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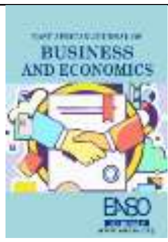

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Original Article

Embracing Technological Advancement: Assessing the Impact of Innovation on Sectorial Employment in Tanzania

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ABSTRACT

Technological innovation is one of the most rapidly advancing and dynamic sector today. It drives growth across all sectors of the economy. However, this rapid growth presents both opportunities and challenges. Taking innovation into account, this study aims to assess the impact of technological innovation on three sectors which are agriculture, industrial, and service sectors. The study employed the autoregressive distributed lag model (ARDL), with data from 2000 to 2022 obtained from the World Bank (WB) and the World Intellectual Property Organization (WIPO). Three ARDL models were used to estimate employment in the agriculture sector, employment in the industrial sector and employment in the service sector with inflation (CPI) and interest rate (INT) as the control variables. The ADF (Augmented Dickey-Fuller) test, PP(Philip-Perron) test, Serial Correlation LM test, BG Heteroscedasticity, and Jarque Bera Normality test were utilized to ensure robust estimates of the models. The findings revealed that innovation has a significant positive influence on employment in the agriculture sector and service sector whereas the industrial sector is negatively influenced by innovation. Nevertheless, inflation has a significant positive effect on employment in the agriculture and service sectors but negatively affects employment in the industrial sector, where a lag in interest rate influence negatively employment in the agricultural sector. Relying on these findings, the study recommends an increase in expenditure on research and development, formulation of policies that will mainstream innovation in all sectors of the economy, and investing more in education and skills development.

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INTRODUCTION

Modern technological advancements as a pivotal aspect of economic development have become a global cornerstone for modernizing and improving the livelihoods of citizens in all spheres (Okumu et al., 2019). Innovation in the 21st century has expanded for both developed and developing nations including Tanzania. In the Global Innovation Index (GII) report by the World Intellectual Property Organization (WIPO) countries such as Switzerland, Sweden, and the United States obtain the highest ranks in the category while Turkey, India, and VietNam possess the middle rank, and Tanzania, Mauritania, and Mozambique are lower ranked indicating underperformance in innovation metrics compared to global leaders (WIPO, 2023). The report provides insights into how these nations are performing regarding innovation capabilities, with Tanzania ranked 113th out of 132 countries in the GII 2023 and 13th in the region. Tanzania has experienced a gradual decline in innovation from 25.6 in 2014 to 17.4 index in 2023 (WIPO, 2023). This ranking highlights Tanzania's ongoing challenges in fostering an innovation-friendly environment (Ndesaulwa & Kikula, 2016).

The National Bureau of Statistics NBS (2022) reports that 12.6% of youths are employed in the service sector, 5.1% in manufacturing, and 62.4% in agriculture. However, unemployment decreased from 10.5% in 2014 to 9.3% in 2020/2021, and youth employment (15–24) increased by approximately 15.2% by 2022 (NBS, 2022). Since this group includes recent graduates from universities and vocational training centers, who are major contributors to innovation and practice, it is essential to assess potential discrepancies and ensure that technological progress contributes positively to economic development and employment stability (Lubua, 2022).

Technological advancement has impacted all sectors of the economy including the agricultural sector, manufacturing sector, and service sector (Filippi et al., 2023). Moreover, each sector experiences unique transformation due to technological innovation, influencing employment patterns and economic dynamics (Emara, 2021). In the agriculture sector, technological innovation has mechanized agricultural practices like using tractors, plowing machines, and harvester machines, increasing production efficiency (Mrabet & Lanouar, 2013). Furthermore, innovation has improved seeds and fertilizers, irrigation systems, and digital platforms which enable farmers to access significant markets and weather forecasts for their productions. In the manufacturing sector, innovation has introduced automation and robots, that facilitate the production and factory operation systems, and improved the quality controls which ensure the quality of products and minimize wastage (Nguyen & Le, 2024). In the service sector, innovation has improved the efficiency and effectiveness in the provision of different services; digital banking systems, e-office, e-commerce, and online education systems (Lubua, 2022). Despite the potential benefits of technological

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advancements, there is growing concern about their impact on employment in Tanzania (Raphael, 2022). The displacement of low-skilled jobs, the creation of new roles requiring advanced skills, and the overall effect on different sectors still need to be explored. This study seeks to address these gaps by examining how technological innovations influence employment trends across key sectors in Tanzania (Mtebe et al., 2020)

In Tanzania specifically, few studies have been made describing the effects of technological innovation on employment. Among others include; Ndesaulwa & Kikula, (2016) on the effects brought by innovation on the Performance of Small and Medium Enterprises in Tanzania, Raphael (2022) on digital skills and self-employment among graduates of Tanzania, and Mtebe et al. (2020) on ICT promoting youth employment in Tanzanian vocational education. All the studies have discussed the impact of technological innovation on employment and tend to generalize the impact of these innovations across the entire economy. Failing to provide a sector-specific analysis that could reveal the distinct effects of technology on critical sectors such as agriculture, manufacturing, and services creates a gap in understanding how different sectors uniquely experience and adapt to technological changes in Tanzania's evolving economic landscape.

