum_{i=0}^{k} \delta_i \Delta LCLERK_{t-i} + \sum_{i=0}^{k} \sigma_i \Delta LCRAFTNTRADE_{t-i} + \sum_{i=0}^{k} \gamma_i \Delta LELEMEN_{t-i} + \sum_{i=0}^{k} \emptyset_i \Delta LMANAGER_{t-i} + \sum_{i=0}^{k} \partial_i \Delta LPLANTNMACH_{t-i} + \sum_{i=0}^{k} \mathrm{C}_i \Delta LPROFESS_{t-i} + \sum_{i=0}^{k} \forall_i \Delta LSALESNSER_{t-i} + \sum_{i=0}^{k} \cup_i \Delta LTECHNICIAN_{t-i} + \sum_{i=0}^{k} \vartheta_i \Delta LDOMWORK_{t-i} + \eta_1 LLABPROD_{t-1} + \eta_2 LCLERK_{t-1} + \eta_3 LCRAFTNTRADE_{t-1} + \eta_4 LELEMEN_{t-1} + \eta_5 LMANAGER_{t-1} + \eta_6 LPLANTNMACH_{t-1} + \eta_7 LPROFESS_{t-1} + \eta_8 LSALESNSER_{t-1} + \eta_9 LTECHNICIAN_{t-1} + \eta_9 LDOMWORK_{t-1} + \varepsilon_t \quad (1)$$

whereby Δ represented the variables' first difference operator, whereas $\Delta LLABPROD_t$ symbolized nonagricultural labor productivity as the dependent variable, expressed in the variable's natural logarithmic form. Moreover, regressands or explanatory variables were represented as LCLERK being the natural logarithmic form of employed clerks over time, LCRAFTNTRADE represented the natural logarithmic form of those employed in crafts and trade occupations, LELEMEN denoted the natural logarithmic form of those employed in elementary occupations, LMANAGER represented the natural logarithmic form of those employed in management occupations. LPLANTNMACH denoted the natural logarithmic form of those employed in plant and machinery occupations, and LPROFESS signified the natural logarithmic form of those employed in professional occupations. Additionally, LSALESNSER denoted the natural logarithmic form of those employed in sales and services occupations, LTECHNICIAN symbolized the natural logarithmic form of those employed as technicians, and LDOMWORK represented the natural logarithmic form of those employed as domestic workers. Moreover, e_t represented the white noise error term, whereas the series $\beta_i, \delta_i, \sigma_i, \gamma_i, \emptyset_i, \partial_i, \zeta_i, \forall_i, \cup_i, \vartheta_i$ denoted the coefficients of the short-run of the independent variables and the dependent variable, whereas the long-run relationships were represented by $\eta_1 \ldots\ldots \eta_9$.

Furthermore, Equation 1 was executed to establish co-integration estimates for nonagricultural labor productivity and the employment series in various occupation types based on the following hypotheses:

- H_0: $\eta_1 = \eta_2 = \eta_3 = \eta_4 \ldots. = \eta_9 = 0$ (was the null; long-run co-integration does not exist).
- H_1: $\eta_1 \neq \eta_2 \neq \eta_3 \neq \eta_4 \ldots. \neq \eta_9 \neq 0$ (was the alternative; long-run co-integration exists).

The null hypothesis suggested the nonexistence of co-integrating relationships among the variables. The bounds test was performed by comparing the value of the F-statistic to critical values of the upper bounds and lower bounds, where a higher F-statistic value relative to the upper bounds critical value proposes existing cointegration, thereby rejecting the null hypothesis in support of the alternative hypothesis. Meanwhile, an F-statistic value lower than the lower bounds critical value proposes the absence of co-integration and thus the null hypothesis would be accepted. Moreover, an F-statistic value between the upper and lower bounds critical values suggests that estimations are inconclusive (Dube & Zhou, 2013).

4. Empirical Analysis and Results

Table 5 presents a summary of study variables expressed as logarithmic transformations according to their natural logarithmic forms. Subsequent reference to all variables involved the description of each series according to its respective representation in log form. Accordingly, Table 3 represents the collective variables considered in examining co-integration among the dependent and independent variables.

