GPiD Global Poverty & Inequality Dynamics Research Network
www.developersdilemma.org
Researching structural change & inclusive growth

ESRC GPID Research Network Working Paper 11

The Rise of the Robot Reserve Army: Automation and the Future of Economic Development, Work and Wages in Developing Countries

Author(s): Lukas Schlogl[1] and Andy Sumner[2]

Affiliation(s): [1,2]Department of International Development, King's College London

Date: 2 July 2018

Email(s): lukas.schlogl@kcl.ac.uk and andrew.sumner@kcl.ac.uk

Notes: The authors are grateful for comments from Tony Addison, Artur Borkowski, Charles Kenny, Kyunghoon Kim, Joerg Mayer, Terry McKinley, Paul Segal, Dharendra Wardhana, Leslie Willcocks, Chunbing Xing and an anonymous reviewer, as well as participants at the Economic and Social Research Council (ESRC) Global Poverty & Inequality Dynamics Research Network workshop, March 27–28, 2018, London. All errors and omissions are our own. This paper was produced as part of an ESRC Global Challenges Research Fund Strategic Research Network (Grant ES/P006299/1).

This paper was also published as Working Paper 487 of the *Center for Global Development*, Washington DC.

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

GCRF Global Challenges Research Fund

ABSTRACT

Employment generation is crucial to spreading the benefits of economic growth broadly and to reducing global poverty. And yet, emerging economies face a contemporary challenge to traditional pathways to employment generation: automation, digitalization, and labor-saving technologies. 1.8 billion jobs or two-thirds of the current labor force of developing countries are estimated to be susceptible to automation from today's technological standpoint. Cumulative advances in industrial automation and labor-saving technologies could further exacerbate this trend. Or will they? This paper does the following: (i) it discusses the literature on automation; and in doing so (ii) discusses definitions and determinants of automation in the context of theories of economic development; (iii) it assesses the empirical estimates of employment-related impacts of automation; (iv) it characterizes the potential public policy responses to automation; and (v) it highlights areas for further exploration in terms of employment and economic development strategies in developing countries. In an adaption of the Lewis model of economic development, the paper uses a simple framework in which the potential for automation creates "unlimited supplies of artificial labor" particularly in the agricultural and industrial sectors due to technological feasibility. This is likely to create a push force for labor to move into the service sector, leading to a bloating of service-sector employment and wage stagnation but not to mass unemployment, at least in the short-to-medium term.

KEYWORDS

technology, employment, economic development, structural change.

About the GPID research network:

The ESRC Global Poverty and Inequality Dynamics (GPID) research network is an international network of academics, civil society organisations, and policymakers. It was launched in 2017 and is funded by the ESRC's Global Challenges Research Fund.

The objective of the ESRC GPID Research Network is to build a new research programme that focuses on the relationship between structural change and inclusive growth.

See: www.gpidnetwork.org

THE DEVELOPER'S DILEMMA

The ESRC Global Poverty and Inequality Dynamics (GPID) research network is concerned with what we have called 'the developer's dilemma'.

This dilemma is a trade-off between two objectives that developing countries are pursuing. Specifically:

1. Economic development via structural transformation and productivity growth based on the intra- and inter-sectoral reallocation of economic activity.
2. Inclusive growth which is typically defined as broad-based economic growth benefiting the poorer in society in particular.

Structural transformation, the former has been thought to push up inequality. Whereas the latter, inclusive growth implies a need for steady or even falling inequality to spread the benefits of growth widely. The 'developer's dilemma' is thus a distribution tension at the heart of economic development.

EXECUTIVE SUMMARY

Automation is likely to affect developing countries in different ways to the way automation affects high-income countries. **The poorer a country is, the more jobs it has that are in principle automatable** because the kinds of jobs common in developing countries—such as routine agricultural work—are substantially more susceptible to automation than the service jobs—which require creative work or face-to-face interaction—that dominate high-income economies. This matters because employment generation is crucial to spreading the benefits of economic growth broadly and to reducing global poverty.

We argue that the rise of a global 'robot reserve army' will have profound effects on labor markets and structural transformation in developing countries, but **rather than causing mass unemployment, AI and robots are more likely to lead to stagnant wages and deindustrialisation**. As agricultural and manufacturing jobs are automated, workers will continue to flood the service sector, driving down wages. This will itself hinder poverty reduction and likely put upward pressure on national inequality, weakening the poverty-reducing power of growth, and potentially placing the existing social contract under strain, or even possibly limiting the emergence of more inclusive social contracts. How developing countries should respond in terms of public policy is a crucial question, affecting not only middle-income developing countries, but even the very poorest countries given the automation trends in agriculture.

Concerns about the effect of technology on jobs are not new to AI or automation. We argue that **the current debate focuses too much on technological capabilities, and not enough on the economic, political, legal, and social factors that will profoundly shape the way automation affects employment**. Questions like profitability, labor regulations, unionization, and corporate-social expectations will be at least as important as technical constraints in determining which jobs get automated, especially in developing countries.

Developing countries face several policy challenges unleashed by automation. Given the pace of technological change, upskilling strategies are likely not to be a panacea. Safety nets and wage subsidies may be desirable, but the question remains how to finance them (without making labor more costly and thus exacerbating a trend towards replacement). Investing in labor-heavy sectors such as infrastructure construction, social, education or healthcare provision may be a way for developing countries to manage disruptive impacts of automation though these would imply major public investments and do not in themselves substitute for a long run strategy for economic development.

"This time, new technology seems to be
making life harder for the emerging world."
(Avent, 2017, p. 171)

1. Introduction

A specter is haunting the industrialized and developing world—the specter of automation. 1.8bn jobs or two-thirds of the current labor force of developing countries are estimated to be susceptible to automation from *today's* technological standpoint, according to the World Bank (2016). Employment generation is crucial to spreading the benefits of economic growth broadly and to reducing global poverty. And yet, emerging economies face a contemporary challenge to traditional pathways to employment generation: automation, digitalization, and labor-saving technologies.

A broad range of international agencies have recently flagged such issues relating to the future of employment, and the consequences of automation and deindustrialization in their global reports (ADB, 2018; Hallward-Driemeier and Nayyar, 2017; ILO, 2017; IMF, 2017; UNCTAD, 2017; UNDP, 2015; UNIDO, 2016; World Bank, 2013, 2016) and the International Labor Organization (ILO) has launched a Global Commission on the Future of Work. Employment prospects have also come into sharp focus because of the contested experiences of "premature deindustrialization" (Palma, 2005; Rodrik, 2016) and weakening employment elasticities of growth.[1]

[1] Heintz (2009) examines employment growth and the productivity growth rate in 35 countries between 1961 and 2008, and finds that increases in the productivity growth rate slow down the rate of employment growth, and that this pattern is getting stronger over time. In the 1960s, a one percentage point increase in the growth rate of productivity reduced employment growth by just 0.07 percentage points. However, in the 2000s, that same one percentage point increase in the growth rate of productivity reduced employment growth by a substantial 0.54 percentage point. Several possible explanations are as follows: (i) it could be that increases in productivity over time are reducing the employment elasticity of growth; (ii) it could be that the proportion of wage labor is increasing; or (iii) it could be that

There is currently significant and rising interest in these issues in the scholarly community (see e.g. Acemoglu & Restrepo, 2017; Arntz, Gregory, & Zierahn, 2016; Grace, Salvatier, Dafoe, Zhang, & Evans, 2017; Mishel & Bivens, 2017; Mokyr, Vickers, & Ziebarth, 2015; Roine & Waldenström, 2014), in the reports of international agencies (see references above), and in the private sector too (Frey, Osborne, & Holmes, 2016; McKinsey Global Institute, 2017a, 2017b; PWC, 2017; World Economic Forum, 2017a). Moreover, the topic has also captured the public interest, reflected by a mushrooming of media reports and popular science books on the issues (e.g. Avent, 2017; Brynjolfsson & McAfee, 2011, 2014; Harari, 2016; Srnicek, 2017, to name but a few). Despite this increasing interest, the effects of automation in particular remain highly contestable and understudied with respect to developing economies, given that most research has focused on high-income Organisation for Economic Co-operation and Development (OECD) countries such as the United States.

These are, however, not only OECD country issues (see discussion of Ahmed, 2017). The World Bank (2016, p. 22f.) estimates 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". However, they note that the impact will be moderated by wage growth and the speed of technology adoption. There are numerous estimates of job displacement and much in the way of gray literature. However, these estimates are based on contestable assumptions and analysis of developing countries is often limited.

increases in real wages, employers' social contributions, or strengthening labor institutions are raising unit labor costs and dampening employment creation, though this is ambiguous in empirical studies. A meta-review of 150 studies of labor institutions (Betcherman, 2012) covering minimum wages, employment protection regulation, unions and collective bargaining, and mandated benefits) with an emphasis on studies in developing countries, found that in most cases, effects are either modest or work in both directions in terms of productivity.

Furthermore, in contrast to a widespread narrative of technological unemployment, a more likely impact in the short-to-medium term at least is slow real-wage growth in low- and medium-skilled jobs as workers face competition from automation. This will itself hinder poverty reduction and likely put upward pressure on national inequality, weakening the poverty-reducing power of growth, and potentially placing the existing social contract under strain, or even possibly limiting the emergence of more inclusive social contracts. How developing countries should respond in terms of public policy is a crucial question, affecting not only middle-income developing countries, but even the very poorest countries given the automation trends in agriculture.

In light of the above, the objective of this paper is to: (i) survey the literature on automation; and in doing so (ii) discuss definitions and determinants of automation in the context of theories of economic development; (iii) assess the empirical estimates of employment-related impacts of automation; (iv) characterize the potential public policy responses to automation and (v) highlight areas for further research in terms of employment and economic development strategies in developing countries.

The paper is structured as follows. Section 2 gives an overview of the trends in technology and discusses definitions and determinants of automation. Section 3 discusses the effect of automation on economic development and employment in developing countries from a theoretical perspective. Section 4 analyzes existing empirical forecasts of automatability and global patterns. Section 5 considers the public policy responses proposed. Finally, Section 6 concludes and highlights areas for further research in terms of employment and economic development strategies in developing countries.

2. Technological transformation: definitions, determinants, and development

2a. Technological trends

Stunning technological advances in robotics and artificial intelligence (AI) are being reported virtually on a daily basis: from the versatile mobile robots of the US engineering company *Boston Dynamics* to autonomous vehicles, vessels, and drones, to 3D-printed buildings and new breakthroughs in machine learning made by firms in the Silicon Valley and beyond. A growing number of empirical studies and several monographs have recently addressed the broader phenomenon of a "digital revolution" which is unfolding at high speed across OECD countries. Interest in the impact of technological change is by no means new of course. As the detailed empirical study of Leontief and Duchin (1984) is testimony to. Indeed, one can trace the subject back to the classical writings of David Ricardo (2010 [1817]) and Karl Marx (2012 [1867]) or Joseph Schumpeter (1943). The bulk of research on the economic implications of digital transformation has so far focused on advanced industrialized economies where the cost of labor is high and manufacturing shows a high degree of mechanization and productivity. Yet, the developing world is both affected by automation trends in high-income countries (HICs) and is itself catching up in terms of automation.

Indicative of this, the International Federation of Robotics (IFR) reports that Asia is currently the "strongest growth market" in a "significant rise in demand for industrial robots worldwide" (IFR, 2016, p. 11f.). A double-digit growth trend includes not only China, Korea, and Japan but also emerging economies in South East Asia. The IFR (2016) estimates that by 2019, more than 250,000 units of multipurpose industrial robots will be installed in Asia on a yearly basis, with the main industries driving demand in robots being the automotive, electrical/electronics, metal, and machinery, as well as the rubber and plastics industries. This only captures the more easily measurable demand for robotics hardware and does not take account of the widespread use of software in the context of economic production. In some domains of automation, emerging economies are, in fact, ahead of many OECD countries, as the opening of Beijing's first driverless subway line in 2017 (Yan, 2017) or the popularity of the mobile phone-based financing platform M-Pesa in Kenya illustrate.

The digitalization and automation of economies raises the question of what lessons the developing world can draw from extant evidence. "Late developers" are facing the digital revolution considerably earlier and under different conditions than today's advanced economies. There is thus an increasing worry that "increased automation in low-wage countries, which have traditionally attracted manufacturing firms, could see them lose their cost advantage and potentially lose their ability of achieving rapid economic growth by shifting workers to factory jobs" which today's high-income countries used to have (Frey, Osborne, & Holmes, 2016). Beyond the perceived threat of "technological unemployment", there are broader questions to be asked about how automation and digitalization influence economic development, employment growth, and structural transformation in developing countries. It may well be that labor displacement is less of an issue than real-wage growth as a result of the potential for automation, for example.

