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Resurgence of informal economy in the US amidst of automation

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Abstract. *A continuous decline in the number of informal economies in the advanced economy has been boosted across the globe by various institutions such as IMF (International Monetary Fund). But a resurrection of the informal economy is being witnessed in the United States (US) with a 102% jump from 1990 to 2018. Over the years technological advancement has impacted the involvement of labour in the production process, with rapid automation in the last three decades this involvement has been reduced a to minimalistic level. In this paper, we tried to build a narrative to explain this resurgence of the informal market in the US. Through our theoretical framework, we commented on how unemployed graduates and the informal economy are associated with automation. The result showed that both variables were positively associated with automation which was confirmatory of the theory put forward. Lastly, we also comment on income inequality and automation which were also positively related.*

Keywords: informal economy, automation, Gini coefficient, unemployment, technology change.

JEL Classification: O33, J23, J24, J46.

1. Introduction

Technological change has been a key variable of economic growth in various growth models in recent eras (see Solow growth model, 1956, pp. 65-94). The importance of technological development can be traced back in history from the Stone Age to the medieval period, but the most synonym and relatable impact of technological change in the context era of development would be the invention of the weaving machine, self-acting mule in spinning, Neilson hot blast, and many more (Mokyr, 2005, pp. 1113-1180) in early 19th century that helped Great Britain and other European countries to break through the mudhole of a low-income trap which was resulted of disparity between population and food growth rate famously known as Malthus theory of population (1798). The historical event referred to as "the great divergent" in the literature of economic history; is more familiarly known as the 1st Industrial Revolution. Since then, four such revolutions have been witnessed by humankind. Each revolution was marked with a technological change of grandeur level and created unrest such as a change in the production process, creating a new market, creating a new product, shift in power, shift in wealth, and enhancement of intellectual property within an economy. Table 1 duly presents the character of the Industrial Revolution given below.

Table 1. Main characteristics of industrial revolutions

Period	Resource of Energy	Innovation	Industries Developed	Transport Means
I: 1760-1900	Coal	Steam Engine	Textile, Steel	Train
II: 1900-1960	Oil, Electricity	Internal Combustion Engine	Metallurgy, Auto, Machine Building	Train, Car
III: 1960-2000	Nuclear Energy, Natural Gas	Computers, Robots	Auto, Chemistry	Car, Plane
IV: 2000-	Green Energies	Internet, 3D Printer, Genetic Engineering	High Tech Industries	Electric Car, Ultra-Fast Train

Source: Prisecaru, P. (2016).

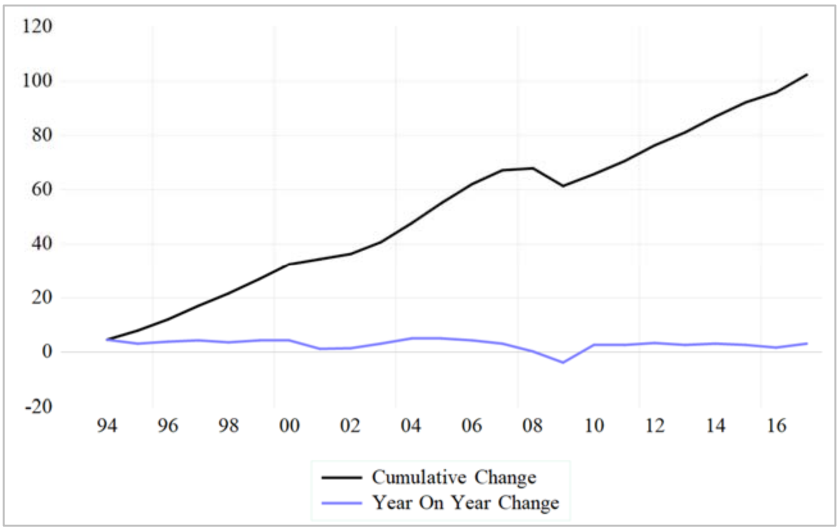
Of all the changes that are associated with technological advancement change in the production process has led to some violent resistance such as Luddite and Swing riots. The fear of losing jobs due to technological advancement through "technological unemployment theory" (Keynes, 1937, pp. 209). In the current era technological change and its impact on the labour market have been a source of great debate; a certain section is in favor of the change claiming that change will bring even greater source employment and others are skeptical about how this technological upliftment will affect the economy with income inequality, unemployment, change skill requirement, & labour welfare.