Table 5. Representation of logged series

Logged variable	Representation
Log of nonagricultural labor productivity	LLABPROD
Log of the number of employed clerks	LCLERK
Log of number of employed in craft and trade	LCRAFTNTRADE
Log of the number of employed in elementary positions	LELEMEN
Log of the number of employes in management positions	LMANAGER
Log of number of employed in plant and machinery	LPLANTNMACH
Log of the number of employed professionals	LPROFESS
Log of number of employed in sales and services	LSALESNSER
Log of the number of employed as technicians	LTECHNICIAN
Log of the number of employed domestic workers	LDOMWORK

Efforts toward ensuring that co-integration estimations were free from spurious regression outputs, the Augmented Dickey Fuller (ADF) test was employed as a test for stationarity. Accordingly, all series were deemed stationary considering the stationarity results provided in Table 6. The variables LLABPROD, LPROFESS and LDOMWORK were stationary at level, while the variables LCLERK, LCRAFTNTRADE, LELEMEN, LMANAGER, LPLANTNMACH LSALESNSER and LTECHNICIAN were revealed to have been stationary at first difference. The estimated stationarity results exhibited a mixed order of integration for the considered time series. A key advantage of the ARDL model is its capacity to handle I(0) and I(1) mixed integration orders.

Table 6. The augmented Dickey-Fuller unit root test results (****** denotes P-value at 1% level of significance and ***** at 5% significance)

Variables	Level				First Difference		Order of integration
	Intercept without trend		With trend		Without trend		
	t-stat	P-value	t-stat	P-value	t-stat	P-value	
LLABPROD	-6.3188	0.0000	-6.4116	0.0000	-6.1355	0.0000	I(0)
LCLERK	-2.4438	0.1350	-2.5588	0.3001	-8.9357	0.0000	I(1)
LCRAFTNTRADE	-2.1917	0.2116	-2.1723	0.4946	-8.2537	0.0000	I(1)

Continuation of Table 6

LELEMEN	-1.4469	0.5524	-2.3582	0.3965	-8.5984	0.0000	I(1)
LMANAGER	-1.9763	0.2961	-2.9558	0.1542	-7.6463	0.0000	I(1)
LPLANTNMACH	-2.6627	0.0873	-2.9409	0.1585	-8.4401	0.0000	I(1)
LPROFESS	-3.0535	0.0364	-4.6623	0.0023	-11.692	0.0000	I(0)
LSALESNSER	-1.5823	0.4845	-1.4729	0.8266	-8.4416	0.0000	I(1)
LTECHNICIAN	-1.3613	0.5942	-3.4662	0.0536	-8.3848	0.0000	I(1)
LDOMWORK	-3.3087	0.0194	-3.6307	0.0366	-7.1109	0.0000	I(0)

Furthermore, Table 7 showcases the selected ARDL model based on the Akaike Information Criteria (AIC), which recommended the model ARDL(4, 0, 0, 1, 1, 0, 1, 0, 1, 1) as the best and most suitable model with optimal lags. The model was found to be statistically significant with a general p-value of 0.000 at one percent significance level. Subsequently, a high R-squared value of 0.927215 implied that the model could explain variations in nonagricultural labor productivity, being able to explain approximately 92.7 per cent of the variability in nonagricultural labor productivity. Equally, no serial correlation (autocorrelation) was identified based on Durbin-Watson's value of 2.014605.

Table 7. Model selection

Akaike Information Criteria (AIC)						
	Selected model	**Trend Specification**	**R-Squared**	**Adj R-Squared**	**Prob (F-statistic)**	**Durbin-Watson stat**
$LLABPROD_t$ (Eq. 1)	(4, 0, 0, 1, 1, 0, 1, 0, 1, 1)	Rest. Constant	0.927215	0.884952	0.0000	2.014605

4.1. Long-Run Co-Integration Results Based on the F-Statistic and Bounds Test

Furthermore, the rejection of the null hypothesis follows that an F-statistic value lies above the lower and upper bounds critical values (Pesaran et al., 2001). Therefore, with an F-statistic value of 6.727908, this value was found to be greater than the lower (2.5) and upper (3.68) critical values and was significant at one percent significance level. This resulted in the rejection of the null hypothesis that no long-run relationship existed between the variables, coincidentally favoring the alternative hypothesis of existing co-integrating relationships between nonagricultural labor productivity and South Africa's occupations.

