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A Short Review on the Economics of Artificial Intelligence

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Abstract

The rapid development of artificial intelligence (AI) is not only a scientific breakthrough but also impacts on human society and economy as well as the development of economics. Research on AI economics is new and growing fast, with a current focus on the productivity and employment effects of AI. This paper reviews recent literature in order to answer three key questions. First, what approaches are being used to represent AI in economic models? Second, will AI technology have a different impact on the economy than previous new technologies? Third, in which aspects will AI have an impact and what is the empirical evidence of these effects of AI? Our review reveals that most empirical studies cannot deny the existence of the Solow Paradox for AI technology, but some studies find that AI would have a different and broader impact than previous technologies such as information technology, although it would follow a similar adoption path. Secondly, the key to incorporating AI into economic models raises fundamental questions including what the human being is and what the role of the human being in economic models is. This also poses the question of whether AI can be an economic agent in such models. Thirdly, studies on the labor market seem to have reached consensus on the stylized fact that AI would increase unemployment within sectors but may create employment gains at the aggregate level. AI also increases the income gap between low- and medium-skilled workers and high-skilled workers. AI's impacts on international trade and education have been largely neglected in the current literature and are worth further research in the future.

Keywords

Artificial Intelligence, Development of Economics, Literature Review

JEL Classification

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1. Introduction

On October 19th 2017, AlphaGo's team published an article in *Nature* to introduce a new version of the artificial intelligence game AlphaGo Zero, which had became much stronger than all previous versions of AlphaGo in 40 days without using any data from human games.[1] In other words, artificial intelligence (AI) can learn or train itself from nothing to defeat human experts. This is not only a breakthrough in the development of artificial intelligence, but also has important implications for human society.

Economists started to be interested in AI mainly due to the observation that the economic share of labor has been falling in recent decades. Figure 1 is from Karabarbounis and Neiman's (2014) study, showing that labor shares in the largest economies have been declining since 1975. Technological progress has been "blamed" as a major culprit in this observation. In particular, as an upfront technology with rapid development, AI has become a focus of economic investigation. Therefore, research on the economic impact of artificial intelligence has attracted much interest among economists in recent years.

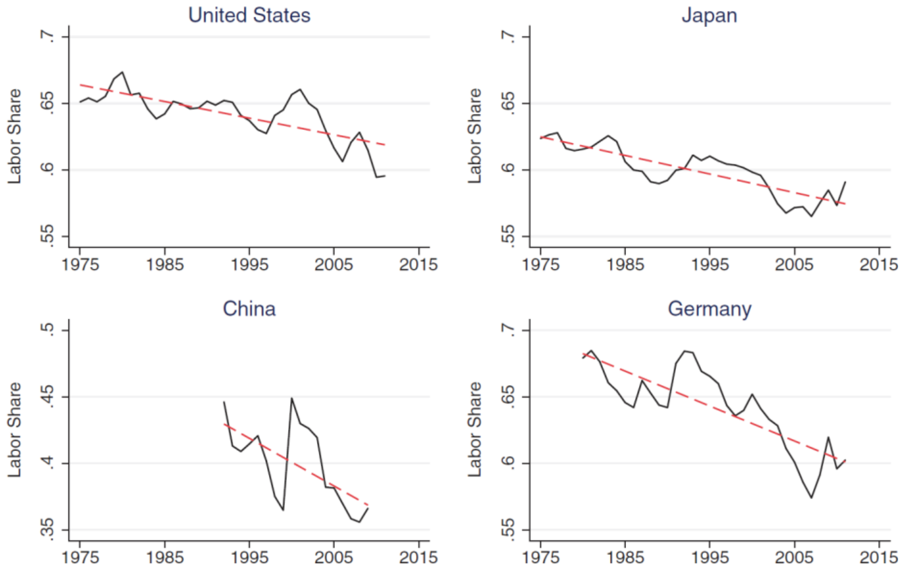


Figure 1. Labor share of the four largest economies

Note: The figure is from Figure II of Karabarbounis and Neiman's (2014) paper.

To review these studies, it is important to first define what AI is in the literature of engineering and economics. It is not unclear in science terms, but vague in economic research. Economists alternatively use "automation", "robotics", "digitalization" or "computerization" to refer to the same concept of artificial intelligence (i.e. AI) in a broader sense. In fact, there are differences between these terms. Agrawal et al. (2017) date AI's commercial birth to 2012. Cockburn et al. (2017) think that the domain of AI contains robotics, neural networks and machine learning, and symbolic systems. "Automation", "digitalization" and "computerization" may only reflect a part of artificial intelligence, and robotics can

[1] "AlphaGo Zero: Learning from scratch", available at https://deepmind.com/blog/alphago-zero-learning-scratch/

be, but is not necessarily, one form of AI. Automation and robots are not necessarily artificial intelligence, as they can simply be programmed to perform a given task or set of tasks and workers can supervise and maintain the robots. A key feature of AI is to process data to decide, for example, whether to offer people a mortgage or not or to take in data from the physical environment and decide what to do or to use that data to learn. AI replaces labor, rather than functioning as a tool that increases the productivity of labor, which traditional technologies did. For convenience, we use the term "artificial intelligence (AI)" in general to refer to all the other terms used in various studies. However, the differences between these terms are discussed in detail in the following section. Interestingly, at first glance, ideas around AI in economics can be grouped into three streams. From many consulting organizations' points of view, AI has great potential to enhance human life quality and economic growth and the natural implication is that industries, investors and consumers should embrace it as a blessing (e.g. BCG, 2015; MGI, 2017). However, policymakers are more concerned with its impact on employment, in that jobs might be destroyed and workers might be replaced by AI. Meanwhile, most economists seem to be on neither side and tend to be more cautious about the future AI world. This cautiousness is mainly due to empirical studies using recent data. Crafts and Mills (2017) found that trend TFP growth has declined steadily from 1.5 to 1.0 per cent per year over the past 50 years. Since the late 1990s, and after the Global Financial Crisis (GFC) in particular, almost all OECD countries have experienced a slowdown in labor productivity growth. This slowdown is also true in emerging and developing economies, whose productivity growth accelerated during the 2000s then peaked around the time of the GFC (Syverson, 2017). This creates a paradox between the potential of a highly automated world in the future and the sad reality of the current economic slowdown, which is referred to, by Robert Gordon (2016) and Brynjolfsson et al. (2017) and many others, as the Solow (1987) Paradox.

