Technological Change, Automation and Employment: A Short Review of Theory and Evidence

K.V.Ramaswamy

Indira Gandhi Institute of Development Research,

Mumbai 400065, India

Email: swamy@igidr.ac.in

Abstract

A selective survey of recent papers in the area of technological change, automation and employment is presented. The objective is to convey analytical ideas and the empirical evidence that have informed studies in this area of contemporary policy relevance. Automation occurs when a machine does work that might previously have been done by a person. How robots and automation affect the availability of jobs for labor force? There are very few emerging studies that address the issue with detailed data on robots usage and employment in different sectors of the economy. Based on our review of available studies and empirical evidence the following statements can be made: (1) Increasing automation and robots adoption do not seem to cause loss of employment in the aggregate (2) Low skilled workers in routine jobs are more likely to suffer job losses. (3) There will be demand for new types of skilled workers or new specializations within occupations. Prospective automation intensifies the degree of uncertainty in labor markets across countries.

Keywords: Technological change, Automation, Robots, Skill Bias, employment

JEL Code: J24, O31 and O33

1. INTRODUCTION

New developments in production technologies taking away jobs or the idea of machines replacing humans is a new source of anxiety in both developed and developing economies. Elon Musk, CEO of Tesla, world's leading manufacturer of electric vehicles and energy storage products, is reported to have said that Artificial Intelligence (AI) is a threat to human civilization[1]. Lead companies in the Global Production Networks (GPNs) in shoe and apparel manufacturing industries like Nike and Adidas are reported to have invested in automation to reduce production costs and lowering lead times.[2] Frequent reports in the media citing research studies that predict automation and digital technologies causing job losses has accentuated the anxiety. In September 2017, HfS research, a global services consulting firm, predicted that Indian IT sector will lose 7 lakh low skilled jobs to automation by 2022.[3] Low skilled workers are those conducting simple entry level process driven tasks with little abstract thinking. High skill workers are those undertaking complicated tasks that require experience, expertise, abstract thinking and autonomy. Knowledge of wage cost differences between low and high skilled jobs will be important in this context. The US Council of Economic Advisers (CEA) ranked occupations originally found to be at risk of automation by Frey and Osborne (2013), by wages per hour.[4] They found that, 83 percent of jobs making less than $20 per hour would come under pressure from automation, as compared to 31 percent of jobs making between $20 and $40 per hour and 4 percent of jobs making above $40 per hour. Another study (Arntz, Gregory and Zierahn, 2016) following similar methodology has reported classification of jobs at risk of automation by education levels and found that less-educated workers (those with less than a high school degree) are more likely to be replaced by automation than highly-educated (those with a bachelor degree) ones. A new report from Oxford Martin School (2016) explores the varying impact that automation of jobs will have on countries and cities around the world. It is called “Technology at Work v2.0: The Future Is Not What It Used to Be”. It is based on new World Bank data that builds on the methodology followed in Frey and Osborne (2013) and finds that 47% of jobs in the US and 57% of jobs on average in the OECD countries are at risk of automation. The risks of job automation in developing countries are found to vary across countries. It is estimated to range from 55% in Uzbekistan to 85% in Ethiopia. In emerging economies the risk of automation is estimated to be relatively high with 77% of jobs in China and 69% in India found to be at risk. Notice that Frey and Osborne (2013) methodology is based on a subjective assessment of the automatability of 702 occupations using judgment of experts in automation technology. The estimated numbers of occupations indicate what is technologically feasible but does not conclusively suggest real implementation as information on costs of automation and profitability of implementation are not taken into consideration. Therefore, it is difficult to be definitive (based on such numbers) about future quantitative employment outcomes of the automation technologies.

In this context, the present paper presents a selective introductory survey of recent literature in the area of technological change, automation and employment. There are very few emerging studies that address the issue with detailed data on robots usage and employment in different sectors of the economy. These studies are related to but quite distinct from the traditional studies of the impact of IT and computers on the labor market. Their focus is different because robots are programmable, flexible (have ‘arms and hands’) and are powered by AI to do multi tasks and they can directly replace tasks performed earlier by workers. The broad objective is to convey analytical ideas and the empirical evidence that have informed the studies in this area of great importance to economists and labor economists in particular. Throughout in this paper our focus is on employment. Studies of technical change and income or wage inequality will not be covered though the interconnections are obvious[5].

2. ANXIETY OF AUTOMATION

Automation occurs when a machine does work that might previously have been done by a person (The White House, 2016a).[6] The term refers to both physical work and mental or cognitive work that might be replaced by Artificial Intelligence (AI hereafter). AI is an umbrella term for a machine's ability to imitate a human's way of sensing things, make deductions and communicate. AI solutions often make use of the methods of machine learning. For example, a machine can be taught to identify phenomena with the help of mathematical and statistical methods. In this case, "teaching" means loading numerous images, numeric values, or text that represent the phenomenon to be learned into an algorithm. As a result of this teaching, the algorithm is gradually able to become increasingly better at identifying a particular phenomenon.[7] “Robots” are machines endowed with AI and should be distinguished from single purpose machines (though controlled by computer numerical codes), for example, sheet metal stamping machines used in manufacturing. The International Federation of Robotics (IFR), measures deliveries of “multipurpose manipulating industrial robots” based on the definitions of the International Organization for Standardization (ISO). The ISO definition refers to a “Manipulating industrial robot as defined by ISO 8373: An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications” (Cited in Graetz and Michaels,2017, page 3).[8] Industrial robots are machines capable of doing different kinds of tasks like painting, welding, ironing, assembling and packaging with minimum human intervention.

