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The COVID-19 effects on automation, remote working and labor productivity in Nigeria

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Abstract
The COVID-19 pandemic, as well as the threat of future pandemics, has shifted the focus of automation technology, forcing many firms to migrate to remote working in order to boost productivity. The goal of this study is to investigate the COVID-19 effect on automation-related jobs, remote work, and labor productivity in Nigeria. The data collected for this research paper was cumulative monthly data from March 2020 to April 2021 via world health organization website for Nigeria confirmed cases of COVID-19 while other data are automation related jobs, remote working and labor productivity in Nigeria. This study uses empirical analysis such as the Johansen co-integration test to assess whether the series are co-integrated, implying the usage of a vector error correction model (VECM) and indicating that the variables have a long-term relationship. A causality test was also carried out, which revealed that COVID-19 had a considerable impact on automation, remote work, and labor productivity in Nigeria. In the meantime, COVID-19, automation-related professions, remote working, and labor productivity are all linked in the short and long run, according to the Johansen cointegration, vector auto regression (VAR), and vector error correction models (VECM). Granger causality demonstrates that COVID-19 occurrences in Nigeria have a causal effect on the risk of automation-related professions, distant work, and labor productivity, demonstrating the study's value.

Keywords: Automation, remote working, labor productivity, COVID-19, causality, Johansen cointegration, VECM, VAR

1. Introduction

COVID-19 has resulted in the largest human and economic disaster in modern history.

Over half a million people have perished as a result, and entire economies have been destroyed as a result. Over millions of Nigerians had either lost their employment or were working less than half of their typical hours at the peak in April (Bartik, *et al.*, 2020) [6].

Furthermore, it has hurt our most financially vulnerable citizens: low-wage workers, part-time workers, sole proprietors, teenagers, and recent immigrants. It's difficult to imagine the crisis has a silver lining. One of these is a deeper sense of community as a result of comprehending that we're all in this together. Another is the acceleration of automation, both of which will boost Nigeria's production and living standards (Bloom *et al*. 2020) [8].

The focus of this essay is on the latter legacy, and how to best adopt policies that address the crisis' reality while not choking economic transformation. The COVID-19 pandemic, as well as the possibility of future pandemics, has hastened the adoption of automation technology, pushing many organizations to convert to remote working in order to increase production.

This study will reveal the influence of COVID-19 on the danger of automation-related occupations, remote working, and labor productivity in Nigeria. Meanwhile, if more people are unable to work from home, the predicted productivity loss as a result of the COVID-19 outbreak will be substantially worse (Bartik and Di Mauro, 2020) [6].

Furthermore, automation, robotics, current information and communication technology, and artificial intelligence have all proven to be incredibly effective in combatting the pandemic and limiting its economic consequences.

These technologies have allowed firms to continue operating by facilitating social separation in the workplace and enabling remote work from home offices.

Even as automation and similar technologies diminish the pandemic's overall economic impact, the COVID-19 shock has resulted in growing social and economic inequality. This is because higher-income, better-educated individuals can take advantage of these opportunities, whereas many lower-income, less-educated workers cannot.

On the other hand, robots and smart technology hold immense promise for disease surveillance and contact tracing, detecting COVID-19 and other diseases without direct touch, and even sterilizing polluted places in hospitals and other public spaces (Blake 2020) [7].

1.1 Objectives of study

1.1.1 The objectives of this research are

To look at the long-term association between COVID-19 cases, automation-related occupations, remote working, and labor productivity in Nigeria to investigate the impact of COVID-19 on the danger of automation-related occupations, remote working, and labor productivity in Nigeria.

1.2 Research hypotheses

1. Ho: There is no long-term link between COVID-19 instances, automation-related jobs, remote working, and labor productivity in Nigeria.
2. H_1: There is no long-term link between COVID-19 instances, automation-related jobs, remote working, and labor productivity in Nigeria.
3. Ho: COVID-19 instances had no substantial causal effect on the risk of automation-related jobs, remote working, or labor productivity.
4. H_1: COVID-19 instances had substantial causal effect on the risk of automation-related jobs, remote working, or labor productivity.

