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Agricultural Production and Agricultural Employment Rate in South Africa: Time Series Analysis Approach

Molobe Joyce Ramakgasha[1]*, Tshephi Kingsley Thaba[2], Nengovhela Rudzani[2]

[1]Department of Agricultural Economics and Animal Production, University of Limpopo, Polokwane, South Africa, [2]University of Limpopo, Polokwane, South Africa. *Email: joycem.jm3@gmail.com

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ABSTRACT

South Africa's agricultural sector, despite facing high unemployment, is acknowledged for creating job opportunities. However, there is concern that the sector's adoption of technology-intensive methods may not necessarily lead to increased employment. The study aims to analyze the intricate relationship between agricultural output and employment in South Africa using time series analysis. This research employed a vector autoregressive (VAR) model to evaluate the link between agricultural production and the rate of agricultural employment in South Africa spanning from 1990 to 2022. The findings indicate that both variables passed levels and became stationarity at the first difference when employing ADF, and a long-term equilibrium relationship between the variables was observed using Johansen cointegration test. Over the short term, there was a significant positive correlation among agricultural production and the agricultural employment rate evidenced from ECT coefficient of 0.139 value. The results of the Granger causality tests indicated unidirectional relationship that agricultural employment Granger-causes agricultural production, signifying that agricultural employment can be used to predict the growth of agricultural production. Study recommended that policies which promote injection of funds to improve production in the agriculture sector needs to be prioritized to maintain and improve employment opportunities.

Keywords: Agricultural Production, Agricultural Employment Rate, Time Series Analysis, Vector Autoregressive, South Africa
JEL Classifications: C32, C4, J21, Q13

1. INTRODUCTION

The agricultural sector is essential to South Africa's economy, contributing significantly to GDP, ensuring food security, and employing a substantial portion of the workforce. In 2022, primary agricultural production reached R419,765 million, contributing an estimated R145,048 million to the GDP. Despite its modest GDP share, primary agriculture remains a crucial sector, playing a significant role in providing employment, especially in rural areas.

The South African agricultural sector is directly linked to job creation, impacting the overall employment rate (Thaba et al., 2020). The complex relationship between agricultural production and employment in this sector has been a debated topic. Several studies, including Lim et al. (2021), Altunöz (2019), and Ibragimov and Ibragimov (2017), have found a connection between production output and employment. This study employs a time series analysis to investigate this relationship at the sectoral level.

The relationship intricacies on how changes in agricultural output impact employment within the sector, considering the agriculture sectoral structure in South Africa is the central point. This relationship allows the investigation or exploring potential agricultural output of an economy, against the employment (Lee et al. 2020). Moreover, it enables an examination of predicting how alterations in agricultural activity may affect sectoral unemployment rates. Okun's law serves as the focal point, reflecting the connection between the goods and services market and the labor market (Okun, 1962).

The recent changes in South Africa's agricultural landscape, marked by technological advancements, policy shifts, and the growing impact of climate change, underscore the importance of understanding the correlation between production levels and employment rates in the agricultural sector. Noteworthy studies by Pizzo (2019) and An et al. (2017) on the relationship between Real Output (Real GDP) and the Unemployment Rate in Latin America, the Caribbean, and various developing economies, respectively, contribute to the exploration of this dynamic interplay. The study emphasizes the significance of this relationship for South Africa's economic and social well-being.

2. LITERATURE REVIEW

The relationship between output and employment rate has gained serious attention recently by academics and policymakers. Most recent studies have primarily concentrated on national level and in certain sectors in the economy forgetting the contribution of agricultural sector to employment especially in the rural areas and the livelihood in general (Pfunzo, 2017). However, a rising trend involves the increasing mechanization and technological advancement of agricultural production, leading to a decline in overall labour demand (Caunedo and Kala, 2021). Modern techniques and machinery on large-scale commercial farms enhance efficiency but reduce reliance on manual labour (Gallardo and Sauer, 2018).

Several studies (Akçoraoğlu, 2010; Ateşoğlu, 1993; Aydıner-Avşar and Onaran, 2010; Wah, 1997) offer empirical support for the connection between manufacturing productivity and employment or unemployment. In Turkey, Aydıner-Avşar and Onaran (2010) found a positive long-term correlation between manufacturing sector output and employment. In Malaysia, Wah (1997) explored the impact of output and technological advancements in manufacturing, determining that increased output led to overall employment growth.

