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# EMPLOYMENT EFFECTS OF TECHNOLOGICAL INNOVATION: EVIDENCE FROM NIGERIA'S ECONOMIC SECTORS

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Technological advancement continues to revolutionize the labor market and has particularly intensified the debate on its employment effect across developing and developed economies. Employing the Autoregressive Distributed Lag (ARDL) framework, this study provides insights into the employment-innovation nexus across the Nigerian economic sectors using the quarterly data from 2011Q1 to 2021Q4. The findings reveal that the employment-innovation nexus is a short-run phenomenon in Nigeria and that technological innovation enhances employment generation in the service sector and the agricultural sector, but it takes a quarter before the positive employment effect occurs. Overall, the results suggest that technological innovation improves employment and reallocates labor across the sectors, which suggests the need to fully operationalize technological innovation across the Nigerian economic sectors in order to tackle the prevailing unemployment conundrum in the country.

**Keywords:** technological innovation, sectoral employment, ARDL, labor market

JEL Classification: C22, E24, O14

## INTRODUCTION

Technological advancement continues to revolutionize the global economy, charting the new paths that were otherwise impracticable in past centuries. The emergence of the fourth industrial revolution (Industry 4.0), the quest for developing knowledge-based economies and the growing spate of globalization further present new opportunities for increased technological advancement. The increasing importance of technological innovation in contemporary times has attracted the attention of academics, researchers and policymakers, among other stakeholders. Thus, there is a growing literature on the determinants and effects of technological innovation (Gyeke-Dako, Oduro, Turkson, Baffour & Abbey, 2016; Piva & Vivarelli, 2017; Krousie, 2018; Okumu, Bballe & Guloba, 2019; Sithole & Buchana, 2021). However, there seems to be a lack of consensus on the labor market effects of technological innovation in the literature, with some studies revealing that technology has employment-creating effects (Piva

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& Vivarelli, 2017; Okumu *et al*, 2019), whereas others argue that it has destructive effects on employment (Campa, 2014; Krousie, 2018; Sithole & Buchana, 2021). Some studies have also shown that technological innovation reallocates labor across economic sectors (Cang, 2017; Yildirim, Yildirim, Erdogan & Kantarci, 2020).

The "creative destruction" concept put forward by J. A. Schumpeter (1942) suggests that technological innovation creates new jobs and destroys old ones, leaving some people better-off and others worse-off. It encourages capital-intensive operations and favors skilled labor, which leads to skill-biased technological change, routine-biased technological change and job polarization (Acemoglu & Autor, 2011; Goos, Manning & Salomons, 2014). The proponents of technological innovation argued that it produced more middle-skill jobs, improved productivity, raised the wage rate of skilled and semi-skilled labor, and increased product varieties, especially in the technology utilizing sector (Aguilera & Barrera, 2016; Piva & Vivarelli, 2017). Recently, the indispensability of technological innovation has been brought to the fore during the COVID-19 pandemic era, as it facilitated product and service delivery despite the lockdown orders of various national governments (Bolaji, Adeoti & Afolabi, 2021; Olanrewaju & Afolabi, 2022).

There is growing advocacy for the full adoption of technological innovation in Nigeria, yet with less consideration for its potential impact on the labor market outcomes, particularly employment. Diverse policy and institutional efforts devoted to the improvement of the adoption of technological innovation and abating unemployment in Nigeria are yet to yield optimal outcomes. For example, Nigeria's ranking on the Global Innovation Index in 2021 is unimpressive, as the country ranked 118 out of 132 countries, thus reflecting low-level technological absorption in the country (World Intellectual Property Organization, 2021). All the more so, the Nigerian labor market is highly saturated given the fact that the unemployment rate is continuing to soar, rising from 7.5% in the first quarter of 2015 to 33.3% in the last quarter of 2020, with youth unemployment contributing remarkably to the growing unemployment rate (National Bureau of Statistics, 2021). This indicates the fact that Nigeria consistently misses out on reaping demographic dividends (Ogunjimi & Oladipupo, 2019) and is likely to be vice-ridden by various social vices and exposed to security challenges (Oji & Afolabi, 2022). Technological innovation can disrupt the labor market, reallocate labor and even displace high-skilled labor, such as doctors, web developers and architects (United Nations, 2017).

Given the fact that the employment effect of technological innovation may differ across economic sectors, this study contributes to the literature by examining the sectoral employment effect of technological innovation in Nigeria. Past studies have provided overwhelming evidence on the employment-innovation nexus, particularly in developed countries, with little evidence on developing economies, including Nigeria (Matuzeviciute, Butkus & Karaliute, 2017; Piva & Vivarelli, 2017; Krousie, 2018; Sithole & Buchana, 2021; Yildirim *et al*, 2020). Most of the studies on the employment-innovation nexus are firm-level and industry-level, with but a few pieces of evidence from aggregate-level studies (Gyeke-Dako *et al*, 2016; Okumu *et al*, 2019). The firm-level studies on the subject matter have two major weaknesses: they fail to fully account for indirect compensation effects (Cang, 2017) and they do not account for the possible crowding-out effects of innovative firms in the labor market (Vivarelli, 2012).