The primary objective of this study is to assess the impact of technological advancements on sectorial employment trends in Tanzania. The specific objectives include (1) to analyze the impact of technological innovation on agricultural employment. (2) to analyze the impacts of technological innovation on industrial employment (3) to evaluate the role of innovation on service sector employment.

Study Hypothesis

H01: Technological innovation has no impact on agricultural sector employment in Tanzania

H02: Technological innovation has no impact on industrial sector employment in Tanzania

H03: Technological innovation has no impact on service sector employment in Tanzania

This study is essential because it provides actionable insights that are assets in technology and skill development. The sector-specific focus is significant to the Tanzanian economy, as understanding the different effects of innovation on each sector allows stakeholders to create tailored plans that promote sectorial achievements and assist those facing technological problems. However, this study will add to the body of knowledge on the relationship between technological innovation and employment in developing nations. It will also provide lessons that other developing countries facing comparable opportunities and challenges in the era of rapid technological change may find useful.

The rest parts of this paper are as follows: Literature Review on employment and technology improvements captures theoretical and empirical literature. The research methodology section is then explained in depth. The results and discussions section displays and explores the results from an econometric model. The conclusion provides a summary of the main conclusions and policy recommendations.

LITERATURE REVIEW

Theoretical Review

Creative Destructive Theory (CDT)

The Creative Destruction Theory (CDT) was introduced by Joseph Schumpeter in the early of 1939s as a theory of economic development (Tülüce & Yurtkur, 2015). According to Schumpeter, innovation triggers a “creative hurricane of destruction” (Chuang & Graham, 2018). Thus, innovation brings about variations and adjustment in the economy, with new technology replacing old technology, reshaping the nature of economies, and

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leading to improved industries and employment opportunities. However, the advancement of technology also causes structural unemployment among workers in different sectors due to a skills mismatch between old jobs and the skills required for new, innovative jobs in the short run (McGuinness et al., 2019). Nonetheless, Schumpeter provides hope for employment trends in the long run, suggesting that people will improve their education, training, and research. As a result, new job opportunities and markets will emerge, ultimately increasing employment in society (Tülüce & Yurtkur, 2015).

Endogenous Economic Growth Theory (EEGT)

The endogenous economic growth theory (EEGT) was formally initialized by Paul Romer in the 1980s (Romer, 1989). According to Romer, technological innovations have an impact on economic growth. The innovation is the result of the efforts of researchers and entrepreneurs who respond to economic inducements (Hepman, 1991). Furthermore, the impact of technological innovation on the aggregate output since technological innovation is one of the factors of the production autonomous of labor and capital. Technological innovations affect economic aggregates and as a result, they increase investments, industrial growth, and consequently job opportunities (Afolabi, 2023). Additionally, science and technological innovation improves workers' personal skills, creativity, and knowledge literacy, which in turn increases the employability and employment opportunities of workers (Kweka & Sooi, 2022).

Empirical Review.

Mrabet & Lanouar (2013) studied the nexus between trade liberalization, technology, and skill development in Tunisia's manufacturing sectors. Secondary data was analyzed. The panel data methodology was incorporated. The results demonstrated that technological advancement and trade liberalization have a favorable impact on the relative employment of the Tunisian manufacturing industry. In a similar vein, a study by Chuang & Graham (2018) put forward how technology affects employment and human resource development. Secondary data and systematic literature review (SLR) were exploited for analysis. This study found that technological innovations like robotics replace the human resource and hence reduce employment. However, (Sart & Sezgni, 2021) discussed the connection between employment and innovation in five vulnerable nations. A panel regression analysis of the secondary data was performed. According to the study, employment, and innovation have a precise relationship.

Obeng-Amponsah & Owusu (2023) conducted a separate study on Ghana's economic growth, employment creation, and technology innovation using the autoregressive distributed lag (ARDL), bound testing approach to cointegration, and Granger causality tests on data from 1995 to 2017. One of the several conclusions is that technology promotes Ghana's employment in both long and short terms.