It might not be a good time to conduct a literature review on AI economics as the discussion has only recently opened up and the research framework is still not clear; however, it might be a good time for such a review so that future directions can be seen. In this paper, we review AI-relevant economic studies, mostly from the past five years, in an attempt to provide a comprehensive understanding of AI's potential impact on an economy and the current development of AI economics, to help find gaps for future research and to provoke more thought on this topic.

This paper starts with a discussion of the definition of AI from both engineering and economic perspectives. Then three questions are proposed and investigated: first, we ask how AI is represented in theoretical economic models by reviewing some important proposed models using different setups; then we address the question of whether AI technology would have a different impact on the economy than previous new technologies through studies where historical trends and theoretical predictions are compared; third, by looking at the empirical evidence on the effects of the early stages of AI we ask, if AI were to prevail, what aspects of the economy would be affected and required to change. Finally, we conclude by identifying some gaps and possible directions for future research on this topic.

2. Definition of AI in the engineering and economics literature

For economists, the definition of AI is both broad and narrow. The most frequently words used by economists referring to AI are “automation” and “robots” or even “machines” (see e.g. Sachs et al., 2015 and Acemoglu and Restrepo, 2017). For an engineer, “automation” and “robots” are very narrow terms to describe the concept of AI. According to Mikell P. Groover (2010), automation is the technology by which a process or procedure is performed with minimal human assistance. However, AI does mean more than “automation” for engineers and scientists. Taddeo and Floridi (2018) point out that AI may be defined as a growing resource of interactive, autonomous, self-learning agency, which enables computational artefacts to perform tasks that otherwise would require human intelligence to be executed successfully. McCarthy (2007) defines AI as the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable.

However, the “narrow” definitions of AI in the economic literature are often unavoidable, especially in empirical studies, as data on machines or robots are at least available to a certain extent, compared to AI data in a broader sense (see e.g. Greatz and Michaels, 2015; Acemoglu and Restrepo, 2017; and Dauth et al., 2017). But if we look at the definitions of AI in theoretical models, they seem very broad. When you assume that AI can substitute for low-skilled labor (e.g. Hémous and Olsen, 2016), it may mean “automation”, but when you assume that human capital or high-skilled labor can also be replaced by AI to generate innovation (e.g. Aghion et al., 2017), then AI can be a more inclusive conceptual term, far more meaningful than “robots”. In this sense AI, in theoretical economic models, can cover a wider range of AI technology than what engineers would envision. Therefore, there exists a gap between empirical studies and theoretical ones.

In this literature review, since both theoretical and empirical studies are discussed, the difference in the definition of AI should be noted. The engineering definition of AI does not necessarily align with what AI means in economic research. In empirical studies, its definition tends to be narrow and specific, while in theoretical studies it tends to be wide and abstract.

3. How to incorporate AI into economic models?

Since AI is defined differently from other technologies, economists are interested in incorporating AI into theoretical economic models to offer alternative theories to address topics such as economic growth, employment and welfare for the future (e.g. Sachs et al., 2015; Hémous and Olsen, 2016; Acemoglu and Restrepo, 2017; Aghion et al., 2017). For models addressing AI-related issues, several points are usually considered: (1) Is AI a substitute or a complement for labor? (2) Will the impact of AI be on the current generation or on later generations? (3) On what level (macro or micro) is AI modeled? In the following discussion, we examine several proposed models based on these three aspects.

Sachs et al. (2015) defined the essential quality of robots (AI in general) as to “allow for output without labor”. It is clear that in their model, AI is a substitute for labor. However, the substitution is not directly embodied in one production function but is reflected in the total homogenous output from two types of firms, i.e. firms with traditional technology and firms using robots. Therefore, substitutability depends on the mix of different production technologies, which is regulated by other model parameters. The model is set to be an overlapping generation (OLG) model; therefore, the impact of AI would have intergenerational effects. Finally, AI (or robots in the model) is modeled on a more aggregate level in the sense that there is no distinction between labor and human capital, or low-skilled and high-skilled workers. Therefore, AI or robots just replace “labor” in general terms. It is notable that this model treats “machines” and “robots” as different inputs in production, although they are both “capital” to households. Whether AI has positive or negative impacts on economic outcomes and welfare depends on the model parameters. Both one-sector and two-sector settings are analyzed and the saving rate is a key parameter in both cases in this model. Sachs et al. (2015) found that when the saving rate is sufficiently low, young workers and future generations will be worse off if the productivity of robots increases and goods that are produced by traditional technology and AI technology are more substitutable. They also argued that redistribution policies should take generational effects into account so that future generations could also benefit from the rise of AI technology.

Hémous and Olsen (2016) adopted a framework in the vein of the “directed technical change” models to examine the impact of AI on economic growth and income inequality. In their production setup, labor is distinguished by low skill and high skill; AI is a perfect substitute for low-skilled workers. In addition, a part of high-skilled workers is hired as AI technology (or automation, as in the paper) researchers, which are investment from non-automated firms as well as the source of innovation. Following this setting, the economic growth in this model goes through three phases. In the first phase, low-skilled wages are low, there is little incentive for AI, and income inequality and labor’s share of GDP are constant. The second is a transitional phase in which rising low-skilled wage induces AI innovation but reduces the labor share and future low-skilled wages. Finally, a steady-state is achieved in the third phase where low-skilled wages grow but at a lower rate than high-skilled wages. Based on the model, Hémous and Olsen pointed out that low-skilled wages actually grow in the long run, but not necessarily if there are middle-skilled workers present in the model.

Acemoglu and Restrepo (2018) also provided a conceptual model to account for AI’s role in economic growth, employment and inequality. Their basic model (the static version) is a task-based model. They assume that there are certain tasks that are automated by technologies in which labor and capital are perfect substitutes, but the extent of substitution is determined by the relative prices of labor and capital. Although in a different form, this setup also reflects the possibility that AI replaces labor just as assumed in Sachs et al. (2015). However, as productivity increases, this model allows new tasks to be created in which labor has a comparative advantage. The model shows a “directed-technical-change” feature but uses a range of tasks to reflect factor augmentation. It develops from a static model to a dynamic endogenous growth model, where the generational issue is not addressed explicitly yet is implied in the dynamics. In an extension of the model, the authors also consider heterogeneous skills and address the inequality problem. In the full model, they find that in the long-run equilibrium if the relative price of capital to labor is sufficiently low, an AI world will result. Under certain assumptions, there exists a stable balanced growth path in which traditional technology and AI technology can co-exist. This stability is achieved by the fact that the changing relative price of factors (i.e. labor and capital) due to AI would lead to a self-correcting dynamic that would create new tasks. They also found that as AI adoption squeezes out low-skilled workers and creates new tasks that benefit high-skilled workers, inequality would increase in both cases, i.e. in an AI world and a world with both traditional and AI technology.