Therefore, this study fills these observed research gaps by conducting a macro-level study on the employment-innovation nexus in Nigeria, with a particular emphasis being placed on sectoral employment. It hinges the relationship between the researched sectoral employment and the matching theory proposed by C. A. Pissarides (1985; 1990). The quarterly data on the selected macroeconomic variables spanning 2011Q1 and 2021Q4 are sourced from reputable databases so as to test the following research hypotheses:

H1: Technological innovation has a statistically significant impact on sectoral employment in Nigeria.

H2: Technological innovation reallocates labor across the Nigerian economic sectors.

The Autoregressive Distributed Lag (ARDL) framework developed by M. H. Pesaran, Y. Shin and R. Smith (2001) is used to analyze the quarterly data and test the research hypotheses.

Following this introductory section, the paper is structured into the following sections: in Section Two, a brief review of the literature and the theoretical framework adopted in this study are presented; Section Three explains the research methodology, while Section Four comprises the empirical analysis. Finally, the conclusions of the study are given in Section Five.

## A BRIEF REVIEW OF THE LITERATURE

There is a quantum of empirical evidence on the nexus between technological innovation and employment. However, there seems to be no consensus on the direction and magnitude of the relationship. Some empirical studies have found that technological innovation is employment-generating (Reenen, 1997; Gyeke-Dako *et al*, 2016; Piva & Vivarelli, 2017; Okumu *et al*, 2019), whereas some other studies have alluded to the fact that technological innovation adversely affects employment (Vivarelli, 2013; Cang, 2017; Yildirim *et al*, 2020). Even more so, there are studies that have found that technology has mixed effects on employment (Postel-Vinay, 2002; Vicini, 2016; Dachs, 2018; Sithole & Buchana, 2021). Some other studies have found no significant relationship between the two macroeconomic variables (Aguilera & Barrera, 2016; Matuzeviciute *et al*, 2017).

The key argument in support of the positive relationship between technological innovation and employment is the fact that, through investment in research and development activities, technological innovation makes the production of new product varieties possible, offering consumers a broad range of products to demand (Okumu *et al*, 2019; Sithole & Buchana, 2021), which is likely to stimulate aggregate demand and compel producers to increase production in order to reach the increasing demand level. One of the most feasible means to address the excess demand problem is to hire more labor to raise the production level. Thus, most producers resort to hiring more labor, thereby reducing the number of the people in the unemployment pool (Raifu & Afolabi, 2022), in which way technological innovation creates new jobs through the introduction of new products (the phenomenon called "product innovation") and fosters employment prospects (Vicini, 2016; Dachs, 2018). In fact, M. Piva and M. Vivarelli (2017) argued that product innovation significantly improved employment growth, particularly in high- and medium-tech sectors.

On the other hand, the employment-reducing effect of technological innovation has been closely linked to process innovation - improvement in the production process (Reenen, 1997; Sithole & Buchana, 2021). The argument behind this is that improvement in technology translates to machines replacing humans or reducing the number of humans in the production process, which worsens unemployment, reduces welfare and broadens income gaps. Specifically, B. Dachs (2018) argued that the lopsided digitalization cost distribution resulting from the skill-biased nature of technological change worsened unemployment and income inequality. Thus, process innovation significantly contributes to job displacement, especially that of low-skilled workers. F. Postel-Vinay (2002) argued that improvement in technological innovation accelerated job obsolescence, thus inducing job displacement, simultaneously lowering employment below its equilibrium level. However, M. Vivarelli (2013) argued that process and product innovation were interrelated, and that process innovation did not always lead to job destruction. Providing support for this stance, I. M. Okumu, E. Bbaale and M. M. Guloba (2019) showed that process innovation had the employment-enhancing effect among African manufacturing firms although J. V. Reenen (1997) argued that only the dominance of product innovation over process innovation would make that possible.

P. Li (2021) evaluated the employment effect of technological innovation in China. The result of the impulse response function showed that technological innovation destroyed jobs in the short run but created jobs in the long run. In a similar fashion, V. Palekhova and O. Kramarenko (2020) examined the employment effect of technological innovation in the financial sector of South Korea, Ukraine, and the United Kingdom. The results showed that the employment level declined as the innovation level increased although the employment effect of innovation varied across the three countries. Precisely, the magnitude of the impact is higher in South Korea and the United Kingdom than in Ukraine. J. I. Ubah, E. K. Bowale, J. O. Ejemeyovwi and Y. Okereke (2021) also evaluated the employment effects of both technological innovation and electricity access in Nigeria using data from 1960 to 2017. The result showed a significant inverse relationship between technology and employment in Nigeria, indicating the fact that technology caused job destruction. Employing the Structural Vector Autoregression (SVAR) model, G. Kindberg-Hanlon (2021) showed that technologies complemented and substituted labor, the substitution effect being more dominant in the short run. Given the high technological development rate in developed countries, employment-displacing technological change is found to be more prevalent in advanced countries with industrial jobs being the most at risk of automation.

