Technequality

Understanding the relation between technological innovations and social inequality

Deliverable D6.2

Is this Time Really Different?
Evidence on the Impact of Technological Revolutions

Version 1.0

31-12-2021

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330

Deliverable	:	D6.2
Title	:	Is this time really different? Evidence on the Impact of Technological Revolutions
Work package	:	WP9
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Reviewer	:	Raymond Montizaan
Document type	:	R
Document level	:	PU
Date	:	31-12-2021
Status	:	final version

TECHNEQUALITY partners

ROA Universiteit Maastricht

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CE Cambridge Econometrics Ltd.

SOFI Stockholms University

WZB Wissenschaftszentrum Berlin für Sozialforschung GGmBH

EUI European University Institute

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330

Document change log

Version	Date	Comments
V0.1	18-04-2021	First draft document
V0.2	11-05-2021	Revision and update of initial document by M. Grigutsch
V0.3	12-06-2021	Comments M. Levels,
V0.4	21-12-2021	Revision by M. Levels
V0.5	24-12-2021	Comments by P. Koutroumpis
V1.0	31-12-2021	Minor additions Mark Levels

Verification and approval

Name	Date	Comments
M. Levels	21-08-2021	-
P. Koutroumpis	31-12-2021	-

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Description of the work package

Some predict that the impact of current waves of automation and robotics on the labour market will substantially be different from the one of earlier waves of technological progress. Due to developments in machine learning, increased computing power, and robotics, many machines may turn from tools into workers and soon outcompete human labour in many jobs. Whether the current developments are as disruptive as some believe them to be is still subject to heated debate. This essay aims to nourish this debate by discussing the state-of-the art of relevant research.

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1. AI.pocalypse Now?

Are machines coming for our jobs? A superficial scan of some of the headlines published in the international press over the past couple of years can from time to time certainly give one the impression that the end of human labour is nigh. The BBC reported on November 29, 2017, that Robot automation will "take 800 million jobs by 2030". On April 18, 2018, The Guardian warned that robots "will take our jobs" and that we "better plan for it before it's too late". On April 25, 2019, Le Monde cited an OECD report, headlining that "Robotization is expected to kill 14% of jobs within 20 years". A little earlier, on July 7th, 2018, the New York Times was quite certain that automation will also hit the middle class, headlining ominously: "High-Skilled White-Collar Work? Machines Can Do That, Too."

The argument behind these ominous headlines appears simple. Jobs are little bundles of tasks. Ample evidence suggests that machines that are powered by AI have the potential to become better at performing more tasks autonomously. Machines have beaten experts at games like chess, go, and poker, and have learned how to play arcade games. Machines have learned how to read and do math better than the vast majority of humans (Elliot, 2017). At least one expert maintains that machines can soon learn to perform every task that requires no more than two minutes of thought. However, not all commentators are convinced that AI will usher in the demise of human labour. The Süddeutsche Zeitung asserted on May 31st, 2018, that robots "will never replace humans". In a special report of April 10th, 2021, The Economist was quite confident: "Robots threaten jobs less than fearmongers claim".

The confusion expressed by the headlines above illustratively reflects the fact that scientists do not agree on what the future will plausibly bring. The news articles all cite freshly published reports and empirical studies, whose predictions about the impact on jobs differs spectacularly. Some expect 60% of all jobs to disappear; others assume it will be 4%. Few actually take job creation into consideration. Systematic literature reviews confirm that empirical research about the impact of AI and AI-driven technology on work is anything but conclusive (Lane and Saint-Martin, 2021; Balliester and Elsheikhi, 2018; Khani-Shekarab & Khani-shekarab, 2021; Chi, Denton & Gursoy, 2020; Au-Yong-Oliveira et al., 2019). Further

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adding to this uncertainty is the doubtful applicability of empirical research to predict the future. Predictions are difficult in any case, not least about potentially disruptive technologies, as science by virtue of its methodological directive to base all inferences solely on past empirical observations is ill-equipped to make them. Current trends are based on data from the past and cannot just be extrapolated into the future without making – sometimes implausible – assumptions. Their predictive power relies quite heavily on the extent to which these assumptions are, in fact, correct.