In their 2014 study, Muzindutsi and Maepa conducted a time series analysis on manufacturing production and non-agricultural employment rate in South Africa. The research revealed that both variables exhibited stationarity at the first difference, indicating a long-term equilibrium relationship. In the short term, a significant positive correlation between manufacturing production and the employment rate was found. The Granger causality test demonstrated a causal link from manufacturing production to the employment rate. Notably, the long-term relationship was identified only in the post-apartheid period, marked by a more open economy compared to the apartheid era. The study concludes that the growth in the South African manufacturing sector is associated with short-term employment opportunities.

Meyer and McCamel (2017) used time series analysis to explore the connection among manufacturing, economic growth, and employment in South Africa after 1994. The research identified a positive long-term relationship between the manufacturing sector, GDP, and employment, although significance was observed only with GDP and not with employment. The results from the vector error correction model (VECM) and Granger causality test suggested no short-term relationships among the variables. Ultimately, the study concluded that an upsurge in manufacturing contributes to GDP growth and has the potential to foster an employment-friendly environment.

In their 2011 study, Igwe and Esonwune aimed to identify factors influencing agricultural production in Nigeria, particularly focusing on government expenditure. Analyzing time-series data from 1994 to 2007, the researchers used multiple regression and correlation analysis. The findings suggested that, despite government expenditure, there was no improvement in agricultural production. However, the study emphasized that total population, annual rainfall, and the total cropped area significantly determine agricultural production.

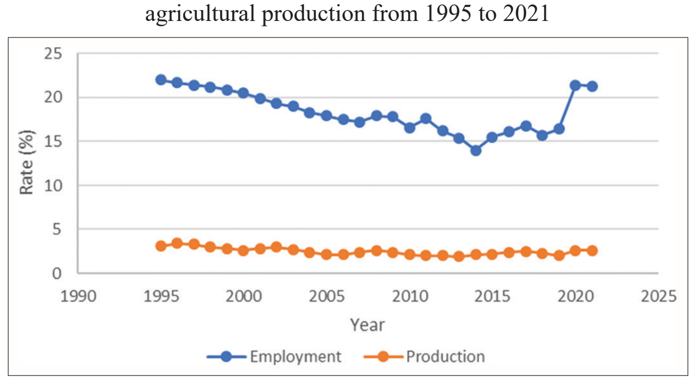
Agricultural employment remains a pressing issue, especially in rural areas where farming serves as a primary income source (Woodhill et al., 2022). Small-scale and subsistence farming, vital for employment, face productivity and resource access challenges. Despite thriving agricultural production contributing to economic growth, the shift to mechanization and large-scale farming has reduced overall employment, posing socio-economic challenges in rural communities. Striking a balance between increased productivity and preserving employment opportunities in agriculture is a complex challenge for South Africa's agricultural landscape.

2.1. Agricultural Production versus Agricultural Employment

Figure 1 offers details on employment and production over past 25 years in South Africa, providing insights into the labour market and production dynamics. The graph offers a nuanced portrayal of the interplay between employment and production trends throughout the years. It emphasizes the importance of comprehending the factors shaping their dynamics for policymakers, businesses, and economists. Delving deeper into specific events or policies at critical junctures in the graph could unveil more profound insights into the intricate connection between workforce dynamics and agricultural production output.

In the initial years, both employment and production declined simultaneously. From 1995 to 2000, employment fell from

Figure 1: The South African agricultural employment and the value of agricultural production from 1995 to 2021



Source: Own computation

22% to 20.5%, and production decreased from 3.1% to 2.6% respectively, possibly reflecting economic challenges or shifts in market demand affecting both sectors. Between 2000 and 2010, employment decreased to 16.6%, while production stabilized at 2.1%, suggesting efficiency gains and technological advancements in agricultural sector. From 2010 to 2015, production remained stable around 2.1-2.2%, despite employment fluctuations, possibly due to improved productivity or technological innovations. In 2020 and 2021, both employment and production grew simultaneously, potentially driven by economic recovery, increased consumer demand, or government initiatives. The close correlation underscores the interdependence of employment and production, influenced by technology, efficiency, economic conditions, demand, and policy interventions.