Petropoulos (2018) argued that technological change has a dual effect which is displacement and productivity effect. The displacement effect refers direct removal of labour from the task, whereas the productivity effect discusses how increasing productivity due to technological advancement will create demand in the labour market. Debate is an integral part of the literature regarding the nature, impact, and potential of automated technology on societal structure among economic thinkers (Autor, 2015, pp. 3-30; Mokyr et al., 2015, pp. 31-50). Economists are against automation, with fears of increasing joblessness and inequality among the population (Ford, 2015). Thompson (2015) fears that the Luddite-like scenario can be replicated shortly in the modern era where the world will be without work. The main victims of the displacement effect will be the labourers performing routine work (Autor et al., 2003, pp. 1279-1333).

One possibility that has been nullified by Acemoglu and Restrepo (2020) is that the technology is not only about the displacement of labour but about reinstatement, thus it will not lead to a fall in labour share in the income pie. Srnicek and William (2015) argued that automation is for the betterment of human life. In the UK the rate of job creation is at an all-time high (ONS, 2019a), despite technological advancement made in the last few decades (Haldane 2015). Skidelsky (2019), the working hours for employees in the UK have reduced tremendously in comparison to other European countries in bygone years. Automation facilitates labour with better work and shorter deadlines (Felstead & Green, 2017, pp. 188-207).

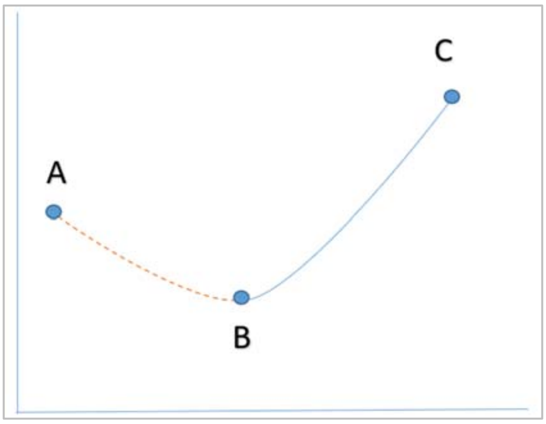
In the US rapid increase in automation is accompanied by an increase in the figure of the informal economy. The informal economy, comprising economic activities that would be added to tax revenue and GDP if they were recorded, is a globally widespread phenomenon (IMF, 2020). If we go by the estimation put forward by the World Bank, the informal economy had fallen from 9.3% of GDP to 8.1% of GDP between 1993 to 2018. But the absolute number of informal economies in dollars is showing a rising trend which is evident from Figure 1, while the year-on-year percentage follows a flat trajectory. By the late 1970s and early 80s, the informal market was estimated to be 20% of the US GDP (Carson, 1984a, pp. 21-37 & 1984b, pp. 106-118; Carter, 1984, pp. 209-221; Feige, 1979a, 1979b, & 2005). The approximate value informal economy in the dollar would be 2514.8 billion if we take 1980 as the median. Comparing this approximate value with the value of 1990 and 2018 (1863 and 4880 billion respectively) we will find a U shape curve. Thus, a break in the pattern is evidenced in Figure 2.

Figure 1. *Showing cumulative and year-on-year change in the informal market*



Source: Author.

Figure 2. *Point A represents the informal economy in 1980 ($ 2514.8 bn), Point B represents the value of 1990 ($ 1863 bn), and Point C represents ($ 4880 bn)*



Source: Author.

Gershuny (1977, 1978a, 1978b, 1979, 1982, & 1983) was interested in how technology innovation will affect the availability of jobs in the formal sector. The impact of the changing nature of jobs, employment, and unemployment on the division of labour was also a worry for Pahl (1980, & 1984). Gershuny asserted that the "self-service" economy is more likely to grow in the future than the service industry would continue to do so. People will resort to the household, the community, and the irregular economy to provide things for themselves that they would otherwise purchase in the formal economy if they were unable to buy formal economy services due to more unemployment and lower income in the formal sector. Thus, the current path of economic development will lead to the displacement of labour from jobs due to automation in the formal economy (Gershuny & Pahl, 1979, pp. 120-131 & 1980, pp. 7-9; Lever, 1988, pp, 87-113).