2b. Automation: definitions and determinants

The concept of automation is more difficult to define than might seem at first glance. Throughout history, humans have used tools to save time and effort when completing laborious tasks and thanks to innovation, such tools have gradually increased in sophistication. Today, the spectrum of "physical capital" ranges from simple manual tools to intelligent machines. One could thus argue that a “robot” is simply a highly advanced version of a tool which requires minimal (manual) human input for completing a task, although currently all machines still require considerable human intervention in their design, production, installation, and maintenance. The potential of AI is to move machines beyond human oversight, at least in everyday operation. An intelligent machine performs a set of complex tasks autonomously and may be capable of adapting to new and changing circumstances, i.e. “learning”. Workhorse animals could be considered a biological equivalent of complex machines and have been used in transportation and agriculture since at least the agricultural revolution in 10,000 BC. Contemporary automation often tends to be associated with physical hardware such as industrial robots, but also includes software which plays a critical role in service automation (see Willcocks & Lacity, 2016, Lacity & Willcocks 2018). The wider process of structural economic change toward an automated economy has been referred to not only as a digital transformation but as the “fourth industrial revolution” (Schwab, 2016).

Under what conditions might such a transformation or revolution take place? Technological feasibility is just *one* condition. Table 1 shows multiple criteria which the decision to automate involves: can a task be automated in a way that reliably produces a good or service at a specified level of quality? Is it profitable to automate that task? Is it legally possible for a firm to replace workers with machines? How do relevant stakeholders such as political groupings, particularly trade unions, and society at large, particularly consumers, respond to automation (and the potentially ensuing lay-offs)?

Table 1 Determinants of the feasibility of automation

Dimension	Factors	Literature
Technological	Type and complexity of the task	Engineering studies, "jobs at risk" studies (e.g. Arntz et al., 2016; Grace et al., 2017; McKinsey Global Institute, 2017a)
Economic	Economic risks and returns given capital and labor costs; intensity of competition	Management/human resources and economics literature (e.g. Hall & Khan, 2003; Siegel, Waldman, & Youngdahl, 1997)
Legal	Labor and capital regulation (e.g. job protection); patents and their ownership.	Institutionalism and political economy (e.g. Acemoglu & Robinson, 2000; Parente & Prescott, 1994; Williams & Edge, 1996)
Political	e.g. unionization of the workforce; questions of public versus private ownership of production and technology.	
Sociocultural	e.g. corporate legitimacy and social expectations	

Source: Authors and references cited.

Corresponding to these criteria, one could split the literature on automation into different theoretical approaches. Much recent research has focused on the first criterion in Table 1: the technological feasibility of automation. Yet, automatable tasks do not necessarily or instantly get automated: one can observe a set of tasks currently being carried out both by humans and machines in different contexts and places. Consider, for instance, subway drivers and autonomous subways, supermarket cashiers, and self-checkout machines, university lecturers, and online courses. The coexistence of automated and non-automated modes of operation of the same task suggests that a narrowly technologically deterministic view is insufficient. There are less tangible—economic, political, social, and cultural—reasons to be factored in. Such factors up until now often seem to have been neglected in research on automation, but could be particularly important in the context of developing countries. Such factors not only determine if automation occurs but the terms of automation vis-a-vis governing institutions.

Consider, for example, the case of Indonesia. In Indonesia, there have been numerous media reports related to automation and employment impacts (e.g. Deny, 2017; *Jakarta Globe*, 2017; Jefriando, 2017; Praditya, 2017; Saragih, 2017; *Tempo*, 2015, 2016a, 2016b, 2016c, 2017; see also international press such as *The Guardian*, 2016). The McKinsey Global Institute (2017c) estimates that around half of all jobs in Indonesia are automatable using existing technologies. One example is that motorway toll booths are being automated to an e-payment system which has placed a question over 20,000 jobs, leading the Minister of Finance to announce at the annual meeting of the International Monetary Fund and the World Bank that automation might create a case for a future universal basic income in Indonesia (*Jakarta Post*, 2017; Jefriando, 2017).

While formerly each toll gate required five employees working in shifts to ensure vehicles had paid the road toll, the cashless system which is being rolled out runs entirely without human operators, thus speeding up the transaction process and reducing traffic congestion. Yet, as of early 2018, the toll road operator PT Jasa Marga asserts that “former tollgate keepers would instead be relocated to different positions within the company (…) and would keep their permanent employee status” (Aisyah, 2017).

There have, indeed, so far, been no reports of mass lay-offs despite the electronic system being implemented. What could be the reason? First, it could be that, as implementation is still in an early stage, lay-offs may be a matter of time, and could happen in a gradual manner. The company may also reduce its future intake of new employees as a result. Second, it could be that, in line with the quote above, PT Jasa Marga, which is currently expanding its business, truly has the capacity to absorb 20,000 people in other sectors of its operation. If that is the case, this raises the important question as to whether by raising overall productivity and competitiveness, automation somehow allowed the company to expand. The latter would mean that automation has the double effect of reducing labor demand per unit of capital in one domain (e.g. manual toll collection) while raising labor demand in complementary domains (e.g. administrative or construction tasks).

Finally, there is a set of institutional reasons that could be an important explanatory factor as to why PT Jasa Marga—a state-owned enterprise and thus facing potential developmental obligations—has not laid off workers: political and social-norms pressures as well as legal constraints could be preventing the toll road operator from firing employees. One could imagine the political backlash of a state-owned enterprise making 20,000 people unemployed. There may be also concerns over strikes, attacks on the new toll-booth machinery, political interventions (including fears of the political replacement of senior management making such decisions) or negative media reports which demonstrably influence business decisions in part of wholly owned SOEs and to some extent in private companies too.

2c. Theoretical perspectives on automation

One could crudely distinguish the existing scholarly literature on automation and digitalization effects into two camps: first, there is an optimists' camp which essentially sees the "business as usual" of market dynamism at work. Technological change, they argue, has been an essential element of "modern economic growth" since the Industrial Revolution, and disruptive innovation has always been met with what Mokyr et al. (2015) call "technological anxiety". This has been the case at least since the arrival of the steam engine and the power loom. Simon Kuznets (1971) in his Nobel lecture argued that the most important feature of modern economic growth is a "combination of a high rate of aggregate growth with disrupting effects and new 'problems' ". Such disruption refers, in particular, to changes in the economic and social structure that technological innovation generates.

Joseph Schumpeter, key theorist of technological innovation, famously coined the notion of "creative destruction" for the "process of industrial mutation that incessantly revolutionizes the economic structure *from within*, incessantly destroying the old one, incessantly creating a new one" and called this the "essential fact about capitalism" (Schumpeter, 1943, p. 42f., emphasis in original). Schumpeter's view on the economics of technology in the context of the Industrial Revolution preceded the neoclassical standard model of growth advanced by Solow (1956). In his aggregate production function, Solow attributed all output growth not accounted for by increases in capital and/or labor to a broad category of "technical change" (Granstrand, 1994, p. 13).

Scholars in this optimistic tradition thus tend to emphasize the historically demonstrated adaptive capacity of market economies to innovation and change with little emphasis on any temporary or permanent 'losers' in the process. Further, they argue that robots and computers take over repetitive, dangerous, unhealthy tasks, and so improve both the quality of work and of products and come with public health benefits. Importantly, automation decreases the cost of production and should thus, in a competitive market, lead to lower prices which benefit all consumers. Not only this, but "automation, by reducing wages relative to the rental rate of capital, encourages the creation of new labor-intensive tasks and generates a powerful self-correcting force towards stability" (Acemoglu & Restrepo, 2015, p. 41). Optimists tend to suggest skills development for the labor force to allow a synergetic relationship of human and non-human work.[2] This is in keeping with Goldin and Katz' (2007) race between technology and skill supply itself drawing on the Tinbergen (1974; 1975) thesis. Further, they might advocate to reduce taxes on labor which would make labor relatively more competitive vis-à-vis robots.

The pessimists' camp, on the other hand, argues that "this time it's different": contemporary iterations of automation and digitalization are viewed as being part of a larger "digital revolution" (Avent, 2017) which is bringing about technologies that are more powerful and versatile than earlier iterations of the Industrial Revolution, and which will wholly or partially replace *human brains* rather than just the *human muscle* replaced by earlier technologies. The digital revolution, it is argued, is creating an array of intelligent, adaptive, general-purpose technologies with hitherto unseen labor-saving potentials for a widening group of tasks. This group of tasks increasingly includes complex, skill-intensive work and formerly hard-to-automate

[2] The word "robot" is etymologically derived from the Slavic word for "work".

manual work like stitching. The relationship of human and non-human work is viewed as more and more *substitutive* rather than *complementary*. In this vein, an in-depth report of the Executive Office of the President of the United States (2016, p. 22) commissioned by Barack Obama warns that "the skills in which humans have maintained a comparative advantage are likely to erode over time as AI and new technologies become more sophisticated". DeLong (2015) argues too that, just like horses once used to dominate economic production, human labor currently dominates it, but that "peak human" may have been reached.

Pessimists argue that automation is putting a downward pressure on wages (reflected in stagnating real wages) and an upward pressure on the rate of profit from capital investment. The detachment of productivity gains and wage growth observed since the 1970s in many OECD countries is brought forward as evidence. Automation, pessimists argue, may ultimately lead to job losses as technologies create fewer jobs than they eliminate ("technological unemployment") or create jobs in sectors which are potentially less desirable and productive ("premature deindustrialization"). Politically, the recommendations of the pessimist camp range from a "robot tax" to redistributive responses such as a universal basic income (with the latter potentially funded by the former) and questions of public versus private ownership of production and technology.

It is fair to say that the second, more pessimistic, camp has been increasingly visible in recent years. Yet, unemployment is generally not considered to be the main issue. With a view to the US, economic experts from the IGM Panel (2014) agree that automation has not (yet) markedly reduced employment but has rather led to a stagnation of median wages, a decoupling of real-wage growth from productivity growth, and a labor market polarization or "hollowing out" of middle-skill employment. Technology can depress or enhance wage growth depending on whether it substitutes or complements tasks (see for discussion, Acemoglu & Autor, 2011; Autor, Katz, & Kearney, 2004; Firpo, Fortin, & Lemieux, 2011; Goos & Manning, 2007).

Further, it should not be taken as given that lower skilled work will necessarily be automated, but it can contribute to a “missing middle” whereby most jobs are low or high skilled, and those in-between are relatively more susceptible to automation, or whereby employment expansion in those middle-skill jobs is weaker than that of low and high-skilled jobs (see Autor, Levy, & Murnane, 2003). The problem thus may not be so much that jobs are lost, rather than that other types of jobs expand in number. People are being driven into the jobs below their skill level, with either lower or slower growing wages than the middle-skill jobs that previously existed.

A key question is what happens to productivity growth in any given country. In short, who ‘captures’ the productivity growth in terms of capital or labor and the functional distribution of income. And how what is captured is then distributed within the capital share (which may be distributed between reinvestment, dividend payments, reserves building, or other activity e.g. rents), or within the labor share which may be distributed between employment growth, real-wage growth, or social security entitlements (see discussion of Atkinson, 2009; Francese & Mulas-Granados, 2015). This matters from an individual income inequality perspective, as reductions in the labor share of income are correlated with rising income inequality between individuals (see for detailed discussion, Chapter 3 of IMF, 2017).

3. Automation and structural transformation in developing countries

3a. Characteristics of developing countries

Developing countries have special characteristics (vis-à-vis OECD countries): they tend to be labor-abundant and have higher rates of population growth than OECD countries. Large proportions of the population are often relatively unskilled and tertiary education is still comparatively limited even in upper middle income developing countries. Compared to advanced high-income countries, they have a larger agricultural sector, and lower employment and value-added shares in industry and manufacturing, as well as a large informal service sector again not only in the world's poorest countries but even in upper middle income countries. Production in such economies is less capital-intensive and productivity levels are thus lower than in high-income countries.

A number of developing countries have substantially shifted economic value-added activity from agriculture and resources to manufacturing and service sectors. For developing countries with such characteristics, a set of questions arises in the context of automation (that are different to the world's very poorest countries): What if industrial production can increasingly be carried out with minimal human labor input? What if robots in high-income countries start to compete with cheap labor? Is it plausible that there could be a disintegration of global value chains via "reshoring", i.e. the repatriation of formerly outsourced production to high-income countries? What if the service sector—where currently the largest share of labor is absorbed in many middle income developing countries—goes through dramatic shifts of labor productivity, thanks to innovations in software and AI? Does automation exacerbate a much-debated "middle-income trap" if it exists at all and thus impede catch-up development? Are there new sectors of economic activity emerging which promise decent employment opportunities for large populations rather than economic growth accompanied by weak employment growth? These questions point towards the importance of situating the role of technology in broader theories of economic development.

3b. Disrupted development? The role of technological change in long-run economic development

The neoclassical standard model of growth attributes a key role to technological change in long-run economic growth. In the Solow (1956) model, growth can be achieved either via an increase in the inputs of production, e.g. an expansion of the labor force or an increase in the capital intensity, or it can happen via greater efficiency in the combination of inputs that generates a larger output. The latter route is known as the dynamics of total factor productivity (TFP) and innovation in automation technologies is generally considered an important factor in raising the TFP.