Moreover, Y. J. Cang (2017) argued that the nature of the employment effect of technological innovation depended on the geographical location and political regime under consideration. For the United States, the study showed that technology destroyed employment in rural and low-tech regions, and that the adverse employment effect of technological innovation was more pronounced in the Obama regime than in the Bush and Clinton regimes. C. Krousie (2018) supported this stance by alluding to the fact that technological innovation displaced labor in the United States although not substantially, as there were more high-skilled than low-skilled labor in the country. Exploring the possibilities of how artificial intelligence would influence the future of work, R. Campa (2014) argued for an imminent end of work and the end of robots while predicting disparity in the future of human societies influenced by the factors such as political awareness, the democratic rule and infrastructural development.

## THE THEORETICAL FRAMEWORK AND METHODOLOGY

This study is built on the theoretical foundation of search and matching theory, the choice of which is based on its exceptional ability to clearly explain the dynamics of the labor market with regard to workers' displacement and rehiring often caused by frictional unemployment (the skill mismatch) and structural unemployment (technology-induced unemployment) (Pissarides, 1990; Mortensen & Pissarides, 1998). The search and matching model describes and explains creative job destructions and the formation of new jobs, which is one of the major thrust of this study. This theory models markets where frictions inhibit economic activities from instantaneously adjusting to market dynamics. The key assumptions underlying search and matching theory are the high heterogeneity of workers and jobs and the risk-neutrality of workers seeking to maximize their utility per unit of time. The unemployed search for jobs following frictional or structural unemployment and can only be matched with the jobs for which they have requisite skills so as to maximize their labor efficiency. C. A. Pissarides (1985) argued that, in the case of uneven matches, some of the least productive employers/workers might become less profitable following a negative aggregate shock, which could lead to the retrenchment of workers and an increase in the number of the labor force in the unemployment pool. On the other hand, employers may immediately hire new workers during or after a positive aggregate shock, given the fact that job hires are conditional on imperfect matching technology.

Drawing from the foregoing discussion, the theoretical model analyzing the effects of technological innovation on employment in Nigeria can be written as follows:

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

where EMP, GDP and INN denote employment, the real GDP (a proxy for the aggregate shock) and technological innovation, respectively. However, in order to capture sectoral effects, employment and the real GDP are disaggregated across the sectoral lines - agriculture, industry and service. In addition, following D. C. Yildirim *et al* (2020), the two key macroeconomic variables (the inflation rate and credit to the private sector) are incorporated in the model as the control variables. Their inclusion hinges on the fact that they are significant drivers of employment in each economic sector and their omission from the estimated model may result in the omitted variable bias (Dogan & Inglesi-Lotz, 2020). Thus, equation (1) can be disaggregated into the three equations as follows:

$$AGR\_EMP_t = \alpha_1 + \alpha_2 INN_1 + \alpha_3 AGR\_Y_t + \alpha_4 INF_t + \alpha_5 CPS_t + \varepsilon_{2t} \quad (2)$$

$$IND\_EMP_t = \beta_1 + \beta_2 INN_1 + \beta_3 IND\_Y_t + \beta_4 INF_t + \beta_5 CPS_t + \varepsilon_{3t} \quad (3)$$

$$SER\_EMP_t = \delta_1 + \delta_2 INN_1 + \delta_3 SER\_Y_t + \delta_4 INF_t + \delta_5 CPS_t + \varepsilon_{4t} \quad (4)$$

where *AGR_EMP, IND_EMP,* and *SER_EMP* denote employment in the agricultural sector, employment in the industrial sector, and employment in the service sector; *INN* stands for innovation; *AGR_Y*, IND_Y, and *SER_Y* denote the agricultural output, the industrial output, and the service output, respectively, and *INF* and *CPS* denote inflation and domestic credit to the private sector, respectively. Some of the common measures of innovation in the literature are information and communication technology (ICT), research and development (R&D) spending, and patents. However, the World Intellectual Property Organization (WIPO) developed a composite index, the Global Innovation Index (GII), that comprehensively captures all innovation indicators. Following V. Palekhova and O. Kramarenko (2020), the GII is adopted in this study as the measure of technological innovation. Based on economic theories, technological innovation could either enhance or destroy employment. Thus, the GII coefficient is expected to have either a positive or a negative sign. The coefficients of the sectoral output and credit to the private sector, however, are expected to have positive signs as these variables have a direct effect on employment prospects (Yildirim *et al*, 2020). On the other hand, inflation reduces real income and the purchasing power of producers, subsequently hampering their capability to employ more labor (Ogunjimi, 2019; Aminu & Ogunjimi, 2019). Thus, the inflation coefficient is expected to be negative.