Dobbs et al., (2015) estimated that artificial intelligence will have about 3000 times of impact as compared to the first industrial revolution mainly because of is 300 times in magnitude and 10 times faster. Thus, understanding its side effects on an economy is utmost. The current literature consists of how automation affects demand in the labour market through displacement, productivity, and most recently reinstatement effect. Another element concomitant with the literature on automation is income inequality. The impact of automation on the informal economy had been ignored and we tried to fill this gap by studying the association between two macroeconomic variables. We presented a theoretical framework to explain the unwanted resurrection of the informal market in the US economy through the robotization of the production process. We argue that as automation dominates the production process, the headcount of employees reduces even though the new task is created due to new technology as the capital-labour ratio largely tilts toward capital thus, increasing the number of unemployed graduates. These replacement and unabsorbed skilled and unskilled labourers are added to the informal market. Lastly, we also comment on the adversity of income disparity that is further widened by automation in three phases: first robotics replace labour, second when replaced labour is absorbed by labour-intensive, third when a lopsided supply of labour with skill overwhelms the labour market.

2. Literature Review

The change in the composition of the US labour force in favour of college graduates is the primary reason for the further disparity in income distribution (Acemoglu, 1998, pp. 1055-1089). The technological upliftment has caused an increase in demand for skilled college graduates since 1970, especially in computer-intensive industries (Autor, 2003, pp. 1279-1333). Thus, the labour ratio in terms of skilled and unskilled and the productivity gap is influencing the composition of jobs, required skills, disparities in wages, and rising unemployment. Autor et al., (2003) stated that the basic effects of computers are to substitute the non-cognitive and manual routine tasks, and complementary to the cognitive and non-routine tasks. Thus, the middle-skilled job is getting eliminated with time (Autor et al., 2006, pp. 189-194). Goos and Manning (2007) in the current era jobs are polarized into lousy jobs and lovely jobs. Berman et al., (1998) argued that technological change should be associated with job destruction but also with the creation of new high-skilled jobs. The computerized-based technology is negatively affecting middle-class jobs, while growth in demand for low and high-skilled jobs is evident (Autor et al., 2006, pp. 189-194; Goos & Manning 2007, pp. 118-133). Acemoglu and Autor (2011) confirmed the polarization effect in the USA, while a mixed result of job polarization was found in the European Union where countries like the UK, France, Germany, Spain, Sweden, and Italy (Darvas, 2016). The primary concern revolves around whether displacement or productivity will exert the dominant effect in this era. (Petropoulous, 2018, pp.119-132). Spencer and Slater (2020) argued that the UK will not be fruitful unless proper institutional reforms are introduced to counter low investment, low wages, and low productivity. Frey and Osborne (2017) reported that the job of forty-seven percent of the labour force is going to disappear due to the installation of automated technology in the production process. In recent years the focussed has shifted from how technology is going a middle-skilled job to across the skill and wage spectrum. The rapid progress in digital technology is expected to wipe out high-skilled jobs as well (Brynjolfsson & McAfee, 2014, pp. 52-3201; Turner, 2018). The development of robotic and artificial intelligence is on the brink of replacing non-routine, cognitive, and manual jobs (Ford, 2015). The fourth industrial revolution had put the labour force across skill requirements as surplus to the demand (Schwab, 2016). The driverless car is the product of the fourth industrial revolution and is expected to replace truck and taxi drivers in huge quantities (Harris & Ennis, 2016). Algorithm-based technology is very well capable of replacing the middle-skilled from the health sector, journalism, and the legal profession. There is also a possibility that the job of caretaker will be replaced by "carbot" (Donnelly, 2015). These scenarios of joblessness will create a greater rift in a capitalistic society (Autor, 2015). Brynjolfsson & McAfee (2014) suggested that policymakers should be investing in human capital so that they cope with technological change, while Ford (2015) believes a shift in policymaking might not help the scenario only way out is to assure of "basic minimum wage". Acemoglu and Restrepo (2019a, 2019b) argue that the productivity effect of automation and artificial intelligence (AI) will create a demand for labour in both the automated relying sector and the non-automated sector. The productivity effect is influenced by the labour market and the strength of productivity increases. Frey and Osborne (2017) suggested the adaptation of automated technology with no immediate constraints. Three main types of tasks that can slow down the replacement effect are (i) perception and manipulation tasks; (ii) creative intelligence tasks; and (iii) social intelligence tasks. However, reconfiguration of tasks and production can reduce such hindrances and speed up the adaptation of new technology. Arntz et al., (2016, 2017) that job composition is an organization choice and will be driven by various factors in the context of the industry to which the organization such as the production process followed by a competitor, availability of labour force for a particular, and design task for the product of such industry, and managerial perspective to such change. Jansson and Karabulut (2019) expeditious robotization is resulting in further wealth disparity. Guinness et al., (2021) skills displacing technological change had impacted 16% of European Union labour with uneven spread across the country with Estonia accounting for 28% of such labour while, Bulgaria has 7% of deskilled labour. Law and Shen (2020) investigated the impact of AI (Artificial Intelligence) in the audit profession and reported there was no displacement effect rather the required skill was changed with improvement in audit quality. At the micro level (town) it was found that broadband availability reduces income inequality (Houngbonon & Liang, 2018). Berk et al., (2010) & Qiu et al., (2020) expanded the literature by investigating the association between capital structure and automation of a firm. They showed that a change in automation by 1 standard deviation increases financial leverage by 4.7%.