Aghion et al. (2017) adopted a simpler production setting to model AI technology, such that it boils down to a constant elasticity of substitution (CES) nesting of labor and capital, which implies that AI (in this case the capital) can replace labor with constant elasticity of substitution. The growth analysis is similar to that in neoclassical models, but this study addresses the question of how AI affects the production of new ideas (innovation). But since AI is taken as an exogenous input in the production of new ideas, they found that ongoing AI development can possibly generate exponential growth when AI increasingly replaces the human being in generating ideas. In terms of the microeconomics of AI, the study does not provide a theoretical model but draws from recent relevant studies. It is predicted that more AI-intensive firms would hire more (or pay more to) high-skilled workers, outsource more low-occupation tasks to other firms, and pay a higher premium to low-occupation workers within the firm.

The common assumption from these models is that AI can replace labor, though to different extents and on different levels. The key element in these models is the relative price of labor and capital. Compared to consulting organizations that are excited about the potential for AI revolution, economists are more realistic and conservative in evaluating the potential economic impact of the massive adoption of AI technologies. In addition, these models emphasize worries that AI would destroy jobs and deepen inequality.

However, many fundamental issues are left untouched when incorporating AI into these economic models. One of them involves what the human being is. In economics, the role of the human being has usually been narrowed down to "labor" and optimization agent at the same time; but in endogenous growth models, "labor" is different from "human capital". The development of AI further challenges the role of the human being in the economic system. Is AI a substitute for "labor", or "human capital", or even a decision-making agent? Does AI bring a new production technology or is it just an input to current production technology? More research into the attributes that distinguish between human beings and AI would help in analyzing the impact of AI more clearly.

Notably, Kavuri and McKibbin (2017) took the perspective of consumers and modeled AI's effects into the utility function rather than the production function. In their theoretical model, technology goods are distinguished from normal goods so that consumers form habits with purchased technology goods, enhancing their leisure activities, while normal goods do not have such a feature. The model then gives a persistent fall in the relative price of technology goods to normal goods and the increased consumption of technology goods would result in the real interest rate being lower than the rate of time preference, reducing the consumption growth of normal goods. They also used US data to empirically confirm the theoretical model predictions. This study is inspirational in the sense that AI can actually affect consumption, in addition to production, while the human being has a role in both. In a more comprehensive framework, AI might be included in both production and consumption systems.

Another aspect that is absent from the recent theoretical modeling work is the international dimension of the AI revolution: how AI may trigger a new round of technological and economic competition across nations through government investment strategies; how AI affects international trade structure; how AI changes global value chains. These topics provide a wide area for future discussion and exploration by economists.

4. How different is AI technology from previous technology innovations?

There have been many important technological changes in history. The Industrial Revolution, so-called "Industry 1.0", was triggered by the invention of the steam engine. Machines began to develop to help the human worker in production, leading to an increase in production capability and productivity. Later, at the beginning of the 20th century, the use of electricity allowed easier access to power so machines could be designed to be more portable and mass production using assembly lines became common. This period can be called "Industry 2.0", and during this time machines were programmed and controlled by workers to increase efficiency, productivity and quality. To some extent, machines started to replace certain functions of labor. Progressing to "Industry 3.0", the invention of computers followed by information and communication technology (ICT) changed the production function dramatically. The structure of labor and the skills required for jobs changed. Although many traditional jobs were destroyed, new jobs were also being created. Computer programs or software were increasingly automated and powerful, but they still needed to be programmed, controlled and applied. Until then, machines still served as tools used in human labor. These technologies affected productivity and the economy (Brynjolfsson et al., 2017). However, the revolution we are facing now, that is, the so-called "Industry 4.0", seems to be significantly different in that it may change the roles of human beings and machines in production as well as in social life. AI technology could give machines "intelligence" and allow them to substitute for human labor in many aspects.

Are previous experiences useful in predicting the consequent economic and social changes this time? In Brynjolfsson and McAfee's (2014) book *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, they described the current point in time as "the early stages of a shift as profound as that brought on by the Industrial Revolution" and said there is "no end of advancement in sight". They optimistically claimed that AI technology would transform global economics, although they noted that there are challenges and risks which they thought were less about economics and more about moral aspects. Similarly, Saniee et al. (2017) also had an optimistic view. With their semi-quantitative analysis (Saniee et al., 2017), they claimed that "there will indeed be a second productivity jump in the United States that will occur in the 2028–2033 timeframe…".

In terms of explaining the Solow Paradox, Brynjolfsson et al. (2017) attributed the current fall in productivity growth mainly to lags in diffusion of upfront AI technologies. They used portable power and information and communication technologies as examples to show that past productivity growth patterns were similar to the current situation and it usually took 25 years of slow growth before new technologies accelerated productivity growth continually over a decade-long period. They expected that AI technologies would also follow such pattern; therefore, the current Solow Paradox is just a lag in technology take-off as happened in history.

However, Acemoglu et al. (2014) found some unexpected results from IT-using manufacturing sectors in the US: major productivity gains are concentrated in IT-producing sectors rather than IT-using sectors, and the so-called labor productivity gains in IT-using sectors are not associated with increasing output as a result of IT-induced cost reduction as expected, but are actually driven by declining output and more rapid decline of employment rather than by technological progress. They claimed that the Solow Paradox has not been resolved with this recent technological progress. However, is this also true for deeper advancements in technological change than IT technology, such as the AI revolution?

Greatz and Michaels (2015) provided the first systemic evaluation of the economic impact of industrial robots. Their study was based on a new dataset, mainly from the reports of the International Federation of Robotics, which is a panel of industries in 17 countries, from 1993 to 2007. They pointed out that AI technology or industrial robots can have different economic impacts from other new technologies such as information and computer technology (ICT). They found that increased use of robots raised countries' average growth rates by about 0.37 percentage points and also increased both total factor productivity and wages. Although there was some evidence that low-skilled and middle-skilled workers may be affected, there was no significant effect from industrial robots on overall employment.

Acemoglu and Restrepo (2017) also used data on industrial robots from the International Federation of Robots to estimate the effect of industrial robots on employment and wages. Their estimation used a constructed measure of exposure to robots across industries in various commuting zones and this approach allowed them to estimate the equilibrium impact of industrial robots on local US labor markets. In contrast to Greatz and Michaels (2015), their results showed that as the intensity of robots increases, employment and wages are reduced. In one of their robustness checks, they also showed that exposure to robots was unrelated to past trends in employment and wages from 1970 to 1990 when robotics technology had not attained rapid development.