Summers (2013) considers a modification of the neoclassical two-factor production function in which output is created via both a *complementary* and a *substitutive* use of capital and labor (see for discussion Atkinson & Bourguignon, 2014, p. xilx). Capital will be "deployed in these two uses to the point where their marginal productivity is the same" (Summers, 2013, p. 4) and a certain mix of capital and labor will result. Summers highlights three implications of labor-saving capital use: (i) production opportunities are augmented and output thus increases; (ii) wage rates fall; and (iii) returns to capital rise. Atkinson and Bourguignon thus argue:

> We can therefore tell a story of macroeconomic development where initially the Solow model applies (…). A rising capital-labor ratio leads to rising wages and a falling rate of return. Beyond a certain point however (…) [labor-substituting capital use] begins to be positive. We then see further growth in the economy, as capital per head rises (…). There is no longer any gain to wage-earners, since they are increasingly being replaced by

> robots/automation. What is more, the capital share rises, independently of the elasticity of substitution. [The modified Solow model] highlights the central distributional dilemma: that the benefits from growth now increasingly accrue through rising profits. (Atkinson & Bourguignon, 2014, p. xilx)

In line with the argument of a distribution dilemma, Roine and Waldenström (2014, p. 79)—though they are skeptical of any "mechanical relationship between inequality and industrialization or technological change"—argue that: "the technological development starting in the 1970s constitute[s] the start of a shift, not from agriculture to industry as in Kuznets' original story, but from traditional industry to an ICT-intensive sector that initially rewards a small part of the population, but eventually will spread, bringing inequality down".[3]

There is thus a theoretical case that automation may be linked to income inequality and wage stagnation. Is there also a case for it leading to technological unemployment? The Solow model and its iterations suggest greater output (i.e. supply) due to automation which should translate into lower prices under conditions of competition. Lower prices in turn should lead to greater quantities demanded which necessitate more net employment of humans.

So, the net effect of using labor-saving technology could still be labor-increasing domestically. It may, however, not be if we took the Summers' model to its extreme: this would mean assuming a *perfectly* labor-saving production function where labor drops out entirely as a

[3] Roine and Waldenström (2014) suggest a new Kuznets curve based on technological developments starting not a sectoral shift of agriculture to industry but a shift from traditional industry to technologically intensive industry. If a given technology makes skilled workers more productive and there is an increase in the relative demand for those workers, the rewards accrue to a small proportion of the population who are skilled workers. Based on Tinbergen's (1974, 1975) hypothesis that the returns to skills are a competition between education and technology, the supply of skilled workers then determines whether or not their wages rise. Roine and Waldenström argue that the drivers of the Kuznets downturn are political and exogenous shocks.

factor of production. In that case, output would be produced solely by non-human production factors.

Solow himself was skeptical of such a scenario. In a book on unemployment in the US written in the 1960s, he noted that “rather spectacular scientific and engineering achievements” have led many “to the conclusion that there is a kind of revolution in progress, connected with the advance of automation” (Solow, 1964, p. 7). Yet, he doubted “that the clichés about automation and structural unemployment are very productive in analyzing the problem or bringing the remedy any closer” (ibid., p. 40) and he is particularly skeptical that automation calls for specific policy responses or a reorganization of the economic framework.

Of course, as noted above, not all labor is equally easy to substitute with machines. The dominant view has been that technology is skills-complementing or skills-biased (see Tinbergen, 1974, 1975). Empirically, models predicting a “skills premium” and rising market inequality due to automation are pervasive (see Acemoglu & Autor, 2011; Autor et al., 2004; Goldin & Katz, 2007; Katz & Autor, 1999; Katz & Murphy, 2013). Others have argued, though, that technological change does not *necessarily* have to be skills-biased and inequality-increasing in every case (see Roine & Waldenström, 2014).

The neoclassical growth model is a one-sector model and thus indifferent to the role of structural change in driving growth as Lewis (1954) intended, in his vision of economic development as a transfer of labor from a low-productivity, “traditional” sector to a higher productivity, “modern” sector. Herrendorf, Rogerson, and Valentinyi (2014), argue empirically that the sectoral composition of economic activity is key to understanding economic development. McMillan and Rodrik (2011, p. 1), also, in taking sectoral and aggregate labor productivity data empirically show that the transfer of labor and other inputs to higher productive activity is a driver of economic development, as Lewis hypothesized. However, they go on to note that structural change can in fact be growth-enhancing *or* growth-reducing, depending on the reallocation of that labor.[4] Assuming technological labor-substitution, what can we say about potential implications for structural economic transformation, i.e. the reallocation of economic resources across sectors with different levels of productivity?

The dual economy model of Lewis (1954) is based, as noted, on a traditional or subsistence sector and a modern sector, where in the former, there is a surplus of unproductive labor that is sustained by receiving an equal share of the total product for reasons of traditional/family-based values. Lewis argued that the driver of economic development was a sectoral movement of labor from the "traditional" or "subsistence" or "non-capitalist" sector (of low productivity, low wage, priced to average product not marginal product, and thus widespread disguised unemployment) to the "modern" or "capitalist" sector (of higher productivity, and where wages are set by productivity in the 'subsistence sector'.

A critical factor is the existence of surplus labor in the traditional sector. Because of this, wages are set just above subsistence across the whole economy, leading to the transfer of labor over time from the traditional to the modern sector, and the capture of labor productivity gains to capitalists as profits, as these are the source of growth via reinvestment. The floor for wages is institutionally set at subsistence. When surplus labor disappears, an integrated labor market and economy emerge, and wages will then start to rise.

[4] McMillan and Rodrik show how structural change had been growth-enhancing in Asia because labor has transferred from low to higher productivity sectors. However, the converse is the case for sub-Saharan Africa and Latin America because labor has been transferred from higher to lower productivity sectors and this has reduced growth rates. They find that countries with a large share of exports in natural resources tend to experience growth-reducing structural transformation and, even if they have higher productivity, cannot absorb surplus labor from agriculture.

The Lewis model was intended as a critique of the neoclassical approach in that labor is available to the modern or capitalist sector of an economy not in a perfectly elastic supply but upward sloping rather than flat, and with a distinction between surplus-producing labor and subsistence labor (the latter of which was a negligible source of net profits for reinvestment, which Lewis saw as the driver for growth).

Diao, McMillan, Rodrik, and Kennedy (2017, pp. 3–4) seek to link the structural dualism of Lewis with the neoclassical model, by arguing that the neoclassical model shows the growth process within the modern sector and the dual model shows the relationship between sectors. In short, the emergence of a modern sector with higher and competitively paid wages, and where profits are reinvested by capital owners, creates a pull force. This pull force attracts labor from the traditional sector. After a period of labor exchange via migration, an inter-sectoral equilibrium is reached, and wages are equalized between sectors.

Following Lewis' dual economy, we could divide up an economy into two sectors: an *automation-prone sector* (APS), consisting of jobs that are easy to perform by machines, and an *automation-resistant sector* (ARS), consisting of jobs that are hard to perform by machines (Figure 1).[5] The former would, for instance, include simple manual routine tasks like lifting, drilling, and so forth and the latter would, for instance, include creative work involving face-to-face interaction.

With a view to the Lewis model of economic development, one could say that automation creates "unlimited supplies of artificial labor" in the APS. The increasing use of robots is thus

[5] This of course has resonance with Baumol (1967) who in a similar fashion divided up the economy into "technologically progressive" and "technologically non-progressive" activities. In the former, productivity-driving, sector "labor is primarily an instrument (…) while in other (…) labor is itself the end product" (ibid., p. 416). One issue is our approach implies a somewhat linear view of structural change that does not take into account the servicification of manufacturing and therefore an overlap between APS and ARS. This would also mean for table 2 that even complementarity could drive structural change in that the services that digitalization adds to manufacturing could drive industrialization.

equivalent to labor force growth in the APS. Arguably, the sheer capacity alone to build and deploy robots creates a new kind of "robot reserve army" in the APS, limiting the bargaining power and wages of labor in that sector. If automation is (technologically, legally, politically, and socially) feasible, the labor force will thus gradually be pushed from the APS into the ARS. There would be automation-driven structural change taking place.

In other words, automation itself constitutes a supply shock which shifts the labor supply curve in the APS to the right, and thus reduces the equilibrium wage in that sector (as well as in the ARS to the extent that labor can be absorbed in that sector). If the unit cost of automated production falls below the reservation wage of workers, a labor surplus is created. Automation thus frees up resources for the completion of non-automatable work.[6] The surplus can either be absorbed by the ARS or, in case that is not possible, can lead to technological unemployment. Like in the Lewis model, the functional distribution of income changes in favor of capital owners.

Is there a "turning point"? In Lewis' standard model, a turning point is reached when surplus labor has fully migrated from the traditional or subsistence sector to the modern industrial sector, and wages start rising in the traditional sector due to an emerging labor shortage. In the model outlined here, there is, arguably, no such turning point. The supply of "artificial labor", i.e. automation, is genuinely unlimited, as it does not depend on the dynamics of demographic growth. In that case, human labor in the APS is fully displaced by machines and only an ARS remains. The ARS is itself, of course, not static but is defined by the technological frontier of the time.

[6] Baumol's "unbalanced growth" model similarly envisaged a labor transition from one to the other sector and aggregate stagnant labor productivity as a result (Baumol, Blackman, & Wolff, 1985; Baumol, 1967; see also Ngai & Pissarides, 2017 for a contemporary iteration of the model). Autor and Dorn (2013), based on a spatial equilibrium model, posit a reallocation of low-skill labor into service occupations (a phenomenon they call "employment polarization" which then entails wage polarization).

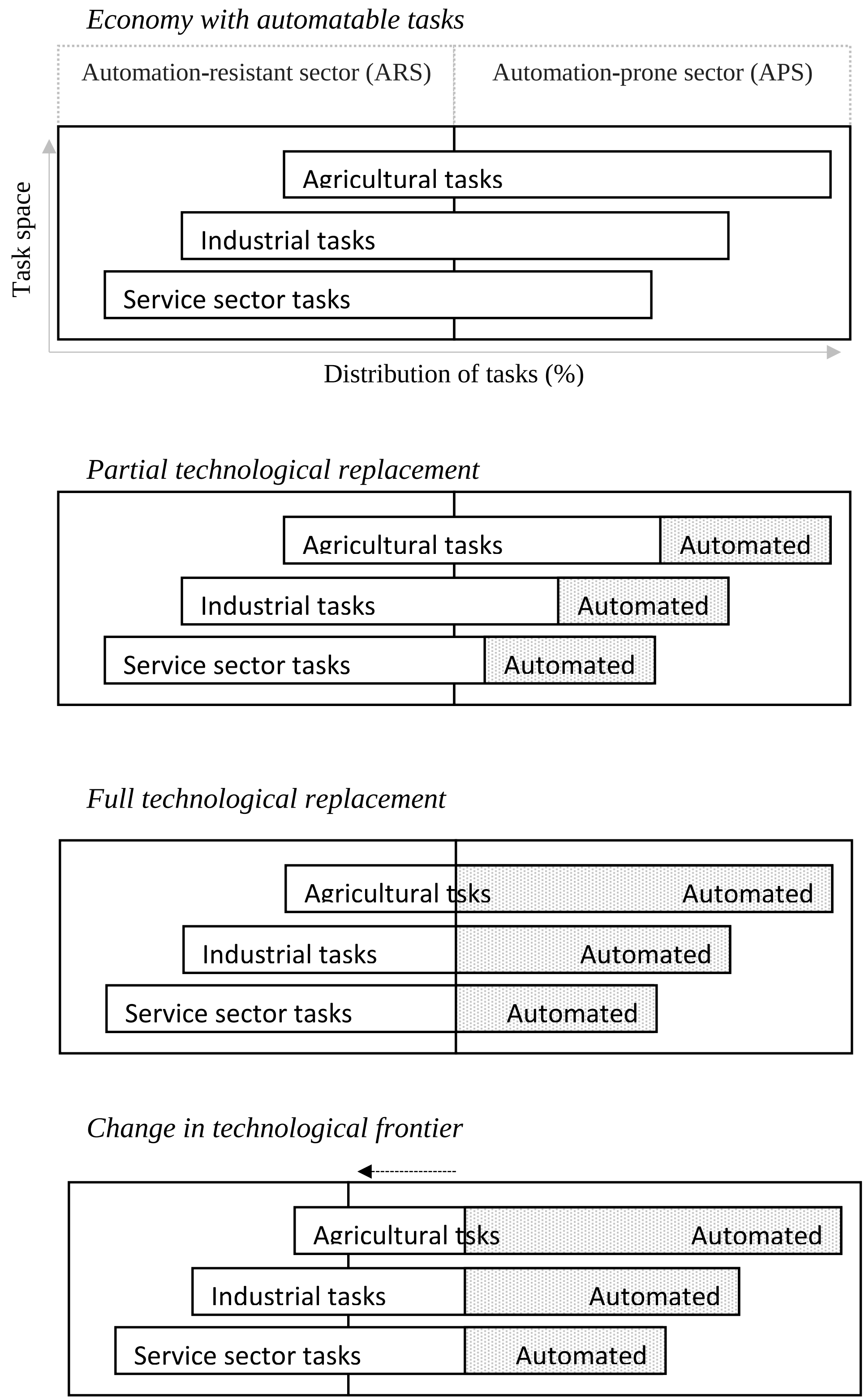
Technological innovation then gives rise to the shift of the frontier and thus re-emergence of a new APS.