3. Theoretical Framework

In a free market, any technological change is inspiring either to reduce the existing cost or increase productivity, thus in the process achieving maximum profitability. To enhance accuracy, efficiency, & productivity, the firms implement automated technology (Png, 2020), at the same time it also reduces the number of injuries and mishappening in the US to 1.2 cases per 100 workers (Gihleb et al., 2022). Automation is that genre of technology that reduces the involvement of human capital in the process of production to a minimalistic level. Thus, the basic condition to adopt automation is that the cost of automation and new tasks created due to automation (W_A) should be less than the total cost of labour that has been retrenched (W_L). In case the firm is adopting automation for increasing its productivity then the necessary condition is that the future profit margin (P_F) should be greater than the present profit margin (P_P). In a scenario where cost reduction is a major concern, the labour share (L_S) of the pie will fall by,

$$L_S = W_L - W_A$$

In the cases where enhancing productivity is the focal point of the adoption of automation, decremental in the share of labour will be greater,

$$L_S = P_F - W_A$$

Assuming, that automation technology does not hit simultaneously across the industries as it is a strategic decision influenced by the organizational structure (Dogan et al., 2018), the displaced labour might get absorbed by labour-intensive or less technological advance industries. However the absorption of displaced labour depends on the strength of the labour market, if the strength is huge then such will not be able to absorb 100% of displaced labour, whereas if the pool of labour is small then displaced labour will be absorbed to the fullest. It is not that hard to believe that the wage bill of these industries is lower than their previous industry which will decrease further due to the availability of a larger pool of labour, again labour share decreases by some units in this industry,

$$L_S = W_{O,i} - W_{O,j}$$

Where $W_{O,i}$ is labour cost at the initial period i & $W_{O,j}$ is labour cost at a subsequent period.

It has been argued that technological upliftment not only brings displacement effect but also creates new job opportunities (Acemoglu, 2018a). These new opportunities are created through technology development and auxiliary industries (for example educational & training institutes, spare part industries, &, etc). Now, the demand for new job profiles will rise resulting in job opportunities in these supportive industries, thus changing the composition of jobs due to an increase in the number of skilled labourers as skilled-based technology overtakes (Acemoglu, 1999, pp. 1259-1278). Since automation reduces human involvement to a minimum level thus, the headcount labour required to perform new technology-integrated tasks will be fewer as compared to the previous headcount. Thus, an increase in the supply of skilled labour will overwhelm the demand (Acemoglu, 1998, pp. 1055-1089); ultimately tilting the labour cost in favor of main industries. So, labour share again falls by,

$$L_S = W_{A,i} - W_{A,j}$$

Where $W_{A,i}$ is labour cost at the initial period i & $W_{A,j}$ is labour cost at a subsequent period.

And all excess supply of labour from the above circumstances is forced to work in informal or unorganized sectors at low wages, insecure jobs, and health risks, & ultimately ending the vicious cycle of poverty.