Table 1: Table of variable description

Variables	Variable acronyms	Variable measurement
Remote working	RW	Continuous quantitative variable
Automation Related Job	Auto	Continuous quantitative variable
Labor productivity	LP	Continuous quantitative variable
Confirmed cases of corona virus pandemic	COVID-19	It is a count data

2. Literature review

COVID-19 Pandemic, the global epidemic, caused by the new coronavirus COVID-19 has wreaked havoc on public health and economic institutions all across the world.

The outbreak started in Wuhan, China, but the virus's origins are still a mystery. The virus was thought to have been transmitted to humans by bats and had an 88 percent resemblance to COVID-19.

The virus spreads exceptionally swiftly compared to similar infections like SARS, and there is currently no agreement on containment techniques. As a result, despite WHO instructions, countries have devised their own measures, which have generally failed to limit the pandemic. These policies include quarantines, travel restrictions, bans on public meetings, and the expansion of public health programs to handle an increase in the number of sick patients and testing needs (Yenel, *et al*, 2020) [19].

With no end in sight, Canada must consider a broader spectrum of strategies for combating the virus as a whole, while also learning from the experiences of other countries. Despite the fact that many topic-specific findings and scientific recommendations have been published, there are few comprehensive studies that cover a wide variety of data collected from different nations on multiple pandemic response tactics. A large-scale assessment like this provides a bird's-eye, analytical perspective on coordinating numerous governing sectors in the realm of public health, from mental health to assisted living facilities.

2.1 Impact of automation on productivity

It is also insightful to look at modern theory on the impact of automation on labor markets, (Acemoglu and Restrepo, 2018) [1]. To do that we need first to define a useful unit for further analysis. The job task is represented by this unit. Each career entails a range of duties, some of which are simple to automate and others that are extremely difficult to automate. A circumstance in which an automated technology can do a work more efficiently and at a lower cost than human labor is referred to as task automation. The rise in the breadth and number of tasks that can be automated can thus be depicted as a result of technology advancements. However, understanding the nature of each occupation is also vital for determining whether or not automation has the ability to expand to more jobs within that occupation.

2.2 COVID-19 on automation, remote-working and labor productivity

The COVID-19 pandemic is an event that has had a tremendous impact on global labor markets.

In many occupations, it has entirely transformed the conditions and character of labor. Many individuals are confined to their homes, and many businesses have been forced to close, leading to an increase in the unemployment rate and the number of applications for unemployment insurance (UI) benefits. During the current difficult market conditions, Bai *et al*. (2020) [5] emphasize the relevance of enterprises' ability to have their workers work from home for their financial survival. They created a firm-level index that determines if a company is suitable for working from home. They discovered that companies with a high work-from-home index have superior financial performance, higher stock returns, and reduced stock volatility.

The pandemic's impact is anticipated to hasten the automation and digitalization wave across our economy's various sectors (Giordani and Rullani 2020) [14]. On the supply side, the pandemic's experience with automation applications has been extremely positive and beneficial:

Drones have been utilized to deliver products and services in various regions of the world, and disinfecting robotic systems have been installed in warehouses to lessen the danger of infection.

Organizations have invested in developing an effective virtual network of inter-colleague exchanges, which has shown to be successful in many circumstances. Business owners that lack the liquidity and privileged access to credit markets required to survive many months of inactivity are likely to be harmed by the pandemic shock (Walsh 2020) [18].

The current trend of huge corporations gaining dominance across multiple industries will be accelerated by the wave of business closures, which will have negative effects for workers (Autor and Reynolds 2020) [4]. This is due to the fact that huge corporations tend to pay a smaller portion of earnings to employees and a larger portion to owners and investors.

2.3 Application of automation, remote-working on labor productivity

As information and communication technologies (ICTs) have advanced in their capabilities, particularly with the increased availability of high-speed internet, remote working (also known as teleworking, telecommuting, distributed work, or flexible work arrangements; Allen *et al*., 2015) [2] has grown in popularity.

According to the definition of remote working, it is "a flexible work arrangement in which workers operate in locations away from their central offices or production facilities, the worker has no personal contact with coworkers there but is able to communicate with them using technology" (Di Martino & Wirth, 2019) [11].