These capabilities clearly distinguish and differentiate current wave of automation based on robots (AI) from standard information technologies (IT) or IT enabled technologies.

The current anxiety of automaton and potential loss of jobs due to robots is not unprecedented (Mokyr, Vikers and Ziebarth, 2015). In early nineteenth century England (1811-16) “the Luddite” riots during which workers smashed textile machinery was partly attributed to fear of displacement by machines.[9] This fear resurfaced in the US in 1960s when unemployment was high. President Kennedy has been quoted to have stated in 1962 “ The major domestic challenge of the sixties is to maintain full employment at a time when automation is replacing men. It is a fact that we have to find over a ten-year period 25,000 new jobs every week to take care of those displaced by machines and those who are coming into the labor market”.[10] Recent unemployment problem following the Great Recession of 2007-09 when 12 million Americans are estimated to have lost their jobs has further accentuated the automation anxiety. One study stated “In July of 2011, 25 months after the recession finally ended, the main US unemployment rate remained at 9.1 %,less than 1 percentage point better than it was at its worst point.”[Brynjolfsson and McAfee, 2011, p.2]. In this context, Erik Brynjolfsson and Andrew McAfee wrote a book called “Race Against The Machine” in 2011 and advanced the argument that digital technologies can now perform mental tasks that had been the exclusive domain of humans in the past and that could cause technological unemployment. In their second book Brynjolfsson and McAfee (2014) present numerous examples of what they call “The Second Machine Age” such as the driverless car, the largely autonomous smart factory, service robots or 3D printing. These technologies are driven by advances in computing power, robotics process automation (RPA) and AI.

Given high levels of unemployment in the US and other EU countries David Autor (Autor 2015a) posed the question whether labour scarcity is actually declining in the US? He draws our attention to two other parallel developments in the US.[11] First, there has been a decline in the wages of non-college educated males between 1979 and 2012. Second, during this period real full-time weekly earnings of male high school graduates fell by 15% and those of male high school dropouts fell by 25%. Male employment to population ratios have fallen in demographic groups (ages 25-39) with low and falling earnings. These two facts read along with the fact of falling share of labour in national income has been interpreted to suggest that the demand for less skilled workers has substantially declined. In other words, a significant fraction of less-educated adults in the US have been unable to find gainful employment at prevailing wages. This is considered as equivalent to technological unemployment (Autor 2015a).[12] A related development in the US and Europe has been the 'polarization' of employment by skill level and the corresponding inequality in wage incomes between three skill groups of high-skill, middle-skill and low-skill occupations (Goos, Manning and Solomons (2014); Autor and Dorn (2013).[13] Large increase in the employment share of high-skill and low-skill groups with a decline in the share of middle-skill group has been characterized as "polarization". In general, the concern has been the falling share of labor in national income in a large number of countries and the increasing wage gap between unskilled and skilled labor (college and high-school educated workers). The corporate gross value added share of corporate labour in a sample of 59 countries declined from 64% in 1975 to 59% in 2012 (Karabarbounis and Neiman, 2014). This recent empirical development has contradicted the stylized fact of constancy of labor income share supposed to be consistent with the received neoclassical theory of economic growth and distribution. This brings us to the analytical models that have provided the framework for discussing the relationship between technological change, automation and employment in the recent literature.

3. FACTOR AUGMENTING TECHNOLOGY versus TASK BASED FRAMEWORK

Technological progress and its effects on factors of production and the distribution of income have been one of the central themes of economic growth and development literature.[14] The pioneering writings of John Hicks (Theory of Wages,1932) introduced the idea of biased technical progress (factor bias in technological change) and further extended by Roy Harrod (1939) and others . It is useful to begin with some clarity on the usage of terms in this literature.[15] Let us assume that production in the economy can be represented by an aggregate production function subject to constant returns to scale that takes the following form:

$$\mathrm{Y}\,(\mathrm{t}) \;=\; \mathrm{F}\,[\mathrm{L}\,(\mathrm{t}), \mathrm{K}\,(\mathrm{t}), \mathrm{A}\,(\mathrm{t})] \text{........ (1)}$$

Where L is labor, K is capital (or skilled labor), t denotes time and A(t) represents technology. Technological change is called L-biased, if it increases the relative marginal product of factor L compared to factor K. The key point to note is that biased technological change shifts out the relative demand curve for the specified factor (labor in this example). As a result its relative marginal product (therefore its relative price) increases at given relative factor proportion. If K in equation (1) denoted skilled-labor, to make it more relevant, then K-biased (skill-biased) technological progress would increase the relative marginal product of skilled labor and the skill premium would emerge as a consequence. A critical parameter in the context of models of biased technical progress is the elasticity of substitution often denoted by sigma (σ). The form of production function that is used to shed light on the underlying mechanism of biased technical progress is the Constant Elasticity of Substitution (CES) production function. The properties of CES production function are well-known and it takes the following form:[16]

$$Y(t) = [(A_L\,(t)\;\, L(t))^{\sigma-1/\sigma} \;+\; (A_K\,(t)\,K(t))^{\sigma-1/\sigma}\;\;]^{\sigma/\sigma-1} \text{......... (2)}$$