Thus, robotization results in a reduction in labour share in three stages (i) when robots are substituted for the labour force (ii) when displaced labour is absorbed by labour-intensive industries (iii) when labour demand for the new task is overwhelmed by supply. And ultimately adds to the informal market of an economy.

4. Hypothesis

a) *H_{A1}: Income inequality is positively correlated to Automation.*

b) *H_{A2}: Unemployment among skilled labour is positively correlated to Automation.*

c) *H_{A3}: Growth in the informal market is positively correlated to Automation.*

5. Methodology

The purpose of the study was to establish an association between automation and various macroeconomic variables which are income inequality, unemployed graduates, & informal market; accordingly, we used statistical tools such as regression, and correlation with longitudinal data of the US. The selection of countries was based on the accessibility and availability of the required data set. The empirical analysis was conducted in three parts.

5.1. Income Inequality and Automation

The Gini coefficient was used as a proxy for income inequality while the industrial robot installed per 1000 workers was used for automation. The data for industrial robots installed was collected from the International Federation of Robotics and the Gini coefficient was collected from the database of the World Bank. The data range for the USA was from 1993 to 2017.

$$Gini = \alpha + \beta Robotics + u_t$$

Where Gini is regressand, robotics is regressor, α is intercept, and u_t is the error term.

A few pre and post-tests were conducted to test the feasibility of regression analysis for establishing the association between two variables. The Augmented Engle-Granger (AEG), and Phillips Ouliaris (PO) were applied to the cointegration between two variables. Jarque Bera, Breusch Godfrey, and ARCH were used for testing normality, autocorrelation, and Homoskedasticity of residual series respectively.

5.2. Unemployed Skilled Labour and Automation

Karl Pearson's coefficient of correlation was used to study the association between Unemployed skilled labour and automation. We have avoided the use of time series regression involving two variables because the series of unemployed graduates was highly distorted and was unfit for cause-and-effect analysis. The series was stationary in second order and at the same possessed some outliers therefore we have gone for a simple correlation to test the association between unemployed graduates and Automation. The industrial robotics installed for 1000 workers was used as a proxy for automation while, the headcount of unemployed graduates was used as a proxy for unemployed skilled labour. Initially, the series of unemployed graduates was in the form of a percentage of the total population and was taken from the World Bank, we have transformed the data according to our requirement by multiplying it with the total population which was itself taken from the database of the World Bank.

5.3. Informal Market and Automation

The series of informal markets was also in the form of a percentage of Gross Domestic Product (GDP) and was converted into an absolute number by multiplying with GDP. The source of both data was the World Bank. As mentioned in, the previous subsection the industrial robotics installed per 1000 workers is used as a proxy for automation. The data were collected from 1993 to 2017. The time series regression was used as a statistical for test the alternative hypothesis *(H_{A3}), the equation used is given below;*

$$Inf = \alpha + \beta Robotics + u_t$$

Where Inf presents the informal market as regressand, robotics is regressor and intercept and error terms are presented through α and $respectively$.

Augmented Engle-Granger and Phillips Ouliaris were conducted to test the cointegration between the informal market and the robotics installed. Various residual diagnostic statistic was used which are Jarque Bera, Breusch Godfrey, and ARCH for normality, autocorrelation, and homoskedasticity respectively.

6. Result and Discussion

6.1. Income Inequality and Automation

6.1.1. Cointegration Test

The result of AEG and Phillips Ouliaris show that both proxy variables were convergent that is they cancel out the trend portion of each other. Since the series are cointegrated the regression can be run at the level without caring stationarity of the series. The test was conducted by taking the Gini coefficient series as the dependent variable, the tau statistic was -5.06, and the z statistic was -25.07 when the Gini coefficient was taken as the dependent variable significant at 0.1% level in the case AEG cointegration test. The result of Phillips Ouliaris was also confirmatory to that AEG with tau statistic and z statistic of -5.17 & -25.42 thus, statistically significant at 0.1% level. The result of the test is presented in Table 1 below:

Table 1. *Cointegration test between Income Inequality and Automation*

Tests	Dependent variable	τ Statistic	Prob	Z Statistic	Prob
AEG	Gini	-5.06	0.0023	-25.07	0.002
Phillips Ouliaris	Gini	-5.17	0.0018	-25.42	0.001

Source: Author.