Because of this, most workers had limited remote working experience prior to COVID19, and neither they nor their employers were prepared to support this practice. Now, the extraordinary COVID19 epidemic in 2020 has caused millions of individuals all across the world to become remote workers, culminating in an unintentional worldwide remote working experiment (Kniffin *et al*., 2021) [16].

While automation can (and has) improved productivity, per capita output, and living standards (see, for example, Brynjolfsson and McAfee 2014, Acemoglu and Restrepo 2018, Graetz and Michaels 2018) [9, 1, 15], two key aspects of automation raise concerns: its disproportionate impact on low-skill workers, and its overall negative impact on the share of income that goes to labor as a percentage of total income. These two factors aggravate income inequality.

Routine and low-skill tasks continue to be easier for robots to execute than non-routine, high-skill tasks (Arntz *et al*. 2017, Frey and Osborne 2017, Dauth *et al*. 2017, Acemoglu and Restrepo 2020) [3, 13, 10, 1]. This suggests that increasing the number of robots or their productivity hurts low-skilled workers far more than high-skilled workers. High-skilled individuals are also more likely to specialize in tasks that benefit from automation, such as robot design and maintenance, monitoring, and management. Low-skilled workers' earnings may stagnate or even drop in the face of automation due to the uneven impact of technology (Lankisch *et al*. 2019) [17].

3. Research methodology

This study focuses solely on the effects of COVID-19 on automation, remote working, and productivity in Nigeria, with data collected monthly from March 2020 to April 2021 via the World Health Organization website (Covid 19.who.int/country) for confirmed cases of COVID-19 in Nigeria, as well as other data on automation-related jobs, remote working, and labor productivity in Nigeria. The Johansen Cointegration test, VECM (vector error correction model), and Granger causality test were used in this study.

3.1 Vector Autoregressive Model (VECM)

The VECM is used in conjunction with a unit root test, also known as a stationarity test, that employs the Augmented Dickey Fuller test (ADF) and the Johansen Cointegration test.

However, the essential premise of an econometrics model is that the series should be stable, and for the VEC model to be applied, the variables must be stationary and cointegrated. VECMs that use a vector autoregressive model focus on endogenous variables and allow variables in the model to be dependent on them at order p lag values. Remember that each variable is viewed as an endogenous variable, and each variable is dependent on its lag values.

The Var model indicated by Var(p) is mathematically defined in a general term below as:

$y_t = a + B_1y_{t-1} + B_2y_{t-2} + \ldots\ldots + B_py_{t-p} + e_t$ and the corresponding VEC model can be written as

$\Delta y_{1,t} = \theta_1 (y_{2,t-1} - \beta y_{1,t-1}) + \mathcal{E}_{1,t}$ represent COVID-19 cases as endogenous and its corresponding lag values

$\Delta y_{2,t} = \theta_1 (y_{2,t-1} - \beta y_{1,t-1}) + \mathcal{E}_{2,t}$ represent automation related jobs as endogenous and its corresponding lag values

$\Delta y_{3,t} = \theta_1 (y_{2,t-1} - \beta y_{1,t-1}) + \mathcal{E}_{3,t}$ represent remote working as endogenous and its corresponding lag values

$\Delta y_{4,t} = \theta_1 (y_{2,t-1} - \beta y_{1,t-1}) + \mathcal{E}_{4,t}$ represent Productivity and its corresponding lag values where B_1 to B_p are the coefficients of the lag values and Y_{t-1} to Y_{t-p} are the corresponding Lag values and e_t, $\mathcal{E}_{1,t}$ to $\mathcal{E}_{3,t}$ is the error term that takes care of all the unaccounted factor in the model. It is imperative to note that there is need to carry out the VECM diagnostic test such as the VECM autocorrelation and normality test so as to ensure we have a robust and valid results.

3.2 Granger causality test

We use the Granger causality test to analyze the causal link of the variables, focusing primarily on the causal relationship among the variables of interest (Eichler, 2012) [12]. X causes Y (X→Y) or X is related to Y (X→Y) are two hypothetical examples. This research will look at whether X causes Y or not. The Granger causality test will also disclose the effect of COVID-19 instances on the danger of automation-related occupations, remote working, and labor productivity in Nigeria.