Where A_L (t) and A_K (t) denote the two technology terms (factor-augmenting parameters) corresponding to labor and capital and σ is the elasticity of substitution parameter between labor and capital, the two specified factors. If $\sigma = 1$ then the production function is Cobb-Douglas and if $\sigma = 0$ then the production function is reduced to Leontief form. The important conceptual idea is to understand that factor-biasedness of technological change (that could be either L-augmenting or K-augmenting) depends on the parameter σ. In order to understand this we need to calculate the relative marginal product of the two factors. It is easy to show that it takes the following form:

$$MP_K / MP_L \quad = \; (A_K\,(t) \,/\, A_L\,(t))^{\sigma-1/\sigma} \quad (K\,(t)/\,L\,(t))^{-1/\sigma} \;\ldots\ldots\; (3)$$

From equation 3, it is evident that the relative marginal product of K is decreasing in its relative abundance measured by K/L due to the substitution effect driven by the negative relationship between relative supplies and relative marginal products. However, the effect of A_K (t) on the relative marginal products depends on σ. If $\sigma > 1$ then an increase in A_K (t) relative to A_L(t) increases the relative marginal product of K and if $\sigma < 1$ then an increase in A_K (t) reduces the relative marginal product of K. In short, when the two factors are gross substitutes ($\sigma > 1$) K-augmenting technical change will turn out to be K-biased. When two factors are gross complements ($\sigma < 1$) K-augmenting change is L-biased. In the case of Cobb-Douglas production function σ=1 and therefore K-augmenting or L-augmenting technological change does not have any factor bias effect[17]. Using equation (2) we can find the marginal product of capital and then find the expression for the income share of capital (= rK/Y). It is related to σ in the following way.[18]

$$MP_K \ x \ K/Y = r.K/Y = (A_K)^{-1/\sigma} \ (K/Y)^{(\sigma-1)/\sigma} \quad .... (4)$$

It is inferred from this that, given the value of A_K, there is direct relationship between income share of capital and capital deepening when $\sigma > 1$.[19] In other words, the income share of labor could decline due to biased technological change, which is biased in favour of capital[20] Notice that in this modeling framework, technological changes only work to augment either capital or labor (that is, improve their productivities) but there is no explicit labour replacing technological change like robotics technologies (guided by Artificial Intelligence), which could replace workers in different occupations or tasks. This insight suggested that models should look beyond factor-augmenting technological change to understand the impact of computers and robotic technology on employment and wages.

3.1 Routine-biased Technical Change

Which types of tasks are likely to be automated using computers? How does one differentiate between task and skill? Autor, Levy and Murname (2003) presented a simple theory of how the rapid adoption of computer technology changes the tasks performed by workers at their jobs and finally the demand for human skills. This task based approach has been further developed and applied others.[21] In this framework, machines substitute for routine tasks performed by workers. Hence it is called routine-biased technical change (RBTC). A task is considered as "routine" if it can be accomplished by machines following explicit programmed rules. However "...there are many tasks that people understand tacitly and accomplish effortlessly but for which neither computer programmers nor anyone else can enunciate the explicit "rules" or procedures" (Autor, 2015b, p.11). Such categories of tasks are labeled 'non-routine" tasks. In other words, if the task involves problem-solving, complex communication activities and tacit knowledge then it is called 'non-routine.[22] In Table 2 we have a shown a representative categorization of routine and non-routine tasks and their potential computerization possibilities based on judgment. Status of several activities is likely to change depending on technological advances in the robotics technology.

The production function in the task-based approach may be written as

Y = F (Routine Labor (LR), Computer Capital (CC), Non-Routine Labour(LN)),

Where LR and LN are routine and non-routine labour inputs and CC is computer capital, all measured in efficiency units. The actual form of this production is assumed to be Cobb-Douglas. The supply of CC is perfectly elastic at market price r per efficiency unit. Over time r will be falling due to exogenous technical advances and the model explains how this fall in CC prices (outcome of technological change) impacts demand for LR and LN within industries and occupations. It is assumed that CC and LR are perfect substitutes ($\sigma=\infty$) in carrying out routine tasks. The elasticity of substitution between LR and LN tasks is same ($\sigma=1$). Importantly, CC is more substitutable for LR than for LN. This model predicts that industries that were intensive in LR tasks in the pre-computer era would make relatively larger investments in computer capital. At the same time they would reduce labor input of LR tasks as they substitute such tasks with CC and increase demand for LN task inputs because CC is a complement to LN input in production. Their empirical study found substantial decline in the share of the labor force employed in occupations intensive in routine cognitive and routine manual tasks between 1970 and 1998 in the US labor force. They observed a negative relationship between industry computerization (percentage of workers using computers at work) and changes in routine task input are uniformly negative in the 1970s, 1980s, and 1990s.

The task-based model has been further extended by Autor and Dorn (2013) to incorporate the services sector to explain the phenomenon of polarizing employment in the