The question then becomes: What industries and tasks comprise the ARS and the APS, respectively? And is demand for the ARS large enough to allow full employment at decent wages? Regarding the first question, it would arguably be a mistake to suspect the location of the ARS primarily in newly emerging post-industrial sectors such as telecommunication or finance. Rather, the little amount of human work performed in modern agriculture is equally as automation-resistant by today's technological standards as resilient jobs in the industrial and the service sectors.[7] The service sector is generally considered to contribute strongly to the ARS, as it involves plenty of non-routine work involving social interactions. The current occupational structure of an economy reflects past (expectations of) automatability.

Regarding the second question, there could be a dilemma whereby a productivity boost in the APS (e.g. in agriculture) creates surplus labor, but the ARS (e.g. the industrial sector) is not able to fully absorb it. So-called premature deindustrialization could be due to such "Lewis 2.0" dynamics: workers might be moving to the service sector because the manufacturing sector has no demand for (unskilled) labor. It is fully imaginable from today's point of view that the industrial sector will at some point be absorbing an equally small number of workers as today's extractive and agricultural sectors are. A set of highly productive manufacturing clusters would then produce most of the physical goods there is demand for, while almost all human labor demand would remain in the service sector.

[7] Of course, both the existence of agricultural subsidies and trade of agricultural products makes an assessment more difficult. Without subsidies, the sector might employ even fewer people. Conversely, OECD countries are not self-sufficient and depend on labor in foreign countries to produce food for export to OECD countries.

Figure 1 Structural change in a "dual economy" defined by automatability



Source: Authors' imagination.

If that is the case, this would indicate that the digital revolution creates problems for analysis based on very broad economic sectors such as “services”: Castells (2010, p. 244) criticizes analysis based on very broad economic sectors for three flaws: (i) the extreme heterogeneity of the service sector creates a “statistically obsolete category” which (ii) underestimates the “revolutionary nature of new information technologies” and (iii) the diversity of advanced societies and interdependence with the global economy from which different employment and occupational structures follow.

The historical productivity revolution in agriculture (or the “Green Revolution” in developing countries) shows how transformative and labor-saving technological change can be. In the British census of 1841, 22% of citizens were registered as being in agricultural employment whereas this number has dropped to below 1% in the present (Office for National Statistics, 2013). Agricultural shares in the developing world, though considerably higher, have also fallen rapidly (to an extent that Eastwood, Kirsten, and Lipton (2007) have argued that developing countries underwent “premature agriculturalization”).

Green revolutions have brought drastic productivity gains, allowing and incentivizing the reallocation of labor toward other—often hitherto non-existent—economic activities and sectors. Many argue that technological leaps in agriculture allowed Western countries to escape a “Malthusian trap” which had kept living standards stagnant throughout most of pre-industrial history (see Clark, 2008). Had there been policies to prevent the agricultural revolution because of job losses, the industrial revolution may not have unfolded in the same way. Historical structural change thus holds lessons, both for how hitherto unknown sectors can absorb labor from shrinking sectors, and what potential risks are involved in counteracting structural change.

The Industrial Revolution provides another point of reference for the digital transformation. Avent (2017, p. 162) argues that the digital revolution is set to repeat the experience of the Industrial Revolution which "bypassed the developing world for long decades". In Avent's view, integration into global supply chains which enabled rapid catch-up growth in the South ("export-led industrialization") was a transitory phenomenon that will soon be replaced by both "reshoring"—the repatriation of outsourced production—or will be limited to small high-tech clusters in developing economies (cf. Yusuf, 2017). Such clusters might not create the large-scale job opportunities that broad-based industrial activity provided historically. According to Avent (2017, p. 163), the digital revolution will thus "make it more difficult in the future for poor countries to repeat the performance of the past twenty years. Once again, rich economies will enjoy a near-monopoly on the sorts of social capital required to generate a rich-world income" such as democracy, property rights, and accountable governance. One could call this the threat of a "disruption" of the catch-up development process.[8]

3c. The fourth industrial reserve army

What can be said about the characteristics of a labor surplus? Lewis (1954), in his seminal text on unlimited supplies of labor, saw himself working "in the classical tradition" of Karl Marx and Adam Smith.

In *Das Kapital*, Karl Marx (2012 [1867]) posited that there is a "progressive production of a relative surplus population or Industrial Reserve Army" (ibid., p. 274) as both a condition and an

[8] The concept of disruption or disruptive innovation goes back to Christensen's (1997) book *The Innovator's Dilemma*. In it, he describes how emerging technologies developed by small challengers can threaten dominant and generally well-managed businesses. Disruption generally means an unanticipated, revolutionary transformation that impacts an established market. Such disruption could happen to global value chains and thus the export-oriented industrialization development model.

outcome of the capitalist mode of production.[9] Overpopulation, in Marx' view, provides a "mass of human material always ready for exploitation" (ibid., p. 276), holding the wages of the active labor force in check and thus feeding a process of capital accumulation. Throughout this process of accumulation, the productiveness of labor constantly expands with growing employment of machinery. This accelerating capital accumulation process leads, in Marx' view, to a "constant transformation of a part of the laboring population into unemployed or half-employed hands" (ibid., p. 278), i.e. a surplus population relative to the labor demand of industry (rather than an absolute overpopulation in a Malthusian sense).

Marx had a clear interest in the relationship of technology and labor in the production process, and he specifically points to the "automatic factories" where "only a very small number continue to find employment", while the majority who get laid off form a "floating surplus population" (ibid., p. 281). He speaks of workers being degraded to the estranging status of an "appendage of a machine" (ibid.) and, in *Das Kapital*, Marx sees the process of technology-driven capitalistic development as an "accumulation of misery" (ibid.). This line of argument is stark techno-pessimism.

Although Lewis' conception of surplus labor as a population defined "relatively to capital and natural resources" sounds Marxian (and also Malthusian), there are some differences in that Lewis really means *disguised* rather than actual unemployment. In other words, Lewis' surplus population receive wages and, moreover, these wages exceed their marginal productivity (cf. Lewis, 1954, p. 141f).[10] Marx (2012, p. 283), on the other hand, distinguished multiple forms of

---

[9] One issue Marx would have raised is the ownership of the intellectual property that drives robots, and the reinvestment of related rents.

[10] For Lewis, wages are set at subsistence level, but since the marginal productivity of surplus workers is assumed to be (close to) zero, *any* wage they get exceeds their marginal contribution: "…large sectors of the economy where the marginal productivity of labour is negligible, zero, or even negative"—i.e. the subsistence sectors (1954, p. 141). And

surplus labor: a "floating" form where workers have to constantly change employers; a "latent" form of precarious agricultural (under)employment; a "stagnant" form characterized by irregular employment at minimal wages; and a "pauperist form" which is made up of criminals and "dangerous classes".

Lewis' conception of surplus labor thus resembles that of Marx' *latent* surplus, whereas he explicitly disagrees with the notion of productivity-driven labor surplus:

> Marx offered a third source of labor to add to the reserve army, namely the unemployment generated by increasing efficiency. (…) Nowadays we reject this argument on empirical grounds. It is clear that the effect of capital accumulation in the past has been to reduce the size of the reserve army, and not to increase it, so we have lost interest in arguments about what is "theoretically" possible. (Lewis, 1954, p. 145)

Lewis was thus a technological optimist. Indeed, if the industrialized/urban/capitalistic sector in his model is *also* assumed to produce surplus labor, the model of labor exchange would arguably break down.

Marx and Lewis concur that the reserve army is central to capital accumulation in modern capitalism. Lewis (1954, p. 145), though, is much more sanguine about this process as he sees the "expansion of new industries or new employment opportunities without any shortage of unskilled labor". When in Section 3b, we proposed to understand automation along the lines of a "Lewis 2.0 model", the idea was thus to incorporate elements of both Marxian and Lewisian thinking: in light

wage earners in that case receive "wages exceeding marginal productivity" (ibid.). The implication is that one can pull out workers from that sector without reducing the total output of the sector (or even increasing it in case of negative marginal productivity).

of current technological development, we may not want to reject Marx' views on automation "on empirical grounds" quite as categorically as Lewis did—even if the impact of reserve army dynamics are more likely wage pressures in the APS rather than the drastic employment-destroying effects of the "automatic factory" that Marx had in mind.

Lewis, on the other hand, may have been right in considering surplus labor primarily as an *engine of structural change* within a dualistic economy framework. Labor that is "set free" may get permanently absorbed in the ARS. The question then is whether such modern-day automation-driven structural change has equally benign effects (particularly under conditions of global competition and an international division of labor), as Lewis assumed traditional structural change to have, within select labor-abundant Asian developing countries.[11]

4. Existing empirical forecasts of the employment effects of automation

It is an empirical question if and in which sectors automation reduces labor demand. As was discussed, automation could reduce employment if the ARS has a low demand for labor. But if productivity gains lead to lower prices and thus higher quantities demanded, net job effects could be positive. Furthermore, the demand for new labor-intensive work could rise as the cost of labor falls relative to capital. Many would argue that the very problem of developing countries is that there is too little, rather than too much, automation and thus lower labor productivity.

[11] Lewis believed in contrast to Asia that Africa had a labor shortage due to agricultural land availability. The constraint to growth in Africa was low agriculture productivity rather than manufacturing growth and required government intervention in agriculture (See Kanbur, 2016, p. 7).

Table 2 presents a further layer to the “Lewis 2.0” model of economic development in an analytical framework to consider automation effects on employment within the two sector model presented earlier. One could speak of an adaptable and a non-adaptable labor force (defined, for instance, by the skills level).

Table 2 The labor dynamics of automation in a dual economy

Technology	Labor	Response	Outcome
Complementary	Adapted	Keep/hire	Structural stability
Substitutive	Adaptable	Retrain/switch task	Structural change
		Lower wage	
	Non-adaptable	Lay off	

Source: Authors’ imagination.

One could then hypothesize the existence of two opposing forces in automation-driven structural change in the developing world: (i) labor is cheaper than in high-income countries, thus more competitive vis-à-vis machines, and there is thus less of an incentive to automate; (ii) conversely, given widespread low-skilled manual routine work, work tasks that are prevalent in developing countries are easier to automate from a technological viewpoint. In other words, the APS will likely be larger in developing countries. Considering the taxonomy that was proposed earlier, this means that automation is arguably more technologically but less economically feasible.

Empirical estimates and forecasts of the potential impact of automation across the world are presented in Table 3 (the table is non-exhaustive). It is immediately evident from the studies in Table 3 that there is no consensus on jobs impacts and substantial variation in current estimates.

Table 3 Estimates of the employment impact of automation

Authors	Region	Findings
Studies of OECD countries		
Frey & Osborne (2013)	US	"47 percent of total US employment is at risk" (ibid., p. 1).
Barany & Siegel (2014)	US	ICTs substitute middle-skill occupations.
Acemoglu & Restrepo (2015)	n/a	"Automation, by reducing wages relative to the rental rate of capital, encourages the creation of new labor-intensive tasks" (ibid., p. 41).
Arntz et al. (2016)	OECD	9% of jobs automatable but "jobs at risk" may not translate into employment loss; large negative job effects "unlikely".
Bessen (2016)	US	During 1984-2007 computer use was associated with a 3% average annual job loss in manufacturing but a 1% increase elsewhere.
Executive Office of the President of the United States (2016)	US	"Economy has repeatedly proven itself capable of handling this scale of change", but jobs at risk "concentrated among lower-paid, lower skilled, and less-educated workers" (ibid., p. 2).
Acemoglu & Restrepo (2017)	US	"One additional robot per thousand workers (…) reduces aggregate employment to population ratio by 0.34 percentage points and aggregate wages by 0.5 percent" (ibid., p. 36).
Atkinson & Wu (2017)	US	Labor market disruption occurring at its lowest rate since the Civil War.
IMF (2017)	Advanced economies	Technological progress "explains about half the overall decline [of the labor income share] in advanced economies, with a larger negative impact on the earnings of middle-skilled workers".
Mishel & Bivens (2017)	US	No evidence that automation leads to joblessness or inequality.
PWC (2017)	OECD	Automation could replace 38% jobs in US, 35% in Germany and 30% in the UK and 21% in Japan by early 2030s.
Studies of developing countries		

Chandy (2017)	Developing countries	"Automation is likely to replace jobs even faster in developing countries than in industrial ones" (ibid., p. 15).
Chang & Huynh (2016)	South East Asia	56% of jobs are at high risk of automation in Association of Southeast Asian Nations (ASEAN) countries.
Frey et al. (2016)	Developing countries	"Developing countries are highly susceptible to the expanding scope of automation" (ibid., p. 18).
Frey and Rahbari (2016)	OECD and Ethiopia, India and China	China will lose 77% of jobs to automation, India 69%, Ethiopia 85% and OECD average 57% jobs lost.
World Bank (2016)	Developing Countries	Two-thirds of all jobs susceptible to automation (1.8bn jobs), but the effects are moderated by lower wages and slower technology adoption.
Avent (2017)	Developing Countries	"New technology seems to be making life harder for the emerging world" (ibid., p. 171).
World Economic Forum (2017b)	Africa	41% of all work activities in South Africa susceptible to automation, 44% in Ethiopia, 46% in Nigeria and 52% in Kenya.
ADB (2018)	Asia	In the period of 2005-2015 in 12 Asian economies there were 101m job losses per annum due to 'modern machine tools and ICT equipment' which were offset by 134m jobs created due to higher demand for goods and services (ibid., p. 77-78).
Global studies		
Grace et al. (2017)	Global	50% chance of AI outperforming humans in all tasks in 45 years and of automating all human jobs in 120 years.
McKinsey Global Institute (2017a)	Global	Using existing technologies, around two-thirds of occupations could have one third of their constitutive tasks automated.

