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Asymmetric Effects of Electricity Consumption and Population Growth on South Africa's Employment in the Private-Sector

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ABSTRACT

This paper empirically investigated the relationship between energy consumption, population growth, and unemployment in South Africa over the period from 1990 to 2022, employing the nonlinear autoregressive distributed lag (NARDL) model. The research aims to analyse how fluctuations in energy consumption and demographic changes influence unemployment rates in the country. By examining the long-run and short-run dynamics among these variables, the study seeks to provide insights into the critical role of energy policies and demographic trends in shaping employment outcomes. The study found that electricity consumption has a nonlinear effect on employment, with positive and negative fluctuations impacting employment differently. Population growth showed no significant effect on private-sector employment in both the short and long run. The results suggest that reduced electricity consumption is associated with increased private-sector employment in South Africa, emphasizing the need for targeted energy policy reforms.

Keywords: Electricity Consumption, Population Growth, Unemployment, NARDL, South Africa
JEL Classifications: Q 41, J 11, E 24, C 22

1. INTRODUCTION

This paper posits that electricity consumption, population growth, and employment are interrelated phenomena that significantly influence the socio-economic dynamics of any nation, particularly in developing economies such as South Africa. As the country pursues economic development, these three factors have become increasingly crucial in shaping its trajectory toward progress and sustainability (Hlongwane and Daw, 2023; Sadikova et al., 2017).

South Africa is experiencing rapid population growth, with projections indicating it will reaching 73 million by 2050 (Wilson, 2020; Fischer and Tramberend, 2019). This expansion has significant implications for the country's energy consumption patterns, which are already strained by increasing demand, aging infrastructure, and a heavy dependence on coal-based energy production (IEA, 2020; Ahmed et al., 2023). The rising energy demand, driven by both population growth and industrial requirements, is placing substantial pressure on the energy sector, resulting in frequent power outages, elevated electricity prices, and heightened energy insecurity (Energy and IEA, 2020).

At the same time, South Africa faces persistently high unemployment, with recent figures exceeding 32.9% (StatsSA, 2023). The relationship between employment, population growth, and electricity consumption is complex. While population growth expands the labour force, a lack of economic growth and job creation can result in higher unemployment rates if they do not keep pace (ILO, 2017). Additionally, energy consumption plays a crucial role in industrial productivity and job creation, particularly in sectors like manufacturing, mining, and agriculture (Apergis and Payne, 2010). Energy shortages and inefficiencies can hinder these sectors, exacerbating the unemployment crisis (Pollin et al., 2020).

As the population continues to grow, the demand for energy increases, potentially affecting employment levels. According to the World Bank (2024), South Africa's population growth rate was 1.3% in 2019, 1.23% in 2020, and 1% in 2021. This growth slowed to 0.84% in 2022, before rising again by 0.87% in 2023. Similarly, official unemployment rates have risen significantly. In 2018, the unemployment rate was 27.1%, which increased by 1.6% in 2019, reaching approximately 29.2% in 2020. By 2023, the unemployment rate had risen to 32.4% (SARB, 2024).

This study aims to explore the dynamic relationships between electricity consumption, population growth, and employment in South Africa. Understanding these interactions is crucial for policymakers seeking to address the country's economic challenges, enhance energy security, and reduce unemployment. Unlike previous studies that assume linear relationships, this study examines nonlinear effects using the NARDL model, contributing new insights to the literature on employment dynamics in South Africa. By investigating the asymmetric effects and interdependencies between these variables, this research intends to offer insights into how South Africa can achieve a sustainable balance between its growing population, increasing electricity consumption, and employment opportunities in a period of economic uncertainty.

2. LITERATURE REVIEW

2.1. Theoretical Literature

This section examines theoretical perspectives on the relationship between energy consumption, population growth, and employment. The key theories identified in the literature are the energy consumption theory, the demographic transition theory, and the Kuznets environmental theory.

Energy consumption theory suggests that higher energy use is associated with increased production capacity, which can lead to greater employment opportunities (Hasanov, 2021). This theory posits a fundamental link between energy use and economic activity, particularly employment and production. It suggests that energy is a critical input in the production process, and variations in energy consumption can directly influence employment levels. In current study, this theory informs the hypothesis that changes in electricity consumption, whether increases or decreases will have significant and potentially asymmetric effects on private-sector employment in South Africa. The NARDL model is employed specifically to capture this asymmetry, aligning with the theory's emphasis on the directional sensitivity of economic outcomes to energy inputs.

The demographic transition theory posits that as populations grow and progress through the stages of demographic transition, energy demand typically rises due to industrialization and urbanization (Caldwell, 2007). This theory explains how changes in population growth rates correspond with economic development phases, often transitioning from high birth and death rates to lower rates as a country develops. The theory posits that demographic changes influence labour supply, savings rates, and employment structures. In this paper, the demographic transition theory guides the hypothesis that population growth exerts significant effects on employment dynamics in South Africa, particularly within the private sector.