3. METHODOLOGY

Conducted in South Africa, this study used time series data from 1995 to 2021 to investigate the complex dynamics between agricultural output and employment in the agricultural sector. StatsSA and World Bank data were employed, and tests including the augmented Dickey-Fuller (ADF) and Johansen cointegration were conducted to assess stationarity and analyze short-run and long-run relationships. The study also used the vector error correction model (VECM) and Granger causality test to evaluate the causal relationship between agricultural output and employment.

3.1. Model Specification

This study aims to assess the connections between agricultural production and the employment rate, utilizing the vector autoregressive (VAR) model, known for effectively modeling complex relationships. The VAR model treats a simultaneous set of variables equally, regressing each endogenous variable on its own lags and the lags of all other variables within a finite-order system, as introduced by Sims in 1980. Hence, as stated by Brooks (2002), the VAR model serves as an initial framework for various analyses, including cointegration analysis and causality tests.

The VAR model employed in this study is a bivariate one, outlined as follows:

$$\mathrm{LEMPL_t} = \sum_{i=1}^{n} \beta_{1i} LEMPL_{t-1} + \sum_{i=1}^{n} Y_{1i} LPROD_{t-1} + e_{1t} \quad (1)$$

$$\mathrm{LPROD_t} = \sum_{i=1}^{n} \beta_{2i} LEMPL_{t-1} + \sum_{i=1}^{n} Y_{2i} LPROD_{t-1} + e_{2t} \quad (2)$$

Where: $LEMPL_t$ is the log of employments rate at period t, $LPROD_t$ denotes the logarithm of agricultural production at time t, $\beta_{1i,}$ $\beta_{2i} Y_{2i}$ and Y_{2i} are the coefficients to be determined; e_{1t} and e_{2t} are error terms known as shocks in a VAR model; and n signifies the number of lags in the VAR model.

3.2. Unit Root Test

In estimating a VAR model, ensuring series stationarity is crucial to avoid spurious regressions with insignificant coefficients (Enders, 2004). This study used the augmented Dickey-Fuller (ADF) test to assess variable stationarity. If variables are stationary, the standard VAR model (Equations 1 and 2) is estimated. If both variables are non-stationary, a cointegration test is applied to determine if a linear combination indicates stationarity, indicating a long-run relationship (Brooks, 2002). Johansen's cointegration test, following Johansen's (1988 and 1991) approach, examined the long-run relationship between the two variables in an unrestricted VAR model.

$$Zt = \sum_{i=1}^{k} A_i Z_{t-1} + \varepsilon_t \quad (3)$$

Where: $Z_t = \frac{LEML_t}{LPROD_t}$ represents a column vector with observations on the logarithmic values of both the employment rate and agricultural production and, ε_t= is the error terms which are assumed not to be auto correlated. Assuming that all variables are co-integrated the VAR model (in Equation 3) can be presented as follows:

$$\Delta \mathrm{Z_t} = \mathrm{n} \mathrm{Z_{t-k}} + \sum_{i=1}^{k-1} {}_i\Delta Z_{t-i} + \varepsilon_\mathrm{t} \quad (4)$$

The matrix Π represents constant dynamic adjustments of first difference of variables respectively to the levels, regardless of time difference (Charemza and Deadman, 1997).

3.3. Vector Error Correction Model (VECM)

The short-term dynamic patterns and the determination of the long-term equilibrium relationship rely on cointegration analysis results (Abdalla and Murinde, 1997). If there is no cointegration between the agricultural employment rate and production, the VAR model in the first difference is applied. Conversely, if both variables exhibit cointegration, the vector error correction model (VECM), as outlined below, is employed.

$$\Delta \mathrm{LEMPL_t} = \sum_{i=1}^{n} \beta_{1i}\, \Delta LEMPL_{t-1} + \sum_{i=1}^{n} Y_{1i}\, \Delta LPROD_{t-1} + a_1 u_{1t} + e_{1t} \quad (5)$$

$$\Delta LPRODt = \sum_{i=1}^{n} \beta_{2i}\, \Delta LEMPL_{t-1} + \sum_{i=1}^{n} Y_{2i}\, \Delta LPROD_{t-1} + a_1 u_{2t} + e_{2t} \quad (6)$$