Source: Sources cited.

Estimates range from alarming scenarios, according to which there is a “50% chance of AI outperforming humans *in all tasks* within 45 years” (Grace et al., 2017, emphasis added), on the one hand, to contrasting claims of there being “no evidence that automation leads to joblessness” (Mishel & Bivens, 2017, p. 1), and the sarcastic recommendation that “everyone should take a deep breath” (Atkinson & Wu, 2017, p. 23).

The seminal study in the recent automation literature is that of Frey and Osborne (2013) for the US, and subsequent studies have reproduced and refined their methodology. They conclude that almost half of the US employment is ‘at risk’. In contrast, Arntz et al. (2016) occupies a middle ground in terms of optimism. The authors argue with some plausibility for a “task-based” rather than an—inevitably over-simplified—"occupation-based” approach to estimating automatability risk. Arntz et al. draw on data from an international survey of adult skills conducted across OECD countries which contains data on the tasks performed for each type of job. The authors use these data to impute a score of automatability, as well as the size of the population at “high risk” of automation. Interestingly, Russia’s occupational structure is deemed least automatable of the 21 countries considered, whereas Germany and Austria top the rank. Put differently, the country with the lowest gross domestic product (GDP) per capita (and per worker) in the data set considered by Arntz et al. (2016) shows the highest resilience to automation. Generally, there is no consistent relationship with GDP per capita and their score of automatability, though, in this OECD data set (which is thus based on a selection of structurally similar economies).

The McKinsey Global Institute (2017c) provides estimates of employment that is susceptible to automation for 52 countries, which is the most comprehensive global data set we know of. Overall, McKinsey is considerably more pessimistic with their estimates of mean automatability, being on average 10 percentage points above that of Arntz et al. Their estimates are more pessimistic in every country and considerably more pessimistic specifically regarding non-OECD countries.[12] Across Western OECD countries only, the estimates of Arntz et al. and McKinsey are, in fact, closely aligned (r^2=0.5). Their automatability estimates of industrialized economies such as Russia, Korea, and Japan, though, differ significantly, with McKinsey being considerably more pessimistic.

Another recent global estimate comes from the World Bank (2016) who provide data for 40 countries and are yet more pessimistic, with average estimates lying 20 percentage points above the McKinsey estimate. The overlap of country coverage between the World Bank and the McKinsey estimates is small (nine countries); among those, the shared variance is relatively low at about 12% (Table 4 shows selected countries). In addition to automatability estimates, the World Bank also provides adjusted estimates which take into account the different speeds of technology diffusion across countries.

Table 4. Estimates of proportion of employment that is automatable in selected countries

	MGI (2017c)	World Bank (2016)
Argentina	48%	65%
China	51%	77%
Costa Rica	52%	68%
Ethiopia	50%	85%
India	52%	69%
Malaysia	51%	68%
Nigeria	46%	65%
South Africa	41%	67%
Thailand	55%	72%

Sources: As cited.

In the next section, we explore the McKinsey Global Institute (2017c) and World Bank (2016) data in more detail.[13]

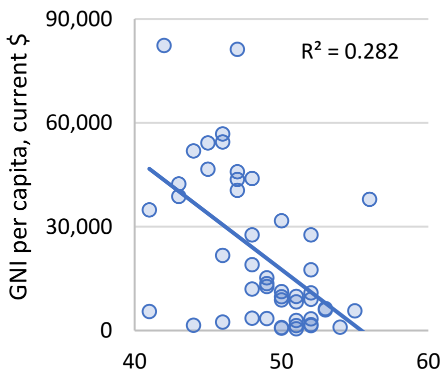
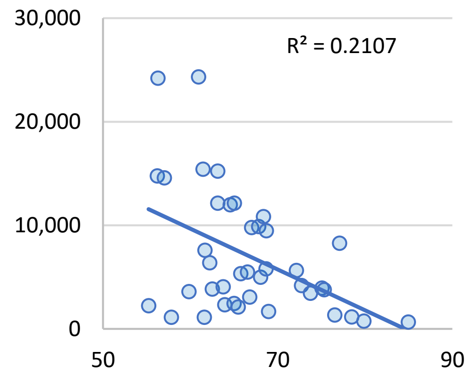
[12] A second MGI report (MGI 2017b) released later the same year was much less pessimistic. It estimated labor displacement at 400m jobs globally which would be offset by 555 million jobs created by increased labor demand.

[13] There are further data sets of IMF (2017) and UNCTAD (2017) which we do not have access to at time of writing.

4a. Empirical patterns of automatability and economic development

Instead of focusing on the levels of automatability per se, which remains fairly contentious we next discus the relationship of automatability and economic development.[14]

Figure 2 The level of economic development and the share of employment susceptible to automation

McKinsey Global Institute (2017c) automatability estimates	World Bank (2016) automatability estimates
	

Source: Authors' estimates based on sources cited.

The first observation to make (and one that was also made by Frey et al., 2016) is that automatability estimates show a relationship with the level of GNI per capita across countries in global comparison (Figure 2). Both sets of estimates are highly significantly ($p<0.01$) negatively correlated with gross national income (GNI) per capita. Thus, the richer an economy, the less automatable the labor force. That said, McKinsey's estimates range from a minimum

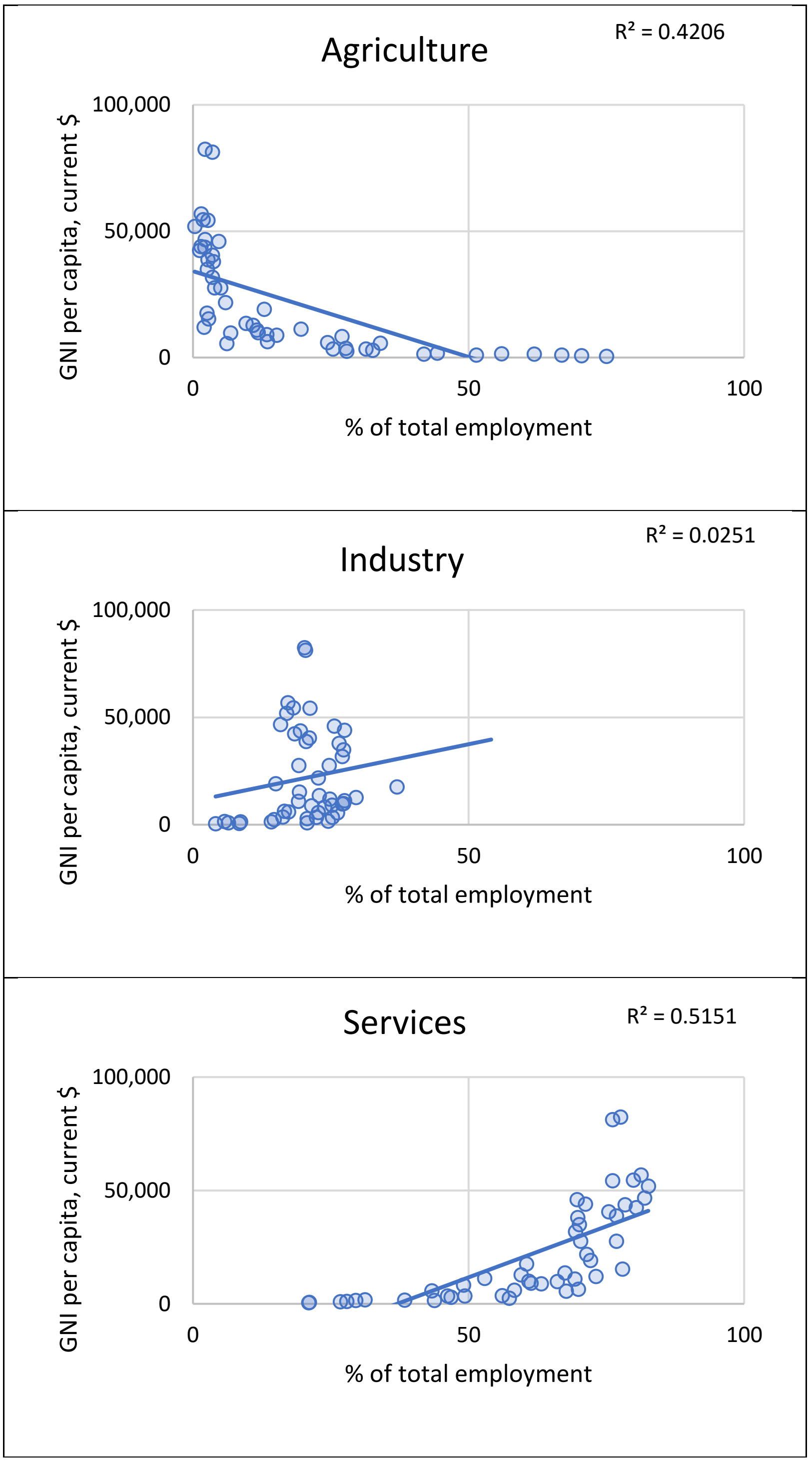
[14] We may overemphasise the technical feasibility angle in this section given the data we use which leads us to an inverse relationship between automatability and per capita income. At the current cost of automation, there is a positive relationship and the curve may turn into an inverted U as costs keeps falling and all jobs in developed countries have been automated, before eventually becoming negative; the question of course is how long away 'eventually' is. Thus our assessment may be too pessimistic.

of 41% to a maximum of 56% and the World Bank's from 55% to 85%, so even the most resilient countries could still see significant labor market disruption. It is interesting to note that the McKinsey Global Institute assigns the lowest automatability estimates to Kuwait and South Africa, the former an entirely oil-fueled Organization of the Petroleum Exporting Countries (OPEC) economy with practically no unemployment, and the latter having one of the highest unemployment rates and most segregated labor markets in the world. Overall, the median estimates of the McKinsey Global Institute for HICs (n=27) is 47, whereas the median for low-income countries (LICs) and lower middle-income countries (LMICs) (n=13) is 51.

It is worth at this point considering the structural characteristics of economies. Figure 3 reproduces the familiar cross-country pattern across three sectors, showing that rich countries generally have very low levels of employment in agriculture and high levels of service sector employment, with the reverse being the case for developing countries. The industry share of employment is uncorrelated with GNI per capita ($p>0.05$) from a cross-country perspective.

Given this overall structural pattern, what then is the relationship between automatability and sectoral characteristics? Figure 4 shows that the pattern is similar, though somewhat less pronounced, to the pattern of GNI per capita and automatability. The service sector share, in particular, is a strong predictor of both McKinsey's and the World Bank's automatability estimates. The more agrarian an economy is, the larger the population performing tasks that machines could theoretically perform.

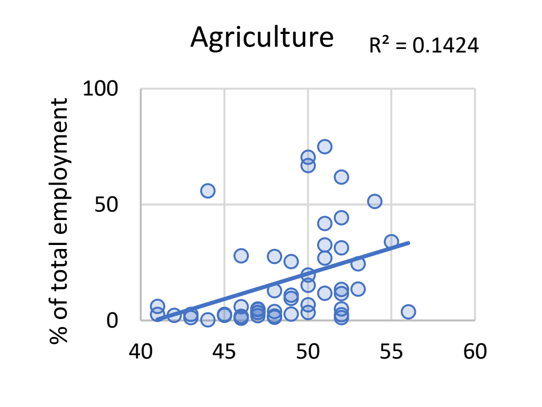
Figure 3 Employment by sectors and GNI per capita (2016 or most recent data)

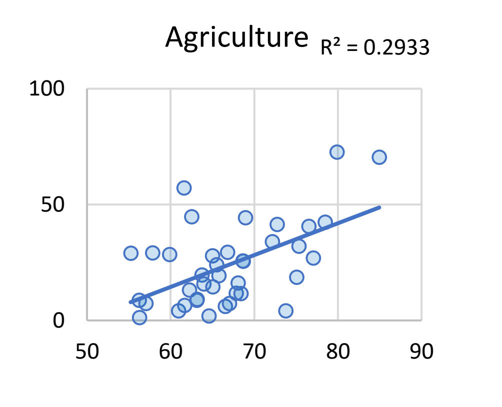


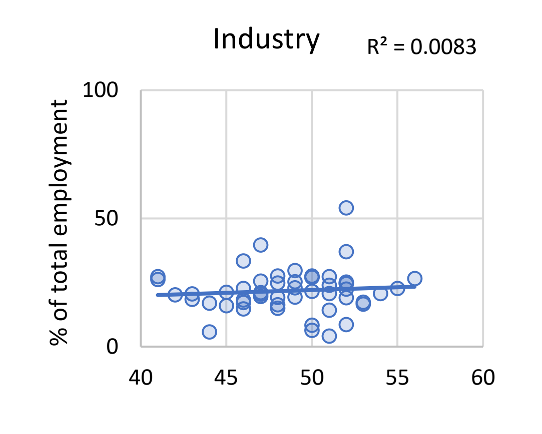
Source: Authors' estimates based on World Bank (2016).