Table 8. F-statistic and bounds test to co-integration results (****** denotes P-value significant at a 1% level of significance)

Estimated models	**F-Stat value**	**I0 Bound**	**I1 Bound**
(Eq.1) $F_{LLABPROD}$ [LLABPROD/(LCLERK, LCRAFTNTRADE, LELEMEN, LMANAGER, LPLANTNMACH, LPROFESS, LSALESNSER, LTECHNICIAN, LDOMWORK)]	6.727908	2.5	3.68

Having found co-integrating relationships in the model, further co-integration estimations were conducted, with findings exhibited in Table 9. Estimations revealed the evidence of long-run relationships in the coefficients of South Africa's number of employed in various occupations with non-agricultural labor productivity. Statistically significant long-run co-integrating relationships were identified for the series LCRAFTNTRADE, LELEMEN, LMANAGER, LSALESNSERV, and LDOMWORK. These results reiterated the findings of the F-statistic value estimated above.

Table 9. Long-run coefficient results of the autoregressive distributed lag model (***, ** and * denote significance at 1%, 5% and 10%, respectively)

Long Run Coefficients				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LCLERK	0.412920	0.368965	1.119131	0.2717
LCRAFTNTRADE	1.051465	0.465020	2.261118	0.0309**
LELEMEN	-2.226357	0.540847	-4.116427	0.0003***
LMANAGER	-0.752005	0.383549	-1.960651	0.0590*
LPLANTNMACH	-0.301439	0.392734	-0.767541	0.4486
LPROFESS	-0.273048	0.222288	-1.228353	0.2286
LSALESNSER	1.527939	0.424028	3.603393	0.0011***
LTECHNICIAN	0.205185	0.376875	0.544439	0.5900
LDOMWORK	0.929552	0.523143	1.776862	0.0854*
C	-0.666228	3.142404	-0.212012	0.8335

Equation (2) served as a function on the derived representation of the output in Table 8. Thus, positive and statistically significant co-integrating long-run relationships were identified between the log of the dependent variable; non-agricultural labor productivity, and the independent variables; log of craft and trade, log of sales and services, and log of domestic work, these relationships were significant at five per cent, one

per cent, and ten per cent significance levels, respectively. Further, implying that a one percent increase (decrease) in the log of craft and trade employed occupations would result in an increase (a decrease) in the log of labor productivity by 1.051465 percent. A one percent increase (decrease) in the log of sales and services employed occupations induces an increase (a decrease) in the log of labor productivity by 1.527939 percent. Also, a one percent increase (decrease) in the log of domestic workers employed occupations would induce an increase (a decrease) in the log of labor productivity by 0.929552 percent. However, long-run co-integration results of the log of plant and machine, log of professional occupations, and log of technician employed occupations were non-statistically significant.

LLABPROD = - 0.6662 + 0.4129*LCLERK + 1.0515*LCRAFTNTRADE -2.2264*LELEMEN - 0.7520*LMANAGER - 0.3014*LPLANTNMACH - 0.2730*LPROFESS + 1.5279*LSALESNSER + 0.2052*LTECHNICIAN + 0.9296*LDOMWORK (2)

Furthermore, the results of the independent variables; log of elementary employment and log of management employment occupations, exhibited negative long-run co-integrating relationships with the dependent variable; log of labor productivity. In particular, this suggests that a one percent increase (decrease) in the log of elementary employment occupations would lead to a decrease (an increase) in the log of labor productivity. Lastly, a one percent increase (decrease) in the log of management employment occupations would result in a decrease (an increase) in the log of labor productivity.

4.2. Short-Run Co-Integration Results Based on the Error Correction Model (ECM)

Having established the existence of co-integrating vectors, short-run estimations were conducted to gauge short-run adjustments from disequilibrium toward long-run equilibrium using the Error Correction Model (ECM) in ARDL mode. The ECM serves as a convenient approach for analysing corrections of preceding periods' disequilibrium toward reaching long-run equilibrium, as suggested in the long-run co-integration results (Asteriou & Hall, 2007; Brooks, 2014). Accordingly, the error correction term (ECT) of the ECM, an "equilibrating" error term that corrects model deviations (Gujarati, 2011), must be significant and negative to uphold the supposed adjustment process upheld eventually (Mukhtar & Rasheed, 2010). Shown in Table 10 are the results of the short-run coefficients of the ECM. The study is for short-run adjustments exhibited an evidence of adjustment processes that restrict long-run errors from proliferating. This was supported by the negative coefficient of the ECT of -1.847110 with a p-value of 0.000, which was statistically significant at 0.01 significance level. This suggested that it takes about one quarter (1/1.847110) for the disequilibrium in the short run to be adjusted in reaching long-run equilibrium.