However, Emara (2021) conducted a study to investigate the implications of technological improvements on employment in Egypt. The study analyzed innovation outputs using secondary data and the vector autoregressive (VAR) model. The conclusion was backed by impulse response functions which showed that a shock to innovation has a negative impact on employment in Egypt. Conversely, Nguyen & Le (2024) studied the influence of technological innovation on jobs in Vietnam. Secondary data from annual enterprise and technological production surveys from 2013 to 2018 were employed. The generalized least squares method (GLS) was used for analysis. The outcomes pinpointed that technological innovation increases employment in Vietnam's manufacturing economy. Likewise, Okumu et al. (2019) conducted a study on how African industrial companies evidence the nexus between innovation and employment growth. The cross-sectional data from the World Bank was

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incorporated and Ordinary Least Squares (OLS) was used for analysis. Several results obtained, portrayed that employment growth is positively attributed to both process and product innovation.

Afolabi (2023) examined how Nigerian economic sectors demonstrate the impact of technology innovation on employment. The ARDL analyzed quarterly data from 2011 to 2021. The findings emphasized the importance of fully implementing technological innovation across Nigeria's economic sectors to alleviate the country's current unemployment crisis. Congruently, Jazdauskaite et al., (2021) assessed the impact of technology innovation on employment. The study examined its impact through correlation and regression analysis. The findings shows that technological innovation has a positive impact on employment. Similarly, Lovergine & Pellero (2018) analyzed the effects of digitalization on the labor market. A secondary review of the literature over the previous five years and quantitative analysis were employed. The study concluded that robotics, artificial intelligence, and digital technological innovation have a direct impact on the labor market.

METHODOLOGY

Data and Data Collection Tools

The study on the impact of technological innovation on sectorial employment in Tanzania employed the secondary time series data running from 2000 to 2022 out of the World Bank and the World Intellectual Property Organization. This involves extracting and downloading data from the website in Excel formats. The data were cleaned and all outliers were replaced by the median value. The credibility of this data remains unquestionable due to rigorous data validation and quality checks on these databases. Furthermore, data were imported into EViews software for further econometric analyses**.**

Empirical Modelling

The impact of technological innovation on sectorial employment can be written as follows:

$$EMP = f(GDP, INN) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

Where EMP denotes employment, GDP denotes real Gross Domestic Product, and INN denotes innovation.

To estimate the sectorial employment, the study ignores the GDP since will be estimated by the sectorial output as the percent of GDP to avoid spurious regression (Okumu et al., 2019). Notably, the study employs the two control variables in the model which are Inflation measured by CPI and Interest rate (INT) which are very important in determining the nexus between employment and innovation (Afolabi, 2023). Thus, equation one can be integrated into three equations to incorporate the control variables in the model.

$$EMP\_AGR_t = \Omega_1 + \Omega_2 INN_t + \Omega_3 Y\_ARG_t + \Omega_4 CPI_t + \Omega_5 INT_t + \varepsilon_{1t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

$$EMP\_IND_t = \alpha_1 + \alpha_2 INN_t + \alpha_3 Y\_IND_t + \alpha_4 CPI_t + \alpha_5 INT_t + \varepsilon_{2t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

$$EMP\_SER_t = \beta_1 + \beta_2 INN_t + \beta_3 Y\_SER_t + \beta_4 CPI_t + \beta_5 INT_t + \varepsilon_{3t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4)}$$

Where EMP_AGR, EMP_IND, and EMP_SER denote the employments in agricultural, industrial, and service sectors respectively; INN represents Innovation; Y_ARG, Y_IND, and Y_SER denote output from the agriculture sector, industrial sector, and service sector respectively, and CPI and INT represent inflation and interest rate respectively. Nevertheless, World Intellectual Property (WIPO) has developed a strong innovation through the Global Innovation Index (GII), which captures all indicators of innovation. Succeeding the study by Mondolo (2022), GII has been adopted in this study to examine technological innovation, and its coefficient is expected either positive or negative. Furthermore, the coefficient of interest rate is expected to be positive since the lower interest rate

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encourages investments and hence expansion of job opportunities (Filippi et al., 2023). Remarkably, inflation lowers purchasing power and hence producers fail to employ more labor, and its coefficient is expected to be negative.