According to Kuznets environmental theory, economic growth driven by energy use may initially lead to increased unemployment but could stabilize or decrease it in the long run if sustainable practices are adopted (United Nations Environment Programme et al., 2011). The Kuznets environmental theory suggests that as economies develop, they initially experience increased environmental and energy intensity, followed by a decline as cleaner technologies and services dominate. In this context, the study hypothesis influenced by the theory would be economic development mediated by electricity consumption patterns has non-linear effects on employment, reflecting shifts in the structure of the economy.

2.2. Empirical Review

2.2.1. The effect of electricity consumption on employment

This paper reviewed empirical evidence from various authors. For example, Graham and Knittel (2023) conducted a study on employment vulnerability across United States counties due to energy transitions. The study analysed employment data from various years up to 2022 and employed county-level econometric assessments. Graham and Knittel (2023) found that the impacts on employment varied by industry and region, with job losses concentrated in high-emission sectors such as manufacturing. In contrast, Narayan and Singh (2007) demonstrated that electricity consumption positively influences employment, as energy is a critical input for industrial and service sector growth. Narayan and Singh (2007) examined the relationship between electricity consumption and employment in India for the period 1974-2004 using the autoregressive distributed lag (ARDL) model.

Odhiambo (2010) employed vector error correction modelling (VECM) to analyse the causal relationship between electricity consumption and employment. The findings indicated a bidirectional causality, suggesting that electricity consumption and employment growth reinforce each other. Odhiambo's study focused on South Africa, using time-series data from 1970 to 2006. In contrast, Zhang and Cheng (2009) investigated the impact of electricity consumption on employment in China during the period 1985-2007. Utilizing Granger causality tests within a cointegration framework, their study identified unidirectional causality from electricity consumption to employment.

In line with Stern (2011), who found that electricity consumption was a significant determinant of employment, particularly in manufacturing sectors, the study utilized a structural vector autoregression (SVAR) model to explore the effect of electricity consumption on employment in the United States using data spanning 1949-2009. Similarly, Apergis and Payne (2010) used a panel cointegration technique to analyse data from Nigeria for the years 1980-2008. They investigated the link between electricity consumption and employment, finding a strong positive relationship that emphasized the importance of stable energy supplies in reducing unemployment in developing economies.

Electricity consumption is a pivotal determinant of labour market dynamics in South Africa, as underscored by a growing body of empirical research. One of the most pressing challenges facing the country's employment landscape is the reliability of electricity supply. Bhorat and Köhler (2023), through an extensive analysis of data spanning from 2008 to 2023, demonstrate that load shedding in South Africa's most acute form of electricity disruption has a statistically significant and negative effect on employment, working hours, and earnings. Their findings reveal that the adverse labour market consequences intensify with the severity of load shedding stages, with the manufacturing sector bearing the brunt of these effects. This strongly suggests that electricity shortages do not merely interrupt production but undermine the core capacity of the economy to sustain and generate employment opportunities.

However, not all forms of electricity consumption equally support employment-oriented growth. Hlongwane and Daw (2023a), using data from 1990 to 2019 and applying an ARDL model, find that renewable electricity consumption has a negative long-run effect on South Africa's economic growth. This counterintuitive result may reflect shortcomings in renewable energy policy design, infrastructure readiness, or integration with labour-intensive sectors. Their study implies that while renewable energy is critical for sustainability, its current form in South Africa is not yet effectively aligned with economic or employment objectives highlighting the need for better-integrated planning during the green transition. Furthermore, demographic pressure compounds the electricity employment nexus. In a related study, Hlongwane and Daw (2023b), examining the period from 2002 to 2021, find a negative and statistically significant relationship between population growth and electricity consumption. The causality runs from population growth to electricity use, indicating that rising demographic demands are placing additional stress on an already strained energy system. If left unaddressed, this mismatch between energy supply and demographic growth risks constraining job creation by restricting the electricity-intensive activities needed to absorb a growing labour force.

In summary, a majority of the reviewed studies confirm a positive association between electricity consumption and employment, with some identifying mutual reinforcement between the two variables. This consensus is particularly strong among studies employing time-series and panel data from India, China, Nigeria, and earlier analyses of South Africa. However, more recent research specific to South Africa introduces complexity, showing that the form and reliability of electricity matter greatly. Load shedding and inefficiencies in renewable energy deployment have demonstrated adverse effects on employment outcomes. Furthermore, demographic pressures exacerbate the challenge, threatening the energy system's ability to sustain job creation. These findings collectively suggest that while electricity remains a cornerstone for employment growth, its impact is conditional on structural, technological, and policy contexts.