The Autoregressive Distributed Lag (ARDL) approach developed by M. H. Pesaran, Y. Shin and R. Smith (2001) is adopted so as to estimate the specified models. The approach is selected for the three major reasons. First, it has an inherent capacity (the bounds test) to check for the existence or otherwise of the long-term relationship among the variables. Second, it accommodates stationary and nonstationary series, provided they are not I(2), i.e. integrated of order two. Third, it simultaneously generates both short- and long-term estimates (Pesaran *et al*, 2001). The ARDL version of the equations 2, 3 and 4 is written as follows:

$$\Delta AGR\_EMP_t = \gamma + \alpha AGR\_EMP_{t-1} + \alpha_1 INN_{t-1} + \alpha_2 AGR\_Y_{t-1} + \alpha_3 INF_{t-1} + \alpha_4 CPS_{t-1} + \sum\nolimits_{j=1}^{n} \o_j \Delta AGR\_EMP_{t-j} + \sum\nolimits_{j=0}^{n} \o_j \Delta INN_{t-j} + \sum\nolimits_{j=0}^{n} \o_j \Delta AGR\_Y_{t-j} + \sum\nolimits_{j=0}^{n} \o_j \Delta INF_{t-j} + \sum\nolimits_{j=0}^{n} \o_j \Delta CPS_{t-j} + \varepsilon_{1t} \quad (5)$$

$$\Delta IND\_EMP_t = \delta + \beta IND\_EMP_{t-1} + \beta_1 INN_{t-1} + \beta_2 IND\_Y_{t-1} + \beta_3 INF_{t-1} + \beta_4 CPS_{t-1} + \sum\nolimits_{j=1}^{n} \theta_j \Delta IND\_EMP_{t-j} + \sum\nolimits_{j=0}^{n} \theta_j \Delta INN_{t-j} + \sum\nolimits_{j=0}^{n} \theta_j \Delta IND\_Y_{t-j} + \sum\nolimits_{j=0}^{n} \theta_j \Delta INF_{t-j} + \sum\nolimits_{j=0}^{n} \theta_j \Delta CPS_{t-j} + \varepsilon_{2t} \quad (6)$$

$$\Delta SER\_EMP_t = \rho + \omega SER\_EMP_{t-1} + \omega_1 INN_{t-1} + \omega_2 SER\_Y_{t-1} + \omega_3 INF_{t-1} + \omega_4 CPS_{t-1} + \sum\nolimits_{j=1}^{n} \varphi_j \Delta SER\_EMP_{t-j} + \sum\nolimits_{j=0}^{n} \varphi_j \Delta INN_{t-j} + \sum\nolimits_{j=0}^{n} \varphi_j \Delta SER\_Y_{t-j} + \sum\nolimits_{j=0}^{n} \varphi_j \Delta INF_{t-j} + \sum\nolimits_{j=0}^{n} \varphi_j \Delta CPS_{t-j} + \varepsilon_{3t} \tag{7}$$

where $\Delta$ is the first difference operator; $\gamma$, $\delta$ and $\rho$ are the intercepts; and $\varepsilon_{it}$ is the white noise residuals. The equations 5, 6 and 7 were estimated in the stepwise manner. In the baseline models, only technological innovation was first regressed on sectoral employment, but the other explanatory variables were subsequently introduced into the model, which essentially served to gain an insight into the individual effect of technological innovation on sectoral employment before and after the introduction of the control variables. The 2011Q1 to 2021Q4 quarterly data on the variables of interest were sourced from the Central Bank of Nigeria (CBN), the World Bank (WB) and the World Intellectual Property Organization (WIPO) databases. Each of the variable has different frequencies. Thus, all the variables were converted into quarterly series using the quadratic data smoothing statistical method (Oloko & Yusuf, 2021). The sources and description of each variable are presented in Table 1.