6.1.2. Regression Test

In Table 2 below; the outcome regression is shown where industrial robotics installed per 1000 workers is regressed on the Gini coefficient. The F statistic of the model was 84.11 with Probability (F-statistic) 0 indicating the model to be significant at the level of 0.05%. R squared and adjusted R squared were 0.78 & 0.77 respectively. The estimator including the intercept was also statistically significant at the level of 0.05%. The association between the two variables was positive, thus we have enough evidence to accept the alternative hypothesis H_{A1} put forward under the theoretical framework. The outcome showed that one unit change in industrial robotics installed per 1000 workers brings about a 0.013-unit change Gini coefficient with an error in the estimation of 0.0014. The t statistic of the estimator was 9.17 and Probability was 0, indicating the estimator was highly significant. The intercept of the model was 0.44 with an error in estimation of 0.002. The intercept was also significant with t statistic & P values of 178.2 & 0.000 respectively. Durbin Watson was 2.04 more than the upper bound of 1.20, indicating no evidence of autocorrelation in the model.

Table 2. *Result of Regression between Income Inequality and Industrial Robots Installed per 1000 workers*

Variables	Constant (α)	Robotics(β_1)
Coefficient	0.44	0.013
Standard Error	0.002	0.0014
t statistic	178.2	9.17
P (value)	0	0
R-squared		0.78
Adjusted R-squared		0.77
F statistic		84.11
P (F-statistic)		0
Durbin-Watson Statistic		2.004

Source: Author.

6.1.3. Post Regression Test

Three residual diagnostic tests were conducted on the feasibility of the outcome regression analysis. Jarque Bera was conducted to test the normality of residual series and the calculated F statistic was 0.61 with a P value of 0.73 indicating the series was statistically normally distributed. To test the homoskedasticity of the series ARCH model was applied and the calculated F statistic was 0.55 with a P value of 0.46 indicating that the series possessed the property of homoskedasticity. Finally, Breusch Godfrey was applied to test the presence of serial correlation. The result confirms that there was no serial correlation in the model with F statistic and P values of 0.02 & 0.97 respectively.

Table 3. *Residual diagnostic test for Income Inequality and Industrial Robots Installed per 1000 workers*

Test	Calculated value	Prob
Jarque Bera	0.61	0.73
ARCH	0.55	0.46
Breusch Godfrey	0.02	0.97

Source: Author.

6.2. Unemployed Skilled Labour and Automation

We started the analysis with testing of cointegration between unemployed graduates and robotics installed per 1000 workers using AEG, & Phillips Ouliaris with a negative result, which is presented in Table 4 below. Then we shifted our focus on the stationarity of the series using Augmented Dicky Fuller (ADF) test for unit root, the outcome is shown in Table 5 below. The unemployed Graduate series was integrated at order second while the second series was integrated at order first. One strike observation was made that with every order of differenced series was exhibiting an increase in the number of outliers which is presented in Figures 3, 4, & 5 given below;

Table 4. *Cointegration test between Unemployed Skilled Labour and Automation*

Tests	Dependent variable	τ Statistic	Prob	Z Statistic	Prob
AEG	Unemployed Graduate	-2.46	0.322	-16.96	0.037
Phillips Ouliaris	Unemployed Graduate	-0.51	0.633	-7.28	0.49

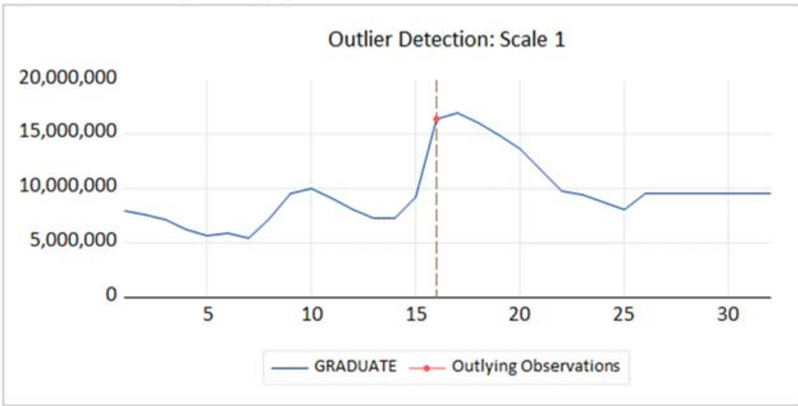
Source: Author.