2.2.2. The effect of population growth on employment

This paper reviewed empirical evidence from various studies. Adamu and Bulus (2024) examined the impact of population growth on unemployment in Nigeria, employing Dynamic Ordinary Least Squares (DOLS) as the estimation technique and using time series data from 1980 to 2022. Their findings revealed that population growth did not significantly affect unemployment during the specified period, indicating no relationship between the two variables.

Binuyo and Ajibola (2023) conducted a similar study on the relationship between population growth and unemployment in Nigeria. They considered economic growth, life expectancy, literacy rate, and population growth as independent variables affecting unemployment. Using the Autoregressive Distributed Lag (ARDL) method as the estimation technique, they found a positive relationship between population growth and unemployment. However, the Granger causality test indicated no bidirectional causal relationship, concluding that neither variable significantly influenced the other.

Ali et al. (2021) investigated population growth and unemployment in Zanzibar, using time series data from 1990 to 2020. They applied the Vector Error Correction Model (VECM) as their estimation technique and included population growth, income per capita, and inflation as explanatory variables for unemployment. Their results showed that population growth positively affects unemployment in both the short and long run, indicating a positive relationship between the two.

Obayori and Udeorah (2020) explored the dynamic effect of population growth on unemployment in Nigeria, employing Dynamic Ordinary Least Squares (DOLS) and using population growth and per capita income as independent variables. Their findings revealed a positive but statistically insignificant relationship between population growth and unemployment, concluding that there is no meaningful relationship between the two variables.

Pratiwi (2020) analysed the effect of population growth and gross regional domestic product on unemployment levels in Makassar. Using annual time series data from 2010 to 2019 and Multiple Linear Regression as the estimation technique, the study concluded that population growth positively impacts unemployment, indicating a positive relationship between the two.

Felicien and Gakuru (2020) examined the impact of foreign direct investment, population growth, and inflation on unemployment in Rwanda. Utilizing annual time series data from 1985 to 2018 and an error correction model (ECM) for analysis, their findings suggested a positive relationship between population growth and unemployment.

Alam et al. (2020) studied the effects of gross domestic product, inflation, population growth, and foreign direct investment on unemployment in Bangladesh. Using ordinary least squares (OLS) with time series data from 1995 to 2019, they found that population growth had a negative but statistically insignificant relationship with unemployment. They concluded that there is no significant relationship between population growth and unemployment, although other variables were found to be significant.

Recent empirical studies in South Africa have explored the relationship between population growth and employment, yielding varied findings. For instance, the Inclusive Society Institute (2021) analysed data from 2011 to 2019 and found that the average annual population growth of 1.65% outpaced job creation, which averaged approximately 278,222 jobs/year, thereby exacerbating unemployment. Similarly, the OECD (2022) highlighted that despite a growing working-age population, employment creation has lagged significantly, particularly among youth. In contrast, the World Bank (2015) argued that with appropriate policy reforms especially in education and labour market flexibility, South Africa could capitalize on its demographic dividend, transforming population growth into an economic opportunity. These findings suggest that while population growth has generally strained employment outcomes in South Africa, its effects are not uniform and can be mitigated or reversed through effective policy interventions.

Across the reviewed literature, there is a mix of consistent and divergent findings regarding the relationship between population growth and unemployment. Several studies, such as those by Binuyo and Ajibola (2023), Ali et al. (2021), Pratiwi (2020), and Felicien and Gakuru (2020) found a positive relationship, suggesting that rising population levels contribute to increased unemployment. This trend reflects concerns about insufficient job creation relative to population expansion, particularly in developing contexts. In contrast, studies by Adamu and Bulus (2024), Obayori and Udeorah (2020), and Alam et al. (2020) found statistically insignificant relationship, indicating that other macroeconomic variables may mediate the impact of population growth on unemployment. The South African context similarly reveals mixed insights. While the Inclusive Society Institute (2021) and OECD (2022) highlight the challenges of rapid population growth outpacing employment generation, the World Bank (2015) offers a more optimistic view, suggesting that with sound policies, population growth could be leveraged as a demographic dividend. These contradictions underscore the importance of context-specific factors such as economic structure, labour market flexibility, and education systems in determining whether population growth becomes a burden or a catalyst for employment.