# RESULTS AND DISCUSSION

## Descriptive statistics

Table 2 provides the basic descriptive statistics of the key variables of interest. It shows the dominance of the Nigerian service sector given its average contribution to the aggregate output (52.4 per cent) and employment (51.2 per cent), which suggests that the Nigerian service sector absorbs more labor and contributes more to the aggregate output than the agricultural and industrial sectors put together. This impressive performance has been attributed to the relative adoption of technological innovation by actors and players in the Nigerian service sector (Ogunjimi, 2020a, 2020b; Afolabi, Olanrewaju & Adekunle, 2022). On the other hand, however, the relatively low contribution of the agricultural and industrial sectors to both the aggregate output and employment in Nigeria is linked to neglecting these sectors in the wake of Nigeria's discovery of crude oil in commercial quantities in the 1970s (Afolabi & Ogunjimi, 2020; Afolabi & Oji, 2021). The average value of the innovation score in Nigeria is also very low and the country ranks perpetually low on the global innovation index, failing to make the top 100 innovative countries in the world (WIPO, 2021), which implies the fact that Nigeria would have to import technology just as it does when other merchandise products are concerned so as to meet the demand of the contemporary knowledge-based economy. On the other hand, the average inflation rate in Nigeria is double-digit, while the average share of domestic

**Table 1** The data description

| Variables | Measurement | Source |
|---|---|---|
| Agricultural sector employment (AGR_EMP) | % of the total employment | WB (2021) |
| Agricultural sector output (AGR_Y) | % of the GDP | CBN (2021) |
| Industrial sector employment (IND_EMP) | % of the total employment | WB (2021) |
| Industrial sector output (IND_Y) | % of the GDP | CBN (2021) |
| Service sector employment (SER_EMP) | % of the total employment | WB (2021) |
| Service sector output (SER_Y) | % of the GDP | CBN (2021) |
| Technological innovation (INN) | Global Innovation Index | WIPO (2022) |
| Inflation (INF) | % | CBN (2021) |
| Domestic credit to private sector (CPS) | % of the GDP | CBN (2021) |

*Source*: Author

credit to the private sector in the total GDP ranges between 0.1 per cent to 31.8 per cent for the period under consideration. Interestingly, the standard deviation of all the variables, except for domestic credit to the private sector, is relatively low, suggesting that the variables are not broadly dispersed from their respective mean values.

**Table 2** The descriptive statistics

| Variables | Mean | Minimum | Maximum | Standard Deviation |
|---|---|---|---|---|
| AGR_EMP | 37.06 | 34.89 | 40.98 | 1.70 |
| IND_EMP | 11.72 | 9.86 | 12.05 | 0.60 |
| SER_EMP | 51.22 | 49.16 | 53.11 | 1.20 |
| AGR_Y | 24.27 | 19.65 | 30.77 | 3.17 |
| IND_Y | 23.35 | 18.05 | 28.83 | 2.50 |
| SER_Y | 52.38 | 46.79 | 55.67 | 2.45 |
| INN | 23.86 | 19.52 | 30.69 | 2.75 |
| INF | 12.23 | 7.82 | 18.45 | 3.22 |
| CPS | 5.29 | 0.10 | 31.77 | 9.68 |

*Source*: Author

## The unit root test

The unit root test is highly important in time-series and panel studies for the determination of the stationary properties of variables, which guides the choice of the estimation technique so as to avoid generating unreliable estimates. The Phillip Perron (PP) and Augmented Dickey Fuller (ADF) approaches are adopted in this study. These unit root test approaches test the null hypothesis (the variables contain the unit root) against its alternative. The decision to accept/reject the hypothesis depends on the probability values of each variable. If the probability value exceeds 10 percent, the null hypothesis will be accepted; it will be rejected otherwise. The unit root test results reported in Table 3 account for the fact that some variables are stationary (I(0)) while others are not (I(1)). Specifically, the variables have a mixed order of integration, which satisfies one of the conditions for adopting the ARDL framework.

## The cointegration test

The findings generated from the unit root test indicate the imperative of determining whether there is a long-term relationship among the variables or not in order to account for it in the ARDL estimation. The bounds test is used in this regard, which tests the null hypothesis of no long-term relationship, which is rejected if the F-statistic exceeds the upper bound critical value but is accepted if it falls below the lower bound critical value. However, uncertainty surrounds the long-term relationship if the F-statistic falls within the range of the upper and lower bound

**Table 3** The results of the unit root tests

| Variables | Phillip Perron (PP) | | | Augmented Dickey Fuller (ADF) | | |
|---|---|---|---|---|---|---|
| | Level | 1st Difference | I(d) | Level | 1st Difference | I(d) |
| AGR_EMP | -3.19**a | - | I(0) | -2.23a | -2.70***a | I(1) |
| IND_EMP | -6.09*a | - | I(0) | -5.91*b | - | I(0) |
| SER_EMP | -1.39b | -3.22**a | I(1) | -2.28b | -3.07**a | I(1) |
| INN | -3.02b | -3.55**a | I(1) | -4.19**b | - | I(0) |
| AGR_Y | -8.12*b | - | I(0) | -2.42b | -2.97**a | I(1) |
| IND_Y | -11.70*b | - | I(0) | -2.59b | -4.14*a | I(1) |
| SER_Y | -10.19*b | - | I(0) | -1.99b | -3.09**a | I(1) |
| INF | -2.11b | -3.32**a | I(1) | -2.99b | -3.69*a | I(1) |
| CPS | -1.44a | -5.20*b | I(1) | -1.61a | -5.29*b | I(1) |

Note: * $p<0.01$, ** $p<0.05$, *** $p<0.1$. 'a' and 'b' denote the model with the constant and the model with the constant and the trend, respectively. I(0) and I(1) indicate stationarity at the level and the first difference, respectively.