Autoregressive Distributed Lag (ARDL) model as advocated by Pesaran. M, Shin. Y and Smith. R in 2001 was employed to estimate the specified model. The choice of the ARDL model remains worthwhile, due to its superiority in estimating the short-run and long-run effects, providing robust results even if the sample size is small, it can work in both stationary and non-stationary provided they are integrated of order one I (1) or I (0) and not I (2) (Pesaran et al., 2001).

$$\Delta EMP\_AGR_t = \gamma + \Omega EMP\_AGR_{t-1} + \Omega_1 INN_{t-1} + \Omega_2 INN_{t-1} + \Omega_2 Y\_AGR_{t-1} + \Omega_3 CPI_{t-1} + \Omega_4 INT_{t-1} + \sum_{j=1}^{n} \theta_j \Delta EMP\_AGR_{t-1} + \sum_{j=0}^{n} \theta_j \Delta INN_{t-j} + \sum_{j=0}^{n} \theta_j \Delta Y\_AGR_{t-1} + \sum_{j=0}^{n} \theta_j \Delta CPI_{t-j} + \sum_{j=0}^{n} \theta_j \Delta INT_{t-j} + \mathcal{E}_{1t} \quad (5)$$

$$\Delta EMP\_IND_t = \sigma + \alpha EMP\_IND_{t-1} + \alpha_1 INN_{t-1} + \alpha_2 INN_{t-1} + \alpha_2 Y\_IND_{t-1} + \alpha_3 CPI_{t-1} + \alpha_4 INT_{t-1} + \sum_{j=1}^{n} \emptyset_j \Delta EMP\_IND_{t-1} + \sum_{j=0}^{n} \emptyset_j \Delta INN_{t-j} + \sum_{j=0}^{n} \emptyset_j \Delta Y\_IND_{t-1} + \sum_{j}^{n} \emptyset_j \Delta CPI_{t-j} + \sum_{j=0}^{n} \emptyset_j \Delta INT_{t-j} + \mathcal{E}_{2t} \quad (6)$$

$$\Delta EMP\_SER_t = \theta + \beta EMP\_SER_{t-1} + \beta_1 INN_{t-1} + \beta_2 INN_{t-1} + \beta_2 Y\_SER_{t-1} + \beta_3 CPI_{t-1} + \beta_4 INT_{t-1} + \sum_{j=1}^{n} \varphi_j \Delta EMP\_SER_{t-1} + \sum_{j=0}^{n} \varphi_j \Delta INN_{t-j} + \sum_{j=0}^{n} \varphi_j \Delta Y\_SER_{t-1} + \sum_{j=0}^{n} \varphi_j \Delta CPI_{t-j} + \sum_{j=0}^{n} \varphi_j \Delta INT_{t-j} + \mathcal{E}_{3t} \quad (7)$$

Where, Δ = first difference, γ, σ, and θ are the intercepts, and $\mathcal{E}_{it}$ represents white noise error terms. Additionally, equation 5, 6, and 7 represent the short-run and long-run cointegrating equations.

FINDINGS & DISCUSSION

Description of the variables

This section provides a label or identifier used to refer the variable, a clear explanation of how the variable is quantified or measured, and the source of the data used for the variable as shown in Table 1.

Table 1: Description of the variables

Variables	Measurement	Source
Employment in the Agriculture sector (EMP_AGR)	Percentage of total employment	World Bank
Agriculture sector output (Y_AGR)	Percentage of total GDP	World Bank
Employment in the Industrial sector (EMP_IND)	Percentage of total employment	World Bank
Industrial sector output (Y_IND)	Percentage of total GDP	World Bank
Employment in the service sector (EMP_SER)	Percentage of total employment	World Bank
Service sector output (Y_SER)	Percentage of total GDP	World Bank
Innovation (INN)	Global Innovation Index (GII)	WIPO
Inflation (CPI)	Consumer Prices (annual %)	World Bank
Interest (INT)	Lending rate (annual %)	International financial statistics

Source: World Bank & WIPO (2023)

Descriptive statistics

This section provides an overview of the data by describing and analyzing a dataset's main features, measure of central tendency, and measure of dispersion

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Table 2: Descriptive Statistics

	EMP_AGR	EMP_IND	EMP_SER	INN	CPI	INT	Y_AGR	Y_IND	Y_SER
Mean	71.3486	5.8155	22.8358	26.4817	5.4398	15.8257	25.7676	8.7532	41.6381
Median	70.8923	5.8985	24.2092	26.5000	5.3187	15.9333	25.7058	8.8174	41.4050
Max	83.0074	8.4721	26.6871	27.0000	7.8707	17.7742	28.7348	9.8615	49.1164
Min	65.5060	2.8263	14.1630	25.6000	3.2903	14.1403	23.2455	7.6659	30.5250
St. Dev	1.5367	1.6193	1.1929	0.3043	1.2200	0.9007	1.3073	0.6375	1.0530
Skew	0.8925	-0.2618	-1.0244	-1.4609	-0.1323	0.1763	0.3243	-0.1708	-0.5052
Kurtosis	2.5627	2.3516	2.7144	2.61338	2.4861	2.7772	2.9309	1.8641	2.5338
Jarque Bera	3.2546	0.6657	4.1011	17.5926	0.3202	0.1669	0.4077	1.3484	1.1868
Prob	0.1983	0.7169	0.1287	0.3431	0.8521	0.9200	0.8138	0.5096	0.5525
Obs	23	23	23	23	23	23	23	23	23