Whilst the above research shows that industrial robots have caused job and earnings losses in the US, Dauth et al. (2017) explored the impact of robots on the German labor market. Despite the fact that there are many more robots around, Germany is still among the world's major manufacturing powerhouses with an exceptionally large employment share. It was around 25% in 2014 (compared to less than 9% in the US) and has declined less dramatically over the last 25 years.

So is this time different? From the current literature, we can see that the Solow Paradox has not yet been satisfactorily resolved. But AI is regarded as a different technology to ICT in the sense that it would impact a broader range of sectors, which would have different implications at the aggregate level, and its future development is unpredictable. However, the adoption of AI might follow a similar path to previous new technologies.

Before this question is answered, McKibbin and Triggs (2019) have gone one step further. They used a computable general equilibrium (CGE) model, *G-Cubed*, to investigate four alternative productivity growth scenarios. Several points are worth noting: even if a global productivity boom induced by AI technology were to happen, there would be certain short-term costs of such a boom, e.g. a sharp rise in interest rates. In addition, first-mover benefits can flow to economies moving closer to the productivity frontier, which justifies AI competition across global economies.

5. What is the empirical evidence on the effects of the early stages of AI?

Although Brynjolfsson and McAfee (2014) thought that the risks of AI technologies were not rooted in economics, economists do worry about many side-effects that AI technology would bring to the economy, including aspects of employment, inequality, education, trade and policy responses to it.

5.1 AI and unemployment

One of the most frequently asked questions is whether AI would displace employment. In recent years, quite a few research papers have addressed changing trends in the labor market and their relationship with AI technology. In Autor et al. (2017) and Autor and Salomons (2017), they explained the falling labor share in GDP using a "Superstar Firm" model, in which the dominant superstar firms benefited from globalization, and technological change would increase the concentration of industries and decrease the labor share. A falling labor share is also observed in other relevant studies (e.g. Karabarbounis and Neiman, 2014; Elsby et al., 2013).

Then there is a big concern that AI is likely to replace existing jobs. Frey and Osborne (2017) devised an index to evaluate the susceptibility of occupations to automation. They found, surprisingly, that a substantial share of employment in service occupations is highly susceptible to automation in the US. In the work of Ford (2009, 2015) and Brynjolfsson and McAfee (2014), the advancement of automation or AI technology was found to cause unemployment. However, Autor and Salomons (2017) found that as productivity rises employment at sectoral levels tends to shrink, although country-level employment generally grows with increased aggregate productivity. This finding is consistent with the stylized fact that the relationship between productivity gains and employment is negative within individual industries but probably positive for the overall economy.

One outstanding study is from Acemoglu and Restrepo (2017). Their study focused on the equilibrium impact of industrial robots on the local labor market. This equilibrium impact considers both the displacement effect and the productivity effect. In contrast to Autor and Salomons' (2017) results and the stylized facts, they identified large and robust negative effects of the use of robots on employment and wages across commuting zones. In particular, they found that "one more robot per thousand workers reduces the employment to population ratio by about 0.18–0.34 percentage points and wages by 0.25–0.5 per cent". Their study calls for more research on the equilibrium effects of AI technologies on labor market outcomes.

5.2 AI and inequality

Inequality induced by AI has been another frequently discussed topic so far. Inequality can be international and national. It is argued that the AI revolution will have an impact on both dimensions. Empirical results (e.g. World Bank, 2016, 2017; UNCTAD, 2017; Chandy and Seidel, 2017) found that within-country inequality has been rising sharply since the 1990s (with a slight decline since 2008) while global inequality has experienced a small decline. Rapid technological change accompanied by globalization during that period benefited developing countries and narrowed the income gap between developed and developing countries. However, in terms of wealth, global inequality did not necessarily decline.

Thomas Piketty (2014) points out that when the return on capital is higher than aggregate growth in an economy, inequality will rise. This might be an argument to support the view that the AI revolution will deepen inequality at the national level, although this general law has been criticized by Acemoglu and Robinson (2015) for neglecting institutional and policy factors contributing to the inequality. At the global level, the industrialization and globalization that once benefited developing countries have reached their peak and the pace of developing countries' growth has already slowed (Baldwin, 2016). Norton (2017a) points out that automation (or AI technology) may further hinder developing countries' catch-up with developed countries as it will shift the balance of "advantage of locating light manufacturing close to consumers rather than close to cheap labor".

On the positive side, there is the possibility of technological leapfrog by developing economies with a limited manufacturing base, according to the World Bank (2017). If countries can leapfrog into using new technologies, there may be no cost to them for not having developed a manufacturing sector at this point. However, if countries need to have developed a manufacturing sector using traditional (Industry 2.0) methods to build the capabilities needed to support more sophisticated processes in the future, the dynamic cost of not industrializing now could be that manufacturing opportunities are closed off in the future (World Bank, 2017).

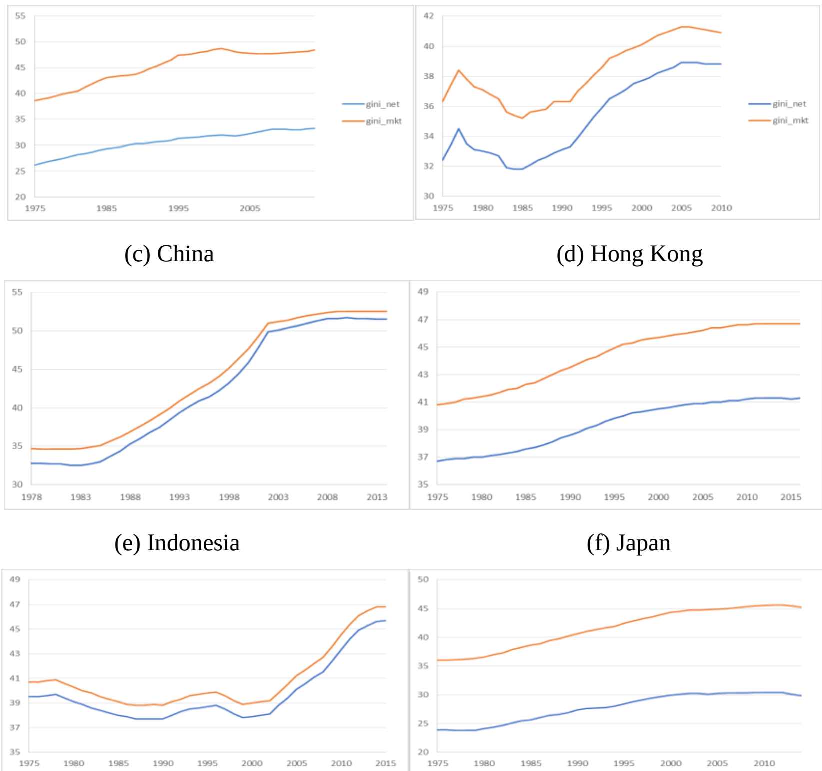
In terms of within-country inequality, Norton (2017b) summarized several mechanisms through which AI technology may enlarge national inequality gaps: (1) boosting the advantage of capital over labor; (2) relative declines in medium- and low-skilled employment shares; (3) weakening of labor institutions; and (4) reduction of tax bases which weakens the government's capacity for redistribution. Although most empirical studies find that AI technology will not destroy aggregate employment (see Section 3.1), it does create inter-sector inequality and will change the labor structure so that the relative share of low-skilled labor is reduced; therefore, inequality is deepened. A very important implication here is that how AI technology is adopted in the economy will determine how society is restructured and who are the losers and winners. In this sense, the welfare effect of AI technology is uncertain. Two recent papers (Zhou and Tyers, 2017; Tyers and Zhou, 2017) have attempted to address this issue.