Table 5. *ADF unit root of Unemployed Graduate*

ADF Test		Unemployed Graduate					
		Level Data		First Differenced		Second Differenced	
Significance	t statistic	Calculated Value	P value	Calculated Value	P value	Calculated Value	P value
1% level	-3.75	-2.17	0.21	-2.94	0.055	-5.19	0
5% level	-2.99						
10% level	-2.63						

Source: Author.

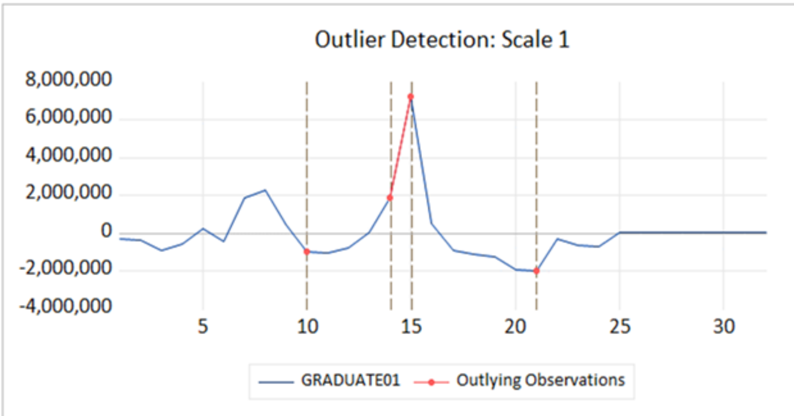
Figure 3. *Outliers of Unemployed Graduate series at the level*



Source: Author.

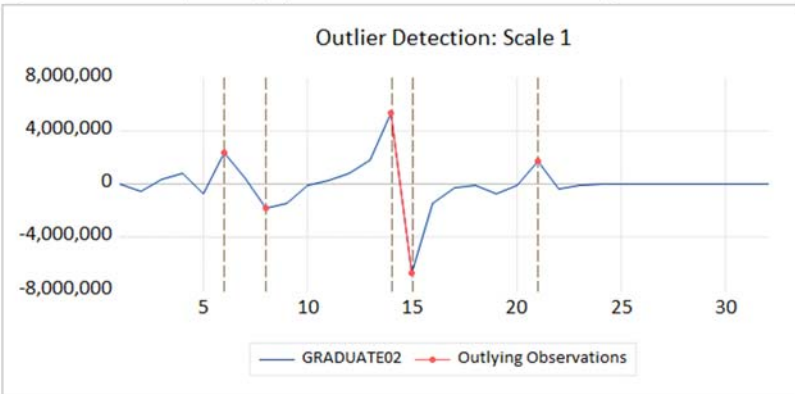
In Figure 3; it is visible that the number of outliers in the series of unemployed graduates is just 1 which increases to 4, and 5 in Figures 4, & 5 when the series was transformed into first and second differences respectively**.**

Figure 4. *Outliers of Unemployed Graduate series at first differenced*



Source: Author.

Figure 5. *Outliers of Unemployed Graduate series at second differenced*



Source: Author.

Since the variability of the dataset increases with the number of outliers and simultaneously reduces the statistical power thus, affecting the magnitude and direction of the estimator (Choi, 2009, pp. 153-165) therefore instead of going for regression analysis we went for Karl Pearson coefficient of correlation as level series is moderately suffer from outliers. The result of the correlation is shown in table 6.

Table 6. *Correlation between unemployed graduates and industrial robotic*

Variables	Unemployed Graduate	Industrial Robots
Unemployed Graduate	1	0.47
Industrial Robots	0.47	1

Source: Author.

The variables were positively correlated with a coefficient of 0.47 indicating that the mean of both the series moved in the same direction. Thus, we have enough evidence to accept H_{A2} that an increase in industrial robots leads to an increase in the headcount of unemployed graduates.