Source: Authors (2024)

Table 2 provides the outlook of the whole data set (Mbwambo et al., 2024). Mean and Median for all variables have a similar output suggesting that the data is normal. The standard deviation is small indicating that the data set converges to its average value (mean). Furthermore, the EMP_IND, EMP_SER, INN, CPI, Y_IND, and Y_SER have a negative and significant small value suggesting a left-tailed skewed, while EMP_AGR and Y_AGR have a negative and significant value justifying a right tail skewed toward large values. The kurtosis value is less than 3, indicating platykurtic distribution toward a normal distribution (Sithole & Buchana, 2021). The descriptive statistics in sum show that, no outliers and, a symmetric and normal distribution of the data set.

Unit root test

This part represents unit root tests which are ADF and PP, to confirm if the time series data are stationary or not before further analysis as represented in Table 3.

Table 3: Test for Stationarity

Augmented Dickey-Fuller (ADF) Test				Phillips-Perron (PP) Test			
Variable	**Test-stat.**	**Critical value**	**Prob.**	**Test-stat.**	**Critical value**	**Prob.**	**Order**
EMP_AGR	-2.9138	-2.6504	0.0614***	-4.1055	-3.7696	0.0047**	I (0)
EMP_IND	-3.5871	-3.2615	0.0557***	-3.7824	-3.6329	0.0473**	I (0)
EMP_SER	-3.1745	-3.0207	0.0370**	-4.4014	-3.7696	0.0024*	I (0)
INN	-5.5989	-3.7696	0.0002*	-5.5809	-3.7696	0.0002*	I (0)
CPI	-4.8758	-3.7880	0.0009*	-4.9610	-3.7880	0.0008*	I (1)
INT	-4.5720	-3.7880	0.0018*	-4.8076	-3.7880	0.0011*	I (1)
Y_AGR	-3.7920	-3.0207	0.0104**	3.3710	3.0124	0.0238**	I (1)
Y_IND	-4.5392	-3.7880	0.0019*	-4.5392	-3.7880	0.0019*	I (1)
Y_SER	-3.7974	-3.7880	0.0098*	-3.7974	-3.7880	0.0098*	I (1)

*Notes: *, **, *** indicate 1%, 5%, and 10% significance level respectively.*

Source: Authors (2024)

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Table 3 shows that employments (EMP_ARG, EMP_IND, and EMP_SER) in all sectors of the economy and innovation (INN) were stationary at levels while output (Y_AGR, Y_IND, Y_SER) in all sectors and control variables (CPI, INT) were stationarity after their first differences. This is supported by ADF and PP tests. Therefore, since some of the variables are stationary at the level and others are stationary after the first difference and neither at the second difference, this confirms an application of the ARDL model.

Cointegration Test

Cointegration was carried out to determine whether variables exhibit long-term relationships regardless of deviating from each other in the short term and the results of the ARDL Bound test for cointegration are shown in Table 4

Table 4: ARDL Cointegration & Bound Test

F-Bound Cointegration Test		Null Hypothesis: No levels of relationship		
Test Statistic	**Value**	**Significance**	**I (0)**	**I (1)**
		Asymptotic: n=1000		
		Model I (EMP_AGR)		
F-statistic	7.2025	10%	2.2	3.09
K	4	5%	2.56	3.49
		1%	3.29	4.37
		Model II (EMP_IND)		
F-statistic	4.9929	10%	2.2	3.09
K	4	5%	2.56	3.49
		1%	3.29	4.37
		Model III (EMP_SER)		
F-statistic	9.2303	10%	2.2	3.09
K	4	5%	2.56	3.49
		1%	3.29	4.37

Source: Authors (2024)

Table 4 shows the ARDL Bound test for three models (EMP_AGR, EMP_IND, and EMP_SER) shows that F-statistics is greater than the lower and upper bound at 1%, 5%, and 10% significant level. Thus, the null hypothesis of no co-integration between variables was rejected. Therefore, variables display long-run association and the Error Correction Model (ECM) may be estimated.