3. METHODOLOGY

3.1. Model specification

In analysing the relationship between electricity consumption, population growth, and private sector employment in South Africa, this paper modifies the NARDL model employed by Kisswani and Kisswani (2019) in their investigation of the employment–oil price nexus: A nonlinear cointegration analysis for the U.S. market:

$$\Delta E_t = \gamma + \alpha 0 E_{t-1} + \alpha_1 P_{t-1}^{+} + \alpha_1 P_{t-1}^{-} + \sum_{i=1}^{m} \delta_{1i} \Delta E_{t-1} + \sum_{i=0}^{q} (\theta_i^{+} \Delta P_{t-1}^{+} + \theta_i^{-} \Delta P_{t-1}^{-}) + u_t \quad \text{(i)}$$

Where E_t represents employment at t times and is a dependent variable, P_t is the real oil price, Δsignifies the difference operator, p and q are the length of the lag, and u_t is a serially uncorrelated error term, α_0, α_1, α_2 represent the long-run coefficients, $\sum_{i=0}^{q} \theta_i^{\pm}$ is coeffients. The model is modified to suit this study objective by replacing is real oil price with electricity consumption (LELC), and including population growth (PG) and total production (LTP), the dependent variable which is employment did not change it takes the following form (TEMP). Hence the model of this study takes the following form.

$$\begin{aligned} \Delta TEMP_t &= \gamma + \alpha_0 TEMP_{t-1} + \alpha_1 LELC_{t-1}^{+} + \alpha_2 LELC_{t-1}^{-} \\ &+ \alpha_3 PG_{t-1}^{+} + \alpha_4 PG_{t-1}^{-} + \alpha_5 LTP_{t-1}^{+} + \alpha_6 LTP_{t-1}^{-} \\ &+ \sum_{i=1}^{m} \delta_{1i} \Delta TEMP_{t-1} + \sum_{i=0}^{q} (\theta_i^{+} \Delta LELC_{t-1}^{+} \\ &+ \theta_i^{-} \Delta LELC_{t-1}^{-} + \theta_i^{+} \Delta PG_{t-1}^{+} + \theta_i^{-} \Delta PG_{t-1}^{-} \\ &+ \theta_i^{+} \Delta LTP_{t-1}^{+} + \theta_i^{-} \Delta LTP_{t-1}^{-}) + u_t \end{aligned} \quad \text{(ii)}$$

Where: TEMP represents total unemployment in the private sector, LELC denotes logged electricity consumption, PG indicates population growth, and LTP refers to logged total production.

3.2. Data Sources

The data for the variables examined in this study was sourced from the SARB and the Energy Statistics database. To empirically test the model, the study utilized annual data spanning the period 1990-2022 in South Africa. This time-series data offers valuable insights into the economic dynamics of the variables under investigation.

3.3. Estimation Techniques

Summary statistics were used to describe the variables, followed by the BDS test developed by Brock et al. (1996) to examine the presence of nonlinearity in the variables. Formal unit root tests, including the Kapetanios, Shin, and Snell (KSS) nonlinear unit root test, were conducted to determine whether the series is stationary or non-stationary. The KSS test, developed by Kapetanios et al. in 2003, addresses the limitations of traditional linear unit root tests, such as the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, particularly when the data exhibit nonlinear characteristics (Kapetanios et al., 2003). The selection of lag structure was also carried out by use of the akaike information criterion (AIC).

The paper aimed to determine whether a long-term relationship exists between the variables by applying the NARDL bounds testing approach to identify at least one vector of asymmetric cointegration in the series. The NARDL bounds test is estimated with an exogenous approach, meaning each variable is treated as the dependent variable in turn. This method was chosen for its advantage of accommodating small sample sizes, unlike the Johansen cointegration approach, which requires a larger sample size for reliable results (Thao and Hua, 2016). Once the nonlinearity test, nonlinear stationarity and asymmetric cointegration was confirmed among the variables under study, the NARDL model was estimated. To analyse the positive and negative changes in electricity consumption and population growth may have asymmetric effects on the on employment in the private sector. Unlike traditional linear models that assume symmetry, NARDL decomposes variables into positive and negative partial sums, allowing separate estimation of their impacts in both the short and long run. It is especially useful when theoretical or empirical evidence suggests that increases and decreases in electricity consumption and population growth do not influence outcomes such as, private sector employment in the same way. This makes NARDL a more realistic and policy-relevant tool for capturing complex economic dynamics. NARDL model developed by Shin et al. (2014), the NARDL model extends the traditional Autoregressive Distributed Lag (ARDL) approach by incorporating asymmetric relationships between variables. Moreover, its mathematical formulation aligns with equation (i).

The NARDL bounds testing uses the F and t-statistics to test for the significance level of lagged variables in a univariate error correlation system when there is uncertainty about the long-run relationship between variables (Pesaran et al., 2001). The null hypothesis that there is no long-term link between the variables is checked against the alternative hypothesis that there is a long-run connection among the series under review. A rule of thumb suggests that if the F-statistic is more than the critical values of the upper bound $I(1)$ then the null hypothesis is not accepted or otherwise. In other words, this implies that there is a long-run connection between the series.