4. Analysis and Discussion

The following analysis was carried out using data on confirmed cases of COVID-19 in Nigeria was collected monthly from March 2020 to April 2021 via the World Health Organization website (covid19.who.int/country), while other data on automation-related jobs, remote working, and labor productivity in Nigeria was collected via www.ceicdata.com and statista.com/statistics based on the stated objectives of this work.

4.1 Descriptive analysis

To assess the trend and underpin the distributional assumption, descriptive statistics for confirmed cases of COVID-19 pandemic with mean and standard deviation values were obtained.

Table 2: Descriptive statistics

Variable	Observation	Mean	Std. Dev.	Min	Max
labor productivity	14	109.739	6.006168	105.479	127.967
remote working	14	61.87143	5.884063	48	66
Automation	14	12	0.921538	9	15
COVID-19	14	87100.21	76795.3	11221	224589

Source: Author's computation using Stata software

In table 2, the confirmed cases of the COVID-19 pandemic have the highest mean value, whereas automation related jobs have the lowest mean value, as seen in the descriptive statistics table above. Meanwhile, confirmed cases of the COVID-19 pandemic have the largest standard deviation, indicating the most variance from the mean, whereas automation has the lowest standard deviation, indicating the least deviation from the mean. The COVID-19 pandemic's highest variability means that it spread swiftly and well beyond expectations among individuals who came into touch with an infected person.

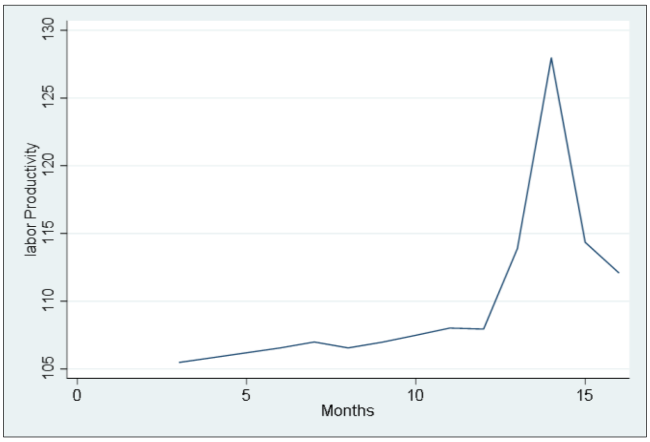

Fig 1: Labor productivity growth from March 2020 to April 2021.

Figure 1 depicts the increase in labor productivity from March 2020, the start of the COVID-19 peak period in Nigeria, through April 2021.

We can observe that productivity was low from March to November 2020, then spiked in December 2020, and then spiked again in January 2021, with a 128 percent increase in labor productivity, before decreasing again from February to April 2021. It is clear from the graph that it is not stationary.

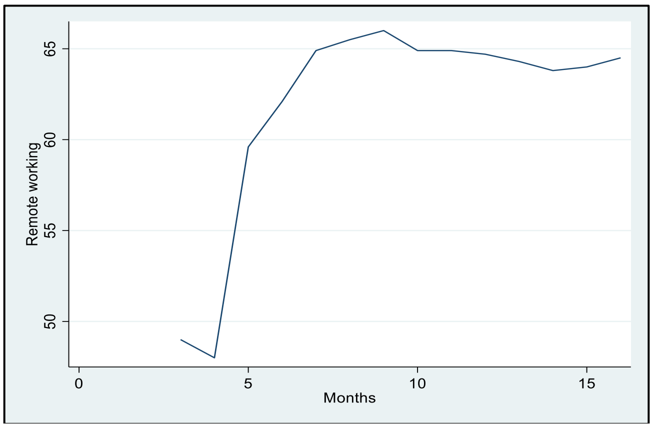

Fig 2: The remote working adopted during the COVID-19 pandemic in Nigeria from March 2020 to April 2021

Figure 2 depicts the remote working practices used in Nigeria during the COVID-19 pandemic, from March 2020 (the start of the peak phase) to April 2021. The graph shows that remote working has been routinely used since March 2020, when the virus was at its peak, in order to contain the spread of the COVID-19 pandemic.