Table 10. Findings of the error correction model for productivity in non-agricultural sectors (* , **, and *** denote significance at 10%, 5% and 1%, respectively)

Co-integrating Form				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(LLPRODUCT(-1))	0.901465	0.120522	7.479687	0.0000
D(LLPRODUCT(-2))	0.819556	0.097799	8.380047	0.0000
D(LLPRODUCT(-3))	0.584897	0.080086	7.303347	0.0000
D(LCLERK)	0.356555	0.529860	0.672922	0.5060
D(LCRAFTNTRADE)	1.951324	0.618196	3.156484	0.0035
D(LELEMEN)	-2.289543	0.979262	-2.338030	0.0260
D(LMANAGER)	1.587637	0.523366	3.033513	0.0049
D(LPLANTNMACH)	-0.258663	0.609229	-0.424575	0.6741
D(LPROFESS)	-0.102334	0.262303	-0.390135	0.6991
D(LSALESNSER)	2.810796	0.711975	3.947886	0.0004
D(LTECHNICIAN)	1.510213	0.617297	2.446492	0.0203
D(LDOMWORK)	4.406774	0.618320	7.127007	0.0000
CointEq(-1)	-1.847110	0.163445	-11.301111	0.0000

Further findings in Table 10 also showed that nonagricultural productivity is positively affected by its lags when a lag specification of four lags was included for the dependent variable. Meaning that the log of nonagricultural labor productivity is positively affected by its lags. positive past values where positive (negative) productivity outcomes are likely to positively (negatively) affect productivity in the subsequent term. Moreover, among the independent variables, coefficients of employed occupations in the log of clerks, the log of plant and machinery occupations, and the log of professional occupations were found to be non-statistically significant. No short-run relationships were found between these variables and the log nonagricultural labor productivity, and the existence of non-existing statistically significant relationships was also the case for these variables eventually.

In contrast, a negative and statistically significant short-run relationship was revealed for nonagricultural labor productivity and the log of elementary occupations, meaning that a one percent increment (decrease) in the log of elementary occupations would induce a decrease (increase) in the log of nonagricultural labor productivity by 2.29 percent.

Having also been negative eventually. In addition, positive and statistically significant short-run relationships were revealed for employed occupations in the log of craft and trade, log of managing occupations, log of sales and services, log of domestic work, and log of technicians. Despite the latter having shown no long-run relationship with the log of nonagricultural productivity, a positive and statistically significant short-run relationship was established. Suggesting that a one percent increase (decrease) in the log of technicians employed occupations would lead to an increase (decrease) in nonagricultural labor productivity by approximately 1.51 percent.

Moreover, a one percent increase (decrease) in the log of craft and trade employed occupations would lead to an increase (decrease) in the log of labor productivity by 1.95 percent. Likewise, a one percent increase (decrease) in the log of management-employed occupations would induce a 1.59 percent increase (decrease) in the log of labor productivity. Additionally, a one percent increase (decrease) in the log of sales and services employed occupations would correspond with a 2.81 percent increase (decrease) in the log of labor productivity. Lastly, a per cent increase (decrease) in the log of domestic work employed occupations results in a 4.41 percent increase (decrease) in the log of nonagricultural labor productivity.

4.3. Granger Causality Tests and Variance Decomposition Estimation

Further estimations of causality relationships prompted the use of the Granger causality test in gauging the potential for directional causal effects among the dependent and independent variables. Based on the output revealed in Table 11, unidirectional casualties were identified from craft and trade occupations to nonagricultural labor productivity, from elementary occupations to nonagricultural labor productivity, and from domestic worker occupations to nonagricultural labor productivity.