Various analytical tests were employed, including autocorrelation tests, diagnostic tests, and stability tests. These tests were conducted to ensure that the model does not suffer from issues such as autoregressive conditional heteroscedasticity (Gujarati and Porter, 2009). Stability diagnostic tests were specifically carried out to verify that the model adheres to the assumptions of classical linear regression and does not suffer from error misspecification. The study utilized the cumulative sum (CUSUM) test and the cumulative sum of squares (CUSUMQ) test, as proposed by Brown et al. (1975). These tests assess the null hypothesis that the model's parameters are stable against the alternative hypothesis of instability. If the CUSUM line crosses one of the 5% significance boundaries, the null hypothesis is rejected, indicating that the model is unstable.

4. EMPIRICAL RESULTS

4.1. Descriptive Statistics of Variables

Before applying time series methods, it is crucial to ensure that the data is properly prepared and understood, which contributes to more reliable and accurate model estimation. Therefore, this study conducted descriptive statistics and the results are presented in Table 1.

Table 1: Descriptive statistics

Measurement	TEMP	LELC	PG	LTP
Mean	0.506061	208.5788	1.324242	89.73939
Median	0.500000	216.0000	1.200000	92.60000
Maximum	4.900000	238.3000	3.100000	104.6000
Minimum	−6.200000	154.5000	0.400000	67.30000
Standard deviation	2.164477	25.86411	0.538534	11.14520
Skewness	−0.806430	−1.016618	1.483370	−0.628566
Kurtosis	4.680873	2.801176	5.528424	2.242298
Jarque-Bera	7.461645	5.7461645	20.89241	2.962428
Probability	0.023973	0.023973	0.000029	0.227362
Sum	16.70000	16.70000	43.70000	2961.400
Sum Sq. Dev.	149.9188	149.9188	9.280606	3974.899
Observations	33	33	33	33

Source: Author's computation using Eviews 10

The results in Table 1 indicate that population growth exhibits a long right-tailed distribution around the mean, with a skewness value of 1.483370. In contrast, total employment in the private sector has a skewness of −0.806430, electricity consumption has a skewness of −1.016618, and total production shows a skewness of −0.628566, indicating long left-tailed distributions for these variables.

Evidence from Table 1 indicates that electricity consumption and total production exhibit platykurtic distributions, characterized by flatter frequency distributions compared to the normal distribution, as their kurtosis values are <3. Conversely, Table 1 shows that total employment in the private sector and population growth are leptokurtic, with sharper peaks relative to a normal distribution, as reflected by their kurtosis values of 4.680873 and 5.528424, respectively, which exceed 3.

Furthermore, the P-value of the Jarque-Bera test for total production is 22.73%, which exceeds the 5% level of significance. This indicates that the null hypothesis that total production is normally distributed is not rejected. Conversely, the p-values for total employment in the private sector, electricity consumption, and population growth are below the 5% significance level, suggesting these variables are not normally distributed. This implies that linear models may not be suitable for these series. Instead, nonlinear models, such as the NARDL technique, are more appropriate for handling non-normally distributed data.

In conclusion, the descriptive statistics provide key insights into the data's distributional characteristics that support the use of the NARDL model. The pronounced skewness and varying kurtosis across variables especially the right-skewed and leptokurtic nature of population growth and the left-skewed distributions of employment and electricity consumption, indicate asymmetric and non-normal data patterns. These findings suggest that changes in the explanatory variables may affect the private sector employment differently depending on their direction and magnitude, reinforcing the relevance of NARDL in capturing such nonlinear and asymmetric dynamics. Hence, the following section represents the linearity test.

4.2. Linearity Tests

It is critical to determine the nonlinearity of the variables before the estimation of the NARDL model and the results of the BDS Linearity Test are presented in Table 2 below. In Table 2 total employment has shown nonlinear characteristics on the following dimensions; 4, 5 and 6.

As presented in Table 2, the alternative hypothesis which suggests the series is nonlinear is accepted, since the P-values of electricity consumption are <1% level of significance in all the dimensions. Table 2 shows that the results for the BDS linearity test indicate that the null hypothesis of linearity on population growth and total production is rejected at 1, 5, and 10 level of significance.

4.3. Non-Linear Stationarity Testing

After conducting a nonlinearity test it is important to estimate a nonlinear unit root test to ensure that the NARDL assumptions

Table 2: BDS linearity test results

Variable	Dimension	BDS test statistic	Probability
TEMP	2	0.001524	0.1188
	3	0.002636	0.2258
	4	−0.062101	0.0000***
	5	−0.066563	0.0000***
	6	−0.071533	0.0000***
LELC	2	0.192378	0.0000***
	3	0.326603	0.0000***
	4	0.416076	0.0000***
	5	0.475875	0.0000***
	6	0.508900	0.0000***
PG	2	0.126622	0.0000***
	3	0.219953	0.0000***
	4	0.267731	0.0000***
	5	0.281185	0.0000***
	6	0.270588	0.0000***
LTP	2	0.186329	0.0000***
	3	0.321028	0.0000***
	4	0.415822	0.0000***
	5	0.468485	0.0000***
	6	0.505335	0.0000***

*Statistically significant at 10% level
**Statistically significant at 5% level
***Statistically significant at 1% level
Source: Author's computation using Eviews 10

and requirements for robust modelling are satisfied. The KSS nonlinear findings are displayed in Table 3.