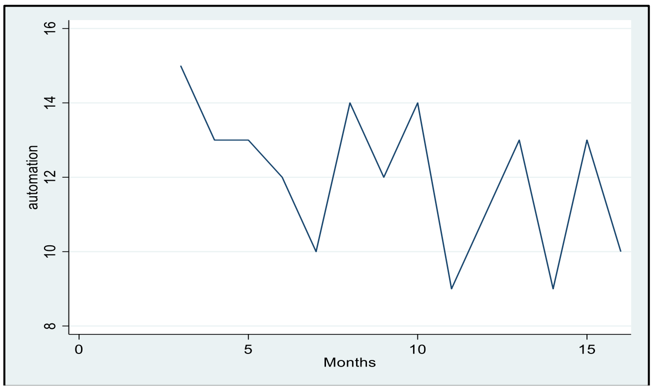

Fig 3: The stationary means on automation for the use of machine and robots etc. were adequately adopted so as to control the spread of the COVID-19 pandemic.

Figure 3 shows that automation, such as the employment of machines and robots, was effectively used to control the spread of the COVID-19 epidemic over the time period under consideration.

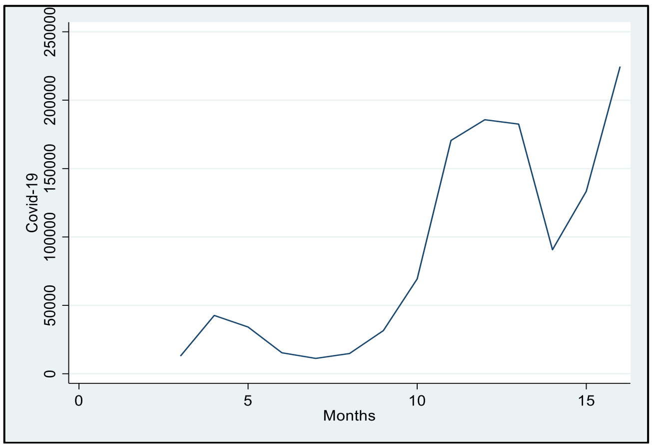

Fig 4: The confirmed cases of COVID-19 pandemic from March 2020 to April 2021

Figure 4 depicts confirmed instances of the COVID-19 pandemic from March 2020 to April 2021, with an increasing growth rate over time.

4.2 Inferential Statistics

As shown in Tables 3 to 11, we used the Augmented Dickey Fuller Stationarity Test to assess the model's prediction ability. The results of the causality analysis revealed that remote working has a causal relationship with labor productivity, automation has a causal relationship with labor productivity, and automation has a causal relationship with remote working's effect on the COVID-19 epidemic.

Table 3: Augmented Dickey Fuller (ADF) Test

Variables	Test-statistic	P-values	Order of Integration
COVID-19 confirmed cases	-3.9046	0.0178	1^{st} order
Automation related Jobs	-7.5085	0.0001	1^{st} order
Remote working	-8.3921	0.0000	1^{st} order
Labor productivity	-6.3679	0.0006	2^{nd} order

Source: Author's computation using Stata software

In Table 3, the results of the ADF test for the given series or variables demonstrate that confirmed cases of COVID-19 (P=0.0178<0.05) are statistically significant at the 5% level and thus stationary after the first difference.

Similarly, occupations associated to automation (P=0.0001<0.01) are statistically significant at the 1% level and are also stationary after the first difference (P=0.0001N0.01).

Similarly, remote working (P=0.00000.01) is statistically significant at the 1% level and so remains stationary after the first difference.

Likewise, labor productivity (P=0.0006<0.01) is statistically significant at the 1% level but becomes stable after the second difference (P=0.0006<0.01). The first three variables' results are integrated of order 1, while the last variable's result is integrated of order 2, satisfying the time series criteria and qualifying the variables for further time series analysis in this study. Cointegration test, Vector correction model, Vector auto regression, and Granger causality test are used to examine the study's aims and research hypotheses as part of the time series analysis.