Table 11. Granger causality tests (*, ** , and *** denote significance at 10%, 5% and 1%, respectively)

Null Hypothesis	F-Statistic	Prob.
CLERK does not Granger Cause NON_AGRI_POSLABOUR_PRODU	0.775	0.4665
NON_AGRI_POSLABOUR_PRODU does not Granger Cause CLERK	0.87418	0.4239
CRAFT_AND_RELATED_TRADE does not Granger Cause NON_AGRI_POSLABOUR_PRODU	4.91926	0.0115**
NON_AGRI_POSLABOUR_PRODU does not Granger Cause CRAFT_AND_RELATED_TRADE	0.0475	0.9537
ELEMENTARY does not Granger Cause NON_AGRI_POSLABOUR_PRODU	2.65755	0.0806*
NON_AGRI_POSLABOUR_PRODU does not Granger Cause ELEMENTARY	0.0066	0.9934
MANAGER does not Granger Cause NON_AGRI_POSLABOUR_PRODU	1.03388	0.3636
NON_AGRI_POSLABOUR_PRODU does not Granger Cause MANAGER	0.94947	0.3942
PLANT_AND_MACHINE_OPERAT does not Granger Cause NON_AGRI_POSLABOUR_PRODU	1.41571	0.2529
NON_AGRI_POSLABOUR_PRODU does not Granger Cause PLANT_AND_MACHINE_OPERAT	0.06549	0.9367
PROFESSIONAL does not Granger Cause NON_AGRI_POSLABOUR_PRODU	0.8796	0.4217
NON_AGRI_POSLABOUR_PRODU does not Granger Cause PROFESSIONAL	1.11224	0.3373
SALES_AND_SERVICES does not Granger Cause NON_AGRI_POSLABOUR_PRODU	0.85312	0.4326
NON_AGRI_POSLABOUR_PRODU does not Granger Cause SALES_AND_SERVICES	0.41712	0.6614
TECHNICIAN does not Granger Cause NON_AGRI_POSLABOUR_PRODU	0.6694	0.5168
NON_AGRI_POSLABOUR_PRODU does not Granger Cause TECHNICIAN	1.45924	0.2428
DOMESTIC_WORKER does not Granger Cause NON_AGRI_POSLABOUR_PRODU	8.74069	0.0006***
NON_AGRI_POSLABOUR_PRODU does not Granger Cause DOMESTIC_WORKER	1.20173	0.3097

These results were found to be statistically significant at 5, 10 1 percent, respectively. It is further suggested that employment trends in craft and trade occupations, elementary occupations, and domestic worker occupations present directional effects on the changes in nonagricultural labor productivity. However, no directional causality was revealed from the remainder of the occupational groups toward nonagricultural labor productivity, and no causality was identified from nonagricultural labor productivity to any of the employment occupational groups.

Moreover, the study also employed tests for variance decomposition, as represented in Table 12.

Table 12. Variance decomposition tests

Variable	Period									
	1	2	3	4	5	6	7	8	9	10
LLPRODUCT(-1)	0.095	0.01	0.003	0.241	0.01	0.004	0.005	0.002	0.086	0.065
LLPRODUCT(-2)	0.039	0.001	0.002	0.066	0.01	0.023	0.014	0.003	0.073	0.003
LLPRODUCT(-3)	0	0	0.096	0.054	0.021	0	0.035	0.014	0.045	0.009
LLPRODUCT(-4)	0.013	0.392	0.184	0.054	0	0.002	0.003	0.002	0.03	0.005
LCLERK	0.006	0.034	0.108	0.003	0.007	0.246	0.4	0.131	0.015	0.023
LCRAFTNTRADE	0.031	0.07	0.363	0.095	0.353	0.002	0.024	0.002	0.002	0.032
LELEMEN	0.001	0.948	0.011	0.011	0.004	0	0.008	0.001	0.015	0
LELEMEN(-1)	0.031	0.64	0.17	0.035	0.03	0.024	0.012	0	0.011	0.016
LMANAGER	0.001	0	0.031	0.193	0.007	0.526	0.11	0.022	0.062	0.016
LMANAGER(-1)	0.011	0.024	0.01	0.227	0.029	0.242	0.004	0.111	0.309	0.024

Variable	Period									
	1	2	3	4	5	6	7	8	9	10
LPLANTNMACH	0.206	0.04	0.015	0.058	0.032	0	0.226	0.394	0.012	0.008
LPROFESS	0	0.013	0.332	0.01	0.216	0.003	0.023	0	0.01	0.117
LPROFESS(-1)	0.016	0.025	0.137	0.021	0.003	0.053	0	0.067	0.188	0.007
LSALESNSER	0.001	0.351	0.136	0.145	0.008	0.241	0.004	0.039	0.033	0.011
LTECHNICIAN	0.098	0.083	0.387	0.074	0.283	0	0.052	0.001	0	0
LTECHNICIAN(-1)	0.104	0.021	0.417	0.004	0.341	0	0.011	0.013	0.006	0.071
LDOMWORK	0.027	0.129	0.527	0.073	0.012	0.063	0.006	0.037	0	0.119
LDOMWORK(-1)	0.002	0.186	0.2	0.472	0.028	0.005	0	0.005	0.015	0.011
C	0.999	0	0	0	0	0	0	0	0	0