As demonstrated in Table 3 the total employment is nonlinear stationary at a 1% level of significance since the t-statistics of −6.405 is more negative than the critical value of −2.82. Table 3 exhibits that the electricity consumption is also nonlinear stationary at a 5% significance level with the t-statistics of −2.724 which is less than the critical value of −2.22. In Table 3 both population growth and total production are nonlinear stationary at a 1% level of significance since the t-statistics of −3.100 and −3.769 are less than the critical value of −2.82, respectively.

4.4. NARDL Optimal Lag Length Selection

Another crucial preliminary test before estimating a NARDL model is optimal lag length because the performance and validity of the model heavily depend on the correct lag structure, and the outcomes are presented in Figure 1 below.

According to the results depicted in Figure 1, the lag structure recommended by the Akaike information criteria is the NARDL (1, 1, 1, 1, 1, 1, 1) model.

4.5. NARDL Bound Test to Asymmetric Cointegration

It is now crucial to assess the NARDL cointegration among the variables of interest, with the findings displayed in Table 4. This study estimated model I, model II, model III, and model IV to identify at least one vector of asymmetric cointegration within the series.

The findings demonstrate that the F-statistics for models I and VI exceed the upper bound critical values of 3.28 and 2.94 at the 5% and 10% significance levels, respectively. This implies that

Table 3: KSS nonlinear unit root test results

Variable	T-statistics	Critical value	Conclusion
TEMP	−6.405***	−2.82	Nonlinear stationary process
LELC	−2.724**	−2.22	Nonlinear stationary process
PG	−3.100***	−2.82	Nonlinear stationary process
LTP	−3.769***	−2.82	Nonlinear stationary process

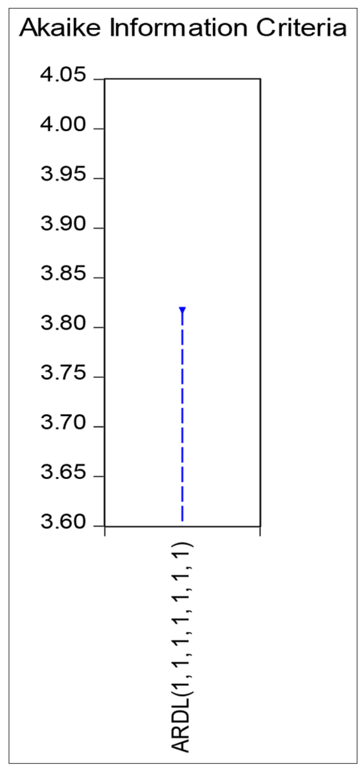
*Statistically significant at 10% level: [−1.92]
**Statistically significant at 5% level: [−2.22]
***Statistically significant at 1% level: [−2.82]
Source: Author's computation using R Package Software

Table 4: NARDL bound test results

Model	F-statistic	Conclusion
$TEMP = f(LELC^{\pm}, PG^{\pm}, LTP^{\pm})$		
$LELC = f(TEMP^{\pm}, PG^{\pm}, LTP^{\pm})$	1.793091	No asymmetric cointegration
$PG = f(TEMP^{\pm}, LELC^{\pm}, LTP^{\pm})$	1.898304	No asymmetric cointegration
$LTP = f(TEMP^{\pm}, LELC^{\pm}, PG^{\pm})$	3.120235*	Asymmetric cointegration

∴ Critical Values: I(0) I(1)
*Statistically significant at 10% level 1.99 2.94
**Statistically significant at 5% level 2.27 3.28
***Statistically significant at 1% level 2.88 3.99
Source: Author's computation using Eviews 10

Figure 1: Optimal lag structure



Source: Author's computation using Eviews 10

there is a long-run non-linear relationship between the variables under study.

4.6. NARDL Long Run and Short Run Model Estimates

Table 5 presents the long-run NARDL results for the relationships between electricity consumption, population growth, total production, and employment in the private sector. In the long run, an increase in electricity consumption leads to a 0.009% decrease in private-sector employment.