*Source*: Author

critical values. In this light, the bounds test results reported in Table 4 are indicative of the nonexistence of the long-term relationship between sectoral employment and technological innovation in Nigeria as the result of the baseline models shows that their respective F-statistics fall below the lower bound critical values at all the significance levels. In a similar fashion, the results of the alternative models show the nonexistence of the long-term relationship among the variables in the employment models in the agricultural and service sectors, whereas the result indicates uncertainty for the employment model in the industrial sector. Succinctly, the link between sectoral employment and technological innovation is a short-term phenomenon in Nigeria, which is suggestive of the fact that whatever impact technological innovation has on sectoral employment, that impact is not permanent.

## Model estimation and discussion

Following the cointegration test results that indicate the nonexistence of the long-term relationship between sectoral employment and technological innovation, the short-term ARDL model is estimated, and the result is given in Table 5. It shows that the effect of technological innovation on employment differs across the sectors. For the agricultural sector, technological innovation has an instantaneous negative impact on employment generation but creates jobs after a period of one quarter. Expectedly, an increase in the adoption of technological innovation in the agricultural sector fosters the replacement of humans with machines as the latter can perform agricultural tasks faster and more efficiently, which explains the immediate negative impact of technological innovation on employment in the agricultural sector and corroborates the finding of J. I. Ubah, E. K. Bowale, J. O. Ejemeyovwi and Y. Okereke (2021), who argued that technology induced job destruction in Nigeria.

In addition, the low level of technological knowhow in Nigeria contributes to the adverse impact of technological innovation on employment in the agricultural sector. This result corroborates the finding of N. Kumar, K. S. Suhag, J. Kumar and R. Singh (2010), who showed that machinery displaced human labor through improvement in farm technology. In a similar manner, technological innovation has a positive but statistically insignificant effect on employment in the industrial sector. This technology-induced employment improvement in the industrial sector could be attributed to the increase in the agricultural output and employment that makes raw materials available for the industry. Given the fact that access to raw material is a major factor hampering the performance of the Nigerian industrial sectors, technological innovation is a viable tool to not

**Table 4** The bounds test result

| Significance Level (k=4) | Lower Bound | Upper Bound | Models | F-statistic |
|---|---|---|---|---|
| 10% | 2.45 | 3.52 | AGR_EMP | 2.48 |
| 5% | 2.86 | 4.01 | IND_EMP | 3.74 |
| 1% | 3.74 | 5.06 | SER_EMP | 1.52 |
| Significance Level (k=1) | | | | |
| 10% | 4.04 | 4.78 | AGR_EMP | 2.86 |
| 5% | 4.94 | 5.73 | IND_EMP | 1.79 |
| 1% | 6.84 | 7.84 | SER_EMP | 0.80 |

Note: k denotes the number of the explanatory variables; AGR_EMP, IND_EMP and SER_EMP denote the employment models in the agricultural, industrial and service sectors, respectively. The critical values are obtained from Pesaran *et al* (2001), Case III: Unrestricted intercept and no trend.

*Source*: Author

only increase the agricultural output but also enhance industrial performance in terms of their contribution to the aggregate output and employment. This result gives credence to the stance of A. Aminu and I. A. Raifu (2019), who alluded to the fact that technology fostered intersectoral linkages and improved the aggregate output and employment.

The narrative is also similar when speaking about the service sector as technological innovation has a significant and instantaneous positive impact on employment in this sector. Given the fact that technological innovation is a product of R&D activities, its deployment and adoption in the service sector for various purposes, including employment, suggest the existence of intra-industry linkages. Comparatively, technological innovation has a more positive impact on the service sector than on the agricultural and industrial sectors, indicating that technological innovation creates more jobs in the service sector than in the other economic sectors in Nigeria. This stance is supported by A. Aminu and I. A. Raifu (2019) and M. Bolaji, J. O. Adeoti and J. A. Afolabi (2021), who alluded to the fact that the service sector benefited more from technological innovation than the other Nigerian economic sectors. Overall, technological innovation not only influences sectoral employment through employment creation and destruction but also reallocates labor across the sectors. Thus, technological innovation plays a complementary role, rather than a substitutionary one, with the labor market outcomes in the Nigerian economic sectors.