Table 4: Johansen Test for cointegration

Trend: constant Number of obs. = 12 **Sample:** 1960m6 -1961m5 Lag = 2					
Maximum Rank	**Parms**	**LL**	**Eigen value**	**Trace statistics**	**Critical value**
0	20	-224.18617	-	471.7722	47.21
1	27	-3.7653683	1.00000	30.9306	29.68
2	32	4.894989	0.76387	13.6099*	15.41
3	35	10.983569	0.63751	1.4328	3.76
4	36	11.699953	0.11254	-	-

Source: Author's computation using Stata software

In Table 4, we can see from the Johansen cointegration test output that one of the cointegration equations has a trace statistic of 30.93 > critical value = 29.68, implying that the cointegration equation is statistically significant and that there is cointegration among the variables, implying a long-term relationship between COVID-19 cases, automation-related jobs, remote working, and a long-term relationship between COVID-19 cases, automation-related jobs, remote working, and a long-term relationship. Because the variables are cointegrated, the use of a vector error correction model is recommended (VECM).

Table 5: Vector Error Correction Model

Sample: 1960m6 -1961m5 Number of obs. = 12 **AIC =** 6.45680 **Log likelihood-** 11.74084 HQIC =6.052865 **Det (Sigma_ml)** – 0.0000832 SBIC 7.547847					
Equation	**Parms**	**RMSE**	**R-sq**	**Chi-square statistics**	**P > chi-square**
labor productivity	6	5.96862	0.4973	5.93541	0.4305
2Remote working	6	0.544981	0.9882	503.1172	0.0000
Automation	6	2.66228	0.5871	8.53214	0.2016
Covid 19	6	55444.6	0.4094	4.158917	0.6552

Source: Author's computation using Stata software

Table 5 shows that each variable is treated as endogenous in the vector error correction model (VECM), and we can see that each variable has six lag values. Since the P = 0.000 < 0.01, remote working and its six lag values are statistically significant, while the other variables are not.

Table 6: Vector auto regression

Sample: 1960m6 -1961m5 Number of obs. = 12 **AIC =** 0.0132773 **Log likelihood =** 35.92034 HQIC = -0.5253121 **FPE =** 0.0000709 SBIC = 1.467997 **Det (Sigma_ml) =** 2.95e-08					
Equation	**Parms**	**RMSE**	**R-sq**	**Chi-square Statistics**	**P > chi-square**
labor productivity	9	4.80308	0.8391	62.56521	0.0000
Remote working	9	0.560665	0.9709	400.2851	0.0000
Automation	9	2.38145	0.5360	13.86112	0.0855
Covid 19	9	59453.3	0.8441	64.96712	0.0000

Source: Author's computation using Stata software

Table 6 illustrate the vector auto regression (VAR) as estimated above and regard all the variables as endogenous such that each variable has 9 lag values and all are statistically significant at 1% level of significant except automation which is significant at 10 % level.

This implies a short run relationship between COVID-19 instances, automation related occupations, remote working and labor productivity in Nigeria.

Table 7 above Granger causality test indicates that confirmed COVID-19 cases cause all of the variables of interest (P = 0.007 < 0.01), implying that confirmed COVID-19 cases have a causal effect on the risk of automation-related jobs, remote working, and labor productivity in Nigeria, which meets objective 2 and research hypothesis 2. Individually, however, COVID-19 has a large impact on labor productivity. In the meantime, the causality results show that remote working has a positive causal relationship with labor productivity, automation has a negative causal relationship with labor productivity, automation has a negative causal relationship with remote working, COVID-19 has a positive causal relationship with labor productivity, COVID-19 has a positive causal relationship with remote working, and covid-1 has a positive causal relationship with remote working. As a result, a diagnostic test is required to ensure that we have a robust and fitting model.

Table 7: Endogenous Labor Productivity, Remote Work, Automation and COVID 19

Selection-order criteria								
Sample: 1960m6 -1961m5 Number of obs. = 12								
Lag	**LL**	**LR**	**Df**	**P**	**PPF**	**AIC**	**HQIC**	**SBIC**
0	-234.696				2.2e+12	39.7827	39.7228	39.9443
1	-195.672	78.046	16	0.000	6.0e+10	35.9455	35.6462	36.7536
2	35.9283	463.19*	16	0.000	0.000071	0.013277*	-.0525312*	1.468*

Source: Author's computation using Stata software

The selection criteria test in table 8 above reveals that the first and second lags are statistically significant, implying that the selection-order criterion diagnosis is met. Because p-values less than alpha 0.05 are statistically significant.