Findings revealed disparities and inconsistencies in the periodic contribution of employment trends to labor productivity as per each subsequent period. In particular, there were inconsistent contributions of the various occupational employment trends toward nonagricultural labor productivity following the rises and decreases in contributions for each occupation. This speaks to the inconsistent performance in the country's labor productivity across different occupational groups.

4.4. Residual Diagnostics

To ascertain the robustness of the model specifications established in Equation (2), the study carried out residual diagnostic tests for heteroscedasticity, serial correlation, and normality tests as a means of avoiding conventional econometric problems that may violate the classical linear assumptions. For the latter to hold, stochastic processes within the model must be met (Chipeta & Meyer., 2018:205-206). Results in Table 13 indicated that the model passed all the underlying diagnostic tests, seeing that the p-values for each test were above 10 per cent, the null hypotheses of no heteroscedasticity and no serial correlation could not be rejected, including the null hypothesis of normally distributed residuals.

Table 13. Residual diagnostics

Test	H0	Prob	Decision
Breusch-Godfrey Serial Correlation LM Test	No serial correlation	0.988	H0 cannot be rejected due to the P-value being above 5%. Thus no serial correlation exists in the model.
Heteroskedasticity Test: Breusch-Pagan-Godfrey	No heteroscedasticity	0.654	H0 cannot be rejected due to the P-value being above 5%. Thus, no heteroscedasticity exists in the model.
Normality test: Jarque-Bera	Residuals are normally distributed	0.571	With a P-value above 5%, we accept H0. Thus, findings show that the series are normally distributed.

Following Lee and Strazicich (2013), the cumulative sum of repetitive residuals (CUSUM) test was estimated, as shown in Figure 1. The CUSUM output revealed that the model was characterized by stable parameters over time and thereby does not produce model instabilities. Further repeating the robustness of the model output for further interpretation and deliberation.

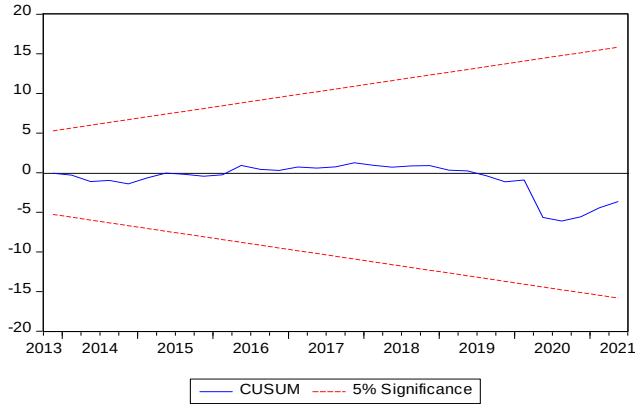

Figure 1. CUSUM stability diagnostic test

5. Discussion of the Results

Table 14 presents a summary of the estimated findings. In line with the findings highlighted by the CIMA (2021), Rehman and Mughal (2013), the present results revealed positive and statistically significant short-run co-integrating relationships between highly skilled managers and non-agricultural labor productivity, including highly skilled technicians and non-agricultural labor productivity. During technological advancements, Dicarlo et al. (2016) add that technological advancements seem to complement such occupations based on their abstract analytical skills. However, for managers and productivity, this relationship did not hold eventually having translated into a negative relationship, whereas the relationship was non-significant yet positive for technicians and productivity. In addition, the relationship between highly skilled professionals and non-agricultural labor productivity was non-significant in the short- and long-run. The failed positive effects of highly skilled occupations, especially in the long run, may be highlighted by the country's failure to foster continued skills development in adapting to the changes and opportunities brought forth by globalization and technical progress, as highlighted by Magwentshu et al. (2019:1) and in line with Dearden et al. (2000), Okumu and Mawejje's (2020) training-induced productivity. Seeing that highly skilled occupations such as managerial jobs are crucial in organizing and directing the flow of middle- and low-skilled occupations, the

country's inability for highly skilled occupations to promote positive and statistically significant labor productivity eventually may be the key contributor to the inconsistent positive labor productivity contributions witnessed across all occupations in the variance decomposition.