The diagnostic tests show that the model results are fit for policy formulation as the models are correctly specified and free from both serial correlation and heteroscedasticity. The adjusted R-squared statistics also show that the models have good fits, and the probability of the F-statistics indicates the models' significance. However, the residuals are not normally distributed for the agricultural and industrial employment models. U. Knief and W. Forstmeier (2021) argued that the non-normality of residuals did not affect the reliability of the estimates. Thus, the results of the agricultural and industrial employment models remain reliable.

There are different determinants of employment in the literature other than technological innovation

**Table 5** The employment-innovation nexus in Nigeria

| Variables | AGR_EMP Model | IND_EMP Model | SER_EMP Model |
|---|---|---|---|
| D(AGR_EMP(-1)) | 0.521* (0.1265) | | |
| D(IND_EMP(-1)) | | 0.490* (0.1057) | |
| D(SER_EMP(-1)) | | | 0.595* (0.1250) |
| D(INN) | -0.128* (0.0237) | 0.011 (0.0086) | 0.119* (0.0263) |
| D(INN(-1)) | 0.063** (0.0296) | | -0.063** (0.0296) |
| C | 1.192** (0.5053) | 1.066* (0.2502) | 1.240 (0.9399) |
| Adjusted R-squared | 0.721 | 0.807 | 0.570 |
| F-statistic | 27.42 [0.0000] | 58.26 [00000] | 14.60 [0.0000] |
| Post-Estimation Tests | | | |
| Jarque-Bera | 49.18 [0.0000] | 192.36 [0.0000] | 0.29 [0.8653] |
| Breusch-Godfrey Serial Correlation LM Test | 0.78 [0.6784] | 1.71 [0.4257] | 4.50 [0.1054] |
| Heteroskedasticity Test: ARCH | 0.01 [0.9402] | 0.11 [0.7448] | 0.02 [0.8858] |
| Ramsey RESET Test | 0.31 [0.5790] | 1.54 [0.2603] | 1.23 [0.2764] |

Note: * $p<0.01$, ** $p<0.05$, *** $p<0.1$. The numbers in block brackets and parentheses are the probability values and the standard errors, respectively.

*Source*: Author

(Palekhova & Kramarenko, 2020; Ubah *et al*, 2021). Therefore, the employment-innovation model is extended to account for the role of the sectoral output, inflation and domestic credit to the private sector. The results are presented in Table 6. Compared to the previously estimated employment-innovation model, there is no difference in the sign of the impact although the magnitude of the impact (of technological innovation on sectoral employment) reduces when the control variables are introduced. For the sectoral output variables, the results reveal that the sectoral output has a positive but insignificant effect on employment across the three sectors under consideration, which suggests that sectoral employment is not primarily driven by the sectoral output in Nigeria. The impact of domestic credit to the private sector appears to be mixed across the sectors. Consistent with the a priori expectation, domestic credit to the private sector exerts a positive influence on employment in the agricultural sector but has a devastating employment effect in the service sector. The result appears to be statistically insignificant for the industrial sector, implying that domestic credit to the private sector is not a determinant of employment in the industrial sector. The finding on the positive link between employment in the agricultural sector and domestic credit to the private sectors corroborates the finding of J. A. Afolabi, B. U. Olanrewaju and W. Adekunle (2022), who showed that domestic credit to the private sector as a measure of financial development had growth-enhancing and employment-generating effects in Nigeria.

The model diagnostics show that the estimated models have a good fit, which is far better than the baseline model (the model with only technological innovation as the explanatory variable) as the explanatory variables provide more explanations to the variation in sectoral employment. All the explanatory variables also jointly predict sectoral

**Table 6** The role of the other factors in the employment-innovation nexus

| Variables | AGR_EMP Model | IND_EMP Model | SER_EMP Model |
|---|---|---|---|
| D(AGR_EMP(-1)) | 0.434* (0.0889) | | |
| D(IND_EMP(-1)) | | 0.528* (0.0956) | |
| D(SER_EMP(-1)) | | | 0.431* (0.1071) |
| D(INN) | -0.094* (0.0207) | 0.004 (0.0078) | 0.093* (0.0234) |
| D(INN(-1)) | 0.046** (0.0216) | | -0.044*** (0.2398) |
| D(AGR_Y) | 0.004 (0.0045) | | |
| D(IND_Y) | | 0.0004 (0.0037) | |
| D(SER_Y) | | | 0.008 (0.0059) |
| D(INF) | 0.010 (0064) | -0.017* (0.0054) | 0.011 (0.007) |
| D(INF(-1)) | | 0.015* (0.0055) | |
| D(CPS) | 0.028* (0.0059) | -0.001 (0.0009) | -0.030* (0.0066) |
| C | 1.142* (0.3252) | 1.282* (0.2790) | -1.272* (0.4599) |
| Adjusted R-squared | 0.827 | 0.836 | 0.763 |
| F-statistic | 40.18 [0.0000] | 42.91 [0.0000] | 23.13 [0.0000] |
| Post-Estimation Tests | | | |
| Jarque-Bera | 3.19 [0.2027] | 78.07 [0.0000] | 0.29 [0.8653] |
| Breusch-Godfrey Serial Correlation LM Test | 4.23 [0.1204] | 4.18 [0.1237] | 4.50 [0.1054] |
| Heteroskedasticity Test: ARCH | 0.05 [0.8249] | 0.96 [0.3281] | 0.02 [0.8858] |
| Ramsey RESET Test | 0.004 [0.9494] | 2.83 [0.1546] | 1.23 [0.2764] |

Note: * $p<0.001$, ** $p<0.05$, *** $p<0.1$. The numbers in block brackets and parentheses are the probability values and the standard errors, respectively.