6.3. Informal Market and Automation

6.3.1. Cointegration Test

The result of AEG and Phillips Ouliaris provides us with enough evidence that both the variables that is informal market and industrial robots installed per 1000 workers (proxies of automation) are cointegrated at zero order at a 10% level of significance. The τ and z statistics of AEG were -3.32 and -15.02 with a P value of 0.083, & 0.070 respectively

The result of Phillips Ouliaris was like that of AEG where τ statistic was -3.35 with a P value of 0.079 and z statistic -14.38 with a P value of 0.089.

Thus, indicating that both the variables are convergent and will cancel out the trend portion of each will make equilibrium at the t period and OLS can be run at level data.

Table 7. *Test of Cointegration between Informal Market and Industrial Robots Installed per 1000 workers*

Tests	Dependent variable	τ Statistic	Prob	Z Statistic	Prob
AEG	Informal Market	-3.32	0.083	-15.02	0.070
Phillips Ouliaris	Informal Market	-3.35	0.079	-14.38	0.089

Source: Author.

6.3.2. Regression Test

In Table 8; the outcome of regression between the informal market and industrial robotics installed per 1000 workers is given below. The R square and adjusted R square of the model were 0.99, and 0.98 respectively with an F statistic of 1525.3 and a P value was 0.000 indicating that the model was statistically significant at 0.1% level. The estimator was also significant at a 0.1% level. A positive association was established between regressand and regressor thus giving enough evidence to accept H_{A3}, one unit change in regressor brings about 1137 changes in regressand with an estimation error of 29.11, and t statistic was 39.05 (P value 0.000). The intercept was also significant with t statistic & P values of 178.2 & 0.000 respectively. Durbin Watson was 1.12 lying between the lower bound and upper bound of 1.055 and 1.20, indicating inconclusive evidence of autocorrelation model, thus we had gone Breusch Godfrey.

Table 8. *Result of Regression Informal Market and Industrial Robots Installed per 1000 workers*

Variables	Constant (α)	Robotics(β_1)
Coefficient	1825.8	1137
Standard Error	49.83	29.11
t statistic	36.63	39.05
P (value)	0.000	0.000
R-squared		0.99
Adjusted R-squared		0.98
F statistic		1525.3
P (F-statistic)		0.000
Durbin-Watson Statistic		1.12

Source: Author.

6.3.3. Post Regression Test

Three residual diagnostic tests were conducted on the feasibility of the outcome regression analysis. Jarque Bera was conducted to test the normality of residual series and the calculated F statistic was 0.38 with a P value of 0.823 indicating the series was statistically normally distributed. To test the homoskedasticity of the series Breusch Pagan Godfrey was applied and the calculated F statistic was 0.18 with a P value of 0.67 indicating that the series possessed the property of homoskedasticity. Finally, Breusch Godfrey was applied to test the presence of auto, and serial correlation. The result confirms that there was no serial correlation in the model with F statistic and P values of 1.52 & 0.24 respectively.

Table 9. Residual diagnostic test for Informal Market and Industrial Robots Installed per 1000 worker

Test	Calculated value	Prob
Jarque Bera	0.38	0.82
Breusch-Pagan-Godfrey	0.18	0.67
Breusch Godfrey	1.52	0.24

Source: Author.

7. Conclusion

The history of technological change is associated with unrest and disharmony between the labour force and those who sat on the pedestal of the production process. Over the years technological advancement has impacted the involvement of labour in the production process, with rapid automation in the last three decades this involvement has been reduced a to minimalistic level. The argument that reinstated effect and creation of new tasks will counter the displacement effect (Acemoglu & Restrepo, 2018a) is not proven right at least in the transition period which is evident from the rising number of unemployed graduates which is positively correlated to automation indicating that robotization of production process is not creating enough new job, thus undermining the role of new task which was emphasized by Acemoglu and Restrepo (2018c). It can also be claimed that the new task created by this automation technology is overwhelmed by the number of qualified candidates applying for it. And finally, the lack of substantial wages and job opportunities (unskilled and skilled labour) is pushing the population toward the informal market, we also commented on how income inequality rises due robotization of industries as the spread of income is concentrated on fewer people as industries reduce the involvement of labour to large extend and then higher concentration skilled and unskilled labour in both automated and unautomated industries (Acemoglu, 1998, pp.1055-1089) respectively reduces overall wage.

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