Similarly, a negative change in electricity consumption results in an increase in private-sector employment in South Africa. The negative coefficient for electricity consumption indicates a negative long-run relationship between electricity consumption and private-sector employment. This suggests a decrease in electricity consumption corresponds to a 0.020% increase in private-sector employment. Both positive and negative changes in electricity consumption are statistically significant. Table 5 shows that both positive and negative changes in population growth are statistically insignificant. It is evident from Table 5 that a positive change in total production leads to an increase in employment in the private sector in South Africa and is statistically significant. This means a unit increase in total production results in a 39.59-unit rise in employment in the private sector. Conversely, as illustrated in Table 5, a negative change in total production causes a decline in employment in the private sector. The positive coefficient of total production indicates a statistically significant positive relationship between total production and employment in the private sector. This suggests that a unit decrease in total production would result in a 40.23-unit reduction in employment in the private sector in the long run.

The following Table 6 presents the NARDL short-run results. In the short run, an increase in electricity consumption leads to a decline in private-sector employment. Specifically, a one-unit increase in electricity consumption results in a 27.33-unit decline in private-sector employment, which is statistically significant. However, the negative change in electricity consumption is statistically insignificant in the short run.

Table 6 shows that both positive and negative changes in population growth are statistically insignificant in relation to employment in the private sector, aligning with the long-run findings. In the short run, an increase in total production leads to a rise in employment in the private sector. This implies a unit increase in total production results in a 39.59-unit increase in private-sector employment in South Africa. Conversely, a decline in total production causes a corresponding decline in private-sector employment. The positive coefficient of total production indicates a positive relationship between total production and private-sector employment in the short run. This means a unit decrease in total production leads to a 40.23-unit decline in private-sector employment in South Africa.

ECT represents the speed of adjustment to equilibrium, as shown in Table 6. Additionally, the error correction term coefficient is −0.741518, with a P=0.000, indicating statistical significance. The negative coefficient suggests that the model will return to equilibrium in the long run after a shock to its short-run dynamics. This implies that the economy will adjust to equilibrium at a rate of 74%. The following section represents the findings of asymmetric effects.

4.7. NARDL Long and Short Run Asymmetric Effects

Table 7 below presents the results of the long- and short-run asymmetry analysis. In the long run, electricity consumption exhibits an asymmetric effect on employment in the private sector.

Similarly, population growth and total production also display asymmetric effects on employment in the private sector over the long run. However, in the short run, electricity consumption, population growth, and total production exhibit a symmetric relationship with employment in the private sector.

Table 5: Long run estimates for NARDL model

Variable	Coefficient	Standard error	T-statistics	Probability
LELC (POS)	−0.009906	0.004604	2.151889	0.0461**
LELC (NEG)	−0.020902	0.006434	3.248575	0.0047***
PG (POS)	−1.985922	2.216450	−0.895992	0.3828
PG (NEG)	0.610351	1.630349	0.374368	0.7128
LTP (POS)	39.59537	19.42105	2.038786	0.0573*
LTP (NEG)	40.23515	11.66145	3.450269	0.0031***

*Statistically significant at 10% level
**Statistically significant at 5% level
***Statistically significant at 1% level
Source: Author's computation using Eviews 10

Table 6: Short run estimates for NARDL model

Variable	Coefficient	Standard error	T-statistics	Probability
D (LELC) POS	−27.33031	9.346418	−2.924148	0.0095***
D (LELC) NEG	24.78069	15.18744	1.631657	0.1211
D (PG) POS	−1.985922	1.242092	−1.598853	0.1283
D (PG) NEG	0.610351	0.904999	0.674422	0.5091
D (LTP) POS	39.59537	11.57321	3.421296	0.0033***
D (LTP) NEG	40.23515	7.968044	5.049565	0.0001***
ECT	−0.741518	0.128170	−5.785441	0.0000***

*Statistically significant at 10% level
**Statistically significant at 5% level
***Statistically significant at 1% level
Source: Author's computation using Eviews 10

Table 7: Long and short run asymmetric effects results

Asymmetric null hypothesis	Long run		Short run	
	T-statistics	Probability	T-statistics	Probability
$LELC^{+} = LELC^{-}$	2.015890	0.0599*	−1.387414	0.1832
$PG^{+} = PG^{-}$	0.106377	0.0949*	−0.853149	0.4054
$LTP^{+} = LTP^{-}$	0.842275	0.0234**	−0.028014	0.9780

*Statistically significant at 10% level
**Statistically significant at 5% level
***Statistically significant at 1% level
Source: Author's computation using Eviews 10

Table 8: Residual diagnostic test results

Test	Null hypothesis	P-value	Conclusion
Breusch-Godfrey	No serial correlation	0.2632	There is no serial correlation
Breusch-Pagan-Godfrey	No heteroscedasticity	0.3988	There is no heteroscedasticity
Jarque-Bera	Residuals are normally distributed	0.7969	Residuals are normally distributed
Ramsey reset test	No misspecification	0.8095	No misspecification in the model

Source: Author's computation using Eviews 10

4.8. NARDL Residuals Diagnostics Tests

This study ensured the robustness of the NARDL model through diagnostic tests. Table 8 presents the results for serial correlation, heteroscedasticity, normality, and the Ramsey RESET test. Table 8 presents the results of the Breusch-Godfrey test, which yields a P = 26.32%, indicating no evidence of serial correlation. Therefore, the null hypothesis of no serial correlation cannot be rejected at the 5% significance level.