Where: u_{1t-1} and μ_{2t-1} are the error correction terms; and α_1 and α_2, are error correction coefficients which are expected to capture the adjustments of change in the employment rate ($\Delta LEMPL_t$) and change in manufacturing production ($\Delta LPROD_t$) towards long-run equilibrium, while the coefficients on $\Delta LEMPL_{t-1}$and $\Delta LPROD_{t-1}$ are expected to capture the short-run dynamics of the VECM model (Abdalla and Murinde, 1997).

Table 1: Descriptive statistics of agricultural production and agricultural employment rate in South Africa

Properties	Agricultural employment rate (Y)	Agricultural production (X)
Mean	18.35	2.50
Median	17.90	2.40
Maximum	22.0	3.40
Minimum	14.0	1.90
Standard Deviation	2.32	0.42

Source: Own computation, 2024

Table 2: Unit root test using augmented Dickey-Fuller test results

Variables	Agricultural employment rate (Y)			
	Levels		1st difference	
	Intercept	Trend and intercept	Intercept	Trend and intercept
ADF statistics	−1.59	−0.25	−4.56	−5.23
Critical values at 5% Level	−2.98	−3.60	−2.99	−3.60
Variables	**Agricultural production (X)**			
	Levels		**1st difference**	
	Intercept	**Trend and intercept**	**Intercept**	**Trend and intercept**
ADF statistics	−2.91	−2.57	−4.61	−3.65
Critical values at 5% level	−2.99	−3.60	−2.99	−3.34

Source: Own computation, 2024

3.4. Granger Causality Test

The Granger Causality test, developed by Granger in 1969, was conducted to assess the predictive usefulness of one time series for another. The selection of lags in the VAR Model, crucial as emphasized by Li and Liu in 2012, relies on evaluating five criteria for lag order selection: Schwarz Information Criterion (SIC), Hannan-Quinn (HQ), Akaike Information Criterion (AIC), general-to-specific sequential Likelihood Ratio test (LR), and Final Prediction Error (FPE) test (Ivanov and Kilian, 2005).

4. RESULTS AND DISCUSSION

Table 1 displays the mean, standard deviation, maximum, and minimum values of the series. The average agricultural employment rate was 18.35%, with a standard deviation of 2.32. Agricultural production, on average, was 2.50%. Remarkably, the extreme values for all variables are approximately in proximity to the mean, indicating minimal variation or dispersion. The relatively low standard deviations further support this observation. Consequently, it can be inferred that there are no substantial fluctuations in the examined agricultural employment rate and production data.

To statistically assess the stationarity attributes of the dataset, the study used the augmented Dickey-Fuller (ADF) unit root test. This test includes the rejection of the null hypothesis of a unit root at a 5% significance level if the absolute value of the ADF statistic is greater than the critical value. From the Table 2, the ADF results for both variables passed the levels and became stationary at first difference, as indicated by the values of 5.23, which is >3.60 for agricultural employment rate, and 3.65, which is >3.34 for agricultural production. These results suggest that the null hypothesis is rejected at the 5% significance level, indicating the absence of a unit root among the time series.

4.1. Johansen Cointegration Test using Trace and Max-Eigen Statistics

As a component of this research, the Johansen cointegration test was executed to examine whether a long-term relationship exists among the variables. The decision rule mandates rejecting the null hypothesis if there is no cointegration between the variables.

The Johansen cointegration test results in Table 3 indicate evidence of cointegration between the two variables. The trace test reveals one cointegration link at a 5% significance level. The null hypothesis, suggesting a rank of 0, was rejected based on a P-value below 5%, confirming the presence of at least one cointegration relationship within the system.