Based on an elemental three-household general equilibrium model, Zhou and Tyers (2017) quantified the links between real income inequality on the one hand and changes in factor abundance, total factor productivity, factor bias, the relative cost of capital goods, labor force participation rates, the fiscal deficit and the unemployment rate on the other hand in China. Relative expansions in stocks of skill and physical capital have, by themselves, mitigated inequality. Yet their effects have been dominated by the combination of structural change and biased technical change, with the latter having a dominant effect. Looking into the future, which is expected to bring continued structural change and a further technical twist away from low-skilled labor, this time toward physical capital due to automation, Zhou and Tyers (2017) found that if the new technology delivers only a shift in technical bias then aggregate performance is impaired by worker displacement that could cause the unemployment rate to rise to anywhere between 20 and 55% and drive low-skilled wages downward. If the government protects the welfare of low-skilled households via tax-funded transfers, the transfer burden, either to maintain the welfare of low-skilled households or to constrain income equality, makes capital owners significant losers in this case. The worker displacement and the capital income tax rate required to contain the rise of income inequality are lessened, the more the new technology also delivers increments to total TFP. But the rates of TFP growth needed are high relative to what has been achieved by China in recent decades and the potential for continuing this pattern, constrained as it is by the shrinkage of opportunities for "catch-up" productivity advances, will rely on the productivity effects of AI and robotic advances.

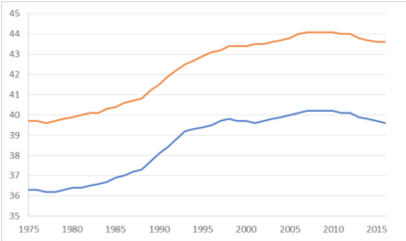
Tyers and Zhou (2017) examined the issue of robotics and income inequality in the US economy using a similar elemental three-household general equilibrium model as in Zhou and Tyers (2017). In this application to the US, changes in factor bias are shown to have been the primary cause of the observed increase in inequality between 1990 and 2016. The widely anticipated future twist away from low-skilled labor toward capital is then examined, in combination with expected changes in population and its skill composition. With downward rigidity of low-skilled wages, the potential is identified for unemployment to rise to extraordinarily high levels, with possible exacerbation from intensive population growth among low-skilled workers and productivity growth that is no greater than that achieved since 1990. Indeed, the results suggest that productivity growth at twice the pace since 1990 would be needed to constrain unemployment, though even this would not slow the concentration of income. The superior policy response is shown to be a generalization of the US “earned income tax credit” system, with financing from taxes on consumption, rather than capital income.

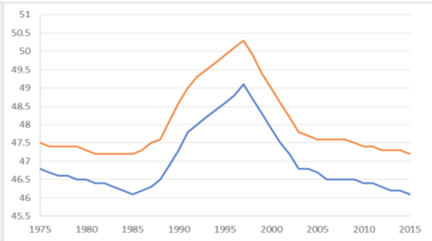
Therefore, we arrive at another stylized fact, that AI-induced productivity growth would cause employment redistribution and trade restructuring that would tend to increase inequality within and across countries. It is clear that automation replaces low-skilled labor and increases demand for workers with higher skill levels. Automation may exert upward pressure on income inequality, at least in the short run. Therefore, access to high-quality education becomes more important. Households that are relatively well-off will be able to provide good education to their children, who will then gain skills and capacity to compete in the labor market in the future. If there is strong inequality of opportunity, income inequality could worsen over generations (Golley, Zhou and Wang, 2017; Son, 2013; Zhang et al. 2013; UN ESCAP, 2017). Policies that aim at reducing inequality of opportunity will help alleviate income inequality (Figure 2) and its negative impact when societies are increasingly faced with the rise of robotics and artificial intelligence. Whether policies such as universal basic income or earned income credit could be adopted to help support the welfare of individuals experiencing job loss due to technical change and to help constrain income inequality is hotly debated (Jessen et al. 2017; Stiglitz, 2017).

(a) Australia (b) Bangladesh



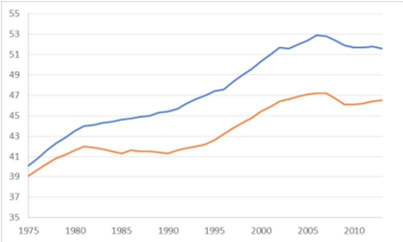
(g) Singapore (h) Philippines

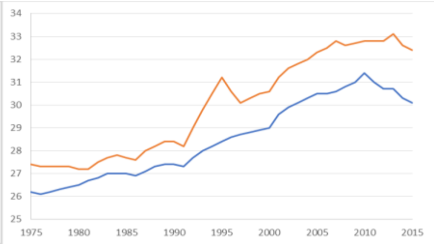




(i) Sri Lanka

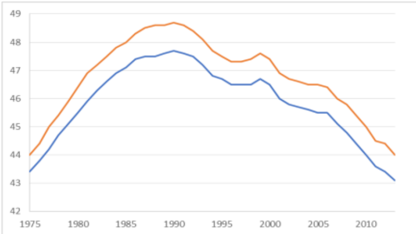
(j) Taiwan

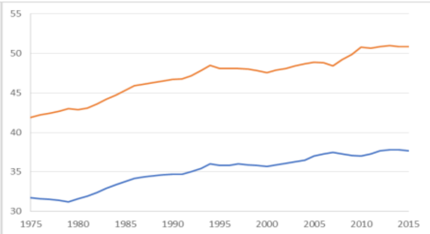




(k) Thailand

(l) The United States





(m) Viet Nam

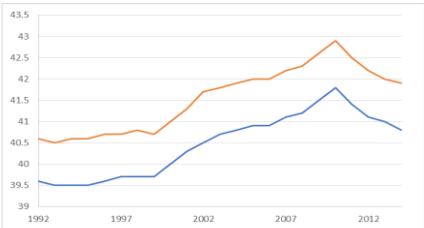


Figure 2 (a)–(m). Gini coefficient pre-tax and pre-transfer and Gini coefficient post-tax and post-transfer in selected economies in the Asia-Pacific region

Source: SWIID database.