ARDL Model Estimation Results

Table 5: ARDL Short-run and Long-run Results for Agriculture Sector- Employment

Variable	Coefficient	Standard Errors	t-Statistic	Probability
		Short-run and Error Correction Model (2, 2, 0, 1, 2)		
D (EMP_AGR (-1))	0.3680	0.0784	4.6933	0.0011**
D(INN)	0.1600	0.1396	1.1469	0.2810
D (INN (-1))	-0.5679	0.1589	-3.5751	0.0060*
D (CPI)	-0.0257	0.0606	-0.4247	0.6810
D (INT)	0.0466	0.0671	-0.6940	0.5052
D (INT (-1))	-0.1950	0.0748	-2.6057	0.0285**
CointEq (-1) *	-0.0864	0.0105	-8.1990	0.0000*
		Long-run ARDL Model (2, 2, 0, 1, 2)		
INN	12.1620	5.4595	2.2276	0.0529***
Y_AGR	-0.9797	0.7360	-1.3310	0.2159
CPI	3.0993	1.2394	2.5006	0.0338**

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INT	3.4781	1.9954	1.7435	0.1152
C	-303.5659	165.1544	-1.8381	0.0992***
R-Squared	0.9352	Mean dependent var		0.7992
Adj. R-Squared	0.9073	S.D. dependent var		0.7040
S.E of regression	0.2143	Akaike info criterion		0.0171
Sum squared resid	0.6427	Schwarz criterion		0.3662
Log-likelihood	6.8110	Hanna-Quinn criterion		0.0936
Durbin-Watson stat	2.3257	Probability of F-statistic = 0.000		

*Notes: *, **, *** indicates 1%, 5% and 10% significance level respectively*

Source: Authors (2024)

Table 5 shows the short-run and long-run ARDL estimates for employment in the agriculture sector. In the short run, the lag of EMP_AGR has positive and significant effects on the current EMP_AGR. Explicitly, a one percent increase in the EMP_AGR sector in the previous year increases the current EMP_AGR sector by 0.368 percent. One percent increase in INN in the previous year decreases the current EMP_AGR sector by 0.568 percent. One percent increase in INT in the previous year decreases the current EMP_AGR sector by 0.195 percent. ECM shows that shocks in explanatory variables will be corrected at a rate of 8.64 percent in one year. In the long run, INN has a positive and significant influence on EMP_AGR, that is one percent increase in innovation, increases EMP_AGR by 12.162 percent. Also, inflation has a positive and significant influence on EMP_AGR, that is one percent increase in inflation, increases EMP_AGR by 3.1 percent. The coefficient of variation (R-squared) was 0.935 which suggests that 93.5 percent of the variations in EMP_AGR were explained by explanatory variables. The probability of the F-statistic is 0.000, which indicates a good model selection.

Table 6: ARDL Short-run and Long-run Results for Industrial Sector- Employment

Variable	Coefficient	Standard Errors	t-Statistic	Probability
Short-run and Error Correction Model (2, 0, 0, 1, 0)				
D (EMP_IND (-1))	-0.0920	0.0254	-3.6203	0.0031**
D(INN)	-0.0919	0.0927	-0.9911	0.0267**
D(CPI)	0.0035	0.0302	0.1144	0.9107
CointEq (-1) *	-0.0920	0.0143	-6.4405	0.0000*
Long-run ARDL Model (2, 0, 0, 1, 0)				
INN	-0.9992	0.9550	-2.2276	0.0479**
Y_IND	-0.9627	0.6563	-1.4670	0.1662
CPI	-0.9826	0.3334	2.9468	0.0113**
INT	0.3120	0.3695	0.0324	0.9747
C	47.9533	31.5326	1.5208	0.01523**
R-Squared	0.7571	Mean dependent var		0.2627
Adj. R-Squared	0.7301	S.D. dependent var		0.1721
S.E of regression	0.0894	Akaike info criterion		-1.8602
Sum squared resid	0.1438	Schwarz criterion		-1.7110
Log-likelihood	22.5318	Hanna-Quinn criterion		-1.8278
Durbin-Watson stat	2.0243	Probability of F-statistic = 0.000		

*Notes: *, **, *** indicates 1%, 5% and 10% significance level respectively*

Source: Authors (2024)

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Table 6 shows the short-run and long-run ARDL estimates for industrial sector employment. In the short run, the lag of EMP_IND has negative and significant effects on the current EMP_IND. One percent increase in the EMP_IND sector in the previous year decreases the current EMP_IND sector by 0.092 percent. One percent increase in INN decreases the EMP_IND sector by 0.092 percent. ECM shows that shocks in explanatory variables will be corrected at a rate of 9.2 percent in one year. In the long run, INN has a negative and significant influence on EMP_IND, that is a one percent increase in INN, decreases EMP_IND by 0.999 percent. Likewise, inflation has a negative and significant influence on EMP_IND, that is one percent decrease in inflation, increases EMP_IND by 0.983 percent. The coefficient of variation (R^2) was 0.757 which suggests that 75.7 percent of the variations in EMP_IND were explained by explanatory variables. The probability of the F-statistic is 0.000, which indicates a good model selection.