Table 3: Result of the cointegration test using trace statistics

Hypothesized No. of CE (s)	Eigenvalue	Trace statistics	0.05 critical value	Prob.**
None*	0.43	17.91	15.49	0.02
At most 1	0.15	3.98	3.84	0.05

Source: Own computation, 2024

Table 4: Result of the cointegration test using Max-Eigen statistics

Hypothesized No. of CE (s)	Eigenvalue	Trace statistics	0.05 critical value	Prob.**
None*	0.43	13.92	14.26	0.06
At most 1	0.15	3.98	8.84	0.05

Source: Own computation, 2024

Table 5: Vector error correction model

Error correction	Employment	Production
CointEq1	0.139199	0.001955
	(0.40424)	(0.07198)
	(0.93407)	(2.57072)
D (EMPL(−1))	−0.573294	−0.001033
	(0.30277)	(0.05391)
	(−1.89350)	(−0.01916)
D (PROD(−1))	0.192499	0.449408
	(1.4993)	(0.38126)
	(1.46173)	(1.17875)
R-Squared	0.721861	0.535616
Adj. R-Squared	0.918155	0.716621

Source: Own computation, 2024

Table 4 displays the outcomes of the cointegration test using maximum eigenvalue statistics for the variables. The test illustrates a cointegrated equation's presence at a 5% significance level. Specifically, the Max-eigen statistics test reveals one cointegration relationship between the two variables at a 5% significance level. Testing the null hypothesis with a rank of 0 showed a P-value below 5%, leading to the rejection of the null hypothesis.

Table 5 displays the error correction term (ECT) with a positive coefficient that is statistically insignificant at the 5% level. The

Table 6: Granger causality test results

Null hypothesis	F-statistics	Prob.
PROD does not granger cause EMPL	1.21	0.39
EMPL does not granger cause PROD	1.20	0.0018

Source: Own computation, 2024

ECT value is 0.139199, indicating consistency with the expected relationship among the variables and meeting the stability condition. This suggests that in the long term, the system will readjust to equilibrium, correcting any short-term imbalances. The current period adjusts for the past period's deviation from short-run equilibrium at a rate of 13.9%. The positive sign and the ECT value, along with a t-statistical value of 0.93407, imply a significant impact of agricultural employment on agricultural production in South Africa. These results align with those of the previous study by Ochada and Ogunniyi (2020), indicating that the agricultural sector and its output have the potential to create employment. The R-squared (R2) value is 0.721861, indicating that 72.1% of the variation in the agricultural employment rate is explained by the explanatory variables, while the remaining 27.9% is attributed to the effects of other variables not encompassed in the model.

Table 6 illustrates a unidirectional causal relationship between the two variables. The rejection of the null hypothesis at the 5% significance level indicates that agricultural employment Granger-causes agricultural production. In simpler terms, agricultural employment serves as a predictor for the growth of agricultural production. This suggests that, in the long run, changes in agricultural production align with variations in agricultural employment. These findings align with Adegboyega's (2020) study, which employed Johansen's cointegration, error correction method, and Granger causality analytical techniques to examine the relationship between agriculture and the unemployment rate in Nigeria. The research results indicated that government funding to enhance agriculture increased employment.

5. CONCLUSION

The primary objective of the study was to investigate the connection between agricultural production and agricultural employment rates in South Africa using a time series analysis approach. Initial analysis results from the augmented Dickey-Fuller (ADF) test suggest that both variables achieved stationarity after the first difference. Once both series became stationary, the study utilized cointegration approaches. It explored the cointegration relationship between agricultural production and agricultural employment rates in South Africa, revealing that the variables exhibit a long-term association. The study employed trace test statistics and Max-Eigen statistics of the Johansen cointegration to confirm this relationship.

The VECM outcomes revealed a positive sign and an ECT value, along with a t-statistical value of 0.93407, indicating a significant impact of agricultural production on agricultural employment in South Africa, suggesting that the agricultural sector's output has the potential to generate employment. Moreover, findings from Granger causality analysis verified the absence of a feedback relationship between agricultural production output and the unemployment rate in South Africa. Instead, a unidirectional causal relationship flows from the unemployment rate to production. Agricultural employment serves as a predictor for the growth of agricultural production, implying that changes in agricultural production align with variations in agricultural employment in the long run.

The study suggests that policymakers, in collaboration with the public and private sectors, should formulate and endorse policies that encourage the infusion of funds to enhance production in the agricultural sector. This is aimed at sustaining and enhancing employment opportunities.

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