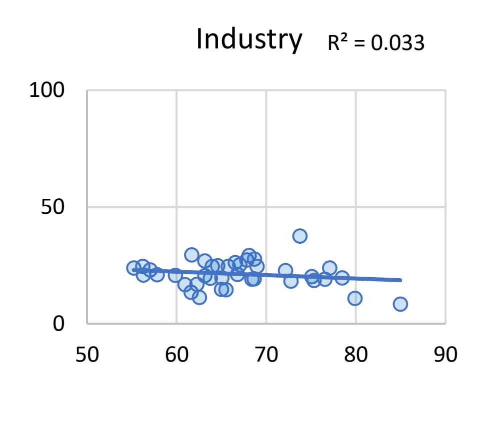
Figure 4 Automatability and share of employment by sectors, 2016

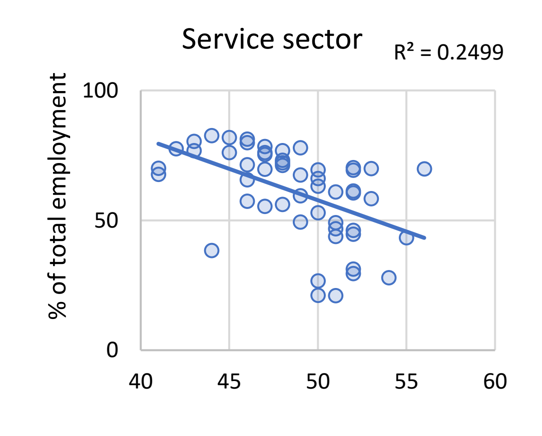
McKinsey Global Institute (2017c) automatability estimates	World Bank (2016) automatability estimates

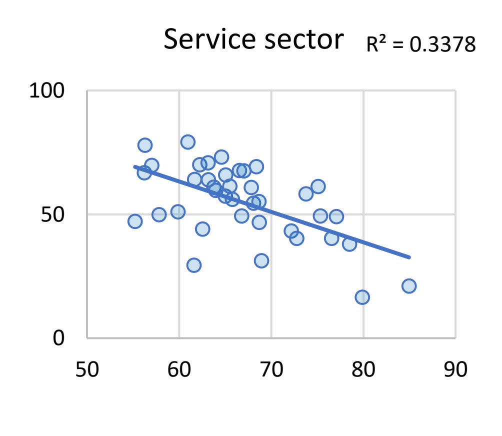












Source: Authors' estimates based on sources cited.

We can thus say, assuming the automatability estimates are reasonable, that the labor force of more service sector-based, richer economies tends to be less replaceable compared to more agriculture-based, poorer economies. This pattern is intuitive and is explained by the complexity and creativity of service-sector work and the amount of face-to-face human interaction involved in it. If we break down the relationship of sectoral employment by level of GNI per capita (Figure 5), the above-mentioned pattern largely holds. Among HICs, there is no relationship between agriculture and automatability simply because there is almost no employment in agriculture. Industrial work is more automatable and service-sector work less automatable across both country groupings, so the level of economic development does not moderate that sectoral relationship.[15]

Generally, we can say the APS is (much) larger in countries with lower income per capita. If countries have to decide how to reallocate employment during structural change and the described cross-country pattern allows any inference about country-level developments over time, an increase in service-sector employment would suggest itself as the only future-proof employment growth model. In HICs, it would suggest structural change away from industrial work and in developing countries away from agriculture.

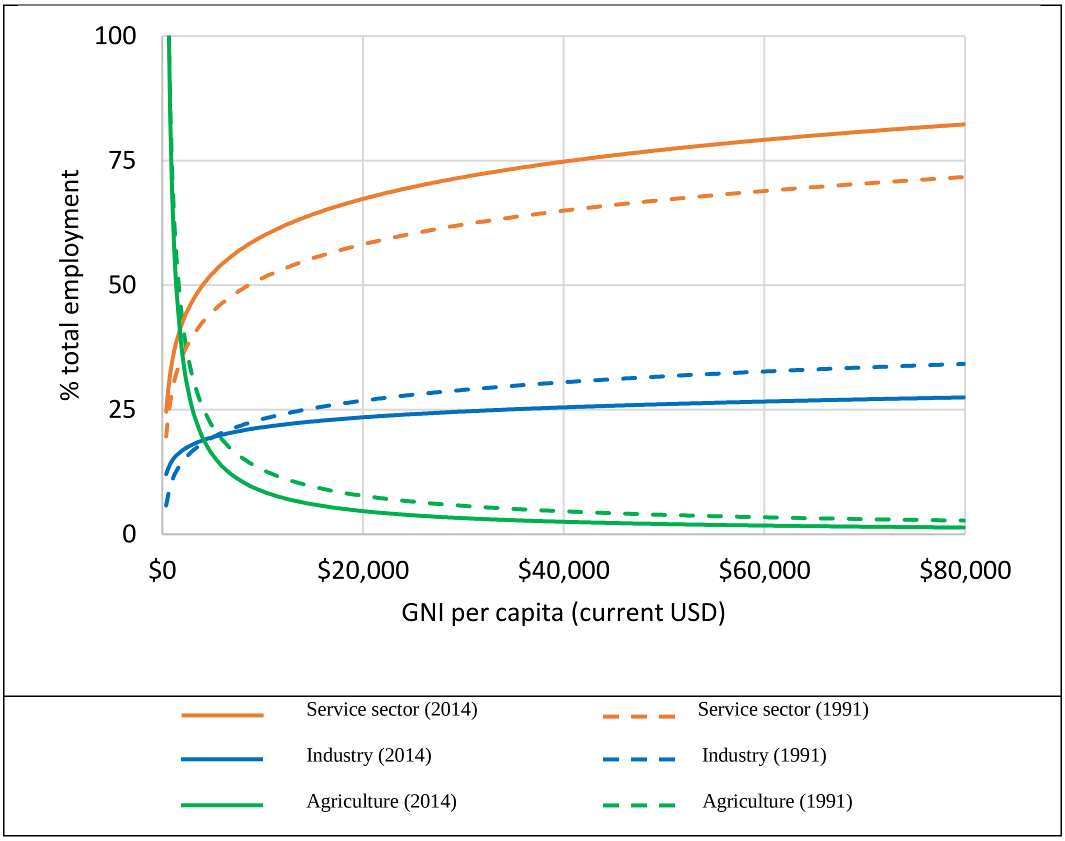
[15] There is a significant ($p<0.05$) positive correlation of industrial employment shares and automatability in HICs. This pattern is also found using the data of Arntz et al. (2016). It can similarly be observed in developing countries (non-HICs) in the McKinsey Global Institute (2017c) data where it is though not significant as data coverage is too limited.

Figure 5 McKinsey Global Institute's automatability estimates and employment across economic sectors by income group

Source: Authors' calculations based on McKinsey Global Institute (2017c) and World Bank (2016).

What does this mean for the future of economic development and structural transformation? Holding all else constant, sectoral differences in the replaceability of labor will sustain a pressure for both further deindustrialization and agriculturalization. This is not a new phenomenon: in fact, the cross-country pattern of sectoral employment shares shown earlier in Figure 3 and reproduced in Figure 6 to compare 1991 and 2014 (fitted lines) shows a surprising degree of continuity over time. What appears to be happening, though, is an expansion of service-sector employment in the richest countries, and a reduction in the share of industrial work compared to the early nineties (this pattern is corroborated by Wood, 2017). In line with this, Chandy (2017, p. 14) speculates that "China may be one of the last countries to ride the wave of industrialization to prosperity". Generally, most of the global cross-country variability of employment shares is found toward the low end of the GNI per capita, whereas countries above a per capita GNI of 20,000 look structurally very similar, i.e. are highly service-based and thus face lower automatability. In general, it is only in the poorest countries that a considerable proportion of labor is in agriculture. However, even in middle income developing countries such as Indonesia and Thailand, a third of the labor force remains in agriculture. Agriculture employs only a few per cent of labor force in wealthy countries. This suggests that in contrast to OECD countries, many jobs in developing countries have likely been automatable for a long time.

Figure 6 Economic development and sectoral employment shares across countries (fitted lines): 1991 and 2014



Source: Authors' estimates based on World Bank (2018) data. Logarithmic functions were used for fitting a line on the cross-country industry and service-sector shares, and power functions were used for agriculture.

5. Automation, politics, and public policy

The discussion thus far points towards the potential for major shifts in employment due to automation. This process will likely have socio-political consequences. Macroeconomic and labor market dynamics determine the quality, quantity, and distribution of citizens' employment opportunities and thus of their wages, living standards, and class status. Such socioeconomic characteristics in turn have a profound bearing on sentiments of (in)security, relative deprivation, and societal equity which can influence political preferences and ultimately political outcomes. There is a large body of literature providing evidence for a causal relationship of this sort (see e.g. for the impact on electoral politics: Anderson, 2000; Lewis-Beck & Stegmaier, 2000; for the impact on political preferences: Finseraas, 2009; Mughan, 2018; see also the substantial literature on economic and class voting, as well as the literature on economic modernization and political values, e.g. Inglehart & Welzel, 2005).

The wider interest in the role of work and (un)employment as underpinnings of political agency goes back to early empirical social research (e.g. Jahoda, Lazarsfeld, & Zeisel, 1933), and even to the classical social theory of Karl Marx and Max Weber. As technological change influences labor market dynamics, an important field of research is the examination of modernization losers as political catalysts: specifically, so-called “technological anxiety” and resistance to innovation (see Mokyr, 1998; Mokyr et al., 2015); the relationship of economic inequality, and political polarization and extremism (see Pontusson & Rueda, 2008); and the political implications of deindustrialization (see Iversen & Cusack, 2000).

Major political implications imply public policy responses. One can characterize policy responses to automation (Figure 7). First, there is a class of policies that try to attenuate or reverse the automation trend. Among those, there are “quasi-Luddite” measures such as taxes and regulation that make domestic automation more (or even prohibitively) costly. Countries could also follow a strategy of what one could call “robot-substituting industrialization” where they impose tariffs on inputs/imports with non-human-produced contents. The problem with such strategies is that protectionism of labor is difficult to implement in an open economy. Luddite policies tend to be in conflict with integration into a globalized competitive market, as they assume that the economy can somehow be insulated from competition with automated production elsewhere. The mirror image of making automation costlier would be to reduce the costs of labor, e.g. by reducing income taxes or social insurance contributions, by reducing minimum wages, or costly labor regulations. The question is how desirable and politically feasible such strategies are.

Second, there is a class of "coping strategies" for the trend toward automation. The most prominent one is to develop the skills of the labor force and (re)train workers in the APS. A widespread policy recommendation is to invest in skills and thus move the labor force away from automatable routine tasks. The problem with this approach is that (i) it is not clear what skills will be automation-resistant for a sufficient time to make the skills investment worthwhile and (ii) whether upskilling is at all realistic given the required time and monetary investment. Competition with currently available technology increasingly seems to require a tertiary education which is still very rare throughout the developing world. Given that even advanced industrialized countries are struggling to keep their labor forces competitive, the success of a skills development strategy alone remains questionable.

A second coping strategy would be to provide economic transition support as well as safety nets, unemployment insurance, or wage subsidies. This approach addresses the distributional skew which automation may create. However, such transfers presuppose the existence of a productive ARS in the first place, from which profits can be siphoned off for redistribution. In the absence of the existence of such a sector, there may be a case for the provision of international aid to support basic income guarantees or automation adjustment assistance overseas.

In many countries, one could say that the coping strategy adopted so far has been to invest in currently labor-intensive sectors such as infrastructure and construction. A—risky but potentially inevitable—long-term coping strategy for developing countries would be to anticipate automation trends and to try to (further) develop a productive post-industrial sector. If industrialization begins to look increasingly unattractive due to reshoring of hitherto outsourced production in value chains, countries would be well advised not to invest in the costly creation of manufacturing clusters but rather in the growth of a long-term ARS. Such an ARS could, for example, involve the social, education and health-care sectors, and some forms of tourism, and infrastructure construction which are generally considered resilient despite increasing service automation. The problem with such an approach is that highly productive and tradeable services are skills-intensive, and non-tradeable services (such as social care, personal services, etc.) are not (yet) highly value-adding, may not be sufficiently scalable, and may generally be too heterogenous to be targeted by post-industrial policies, in a similar way that industrial policies targeted the emergence of industrial clusters.

Figure 7 The space of potential public policy responses to automation

	Coping	Containment
Managing structural change	*Adaptability of labor* •Skills upgrading *Employment generation* •Post-industrialization/ARS •Investment in labor-intensive sectors •Public works programs	*Labor costs and regulation* •Tax cuts on labor •Wage subsidies •Lower minimum wage *Employment protection* •Job protection legislation *Automation costs and regulation* •Taxes on automation •Regulation that complicates automation •Tariffs on imports of non-primary goods
Managing inclusivity	*Unemployment protection* •Transition support •Unemployment insurance •Universal basic income •Active labor market policies	

Source: Authors' elaboration.