Table 8: Jerque-Bera Test

Equation	Chi-square statistics	Df	P chi-square
labor productivity	2.006	2	0.36678
Remote working	0.258	2	0.87905
Automation	1.693	2	0.42890
Covid 19	1.095	2	0.57836
All	5.052	8	0.75201

Source: Author's computation using Stata software

Table 9: Skewness Test

Equation	Skewness	Chi-square statistics	df	P chi-square
labor productivity	0.81829	1.562	1	0.21131
Remote working	-0.33215	0.257	1	0.61190
Automation	-0.71586	1.196	1	0.27417
Covid 19	0.65276	0.994	1	0.31871
All		4.010	4	0.40469

Source: Author's computation using Stata software

Table 10: Kurtosis Test

Equation	Kurtosis	Chi-square statistics	df	P chi-square
labor productivity	3.8721	0.444	1	0.50539
Remote working	2.9733	0.000	1	0.98371
Automation	3.9233	0.497	1	0.48076
Covid 19	3.4195	0.101	1	0.75076
All		1.042	4	0.90333

Source: Author's computation using Stata software

In Tables 8 to 10 above normality test using Jerque-Bera, Skewneaa and Kurtosis test shows that labor productivity, remote working, automation related jobs and COVID-19 confirmed cases are normally distributed at 5 percent level of significance.

Table 11: Lagrange Multiply Test

Lag	Chi-square statistics	Df	P chi-square
1	6.8259	16	0.97647
2	21.7286	16	0.15217
Ho: No autocorrelation at lag order			

Source: Output Stata Software Package Lagrange Multiply Test.

The autocorrelation test in table 11 reveals that *P*>0.05, implying that there is no autocorrelation at lag order, meaning that the model does not have an autocorrelation problem.

5. Summary of findings, Conclusion and Recommendation

5.1 Summary of findings

The impact of COVID-19 on automation, remote work, and productivity in Nigeria was investigated in this study. COVID-19, automation-related occupations, remote working, and labor productivity are all linked in the short and long run, according to the Johansen cointegration, vector auto regression, and vector error correction models.

Bloom and Thwaites' 2020 [8] findings support this, claiming that rising automation and resource reallocation will raise productivity and living standards in Nigeria.

Meanwhile, Granger causality demonstrates that COVID-19 instances in Nigeria have a causal effect on the risk of automation-related vocations, remote work, and labor productivity, demonstrating the significance of the study.

5.2 Conclusion

The COVID-19 shock and the influence of automation on employment need the establishment of careful policies directed primarily at low-skill, low-wage workers. Adoption of appropriate public stimulus packages that encourage businesses to adopt digital solutions while also providing the necessary economic incentives to prioritize investments.

Modern technology and robotic systems can assist firms in quickly overcoming the negative effects of pandemic shock while keeping their personnel safe. Many countries used their public finance accounts to fund such initiatives during the COVID-19 crisis.

Both employees and employers benefit from them. They provide some protection against dismissal in the first case by providing workers with a minimum source of income during the crisis. Employers, on the other hand, can rely on their current employees when they commence manufacturing and other commercial activities under this arrangement, saving them money on new employee recruitment.

6. Recommendations

As complementary tasks that are more difficult to automate, education and training programs should be given specific attention, with an emphasis on the types of abilities employees will need to communicate with intelligent machines in the workplace.

Simultaneously, persuading professionals to engage in lifelong learning activities in their areas of specialization is crucial. To do this, training programs for unemployed people must be implemented in order to boost their prospects of obtaining new work. At the same time, we must reform employment contracts to include retraining possibilities.

To stay up with technological changes, various vocations have varying training requirements. As a result, the possibility for training while working should be designed with the occupation's characteristics in mind, as well as how these characteristics change over time as a result of technology improvements.

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