US. First, they point out that employment changes in the US between 1980 and 2005 were strongly U-shaped in skill level. The relative employment share of middle level skill declined but those at the tails (high-skill and low-skill) gained relatively. This is referred to as employment polarization as we noted earlier. Second they formulate a task-based model to explain this polarization. In their model technological change takes the form of decline in the cost of computerization of routine tasks. There are two sectors in the economy. The first sector is engaged in the production of "goods" and the second sector produces "services". They define "goods" to include manufacturing as well as skilled services like banking and education. The dominant activity of services sector is the provision of low-skill in-person services like hair-cutting, house-keeping, food service etc. There are three types of labour (task) inputs available in the economy, namely, manual labor (LM), routine labour (LR) and abstract labour (LA). Computer capital (CC) is the fourth factor which can be used as intermediate good as well as provider of routine task services. All inputs are measured in efficiency units. Goods are produced by the following production function: Yg =F (LR, LA, CC). In this production function LR and LA are substitutes with $\sigma=1$. LR and CC have an elasticity of substitution $\sigma>1$. Therefore, by implication CC is a relative complement to LA and a relative substitute for LR. Services are produced using only routine–manual labor using a fixed coefficient production function as follows: Ys = αLM, where LM is manual labor. If we assume the elasticity of substitution in production between CC and LR is high relative to the elasticity of substitution in consumption between goods and services, then it is straight forward to see that as the prices of CC falls, CC is substituted for LR and excess LR in production causes wages of LR to fall to such an extent that it is lower than manual labor in services sector. LR flows from goods production to services sector causing employment polarization in the economy. This outcome is possible because routine tasks have well-defined procedures which are easy to computerize. However routine-manual tasks like those in services occupation like housekeeping or janitorial services have been found to be expensive to computerize. Computers are complements in non-routine or abstract tasks and substitute for routine tasks but do not have direct role in performing routine-manual tasks. As costs of computerization falls over time, routine non-manual tasks in goods production get automated (employment share falls) and the productivity of abstract labour improves (they remain in goods production). Computerization lowers the relative wages of LR (relative to LM) and they workers in goods production shift to routine-manual tasks in services occupations. Consequently, employment polarization emerges in the labour market with lower share of mid-skill group and high share of high-skill and low-skill service occupations.

Table 1: Potential Computerization of Workplace Tasks	
Analytic or Non-Manual Tasks	
Routine	**Non-Routine (abstract labour)**
Record-book-keeping, Calculation, Clerical work Repetitive customer service (e.g., bank teller) or monitoring activity	Forming/testing hypotheses Medical diagnosis, Legal writing Marketing/selling, Personnel management or coordinating tasks
Substantial substitution ↑	Strong complementarities ↑
Manual Tasks	
Picking or Sorting, Machine Operators Repetitive line assembly	Janitorial services ,Personal care like Nursing and Child care, Housekeeping, Table-services in restaurants
Substantial substitution ↑	Limited opportunities for substitution or complementarity ↑
Source: Based on Autor, Levy and Murname (2003)	

Technological advances lead to automation of tasks in specific occupations. Bessen (2017) following the task-based model literature develops a model that integrates technology (automation of tasks) and occupations. He begins with the observation that automating a task is not equivalent to automating an occupation. Complete automation of all tasks within an occupation results in net loss of jobs but partial automation does not. Bessen draws our attention to the 1980s when desktop publishing software automated some tasks of type setting in publishing industry. Computerized publishing reduced employment of typesetters and compositors but increased the employment of graphic designers. In this case there is substitution of one occupation (typesetters) by another (designers using computers). Technological change affect jobs by making occupations substitute or complement each other. Computer use (automation) is labor augmenting and therefore reduces the price of occupational service measured in efficiency units. The firm produces output using multiple occupational services and capital K: Y= f (L1, L2, L3…, K), where Li is the i^{th} occupational service. Factor augmentation (productivity improvement due to computer use) of occupation j will decrease or increase occupations j and k depending on the elasticity of substitution between k and j, elasticity of demand for product Y, and share of wage-bill going to service j. This follows from standard neoclassical theory of demand for factors of production. Here instead of factors occupational services are distinguished. Bessen (2017) goes on to argue that computer use is highly correlated with the rated "degree of automation" of an occupation. He uses data from Current Population Surveys (CPS) in the US, which reported response of adult workers whether they directly used computer at work. He studies 317 occupations through the years 1984 to 2003 and finds that occupations that use computers substitute of other occupations. In other words, inter-occupational substitution offsets the direct growth effects of computer use. On average computer use is found to be associated with small employment growth and not job losses.[23]