6. Conclusions

This paper has surveyed the literature on automation and in doing so discussed definitions and determinants of automation in the context of theories of economic development, assessed the empirical estimates of employment-related impacts of automation and outlined the public policy responses to automation. We have shown that the contentious debate on automation is not new. Its origins can be traced back to classical political economy and thinking on economic development, and both the optimistic and pessimistic camps that have emerged over time have made valid points. To understand the employment dynamics of automation-driven structural change, the paper used a simple framework in the tradition of W. Arthur Lewis (and William Baumol) and with recognition of Marx' reserve army thinking.

In conclusion, we would argue that the main implications of advances in technology and automation are not mass lay-offs and technological unemployment necessarily (though both are plausible under certain scenarios) in developing countries, but an increasing pressure toward deindustrialization and agriculturalization. Empirically, the impact of automation is complex to estimate, and most studies have tended toward technologically deterministic approaches. Theoretically, the net effect on jobs could be both positive (lower prices lead to higher quantities demanded and thus more labor demand) and also negative (displaced labor is not absorbed in the ARS). Manual routine work, especially in agriculture, remains prevalent throughout the developing world, which is an important concern. Overall, the focus of many studies on employment is arguably too narrow, and there are broader questions about the impact of the digital revolution on structural change and strategies of economic development to be addressed.

The developing world could well experience more negative impacts from automation than the developed world, since (i) there are substantially more jobs to be lost through labor-substituting technical progress than in the rich world and (ii) new industries may stop outsourcing production to the developing world. We argue that it is likely that real wages may stagnate rather than unemployment rise per se in the developing world which implies socio-political consequences. This line of argument is, of course, particularly tailored to the characteristics of labor-abundant open economies and may not be generalizable beyond that.

One way or another, technological innovation is causing disruption and thus poses questions for public policy. We would express skepticism about the often-voiced call for skills-based development strategies alone. Social safety nets, on the other hand, do seem to offer one strategy; yet, to the extent that they raise the cost of labor, could exacerbate the trend toward technological substitution. In this context, discussions about a living-wage level universal basic income (UBI) somewhat smack of a “first-world problem”: to be able to worry about the redistribution of profits due to productivity gains assumes the luxury of jurisdiction over those profits, which many developing countries may not have. So, what to do?

We see the policy space for developing countries split between coping and containment strategies and constrained by globalization. Protectionist trade policy in the North could well accelerate reshoring, and hence the impacts on the developing world that this paper discusses. In the long term, utopian as it may seem now, the moral case for an *global* UBI-style redistribution framework financed by profits from high-productivity production clusters in high-income countries may become overwhelming, but it is difficult to see how such a framework would be politically enacted. For the moment, in any case, workers in developing countries are facing an uphill battle against a growing “Robot Reserve Army”.

Avenues for future research are numerous. Here we simply set out a range of indicative questions. The core research question is, given a context of automation and digitalization, how are developing countries to increase the quantity and quality of employment growth? The core question can be broken down into three clusters of (indicative) sub-questions. First, regarding the poverty–employment nexus: How/when/why does productivity growth translate into employment growth? What determines the distribution of productivity gains in terms of the functional distribution of income between capital and labor? Second, regarding the automation–employment nexus: Which tasks are being automated and by when? How do automation and digitalization impact different developing countries, considering their specific production, employment, and export structures, and differing contexts? Third, regarding political and policy implications: What have been or are likely to be the political consequences of changes in employment due to automation and digitalization? Under what conditions and circumstances can technological change and deindustrialization be inclusive? What factors incentivize and constrain the adoption of labor-saving technologies? And how have national and sub-national governments responded to date? How have existing deindustrialization, automation, and its socioeconomic effects expressed themselves (or not) politically? What are the public policy options for governments? In sum, there are numerous questions arising for the future of economic development that automation throws up. Understanding the more precise impacts of automation on the economic development of developing countries can only be well understood if such questions are urgently pursued.

In conclusion, we would make three points. First, automation is challenging the competitive advantage of low-cost labor of late developers. Second, many developing countries have a vulnerable labor force in terms of wage stagnation and premature deindustrialization could loom. However, unemployment is not (yet) the problem. Third, we need to ask different policy and research questions and be concerned about the jobs impact of technology and the political economy of automation rather than just automatability in principle. In that vein the Lewis model and surplus labor theory could once more help us understand the dynamics of economic development and structural transformation.

References

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In O. Ashenfelter & D. Card (Eds.), *Handbook of Labor Economics* (Vol. 4B, pp. 1043–1171). Amsterdam: Elsevier.

Acemoglu, D., & Restrepo, P. (2015). The race between machine and man: Implications of technology for growth, factor shares and employment. *SSRN Electronic Journal*, DOI: 10.2139/ssrn.2781320

Acemoglu, D., & Restrepo, P. (2017). *Robots and jobs: Evidence from US labor markets*. NBER Working Paper Series No. 23285. Cambridge, MA: NBER. Retrieved from http://www.nber.org/papers/w23285

Acemoglu, D., & Robinson, J. A. (2000). Political losers as a barrier to economic development. *American Economic Review Papers and Proceedings*, *90*, 126–130.

ADB (Asian Development Bank) (2018) Asian Development Outlook 2018: How Technology Affects Jobs. Manila: ADB.

Ahmed, M. (2017). “Technological Revolution and the Future of Work.” Center for Global Development Blog. Retrieved from: https://www.cgdev.org/blog/technological-revolution-and-future-work (May 25, 2018).

Aisyah, R. (2017, November 3). No layoffs after full cashless payment: Toll road operator. *The Jakarta Post*. Retrieved from http://www.thejakartapost.com/news/2017/11/03/no-layoffs-after-full-cashless-payment-toll-road-operator.html

Anderson, C. J. (2000). Economic voting and political context: A comparative perspective. *Electoral Studies, 19*(2–3), 151–170.

Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis. *OECD Social, Employment and Migration Working Papers, 2*(189), 47–54.

Atkinson, A. B. (2009). Factor shares: The principal problem of political economy. *Oxford Review of Economic Policy, 25*(1), 3–16.

Atkinson, A. B., & Bourguignon, F. (2014). Introduction: Income distribution today. In A. B. Atkinson & F. Bourguignon (Eds.), *Handbook of Income Distribution, Volume 2A* (pp. xvii–lxiv). Oxford and Amsterdam: Elsevier.

Atkinson, R. D., & Wu, J. (2017). *False alarmism: Technological disruption and the U.S. labor market, 1850–2015*. @Work Series. Retrieved from http://www2.itif.org/2017-false-alarmism-technological-disruption.pdf

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US Labor Market. *American Economic Review, 103*(5), 1553–1597.

Autor, D. H., Katz, L. F., & Kearney, M. S. (2004). The polarization of the U.S. labor market. *AEA Papers and Proceedings, 96*(2), 189–194.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics, 118*(4), 1279–1333.

Avent, R. (2017). *The wealth of humans: Work and its absence in the twenty-first century*. London: Penguin Random House.

Barany, Z. and Siegel, C. (2014). Job Polarization and Structural Change. Retrieved from https://www.aeaweb.org/conference/2015/retrieve.php?pdfid=237.

Baumol, W. J. (1967). Macroeconomics of unbalanced growth: The anatomy of urban crisis. *The American Economic Review, 57*(3), 415–426.

Baumol, W. J., Anne, S. U. E., Blackman, B., & Wolff, E. N. (1985). Unbalanced growth revisited: Asymptotic stagnancy and new evidence. *The American Economic Review*, *75*(4), 806–817.

Frey, C. B., & Osborne, M. A. (2013). *The Future of Employment: How Susceptible Are Jobs to Computerisation?* Oxford Martin School, University of Oxford Working Paper. University of Oxford, UK. Retrieved from https://www.oxfordmartin.ox.ac.uk/downloads/academic/future-of-employment.pdf

Berman, E., Bound, J., & Machin, S. (1998). Implications of skill-biased technological change: International evidence. *The Quarterly Journal of Economics, 113*(4), 1245–1279.

Bessen, J. (2016). *How computer automation affects occupations: Technology, jobs, and* *skills* (Law & Economics Working Paper No. 15–49). Boston, MA. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2690435

Betcherman, G. (2012). *Labor market institutions: A review of the literature*. World Bank Policy Research Working Paper Series No. 6276. Washington, DC: World Bank.

Brynjolfsson, E., & McAfee, A. (2011). *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy*. Lexington, MA: Digital Frontier Press.

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

Castells, M. (2010). *The rise of the network society: The information age: economy, society, and culture*. Hoboken, NJ: Wiley Blackwell.

Chandy, L. (2017). *The future of work in the developing world. Brookings Blum roundtable 2016 post-conference report*. Washington, DC: Brookings Institution.

Chang, J.-H., & Huynh, P. (2016). *ASEAN in Transformation: The future of jobs at risk of automation* (Bureau for Employers' Activities Working Paper No. 9). Bangkok. Retrieved from http://www.ilo.org/wcmsp5/groups/public/---ed_dialogue/---act_emp/documents/publication/wcms_579554.pdf

Christensen, C. (1997). *The innovator's dilemma: When new technologies cause great firms to fail*. Boston, MA: Harvard Business Review Press.

Clark, G. (2008). *A farewell to alms: A brief economic history of the world*. Princeton, NJ and Oxford: Princeton University Press.

DeLong, B. (2015). *Technological progress anxiety: Thinking about "peak horse" and the possibility of "peak human".* Retrieved from http://equitablegrowth.org/equitablog/technological-progress-anxiety-thinking-about-peak-horse-and-the-possibility-of-peak-human/

Deny, S. (2017, August 24). Sri mulyani khawatir generasi muda ri kalah dengan robot. *Liputan 6*. Retrieved from http://bisnis.liputan6.com/read/3069606/sri-mulyani-khawatir-generasi-muda-ri-kalah-dengan-robot

Diao, X., McMillan, M., Rodrik, D., & Kennedy, J. F. (2017). *The recent growth boom in developing economies: A structural-change perspective*. NBER Working Paper Series No. 23132. Cambridge, MA: NBER. Retrieved from http://www.nber.org/papers/w23132

Eastwood, R., Kirsten, J., & Lipton, M. (2007). Premature deagriculturalisation? Land inequality and rural dependency in Limpopo province, South Africa. *The Journal of Development Studies, 42*(8), 1325–1349.

Executive Office of the President of the United States. (2016). *Preparing for the future of artificial intelligence*. Washington, DC. Retrieved from https://obamawhitehouse.archives.gov/sites/default/files/whitehouse_files/microsites/ostp/NSTC/preparing_for_the_future_of_ai.pdf

Finseraas, H. (2009). Income inequality and demand for redistribution: A multilevel analysis of European public opinion. *Scandinavian Political Studies, 32*(1), 94–119.

Firpo, S. P., Fortin, N. M., & Lemieux, T. (2011). *Occupational tasks and changes in the wage structure*.IZA Discussion Paper No. 5542). Bonn: IZA. Retrieved from http://ftp.iza.org/dp5542.pdf

Francese, M., & Mulas-Granados, C. (2015). *Functional income distribution and its role in explaining inequality*. IMF Working Papers 15/244. Washington, DC: IMF. Retrieved from https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Functional-Income-Distribution-and-Its-Role-in-Explaining-Inequality-43415

Frey, C. B., Osborne, M. A., & Holmes, C. (2016). *Technology at work v2.0: The future is not what it used to be* (Citi GPS: Global Perspectives & Solutions). Oxford. Retrieved from http://www.oxfordmartin.ox.ac.uk/downloads/reports/Citi_GPS_Technology_Work_2.pdf

Frey, C. B. and E. Rahbari. 2016. Do Labor-Saving Technologies Spell the Death of Jobs in the Developing World. Paper prepared for the 2016 Brookings Blum Roundtable.

Goldin, C., & Katz, L. F. (2007). *The race between education and technology: The evolution of U.S. educational wage differentials, 1890 to 2005*. NBER Working Paper Series No. 12984. Cambridge, MA: NBER. Retrieved from http://www.nber.org/papers/w12984

Goos, M., & Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *Review of Economics and Statistics, 89*(1), 118–133.

Grace, K., Salvatier, J., Dafoe, A., Zhang, B., & Evans, O. (2017). *When will AI exceed human performance? Evidence from AI experts* (arXiv No. 1705.08807v2). Retrieved from http://arxiv.org/abs/1705.08807

Granstrand, O. (1994). *Economics of technology*. Amsterdam: North-Holland.

Hall, B. H., & Khan, B. (2003). *Adoption of new technology*. NBER Working Paper Series No. 9730.Cambridge, MA: NBER. Retrieved from http://www.nber.org/papers/w9730

Hallward-Driemeier, M. and Nayyar, G. (2017). Trouble in the Making? : The Future of Manufacturing-Led Development. Washington, DC: World Bank.

Harari, Y. N. (2016). *Homo deus: A brief history of tomorrow*. London: Harvill Secker.