Table 7: ARDL Short-run and Long-run Results for Service Sector- Employment

Variable	Coefficient	Standard Errors	t-Statistic	Probability
Short-run and Error Correction Model (2, 1, 1, 2, 0)				
D (EMP_SER (-1))	0.7764	0.1851	4.1956	0.0018*
D(INN)	0.4079	0.2173	1.8775	0.0899***
D(Y_SER)	0.100263	0.0643	1.5589	0.1501
D(CPI)	0.1772	0.0629	2.8164	0.0183**
D (CPI (-1))	-0.3295	0.1014	3.2507	0.0087*
Long-run ARDL Model (2, 1, 1, 2, 0)				
INN	3.5791	0.9856	3.6313	0.0046
Y_SER	-0.8656	0.1015	-8.5295	0.000
CPI	1.6696	0.2712	6.1568	0.0001
INT	03574	0.2068	1.7279	0.1147
C	-49.6865	36.6294	-1.8658	0.0916
R-Squared	0.9981	Mean dependent var		23.6337
Adj. R-Squared	0.1936	S.D. dependent var		3.1373
S.E of regression	0.3747	Akaike info criterion		-0.1407
Sum squared resid	12.4772	Schwarz criterion		0.4064
Log-likelihood	524.3612	Hanna-Quinn criterion		-0.0219
Durbin-Watson stat	2.1949	Probability of F-statistic = 0.000		

*Notes: *, **, *** indicates 1%, 5% and 10% significance level respectively*

Source: Authors (2024)

Table 7 shows the short-run and long-run ARDL estimates for service sector employment. In the short run, the lag of EMP_SER has positive and significant effects on the current EMP_SER. Openly, a one percent increase in the EMP_SER sector in the previous year increases the current EMP_SER sector by 0.776 percent. One percent increase in INN increases the EMP_SER sector by 0.408 percent. Further, a One percent increase in inflation increases the EMP_SER sector by 0.177, and ECM shows that shocks in explanatory variables will be corrected at a rate of 29.1 percent in one year. In the long run, INN has a positive and significant influence on EMP_SER, that is one percent increase in INN, increases EMP_SER by 3.58 percent. Also, Y_SER has a negative and significant influence on EMP_SER, that is one percent increase in Y_SER, decreases EMP_SER by 0.866 percent. Remarkably, inflation has a positive and significant influence on EMP_SER, that is one percent increase in inflation, increases EMP_SER by 1.67 percent. The coefficient of variation (R^2) was 0.998 which suggests that 99.8 percent of the variations in EMP_SER were

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explained by explanatory variables. The probability of the F-statistic is 0.000, which indicates a good model selection.

Table 8: Models Diagnostic Tests

	BG-Serial LM Correlation Test	Heteroscedasticity: ARCH Test	Jarque Bera Test for Normality	Ramsey Reset Test
EMP_AGR Model	2.2680 (0.1740)	18.3966 (0.9997)	1.1832 (0.5534)	0.0689 (0.5467)
EMP_IND Model	2.2474 (0.3251)	9.7245 (0.2047)	1.6345 (0.0786)	3.4361 (0.1446)
EMP_SER Model	2.9611 (0.2275)	10.7202 (0.3797)	1.2456 (0.6120)	2.8491 (0.7023)

Notes: The number in the bracket is the probability of Chi2 (χ^2) of the respective diagnostic test.

Source: Authotrs (2024)

Table 8 shows the post-models diagnostic test, serial correction, heteroscedasticity, and Jarque Bera test showed that coefficients and their probability values are greater than 5% level of significance. This suggests that the null hypotheses of serial correlation, heteroscedasticity, and non-normal are rejected at a 5% significant level and therefore, models are free from serial correlations, and heteroscedasticity, and conform to classical normal regression assumptions. Further, the Ramsey Reset test shows no omissions of important variables in this study.