A question of direct interest is how robots replace human labor and why this might lower the quantity of jobs in the labor market and what are the general equilibrium effects? This question is addressed by Acemoglu and Restrepo (2017) and they provide some empirical estimates based on local labor markets data in the US (US commuting zones).[24] In this model each industry produces output by combining a continuum of tasks $s \in [0, S]$ and they are combined in fixed proportions. Only subsets of these tasks, say [0, M], in each industry are "technologically automated" and can be performed by robots and the remaining set of tasks are performed by using labour alone. In other words, industrial robots are modeled as machines that can perform some of the tasks previously carried out by workers in the given industry. They highlight three different forces affecting demand for labor (partial equilibrium) in this set up: (a) Displacement Effect: robots displace workers and reduce the demand for labor. This happens because a given amount of output can be produced with fewer workers when robots are used. (b) price-productivity effect: use of robots (automation) lowers the cost of production in the given industry (lowers the price of output) and this leads to higher industry output and increases its demand for labor. (c) scale-productivity effect: the reduction in costs results in the expansion of output of all industries (aggregate output) and raising demand for labour in all industries. The final (general equilibrium effect) outcome in terms of employment depends on the strength of price-scale-productivity effect relative to the displacement effect. The magnitude of the productivity effect depends on the cost savings from the substitution of robots to human labor (automation). In their empirical exercise they go on measure the US exposure to robots (penetration ratio of robots to baseline employment). In other words, the response of employment and wages to adoption of robots can be measured. In their econometric work, they use the stock of robots by industry from the IFR. IFR data is based on yearly surveys of robot suppliers.[25] In manufacturing, they use data for the use of robots in 13 roughly three-digit industries. Their regression analysis focuses on 722 commuting zones in the US. Commuting zones are clusters of US counties with a minimum population of 100,000. They estimate the impact of industrial robots on employment between 1990 and 2007 (before the onset of recession) on US local labor markets. The US increased robots adoption by approximately one new robot by per thousand workers from 1993 to 1997. This is equivalent to an increase of 120,000 robots over the same time period. They measure the impact of robots by regressing the change in employment on the exposure to robots in each local labor market. A commuting zone with an exposure to robots equal to the US average experienced 0.37 percentage point lower employment to population ratio or equivalently reduction of employment of 6.2 workers (assuming no trade between commuting zones). They report a range of estimates based on alternative assumptions and find that employment loss to range between 3 (manufacturing sector only) and 5.6 (national economy) workers losing their jobs as result of the introduction of one more robot in the US national economy. They argue that the total number of jobs lost is approximately 360,000 to 670,000 (Acemoglu and Restrepo, 2017, p.36). In other words, in the total US economy robots use caused an annual job loss that range from 21,000 to 39,000 during the period 1990 to 2007. These estimates of job loss have to be cautiously interpreted because IFR data do not measure actual robot use by sub-national units like commuting zones. They are estimated by using distribution of employment by industry in commuting zones and the industrial distribution of robots usage in European countries. This is an innovative first step as the authors themselves point out their methodology measures "only the effect of robots on employment in a commuting zone relative to other commuting zones that have become less exposed to robots" [Acemoglu and Restrepo,2017,p.37]. And they have not been able to capture the technological responses to factor price changes due to the introduction of robots as predicted by their theoretical model.

Graetz and Michaels (2017) have used data on actual robot use within countries (by industries) to measure the impact of robots on productivity, wages and employment. Their cross-country study used panel data on robot adoption (based on the same source that is, IFR data) within industries (14 in number) in 17 countries from 1993 to 2007. First, they observed a steep fall in the price of robots in six developed economies. In 2005 the quality-adjusted prices of industrial robots were about one fifth of their 1990 level. During this period they found robot density (the stock of robots per million hours worked) in 17 countries increased over this period by more than 150 percent, from 0.58 to 1.48. Interestingly they found industries that experienced rapid increases in robot density also found to have higher rate of growth of labor productivity. This raised the issue of reverse causality (growth in productivity leading to robot density!). In order to rule out this possibility they construct two instrumental variables. First is called “replaceable” and it is constructed using data on “robot applications” which classify the tasks performed by robots. It measures the fraction of each industry’s hours worked in 1980 that was performed by occupations that subsequently became prone to replacement by robots. Second is called “reaching & handling,” which builds on technological advances made in the use of robotic arms. Here they measure the extent to which industries used occupations requiring reaching and handling tasks, compared to other physical tasks in 1980. These two indices are used as instruments for robot densification and the method of two-stage least squares (2SLS) estimates showed that robot densification led to increased labor productivity and not the other way.

The model underlying their study is also based on task-based approach. Workers are assumed to perform all tasks, while robots can only be used in a limited set of tasks whose share varies by industry. There is a choice of technology between one that uses both robots and labor, and one that only uses labor. In tasks that can be performed by robots, robots and workers are perfect substitutes. Robots can be hired at an exogenous rental rate of r. The technology choice rule for a firm is simple: adopt robots when profits from doing so exceed profits from using the labor-only technology by at least the fixed setup cost. They prove that robots are only adopted in sectors whose share of replaceable tasks exceeds a critical value. How employment changes when robots become cheaper? The answer depends on two critical parameters namely, elasticity of substitution (σ) and the elasticity of demand (ε). A fall in the rental rate R leads to a rise (a fall, no change) in the robot-using industries’ employment relative to that of the others if and only if $\varepsilon > \sigma$ ($\varepsilon<\sigma$, $\sigma = \varepsilon$). The intuition is straight forward. A decline in robot prices induces firms to substitute robots for labor and at the same time reduce their relative output price. Consumers, in turn, buy relatively more of the robot-using industries' output (relatively cheaper). The increased demand for output causes greater relative demand for labor if $\varepsilon > \sigma$ (consumer response greater than the firm's response to fall in relative price of robot).

Their findings suggest that increased robot use contributed approximately 0.37 percentage points to annual labor productivity growth but did not significantly reduce total employment. They have reported estimates of the share of hours worked by high-skilled (usually college graduates), low skill (typically high school dropouts) and middle-skilled workers (those with intermediate levels of schooling). The impact of robots adoption on low-skill group is found to be consistently negative.[26] Robots adoption is found to be associated with reduction of employment share of low-skilled workers. This result of Graetez and Michaels (2017) contradict the argument that use of robots adversely affects the middle-skill workers reported by other studies in the literature.