Heintz, J. (2009). *Employment, economic development and poverty reduction: Critical issues and policy challenges*. Geneva: UNRISD.

Herrendorf, B., Rogerson, R., & Valentinyi, A. (2014). *Growth and structural transformation*. NBER Working Paper Series No. 18996. Cambridge, MA: NBER. Retrieved from http://www.nber.org/papers/w18996

IFR. (2016). *Executive summary: world robotics 2016 service robots* (International Federation of Robotics). Retrieved from http://www.ifr.org/fileadmin/user_upload/downloads/World_Robotics/2016/Executive_Summary_WR_Industrial_Robots_2016.pdf

IGM Panel. (2014, February 25). Robots. *IGM Forum*. Retrieved from http://www.igmchicago.org/surveys/robots

ILO. (2017). *The future of work we want: A global dialogue*. Geneva: International Labor Organization. Retrieved from http://www.ilo.org/global/topics/future-of-work/WCMS_570282/lang--en/index.htm

IMF. (2017). *World Economic Outlook, April 2017: Gaining momentum?* Washington, DC: IMF. Retrieved from http://www.imf.org/en/Publications/WEO/Issues/2017/04/04/world-economic-outlook-april-2017

Inglehart, R., & Welzel, C. (2005). *Modernization, cultural change, and democracy: The human development sequence*. Cambridge and New York, NY: Cambridge University Press.

Iversen, T., & Cusack, T. R. (2000). The causes of welfare state expansion: Deindustrialization or globalization. *World Politics*, *52*(3), 313–349.

Jahoda, M., Lazarsfeld, P. F., & Zeisel, H. (1933). *Marienthal: The sociography of an unemployed community*. Leipzig: Hirzel Verlag.

Jakarta Globe. (2017, October 13). Indonesia to consider universal basic income. *Jakarta Globe.* Retrieved from http://jakartaglobe.id/business/indonesia-to-study-universal-basic-income/

Jakarta Post. (2017, September 14). Non-cash toll will affect 10,000 workers in Jakarta. *The Jakarta Post*. Retrieved from http://www.thejakartapost.com/news/2017/09/14/non-cash-toll-will-affect-10000-workers-in-jakarta.html

Jefriando, M. (2017, October 12). Sri mulyani bicara soal robot ancam pekerjaan manusia. *Detik*. Retrieved from https://finance.detik.com/berita-ekonomi-bisnis/3680492/sri-mulyani-bicara-soal-robot-ancam-pekerjaan-manusia

Kanbur, R. (2016). 'W. Arthur Lewis and the Roots of Ghanaian Economic Policy', Working Paper. Charles H. Dyson School of Applied Economics and Management Cornell University, Ithaca, New York.

Katz, L. F., & Autor, D. H. (1999). Changes in the wage structure and earnings inequality. In O. Ashenfeher & D. Card (Eds.), *Handbook of Labor Economics* (Vol. 3, pp. 1463–1555). Amsterdam: Elsevier.

Katz, L. F., & Murphy, K. M. (2013). Changes in relative wages, 1963-1987: Supply and demand factors. *The Quarterly Journal of Economics*, *107*(1), 35–78.

Kuznets, S. (1971). *Modern economic growth: Findings and reflections. Lecture to the memory of Alfred Nobel*. Stockholm: The Nobel Foundation. Retrieved from http://www.nobelprize.org/nobel_prizes/economic-sciences/laureates/1971/kuznets-lecture.html

Lacity, M. and Willcocks, L. P. (2018). *Robotic Process and Cognitive Automation: The Next Phase.* Stratford: Steve Brookes Publishing.

Leontief, W., & Duchin, F. (1984). The impacts of automation on employment, 1963–2000. *CATESOL Journal, 5*(1), 1963–2000. Retrieved from http://files.eric.ed.gov/fulltext/ED241743.pdf

Lewis, W. A. (1954). Economic development with unlimited supplies of labour. *The Manchester School of Economic and Social Studies, 22*(2), 139–191.

Lewis-Beck, M. S., & Stegmaier, M. (2000). Economic determinants of electoral outcomes. *Annual Review of Political Science, (3)*, 183–219.

Marx, K. (2012 [1867]). *Das Kapital: A critique of political economy*. Washington, DC: Regnery Publishing.

McKinsey Global Institute. (2017a). *A future that works: Automation, employment, and productivity*. Retrieved from https://www.mckinsey.com/~/media/McKinsey/Global%20Themes/Digital%20Disrupti on/Harnessing%20automation%20for%20a%20future%20that%20works/MGI-A-future-that-works_Full-report.ashx

McKinsey Global Institute. (2017b). *Jobs lost, jobs gained: Workforce transitions in a time of automation*. Retrieved from https://www.mckinsey.com/~/media/McKinsey/Global%20Themes/Future%20of%20Organizations/What%20the%20future%20of%20work%20will%20mean%20for%20jobs%20skills%20and%20wages/MGI-Jobs-Lost-Jobs-Gained-Report-December-6-2017.ashx

McKinsey Global Institute. (2017c). *Where machines could replace humans — and where they can't (yet)*. Retrieved from https://public.tableau.com/en-us/s/gallery/where-machines-could-replace-humans

McMillan, M. S., & Rodrik, D. (2011). *Globalization, structural change and productivity growth*. NBER Working Paper Series No. 17143. Cambridge, MA: NBER. Retrieved from http://www.nber.org/papers/w17143

Mishel, L., & Bivens, J. (2017). *The zombie robot argument lurches on: There is no evidence that automation leads to joblessness or inequality*. Washington, DC: Economic Policy Institute. Retrieved from http://www.epi.org/files/pdf/126750.pdf

Mokyr, J. (1998). The political economy of technological change: Resistance and innovation in economic history. In M. Berg & K. Bruland (Eds.), *Technological Revolutions in Europe* (pp. 39–64). Cheltenham: Edward Elgar Publishers.

Mokyr, J., Vickers, C., & Ziebarth, N. L. (2015). The history of technological anxiety and the future of economic growth: Is this time different? *Journal of Economic Perspectives*, *29*(3), 31–50.

Mughan, A. (2018). Economic insecurity and welfare preferences: A micro-level analysis. *Comparative Politics 39*(3), 293–310. Retrieved from http://www.jstor.org/stable/20434042

Ngai, L. R., & Pissarides, C. A. (2017). Structural change in a multi-sector model of growth. *American Economic Review 97*(1), 429–443.

Office for National Statistics. (2013). *170 years of industrial change across England and Wales*. Retrieved from http://webarchive.nationalarchives.gov.uk/20160106001413/http://www.ons.gov.uk/ons/rel/census/2011-census-analysis/170-years-of-industry/170-years-of-industrial-changeponent.html

Palma, J. G. (2005). Four sources of "de-industrialization" and a new concept of the "Dutch Disease". In J. A. Ocampo (Ed.), *Beyond Reforms: Structural Dynamic and Macroeconomic Vulnerability* (pp. 71–116). Palo Alto, CA and Washington, DC: Stanford University Press and World Bank.

Parente, S. L., & Prescott, E. C. (1994). Barriers to technology adoption and development. *Journal of Political Economy*, *102*(2), 298–321.

Pontusson, J., & Rueda, D. (2008). Inequality as a source of political polarization: A comparative analysis of twelve OECD countries. In P. Beramendi & C. Anderson (Eds.), *Democracy, Inequality, and Representation: A Comparative Perspective* (pp. 312–353). New York: Russell Sage Foundation.

Praditya, I. I. (2017, August 17). 72 tahun merdeka, ri masih hadapi deindustrialisasi. *Liputan 6*. Retrieved from http://bisnis.liputan6.com/read/3061377/72-tahun-merdeka-ri-masih-hadapi-deindustrialisasi

PWC (PricewaterhouseCoopers) (2017). UK Economic Outlook

Ricardo, D. (2010). On the Principles of Political Economy, and Taxation. Urbana, Illinois: Project Gutenberg.
http://www.gutenberg.org/files/33310/33310-h/33310-h.htm.

Rodrik, D. (2016). Premature deindustrialization. *Journal of Economic Growth 21*(1), 1–33.

Roine, J., & Waldenström, D. (2014). *Long-run trends in the distribution of income and wealth*. IZA Discussion Paper No. 8157. Bonn: IZA. Retrieved from http://ftp.iza.org/dp8157.pdf

Saragih, F. A. (2017, September 16). Otomatisasi tol dianggap kejahatan. *Kompas.com*. Retrieved from http://ekonomi.kompas.com/read/2017/09/16/080100530/otomatisasi-tol-dianggap-kejahatan

Schumpeter, J. A. (1943). *Capitalism, socialism and democracy*. Abingdon-on-Thames: Routledge.

Schwab, K. (2016). *The fourth industrial revolution*. Geneva: Portfolio Penguin.

Siegel, D. S., Waldman, D. A., & Youngdahl, W. E. (1997). The adoption of advanced manufacturing technologies: Human resource management implications. *IEEE Transactions on Engineering Management*, *44*(3), 288–298.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, *70*(1), 65–94.

Solow, R. M. (1964). *The nature and sources of unemployment in the United States*. Stockholm: Almqvist & Wicksell.

Srnicek, N. (2017). *Platform capitalism*. Cambridge and Malden, MA: Polity Press.

Summers, L. H. (2013). Economic possibilities for our children: The 2013 Martin Feldstein lecture. *NBER Reporter, (4),* 4–6. Retrieved from http://www.nber.org/reporter/2013number4/2013no4.pdf

Tempo. (2015, December 14). Provinsi di Indonesia ini alami gejala deindustrialisasi. *Tempo.co.* Retrieved from https://bisnis.tempo.co/read/727694/provinsi-di-indonesia-ini-alami-gejala-deindustrialisasi

Tempo. (2016a, January 12). Bali bans the operation of Uber Taxi. *Tempo.co.* Retrieved from https://en.tempo.co/read/news/2016/01/21/056738210/Bali-Bans-the-Operation-of-Uber-Taxi

Tempo. (2016b, March 21). Protes Uber dan Grab, sopir se-Jakarta akan unjuk rasa. *Tempo.co.* Retrieved from https://metro.tempo.co/read/755352/protes-uber-dan-grab-sopir-se-jakarta-akan-unjuk-rasa

Tempo. (2016c, September 27). 200 Ribu pekerja terancam phk karena otomatisasi gardu tol. *Tempo.co*. Retrieved from https://bisnis.tempo.co/read/807738/200-ribu-pekerja-terancam-phk-karena-otomatisasi-gardu-tol

Tempo. (2017, February 20). Era Digital, jumlah pengangguran meningkat. *Tempo.co*. Retrieved from https://tekno.tempo.co/read/848320/era-digital-jumlah-pengangguran-meningkat

The Guardian. (2016, March 22). Traffic chaos and violence as thousands of taxi drivers protest against Uber in Jakarta. *The Guardian*. Retrieved from https://www.theguardian.com/world/2016/mar/22/traffic-chaos-and-violence-as-thousands-of-taxi-drivers-protest-uber-in-jakarta

Tinbergen, J. (1974). Substitution of graduate by other labour. *Kyklos*, *27*(2), 217–226.

Tinbergen, J. (1975). Substitution of academically trained by other manpower. *Review of World Economics*, *111*(3), 466–476.

UNCTAD. (2017). *Trade and development report 2017 – beyond austerity: Towards a global new deal*. New York and Geneva: UNCTAD.

UNDP. (2015). *Work for human development. Human development report*. New York: UNDP.

UNIDO. (2016). *Industrial development report 2016: The role of technology and innovation in inclusive and sustainable industrial development*. Vienna: UNIDO.

Willcocks, Leslie P., and Mary Lacity. (2016). Service Automation: Robots and the Future of Work. Steve Brookes Publishing: Stratford.

Williams, R., & Edge, D. (1996). The social shaping of technology. *Research Policy*, *25*(6), 865–899.

Wood, Adrian. (2017). Variation in Structural Change around the World, 1985–2015: Patterns, Causes, and Implications. UNU-WIDER Working Paper. UNU-WIDER: Helsinki. Retrieved from: https://www.wider.unu.edu/sites/default/files/wp2017-34.pdf.

World Bank. (2013). *World Development Report: Jobs.* Washington, DC: World Bank.

World Bank. (2016). *World Development Report: Digital dividends*. Washington, DC: World Bank.

World Bank. (2018). *World development indicators*. Retrieved from data.worldbank.org/data-catalog/world-development-indicators

World Economic Forum. (2017a). *Impact of the fourth industrial revolution on supply chains*. Geneva: WEF.

World Economic Forum. (2017b). *The future of jobs and skills in the Middle East and North Africa: Preparing the region for the fourth industrial revolution* (Executive Briefing). Geneva: WEF.

Yan, A. (2017, June 12). Beijing's first driverless subway line starts test run. *CGTN*. Retrieved from https://news.cgtn.com/news/3d557a4d3249444e/share_p.html

Yusuf, S. (2017). "Automation, AI, and the Emerging Economies." Center for Global Development Blog. Retrieved from https://www.cgdev.org/publication/automation-ai-and-emerging-economies (May 25, 2018).