Note: The orange line is the Gini index of inequality in equivalized household disposable (post-tax and post-transfer) income. The blue line is the Gini index of income inequality in equivalized household (pre-tax and pre-transfer) income.

5.3 AI and education

AI and education interact in both directions. On the one hand, AI has changed the way, the content and the places education is delivered; on the other hand, education is the source of technological innovation and therefore impacts the development of AI.

With the rise of automation and artificial intelligence, how could individuals adapt to these rapid technological changes? On the one hand, automation and artificial intelligence may demand more workers who have skills in programming and mathematics. On the other hand, the new technologies may reach a stage of maturity whereby people no longer need advanced maths or programming skills to utilize the technology, that is, the “singularity” in which machines surpass humans and machines produce more machines (Nordhaus, 2015; Korinek and Stiglitz, 2017). At that stage, skills in liberal arts would become more important and the most important skills are likely to be emotional and communication skills (Baldwin, 2019). Before the "singularity" is reached, however, problem-solving and analytical skills, and mathematics and programming skills are likely to be increasingly in demand in the future.

Forbes published an article "How AI Impacts Education" on December 27th, 2017[2], describing the potential for AI to replace human labor in grading, the admission process, tutoring outside classrooms, personalized online courses, interactive teaching resources and immersive technology used in classrooms, etc. The author stated that students, teachers and administrators all benefit from a smarter, more personalized approach to education with AI being more integrated into the education system.

AI technology would also modify what education contains. Riccardo Campa (2017) argued that AI not only impacts low- and medium-skilled workers but also affects highly educated workers; therefore, more maths, science and engineering in education would not be sufficient to prevent future massive unemployment due to thriving AI technology. He emphasized that different types of abilities such as critical thinking, artistic creativity, philosophical understanding, and social sensitivity would be most important in future education. This is somewhat similar to the point that Jeffrey Sachs made at the NBER conference on the economics of AI (Toronto, 2017): what humans can do in the AI era is just to be human beings because this is what robots or AI cannot do. Then leads to a philosophical question: what is a human being? As mentioned before, in economics, it is also a valid question to ask and rethink over time. For a long time, the functionality of human beings has been explored and emphasized in economics; however, AI economics challenges economists to include other values and dimensions of humanity in their economic models and rebuild the concept of "economic agents". Another valid question to think about is preferences for human or AI-provided services. If people have strong preferences for human-provided services, then substitutability between human and AI-provided services will be low.

5.4 AI and trade

Here let's think about the potential effects of automation on trade activities and consequently on employment. Although the shrinking labor cost differential is favorable for reshoring, counterforces exist. Firstly, the advantages of producing in close proximity to the customer do not favor reshoring if the customer is not located in the home country or region of the company. Offshoring is not only motivated by seeking lower cost, but is also a step to entering new markets and being closer to customers in foreign countries. So for some firms, closeness to customers works in favor of staying offshore and was already an essential motive for previous offshoring decisions. According to Sebastian Duchamp, a GE spokesman: "The global environment for manufacturing is changing in a way where we must

[2] https://www.forbes.com/sites/theyec/2017/12/27/how-ai-impacts-education/#1e58484d792e

innovate differently…innovation has to be in the markets you play in, close to your customers; and close to access [to] the best talent wherever it exists in the world." GE, like other companies, is responding to the trend in what's called "mass customization" or making products to meet an individual customer's preferences. As a result, companies are finding it more suitable to have plants closer to their markets and to their research and development units. Industry 4.0 enhances production for customized products and hence may better serve local customers and help prevent offshoring.

Secondly, there are steps in production in certain industries that are hard to automate, as yet. For example, in the sportswear industry, the chief executive of Adidas said "Asian plants will become more automated, but there were some processes of the roughly 120 steps in creating an Adidas shoe that remain stubbornly resistant to automation…The biggest challenge the shoe industry has is how do you create a robot that puts the lace into the shoe...I'm not kidding. That's a completely manual process today. There is no technology for that."[3] Bottlenecks in automation technologies will slow down reshoring activities.

Thirdly, being a supplier reduces the likelihood of reshoring in all specifications of the regression. This can be explained by the fact that many suppliers have offshore production to follow their clients. These customer relations seem to provide an effective "glue" to keep manufacturing activities at foreign locations, even if external factors such as wages or costs of materials change (Dachs et al. 2012). If Industry 4.0 strengthens supply linkages between firms, it could act as a force preventing reshoring. For systematic reviews of manufacturing reshoring, please refer to Brennan et al. (2015), Stentoft et al. (2016), Dachs et al. (2012) and Delis et al. (2017). How new technologies will affect reshoring is still under debate.

For advanced economies, the risk to employment is still likely to prevail even if reshoring does occur. This is because new manufacturing plants in advanced economies may translate into more jobs for robots than for humans. Lower costs of automation technologies could mean that firms are simply completing the transition that would have taken place earlier without offshoring. Therefore, reshoring may not necessarily boost employment. Chances are that if there were any positive effect on employment, automated factories would require highly skilled workers, often with training in technology and computers. For developing economies, the concern is firstly that the increased use of robots in developed countries risks eroding the traditional labor-cost advantage of developing countries; secondly that robot use is working to the advantage of countries with established industrial capacity; and thirdly that the share of occupations that could experience significant automation is actually higher in developing countries than in more advanced ones, where many of these jobs have already disappeared. This could further damage growth prospects in developing countries where manufacturing has stalled or that are already experiencing "premature deindustrialization" (World Bank, 2017; UNCTAD, 2016). Furthermore, if future international competition hinges on the intensification of the use of robots, the

[3] https://qz.com/966882/robots-cant-lace-shoes-so-sneaker-production-cant-be-fully-automated-just-yet/

observed effects of automation on employment and wages in advanced economies may also take place in developing economies as these robots are increasingly adopted.