4. CONCLUDING OBSERVATIONS

Use of robots and automation is the most recent technological advance in production activity and studies of their impact on employment and wages naturally fall under the rubric of studies of technological change, growth and labor markets. The use of industrial robots is currently estimated to be around 1.6 million in 2015 (UNCTAD 2017). It is estimated to increase to 2.5 million by 2019 and to 4 to 6 million by 2025 (two alternative projections by Boston Consulting Group (BCG, here after), 2015). How robots and automation affect availability of jobs for labor force? There are very few emerging studies that address the issue with detailed data on robots usage and employment in different sectors of the economy. These recent studies have attempted to explain the impact of robots on employment and jobs in the task-based model framework. They are found to be very useful in explicating the underlying mechanisms. A reading of this literature suggests that both optimistic as well as pessimistic scenarios are possible. If we assume that robots can only substitute for routine jobs (as in Acemoglu and Autor (2011) and others) then the outcome is likely to be optimistic or less pessimistic. This is because of two reasons. First, there always remain large classes of occupations not amenable to automation. Second, it is possible for the introduction of new tasks in which labor has a comparative advantage (Acemoglu and Restrepo, 2016) and that can offset the loss of occupations due to automation. On the contrary, as assumed in the recent paper by Susskind (2017) the range of tasks which robots can substitute could be much larger. It is possible, following Susskind (2017), to distinguish between two types of capital. They are 'traditional capital' and 'advanced capital', the former refers to machinery that cannot perform the same type of tasks as labour and the latter (read robots) can perform tasks performed by labor including complex tasks. In short, robots can perform even the so-called non-routine complex tasks in which human labor was assumed to have comparative advantage. Labor can be viewed as performing a set of tasks complemented by traditional capital. But advanced capital can displace all such tasks and compete away the comparative advantage of human in all such tasks. Then the share of labor total available tasks could dramatically shrink. This suggests a pessimistic scenario that can be visualized given the technological advances in automation and robotics.[27] However it is hard to predict the actual outcome and the likely response of different decision making units in the economy to the threat of automation.

Based on our review of available studies and empirical evidence the following statements can be made: (1) Increasing automation and robots adoption do not seem to cause loss of employment in the aggregate (2) Low skilled workers in routine jobs are more likely to suffer job losses.(3) There will be demand for new types of skilled workers or new specialization within occupations.. Example, U.S. demand for software engineers who program computers to understand human speech grew faster than workers with any other skill.[28] In short, there could be sea change in terms demand for diversified skills. The acquisition of new skills (occupation-specific) may be challenging for workforce and may require investment (Bessen 2017)

It is important to recognize that technical capabilities (functionality) of industrial robots are rapidly improving and their operating costs are declining in recent years. Newer robots can be more flexible and do more tasks. The cost of purchasing and installing robotics for spot welding in the US automotive industry has declined from $182,000 in 2005 to $133,000 in 2014 and expected to decline further to $103,000 by 2025 (BCG, 2015). Another example is equally instructive. In the US electronic and electrical; equipment industry, the cost of a generic robotics system is estimated to be $28 per hour, which is expected to fall below $20 per hour by 2020 which is below the cost of human labor (including benefits).

This type of cost reduction is likely spread across different industries. Does it mean the proportion of automated tasks is likely to reach 100 percent? The answer is in the negative because of two factors: (a) inter-industry differences in relative cost-effectiveness of robots adoption (b) differences in the ease or difficulty of adopting robots due to task specific or industry specific features. The first factor is straightforward. Industries with labour costs of more than 15 or 30 percent (just a thumb rule) of total costs will have greater incentive to adopt robots. Countries high per hour of labor costs like Australia ($55 per hour in 2014) will have more incentive than India ($5.24 in 2014) to adopt robots. The second factor is more relevant for developing countries because certain tasks in labor intensive industries are not amenable to use of robots or more accurately to use of cost-effective robots. Automated cutting machines are now becoming a widely available technology, and robots capable of sewing – called 'Sewbots Technology'. But picking up pieces of cloth, align them and fed them to sewing machine to be sewn into garment are done efficiently by humans. Cost of such robots per hour is likely to remain exceedingly high and pose less threat to low skilled workers in developing countries.[29] Manufacturers of footwear are yet to find a method for putting shoe laces though smart shoes which has been a completely manual process. It takes approximately 120 steps involved in manufacturing sneakers but robots have not yet been able to master, at least not on an industrial scale, according to Adidas CEO Kasper Rorsted.[30] Its competitor Nike has invested in automation to produce high end sports shoes called Flyknit. The most difficult part of a sneaker is it upper that contains 40 different parts. A pair of Nike Roshe shoes costs $75 without Flyknit uppers, compared to as much as $130 with Flyknit uppers.[31] Nike has introduced automation along with its technology collaborating companies like Flex and Grabit, innovations like laser-cutting, automated gluing etc. They have been introduced to bring production closer to the high end US customer. Our discussion of substation in consumption and substitution in production is relevant here. Nothing like clear prediction is possible here. Secondly, new technologies (Internet of Things that enables devises to talk to each other, collaborative robots[32] called 'Cobots' etc., which do not necessarily displace workers) contribute to enhance productivity and at the same create demand for labor that complements production and services activities. In other words new machines can improve productivity and therefore generate demand for labor in other sectors and industries apart from demand for new occupation-specific jobs within the same industry. The challenge is how to augment the supply of required skilled people with the right kind of education and training to match the demand for diversified skills in the near future. Overall, our reading of the literature on automation and employment suggest that the overall macroeconomic effects of automation are not clearly understood. However one fact is abundantly clear. The new development on technologies (or the lack of understanding of their impacts) greatly adds to the uncertainty of labour market outcomes in terms of employment and wages in different countries.

References:

Acemoglu, Daron. (2009), *Introduction to Modern Economic Growth*, Princeton: Princeton University Press.

Acemoglu, Daron. (2002), "Technical change, inequality, and the Labor market," *Journal of Economic Literature*, 40(1): 7-72.