*Source*: Author

employment as depicted by the probability value of the respective models. In a similar fashion, the postestimation test results show the reliability of the model estimates for policy prescriptions as the models have a correct specification, are homoscedastic and not serially correlated. In addition, the residual of each model is normally distributed, except for the model of employment in the industrial sector. In general, the diagnostic and postestimation test results signal the soundness of the policy options that might emanate from the findings.

## CONCLUSION

Employing the ARDL framework and using the quarterly data spanning the period between 2011Q1 and 2021Q4, this study focused on demystifying the effect of technological innovation on employment across the Nigerian economic sectors. The analysis was carried out in two stages. First, the employment-innovation nexus was evaluated. Second, the role of the sectoral output, inflation and domestic credit to the private sectors in the employment-innovation nexus was thereafter analyzed. The result of the ARDL models revealed that the relationship between employment and technological innovation in Nigeria was a short-term phenomenon. The short-term estimates revealed the fact that technological innovation improved employment creation in the service sector but reduced employment generation in the agricultural sector. However, employment generation occurred one quarter after technological innovation had been introduced. The results also signaled the reallocation of labor across the Nigerian economic sectors.

The empirical results of the preset hypotheses suggest that the hypotheses should be accepted. The synopsis of the results of the hypotheses reads as follows:

- Technological innovation substantially improves employment generation in the service sector, as well as the agricultural sector, although the magnitude of the impact is higher in the service sector than in the agricultural sector.
- The agricultural sector's employment-creating capacity is less responsive to changes in technological innovation than the service sector's as it takes about three months before the introduction of the new technology can generate employment in the agricultural sector.
- Technological innovation has the labor-reallocating capacity as it displaces and absorbs labor across the considered sectors.

The key practical policy implication of these findings is the need to fully operationalize and adopt technological innovation, especially in the Nigerian agricultural and service sectors, which can be done by implementing extant science, technology and innovation (STI) policies and formulating the new policies that mainstream innovation into sectoral productive operations as well. This effort will not only increase the productivity of the existing employees across the sectoral groups, but it will also create new jobs that will reduce the number of the labor force in the unemployment pool.

The key limitations of this study are twofold. First, it assumes linearity in the technology-employment nexus in Nigeria. Second, the data paucity limited the scope of the study. The findings of this study remain valid notwithstanding these limitations. Future research may explore nonlinear approaches so as to evaluate the asymmetric relationship between technological innovation and employment in Nigeria and other developing countries.

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# UČINCI TEHNOLOŠKIH INOVACIJA U DOMENU ZAPOŠLJAVANJA: DOKAZI IZ PRIVREDNIH SEKTORA NIGERIJE

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Tehnološki napredak neprekidno unosi korenite promene na tržištu rada, a naročito je podstakao raspravu o učincima tehnoloških inovacija u domenu zapošljavanja ne samo u ekonomijama u razvoju, već i u razvijenim ekonomijama. U ovoj studiji se primenjuje autoregresioni model raspoređenih docnji (ARDL), što omogućava sagledavanje veze između zapošljavanja i inovacija u svim privrednim sektorima Nigerije u periodu od prvog kvartala 2011. do četvrtog kvartala 2021. godine. Saznanja do kojih se u studiji došlo pokazuju da je veza između zapošljavanja i tehnoloških inovacija u Nigeriji kratkoročan fenomen i da tehnološke inovacije podstiču zapošljavanje u uslužnom i poljoprivrednom sektoru, ali je potreban jedan kvartal da bi se osetili pozitivni učinci tih inovacija u domenu zapošljavanja. Dobijeni rezultati ukazuju na činjenicu da tehnološke inovacije pospešuju zapošljavanje i preraspodelu radne snage u svim sektorima, što ukazuje na potrebu pune operacionalizacije tehnoloških inovacija u svim privrednim sektorima u Nigeriji kako bi se pristupilo rešavanju složenog pitanja trenutne nezaposlenosti u ovoj zemlji.

**Ključne reči:** tehnološke inovacije, sektorska zaposlenost, autoregresioni model raspoređenih docnji, tržište rada

JEL Classification: C22, E24, O14