So far the academic research has focused on AI impact at the national level but overlooked its international dimension, especially strategic implications between countries triggered by AI technology development. Goldfarb and Trefler (2017) pointed out that trade policy should take into account the characteristics of AI technology, including economies of scale, creative knowledge, and the geography of knowledge diffusion. They also suggested that policies, such as data localization rules, limited access to government data and industry regulation, may be used to protect domestic firms. Clearly, there is much more research space to be explored regarding the impact of AI on international trade.

5.5 The timeframe and the scale of the AI revolution

The timing of the adoption of AI technology on a large scale is unpredictable, but many studies agree that it could take decades. As mentioned before, Brynjolfsson et al. (2017) argued that the time lag to technology diffusion might explain the Solow Paradox. They used two examples to show the long time span of introducing innovative technologies. On example is portable power (1890–1940) and the other example is information technology (1970–2016). They observe some similarity in pattern for both eras: (1) it took 50 years for each new innovative technology to be placed into production after this technology had been invented; (2) in both eras there was initially slow productivity growth over about 25 years; and (3) then there was a decade-long acceleration in productivity growth.

There is no serious academic research providing projections or predictions regarding the timeframe and the scale of the AI revolution, but many consulting institutions do give some information on it. For example, the BCG report (BCG, 2015) claimed that Germany's Industry 4.0, which is based on AI technology, will stimulate employment increases of 6% over the next ten years (i.e. 2015-2025). According to Accenture (2016)[4], AI has the potential to boost labor productivity by up to 40% by 2035 in the 12 developed economies studied. McKinsey's report (MGI, 2017) presents two extreme scenarios: one is the "earliest" scenario of faster automation; the other is the "latest" scenario where adoption of automation technology is slow (see Figure 3).

In general terms, all of these consulting institutions have high estimates of future productivity growth. They are all optimistic toward AI technology and indicate potential positive impact not only on productivity, economic growth and business opportunities but also on employment. Although these predictions are not necessarily convincing, they do shed some light on the future picture of a world with AI technologies.

[4] https://newsroom.accenture.com/news/accenture-report-artificial-intelligence-has-potential-to-increase-corporate-profitability-in-16-industries-by-an-average-of-38-percent-by-2035.htm

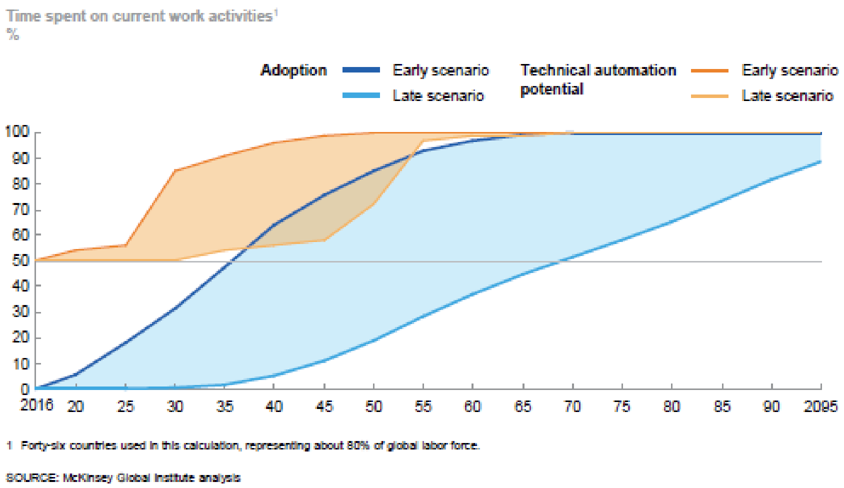


Figure 3. Early and late scenarios of adopting automation technology

Note: This figure is from the McKinsey report (McKinsey, 2017) Exhibit 15 on page 70.

6. Conclusion

The development of AI technology poses new challenges not only for the economy but also for economics research. In this paper, we reviewed recent literature on AI economics by posing three questions. First, we investigate how AI is introduced and dealt with in economic models. Second, is the impact of AI technology different from that of previous technological changes? Finally, what are the major empirical impacts of AI that have attracted economic research in this area?

The first question opens up an exciting area to explore; it is also the most challenging, though. Almost all of the current economic models addressing AI assume AI is a substitute for the human being to some extent and on different levels. Although with different assumptions and setups, these models predict that the economy could have different growth paths under certain parameters and conditions, among which the evolving relative price of capital to labor is a key twist. All these models confirm concerns that AI would destroy jobs, at least to a certain extent, and that AI would increase inequality. To provoke further thoughts on modeling, we point out that some fundamental issues should first be resolved before incorporating AI into the model, one of which is the essential attributes distinguishing between human beings and AI, i.e. the role of AI and human beings in the economic system, from both the production and the consumption sides. Of course, this is not just an economic issue, it is also a moral and even philosophical question that has been discussed for a long time. But we need to establish this "value" judgment before heading to modeling. Another aspect worth noting is the international impact of AI, which relates to global AI competition, global value chains and international trade policies.

For the second question, we found that so far, empirical studies cannot deny that the Solow Paradox remains unresolved, which implies that AI would also fall in this paradox as does other technological progress. But that may be a limitation of empirical studies when we are actually looking into the unpredictable future. Some studies believe that AI would have a larger and broader economic impact, but its adoption may follow a similar path as previous new technologies that have had adaptation lags.

To answer the third question, we consider several aspects. Some have been addressed more thoroughly while some have been insufficiently discussed. Employment and inequality are the current focus of economists. When we look at empirical studies of historical trends (e.g. Graetz and Michaels, 2015; Autor and Salomons, 2017; Brynjolfsson et al., 2017), some stylized facts have been generally but not necessarily agreed on: (1) the growth rate of labor productivity has slowed down in recent decades, especially after the GFC; (2) the relationship between productivity gains and employment is negative within individual industries but probably positive for the overall economy; (3) productivity growth would cause employment redistribution and tend to increase inequality. However, in terms of topics like education and international trade, the research is insufficient. These under-addressed aspects are important in the sense that policy implications from these areas would be valuable in offsetting the negative effects on employment and inequality as well as preparing people for future AI development.

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H. and Price, B., 2014. Return of the Solow Paradox? IT, Productivity, and Employment in US Manufacturing. *American Economic Review*, 104(5), 394–99.

Acemoglu, D. and Restrepo, P., 2017. Robots and Jobs: Evidence from U.S. Labor Markets. *NBER Working Paper* No. 23285, March.