Acemoglu, Daron and David Autor (2011), "Skills, tasks and technologies: Implications for employment and earnings" In: Card, D and Ashenfelter, O, eds. *Handbook of Labor Economics*, Volume 4B. Amsterdam and New York, North Holland: 1043–1171.

Acemoglu, Daron and Pascual Restrepo (2016), "The Race between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment" NBER Working Paper No. 22252, National Bureau of Economic Research, Cambridge, MA.

Acemoglu, Daron and Pascual Restrepo (2017), "Robots and jobs: Evidence from US Labour Markets". Working Paper No. 23285, National Bureau of Economic Research, Cambridge, MA.

Arntz, Melanie, Terry Gregory, Ulrich Zierahn, (2016), "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis", OECD Social, Employment and Migration Working Papers, No. 189, OECD Publishing, Paris. http://dx.doi.org/10.1787/5jlz9h56dvq7-en, accessed September 25, 2017.

Autor, David, Frank Levy and Richard Murnane, (2003), "The skill content of recent technological change: An empirical exploration", *Quarterly Journal of Economics*, 118(4):1279–1333.

Autor, David and David Dorn, (2013), “The growth of low-skill service jobs and the polarization of the US labor market”, *American Economic Review*, 103(5): 1553–1597

Autor, David (2015a), “Paradox of Abundance” in Subramanian Rangan (edited), *Performance and Progress: Essays on Capitalism, Business, and Society*, Oxford University Press, Oxford.

_____________ (2015b), “Why Are There Still So Many Jobs? The History and Future of Workplace Automation”. *Journal of Economic Perspectives,* 29 (3): 3-30.

Bessen, James (2016), “*How Computer Automation Affects Occupations: Technology, Jobs, and Skills*”, Boston Univ. School of Law, Law and Economics Research Paper No. 15-49. Available at SSRN: https://ssrn.com/abstract=2690435 or http://dx.doi.org/10.2139/ssrn.2690435.

Boston Consulting Group (2015), “*The Robotics Revolution: The Next Great Leap in Manufacturing*”, available at https://www.bcg.com/perspectives/197062, accessed October 30, 2017

Brynjolfsson, Erik, and Andrew McAfee (2011), *Race Against the Machine*. New York: Digital Frontier Press

Brynjolfsson, Erik, and Andrew McAfee (2014), *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W. W. Norton & Company.

Conniff, Richard (2011), “*What the Luddites Really Fought Against* “, in Smithsonian Magazine, March 2011, available at http://www.smithsonianmag.com/history/what-the-luddites-really-fought-against-264412/ accessed September 26, 2017

Dunlop, John (Editor) (1962), *Automation and Technological Change*, Englewood Cliffs, New Jersey: Prentice-Hall Inc.

Fergusson, C.E. (1969), *The Neoclassical Theory of Production and Distribution*, Cambridge University Press: London.

Financial Times (2016), "Meet the cobots: humans and robots together on the factory floor", May 5, 2016, available at https://www.ft.com/content/6d5d609e-02e2-11e6-af1d-c47326021344, accessed October 24, 2017.

Financial Times (2017a), "Stitched up by robots: the threat to emerging economies", in The Financial Times, July 18, 2017, available at https://www.ft.com/content/9f146ab6-621c-11e7-91a7-502f7ee26895, accessed October 26, 2017.

Financial Times (2017b), "Nike's focus on robotics threatens Asia's low-cost workforce" in The Financial Times, October 22, 2017, available at https://www.ft.com/content/585866fc-a841-11e7-ab55-27219df83c97, accessed October 30, 2017.

Fortune (2017a), "Why Elon Musk Is Wrong About", July 27, 2017, available at http://fortune.com/2017/07/27/elon-musk-mark-zuckerberg-ai-debate-work, accessed October 23, 2017.

Fortune (2017b), "These Robots Are Using Static Electricity to Make Nike Sneakers", Fortune, August 30, 2017, available at http://fortune.com/2017/08/30/robots-static-electricity-nike-sneakers, accessed October 30, 2017.

Frey, Carl Benedikt and Michael Osborne, (2013): *The future of employment: How susceptible are jobs to computerisation?* Oxford Martin School Working Paper, Oxford. Available at: http:// www.oxfordmartin.ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf, accessed October 15, 2017.

Goos, Maarten, Alan Manning, Anna Salomons, (2014): "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, 104(8), 2509–26.

Graetz, Georg, and Guy Michaels, (2017): "*Robots at Work*," available at http://personal.lse.ac.uk/michaels/Graetz_Michaels_Robots.pdf (a revised version CEP Discussion Paper No. 1335), accessed October 25, 2017.

HfS (2017): "*Impact of Automation and AI on Services Jobs; 2016-2022*" available at https://www.hfsresearch.com/market-analyses/impact-of-automation-and-ai-on-services-jobs-2016-2022,accessed October 24, 2017.

International Federation of Robotics (2017): *The Impact of Robots on Productivity, Employment and Jobs*, available at https://ifr.org/ifr-press-releases/news/position-paper, accessed October 25, 017.

Karabarbounis, Loukas, and Brent Neiman, (2014): "The Global Decline of the Labor share". *Quarterly Journal of Economics*, 129(1): 61–103.

Mokyr, Joel, Chris Vickers, and Nicolas Ziebarth, (2015): "The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different?" *Journal of Economic Perspectives*, 29(3): 31-50.

Oxford Martin School (2016):"*Technology at Work v2: The Future Is Not What It Used To Be*", available at (http://www.oxfordmartin.ox.ac.uk/downloads/reports/Citi_GPS_Technology_Work_2.pdf), accessed October 3, 2017.