Table 9: Granger Causation Test among Variables

Null Hypothesis	Obs	F-Statistic	Probability
INT does not Granger Cause CPI	21	6.17953	0.0103*
CPI does not Granger Cause Y_AGR	21	3.46770	0.0561***
CPI does not Granger Cause EMP_IND	21	8.50772	0.0030*
INN does not Granger Cause Y_IND	21	5.11079	0.0192**

*Notes: *, **, *** indicates 1%, 5% and 10% significance level respectively*

Source: Authors (2024)

Table 9 shows the granger causation among variables, INT granger causes CPI. There is a unidirectional predictive relationship between INT and CPI. CPI granger causes Y_AGR, which means there is a direct association between CPI and Y_AGR. CPI granger causes EMP_IND, which means there is a significant connection between CPI and EMP_IND. INN granger causes Y_IND, which means there is a causal relationship between INN and Y_IND.

DISCUSSIONS

The study on the impacts of technological innovation on sectorial employment in Tanzania has shown that innovation affects all three sectors of the economy namely; the agriculture sector, industrial sector, and service sector. Implicitly, the study showed that innovation has impacted the agriculture sector employment negatively in the short run but positively in the long run. This is not surprising since innovation in the long run improves agricultural productivity through modernized agricultural seeds and pesticide technologies like robotics and drone machines which encourages more investments and hence creation of employment. These results are in line with Chuang & Graham (2018); Afolabi (2023) and Evangelista & Savona (2003). The study also showed that

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interest rates hurt employment in the agriculture sector, this has been evidenced that higher interest rate reduces loans available for investments in the agricultural sector which could ultimately demand more workers (Mbwambo et al., 2024). However, the findings have confirmed that there is an influence of inflation rate (CPI) on agricultural sector employment in the long- run, this implies that moderate inflation on foodstuffs encourages farmers and investors to produce more output to maximize their profit margins (Afolabi, 2023).

Furthermore, findings have shown that technological innovation has a negative impact in the short run and long run, this is because innovation in the industrial sector is accompanied by automation of machines and the use of robotics in the operation process which replace human workers. Moreover, the result has shown that inflation in the long run reduces employment in industrial sectors. This is not shocking since higher prices reduce consumer purchasing power, which reduces productivity and hence demand for labor decreases. These findings are congruent with Afolabi, (2023); McGuinness et al. (2019); Okumu et al. (2019) but contrary to studies by Nguyen & Le (2024) and Lovergine & Pellero, (2018).

Correspondingly, the study finding has shown that technological innovation has a positive influence on service sector employment in both the short-run and long-run. This is not surprising since innovation increases the service efficiency in both government and private sectors like the use of e-commerce, and e-office, which enhances job opportunities like digital marketing, cybersecurity, and mobile money services. Furthermore, the study has shown inflation rates and output in service sectors contribute to employment in the service sector positively in the long run. These results are in a similar vein as a study by Drahansky et al. (2016); Baita & Adzima (2021); Kazlauskienė & Šakalytė (2013); and (Afolabi, 2023).

CONCLUSION AND RECOMMENDATION

Conclusion

This study aims to assess the impact of technological innovation on agriculture, industrial, and service sector employments in Tanzania. Three econometric models (ARDL) were employed to arrive at the findings which showed that, lag of employment in the agriculture sector was found to have a positive influence on employment in the agriculture sector in the short-run, while innovation and lag of interest rate had a negative effect in short-run, while innovation and inflation found to have positive effects in long-run. Employment in the industrial sector on the other hand is negatively influenced by the lag of employment in the industrial sector and innovation in the short-run, and innovation and inflation in the long-run. Further, the lag of employment in the service sector, innovation, and inflation were found to have a positive effect on employment in the service sector while the lag of inflation had a negative effect in the short-run. Unsurprisingly innovation and inflation positively influence employment in the service sector whereas output in the service sector negatively influences employment in the service sector.

Recommendation

The study on the impact of technological innovation on sectorial employment in Tanzania has shown that innovation influences all sectors of the economy; this brings attention to researchers, policymakers, and the government on the best way to promote innovation in the economy. Based on the findings, the study recommends the following:

First; Increasing expenditure on research and development (R&D) to encourage young innovators and entrepreneurs on the best way to digitalize their ideas and innovation in services, products, and processes. This will increase competitiveness in the global world and also increase economic growth in Tanzania**.**

Second; Formulation of policies that will mainstream innovation in all sectors of the economy will reduce unemployment rates. For example, the

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agricultural sector employs about 65% of total employment. This may include and not limited to innovation incentive programs, youth and women empowerment, and public-private partnerships.

Third: Investment in education and skills development; firming up education in Science, Technology, Engineering, and Mathematics (STEM) which are essential to construct a foundation for innovation, entrepreneurship education by introducing entrepreneurship education at various levels of schooling can encourage a culture of innovation and risk-taking among young people, expanding vocational and technical training programs can help equip the workforce with the practical skills needed for innovation in manufacturing, agriculture, and service sectors.

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