Additionally, Table 8 shows that the Breusch-Pagan-Godfrey test was employed in this study to examine heteroscedasticity in the model. The test results indicate that the null hypothesis of homoscedasticity asserting constant variance of the residuals cannot be rejected, as the P = 39.88% exceeds the 5% significance threshold. Furthermore, the normality of the error terms was evaluated using the Jarque-Bera test. As reported in Table 8, the P-value for the Jarque-Bera statistic is 79.69%, supporting the acceptance of the null hypothesis that the residuals follow a normal distribution, given that the P-value exceeds the 5% significance level.

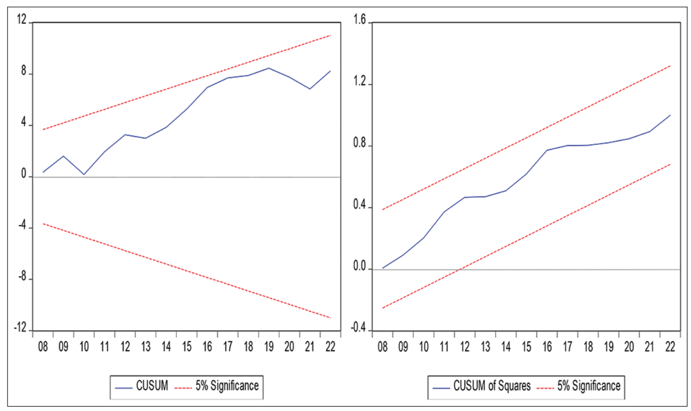
The results of the Ramsey RESET test, presented in Table 8, show no evidence of model misspecification, as the P = 80.95% exceeds the 5% significance level. Therefore, the null hypothesis, which states that the NARDL model is correctly specified, is not rejected.

In summary, diagnostic tests are crucial for ensuring model validity. The serial correlation test checks that error terms are independent over time to avoid biased inference, the heteroscedasticity test ensures that residual variance is constant, which is vital for reliable standard errors, the Jarque-Bera test verifies the normality of residuals, supporting the accuracy of hypothesis tests and the Ramsey RESET test assesses whether the model is correctly specified. Together, these tests confirm that the model produces unbiased, efficient, and trustworthy results. The following section presents the CUSUM and CUSUM of Squares results.

4.9. NARDL Dynamic Stability Test

This paper also examines the stability of the NARDL model at the 5% significance level. To assess stability, recursive estimations of the NARDL model are performed using the CUSUM and CUSUMQ tests, with the results presented in Figure 2 below.

Figure 2: NARDL dynamic stability test results



Source: Author's computation using Eviews 10

The findings in Figure 2 indicate that the NARDL model is stable, as the CUSUM and CUSUMQ lines remain within the 5% significance threshold. Therefore, the hypothesis of model instability is rejected.

5. CONCLUSIONS AND POLICY RECOMMENDATIONS

This study used the nonlinear autoregressive distributed lag (NARDL) model to examine the asymmetric impacts of population growth and energy consumption on employment in the private sector of South Africa. The findings showed a substantial nonlinear link between employment and electricity consumption, with varying effects on employment levels from increases and decreases in energy consumption. However, neither the short-term nor long-term effects of population growth on private-sector employment were statistically significant. These results highlight the relationship that exists in the South African setting between labour market outcomes, population trends, and energy usage.

The results contribute to the body of literature on energy economics and labour market dynamics by emphasising the asymmetric relationship between energy consumption and employment. This implies the necessity for more complex theoretical frameworks that take into consideration the nonlinearity of the relationships between energy and employment, especially in emerging nations. The findings imply that, in order to optimise employment benefits, energy management programs should concentrate on both expanding supply and maximising energy efficiency for practitioners and enterprises. To reduce the detrimental consequences of energy shortages on employment, industries that rely on power should investigate energy-saving technology and diversify their manufacturing methods. Policymakers must think about enacting energy regulations that minimise labour market disruptions while encouraging economical and sustainable electricity use. This could involve labour market reforms targeted at sectors less susceptible to energy volatility, investments in renewable energy sources, and targeted subsidies for energy-efficient technologies. Even if population growth did not significantly affect employment, long-term economic stability still depends on policies like skill development programs and job creation initiatives that increase labour market absorption capacities.

To provide a more thorough picture of employment dynamics, future research might examine the effect of additional economic factors such government policy changes, sector-specific employment patterns, and technological innovation. The generalizability of the observed effects across various economic circumstances may also be better understood by extending the analysis to include cross-country comparisons.

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