Agrawal, A., Gans, J. and Goldfarb, A., 2017. What to Expect from Artificial Intelligence. *Sloan Management Review*, Feb 7.

Autor, D., Dorn, D., Katz, L.F., Patterson, C. and Reenen, J.V., 2017. The Fall of the Labor Share and the Rise of Superstar Firms. *NBER Working Paper* No. 23396, May.

Autor, D. and Salomons, A., 2017. Robocalypse Now–Does Productivity Growth Threaten Employment? *MIT working paper*.

Baldwin, R., 2016. *The great convergence: information technology and the new globalization*. Harvard University Press.

BCG, 2015. *Industry 4.0: The Future of Productivity and Growth in Manufacturing Industries. Technical Report*. Boston Consulting Group. https://www.bcg.com/en-au/publications/2015/engineered_products_project_business_industry_4_future_productivity_growth_manufacturing_industries.aspx.

Brennan, L., Ferdows, K., Godsell, J., Golini, R., Keegan, R., Kinkel, S., Srai, J.S. and Taylor, M., 2015. Manufacturing in the world: where next? *International Journal of Operations & Production Management*, 36 (9), 1253–1274.

Brynjolfsson, E., and McAfee, A., 2014. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company, New York.

Campa, R., 2017. Automation, Education, Unemployment: A Scenario Analysis. *Studia Paedagogica Ignatiana* 1, 23–39.

Chandy, L. and Seidel, B., 2017. How much do we really know about inequality within countries around the world? Adjusting Gini coefficients for missing top incomes. *Brookings*. www.brookings.edu/opinions/how-much-do-we-really-know-about-inequalitywithin-countries-around-the-world/

Crafts, N. and Mills, T.C., 2017. Predicting Medium-Term TFP Growth in the United States: Econometrics vs 'Techno-Optimism'. *National Institute Economic Review*, 242(1), R60–R67.

Dachs, B., Borowiecki, M., Kinkel, S., Schmall, T.C., 2012. The Offshoring of Production Activities in European Manufacturing. *MPRA Working Paper.*

Delis, A., Driffield, N. and Temouri, Y., 2017. The global recession and the shift to re-shoring: Myth or reality? *Journal of Business Research*, article in press, http://dx.doi.org/10.1016/j.jbusres.2017.09.054

Elsby, M., Hobijn, B. and Sahin, A., 2013. The Decline of the U.S. Labor Share. *Brookings Papers on Economic Activity*, 1–42.

Ford, M., 2009. *The Lights in the Tunnel: Automation, Accelerating Technology and the Economy of the Future*. CreateSpace Independent Publishing Platform.

Ford, M., 2015. *The Rise of the Robots*, Basic Books, New York.

Frey, C. B., and Osborne, M. A., 2017. The Future of Employment: How Susceptible are Jobs to Computerisation? *Technological Forecasting and Social Change*, 114, 254–280.

Graetz, G. and Michaels, G., 2015. Robots at Work. *CEP Discussion Paper* No 1335.

Groover, M.P., 2014. *Fundamentals of Modern Manufacturing: Materials, Processes, and Systems (4th Edition)*. John Wiley & Sons, Hoboken.

Hémous, D. and Olsen, M., 2016. The Rise of the Machines: Automation, Horizontal Innovation and Income Inequality. *IESE Business School Working Paper* No. WP1110-E. http://dx.doi.org/10.2139/ssrn.2328774

Karabarbounis, L. and Neiman, B., 2014. The Global Decline of the Labor Share. *Quarterly Journal of Economics*, 129(1), 61–103.

Kavuri, A.S. and McKibbin, W.J., 2017. Technology and leisure: Macroeconomic Implications. *CAMA Working Paper*, No. 43/2017.

Korinek, A. and Stiglitz, J.E., 2017. Artificial intelligence, worker-replacing technological progress and income distribution. *NBER Working Paper*, No. 24174.

McCarthy, J., 2007. “What is artificial intelligence?” online available at http://www-formal.stanford.edu/jmc/whatisai.pdf

McKibbin, W.J. and Triggs, A., 2019. Stagnation vs Singularity: The Global Implications of Alternative Productivity Growth Scenarios. *CAMA Working Paper*, No. 26/2019.

MGI, 2017. *A future that works: Automation, employment, and productivity*. Technical Report. McKinsey Global Institute.

https://www.mckinsey.com/~/media/McKinsey/Global%20Themes/Digital%20Disruption/Harnessing%20automation%20for%20a%20future%20that%20works/MGI-A-future-that-works_Full-report.ashx.

Nordhaus, W., 2015. Are we approaching an economic singularity? Information technology and the future of economic growth. *NBER Working Paper*, No. 21547. Cambridge, MA. September. https://www.nber.org/papers/w21547.pdf.

Norton, A., 2017a. Automation will end the dream of rapid economic growth for poorer countries. The Guardian. www.theguardian.com/sustainable-business/2016/sep/20/robots-automationend-rapid-economic-growth-poorer-countries-africa-asia.

Norton, A., 2017b. Automation and inequality: The changing world of work in the global South.

Issue Paper. http://pubs.iied.org/pdfs/11506IIED.pdf

Piketty, T., 2014. *Capital in the Twenty-First Century*. Harvard University Press.

Sachs, J.D., Benzell, S.G. and LaGarda, G., 2015. Robots: Curse or Blessing? A Basic Framework. *NBER Working Papers*, 21091.

Saniee, I., Kamat, S., Prakash, S. and Weldon, M., 2017. Will productivity growth return in the new digital era? *Bell Labs Technical Journal*, 22, 1–18. https://ieeexplore.ieee.org/document/7951155.

Solow, R., 1987. We'd Better Watch Out. *New York Times Book Review*, July 12: 36.

Stentolft, J., Olharger, J., Heikkila, J. and Thomas, L., 2016. Manufacturing backshoring: A systematic literature review. *Operations Management Research*, 9 (3-4), 53–61.

Syverson, C., 2017. Challenges to Mismeasurement Explanations for the US Productivity Slowdown. *Journal of Economic Perspectives*, 31(2), 165–86.

Taddeo, M. and Floridi, L., 2018. How can AI be a force for good: an ethical framework will help harness the potential of AI while keeping humans in control. *Science*, 361, 751–752.

UNCTAD, 2017. Trade and Development Report 2017—Beyond austerity: Towards a new global deal.

World Bank, 2016. *World Development Report 2016: Digital Dividends*.

World Bank, 2017. *Trouble in the making? The future of manufacturing-led development*. Online available at https://openknowledge.worldbank.org/handle/10986/27946