Quartz (2017): "*One very basic job in sneaker manufacturing is testing the limits of automation*", Marc Bain in Quartz, April 24, 2017, available at https://qz.com/966882/robots-cant-lace-shoes-so-sneaker-production-cant-be-fully-automated-just-yet/ accessed October 30, 2017.

Susskind, Daniel (2017): "*A Model of Technological Unemployment*," University of Oxford Working Paper No.819, Revised July 2017, available at https://www.economics.ox.ac.uk/materials/papers/15126/819-susskind-a-model-of-technological-unemployment-july-2017.pdf, accessed October 30, 2017.

The White House (2016a): "*Preparing for the Future of Artificial Intelligence*," October 2016, available at (https://www.whitehouse.gov/sites/default/files/whitehouse_files/microsites/ostp/NSTC/preparing_for_the_future_of_ai.pdf), accessed October 10, 2017.

The White House (2016b): "*Artificial Intelligence, Automation, and the Economy*", December 2016, available at https://obamawhitehouse.archives.gov/sites/whitehouse.gov/files/documents/Artificial-Intelligence-Automation-Economy.PDF, accessed October 10, 2017.

UNCTAD (2017): *Trade and Development Report 2017*, United Nations, Geneva.

---

[1] Fortune (2017a)
[2] Financial Times (2017b)
[3] HfS Research (2017)
[4] White House(2016b)
[5] Studies of income inequality are inspired by the large decline in income share of labor in the developed countries. The declining labor share has turned out to be a global phenomenon and has been at the center of inequality debate.
[6] Office of the President of the United States has issued two reports which contain excellent discussion of the issue of Automation and economy. The first report cited here gives a clear discussion of technical terms and their origin.
[7] See https://www.arcusys.com/blog/the-tools-of-the-future-today-what-is-robotic-process-automation-artificial-intelligence-and-machine-learning, accessed on September 25,2017
[8] UNCTAD (2017) and IFR (2017). Different types of robots are in use like those for professional use and robots for domestic/household tasks.
[9] Recently it was pointed out that they were not actually against machines but against wrongful use of machines and poor wages See (Conniff, 2011).
[10] Dunlop (1962, p.1).
[11] This paragraph is based on Autor(2015a)
[12] Autor (2015a) calls this "Paradox of Abundance" and the continuing substitution of abundant capital for scarce labor has reduced the 'scarcity' value of labor. He attributes this to three factors, namely, capital biased technological change, deunionization and globalization. For details see the original paper Autor (2015a).
[13] See also several other earlier papers cited in Goos, Manning and Salomon (2014)
[14] We will not attempt an extensive survey of this literature. Several good surveys and text book discussions are already available (see Acemoglu (2002 and 2009). See Ferguson (1969) for an early detailed presentation of neoclassical theory production and distribution.

[15] The following brief explanation borrows from Acemoglu (2009). See the cited text for an excellent detailed discussion of directed technical change in economic growth models.
[16] We are assuming share parameters αl and αk are equal, that is αl=αk=1/2, to simplify the exposition.
[17] The income share of labor (= wL/Y) will be constant over time under the assumption of Cobb-Douglas production function. This implication is found to be inconsistent with empirical data in both developed and developing countries where labor share is found to have declined in recent years of globalization and that has led to alternative models to understand the reasons for this decline in labor share. See (Karabarbounis and Neiman. 2014).
[18] We have dropped time subscript for simplification.
[19] This is the basis for the argument by Thomas Piketty (see Thomas Piketty Responds to Criticisms from the Left, interview with Piketty in Potemkin Review, available at http://www.potemkinreview.com/pikettyinterview.html, January 2015, 2017) that rising income share of capital and capital to output ratio could be obtained even in neoclassical frameworks.
[20] Similar production function with two types of labor has been used to explain the skill-biased technological change (SBTC) which leads to wage gap between skilled and unskilled workers. Acemogulu and Autor (2011) call it the canonical model
[21] Acemoglu and Autor (2011), Goos, Manning and Salomon (2014)
[22] Autor (2015b) contains a discussion of tacit knowledge in non-routine tasks.
[23] I must add that the above summary hardly does justice to the insightful and detailed analysis of Bessen (2017)
[24] Their model is derived from the task-based model framework of Acemoglu and Autor (2011) and Acemoglu and Restrepo (2016). The description of their model here is highly simplified to convey their central argument. See the cited original papers for details.
[25] The IFR aims to capture the universe of robot suppliers: "The statistical data collected in the present World Robotics are based on consolidated data provided by nearly all industrial robot suppliers world-wide" (IFR, 2012, p.19) cited in Graetz and Michaels (2017).
[26] Regression coefficient of Low in Table 4 (Graetez and Michaels (2017),p.44)
[27] Susskind calls this 'new pessimism at work' (Susskind 2017,p. 5)
[28] The Economic Times, November 2, 2017,available at https://economictimes.indiatimes.com/jobs/techies-watch-out-these-guys-are-coming-to-take-away-your-jobs/printarticle/61449224.cms, accessed November 3,2017
[29] Financial Times (2017a)
[30] Quartz (2017, p.2), "The biggest challenge the shoe industry has is how you create a robot that puts the lace into the shoe," he said. "I'm not kidding. That's a complete manual process today. There is no technology for that."
[31] Financial Times (2017b)
[32] Financial Times (2016)