Table 14. ARDL and the Granger causality output results summary

Types of occupational skills	Short-run cointegration with nonagricultural labor productivity		Long-run cointegration with non-agricultural labor productivity		Granger causality
High-skill					
Managers	Positive	Significant	Negative	Significant	None
Professionals	Negative	Non-significant	Negative	Non-significant	None
Technicians	Positive	Significant	Positive	Non-significant	None
Semi- or middle-skill					
Clerks	Positive	Non-significant	Positive	Non-significant	None
Craft and trade	Positive	Significant	Positive	Significant	Unidirectional
Sales and services	Positive	Significant	Positive	Significant	None
Plant operators	Negative	Non-significant	Negative	Non-significant	None
Unskilled or low-skilled					
Elementary occupations	Negative	Significant	Negative	Significant	Unidirectional
Domestic workers	Positive	Significant	Positive	Significant	Unidirectional

As for the semi-skilled occupations, only sales and services occupations and crafts and trade-related occupations held positive and statistically significant co-integrating relationships with non-agricultural labor productivity in both the short- and long-run, having also presented significant and unidirectional effects on non-agricultural labor productivity for crafts and trade skills. The latter is supported by the trends in South Africa's crafts and trade sector. Echoing these findings are the Department of Arts and Culture (2020) held sentiments of a diverse, colorful and vibrant craft sector. Despite the fraught economic challenges, Perryer (2019) highlighted that South Africa's development of trade infrastructure coupled with the growing tourist market, during increasing trade openness, has transformed crafts into a vehicle for financial self-reliance, especially for women who seem to dominate this industry. Moreover, semi-skilled occupations comprising clerks and plant operators had non-statistically significant labor productivity effects. This could be aligned with disruptions in South Africa's ongoing economic transitions toward value-added activities in which emerging technological systems and processes may look to replace most middle-skilled jobs said to have high routine intensity, as cited by Marcolin et al. (2016). This is similar to the findings by Baptist and Teal (2014) who identified variations in productivity in countries like South Africa due to technological changes.

Furthermore, unskilled elementary occupations were found to negatively impact nonagricultural labor productivity in both the short- and long-run based on statistically significant evidence, with an indication of unidirectional causality existing from the former to the latter. Likewise, coinciding with Rehman and Mughal's (2013) results of a negative relationship between unskilled labor and labor productivity. Following Marcolin et al. (2016), elementary occupations and plant and machinery operations are among the most routinized jobs and would thus be most affected in the case of disruptions caused by the introduction of advanced technological systems. Dicarlo et al. (2016:4) add that computers look to substitute well acknowledged to be characterized by routine tasks.

6. Conclusions and Recommendations

Some of the propositions for non-statistically significant productivity effects of high-level skills, especially in the long run, require that firms address critical operational shortcomings that focus on adopting and managing organizational structure and resources according to the changing business market environment relative to changes in globalization and technological progress. This also entails the use of digitalization in a way that boosts employment relationships and communication. The International Labour Organization (ILO, 2018) posits that inadequate skills development and education tend to confine countries to a vicious cycle of low productivity, low wages, and low education. Henceforth, there is a dire need for the upscaling of skills, education, innovation, and development via the provision of transformative programs that reflect existing conditions of the jobs demand market. This would guide and update career paths in matching skills and learning programs to changes in the technological and globalisation-led business environment for more adaptive specialisation. In doing so, career-effective development programs are needed in guiding post-secondary school graduates toward more adaptive and significant career choices, which may alleviate job mismatches and thus promote labor productivity, as cited by Pritchett (2001). More structural change is needed to foster demand for skills and allow easy transfer of labor within and across sectors or firms. Following Abdel-Abdel-Wahab (2008), firms also need to ensure that the training of

middle- and low-level skills is well concentrated on productivity cantered efforts other than just health and safety standards coaching. Also, considering Keep et al. (2006), it is also necessary that firms focus on addressing the real shortcomings of managing and motivating workers, which seem to negatively affect productivity levels if not dealt with.

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