Worries about effects of technological transformations are, of course, of all ages. Classic economic and social thinkers have regularly discussed the disruptive potential of machines. David Ricardo for example argued that, if machines could eliminate the need for much of human labour, wages for workers could well fall below subsistence level (Frey, 2019, p. 9; Brynjolfsson & McAfee, 2011, p. 38). John Maynard Keynes famously coined the concept of ‘technological unemployment’, which he defined as “unemployment due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour” (Levels, Somers, & Fregin, 2019, p. 4). He predicted that technological unemployment was possible (Keynes, 2010 [1930]); a prediction that more recently was taken up by thinkers about robotization (Leontiev, 1983 and Ford, 2015). Keynes also considered long term effects on human labour: roughly by the year 2030, he thought, the work week would be reduced to fifteen hours (Keynes, 2010 [1930]). Classical thinkers also argue that technology would change the nature of work. Adam Smith (1801, p. 1040) maintained that the division of labour would not just raise productivity, but also increase the monotony of those working in mechanized factories. And of course, Karl Marx argued that the division of labour and the technological means of production would lead to estrangement of workers from the products of their labour, from the labouring process, from humanity, and from one another (Marx, 1844).

The fact is, though, that most of the more extreme predictions have not come to pass. Most pertinently, mass technological unemployment thus far remains a theoretical possibility. So, the question one has to ask is: why would this Fourth Industrial Revolution be any different from the previous ones? Why would artificial intelligence mark the advent of something fundamentally different, be it better or worse? What evidence is available to help us

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understand what the impact of artificial intelligence on work and workers? And how sound is that evidence?

First, what would make this time different? Many scholars identify artificial intelligence (AI) as the key technology in current economic changes. The US government (2016, p. 8) and the UN (Bruckner et al., 2017, p. 5) have characterized the technologies of the first and second industrial revolutions as replacements for muscle power, whereas digital technologies are substitutes for brainpower. Schwab (2015) argues that current advances are “characterized by a fusion of technologies that is blurring the lines between the physical, digital, and biological spheres” (in short, cyber-physical systems), amongst which artificial intelligence is one of many other relevant sources, such as “robotics, the Internet of Things, autonomous vehicles, 3-D printing, nanotechnology, biotechnology, materials science, energy storage, and quantum computing”. According to Schwab, it is in the combination of these that we find the fundamental difference with previous waves of technological revolutions.

Various commentators insist that the societal consequences of the Fourth Industrial Revolution could be severe, if we do not put policies into place to cushion these consequences (Schwab, 2015; Brynjolffson and McAfee, 2014; Levels, Somers, & Fregin, 2019). Given the scope of the potential societal impact automation could have, reducing uncertainty is of crucial importance for understanding and managing its risk. This essay therefore aims to aid our understanding of the societal risks that automation poses for labour markets, work, and workers. It provides an overview of the scholarly discourse surrounding the effects of artificial intelligence on the labour market.

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2. Theoretical and historical considerations

Historical overview of technology and employment

The end of work is proclaimed regularly, for example by Jeremy Rifkin in his 1995 book with the same title, through the angle that less and less human labour would be needed to produce the goods and services we desire. Brynjolfsson and McAfee (2011) subscribe to similar 'end of work' arguments. Daniel Susskind (2020) also talks about a world without work.

So why has this not happened yet? Macroeconomic theory offers various explanations. If human labour is increasingly substituted by machines, three types of compensating general equilibrium mechanisms can prevent mass unemployment. First, automation can make production more efficient, which decreases prices of goods, which leads to a higher demand for these now cheaper goods; this could not only compensate for (a part of) the initial loss of employment, but also shift spending in favour of human-produced goods and thereby create jobs in labour intensive sectors. Second, automation increases productivity, which in turn may increase labour demand in jobs with non-automated tasks. Third, even when unemployment rises several redistributive and re- skilling policies have been and can further be put in place. Education systems ensure that workers are endowed with human capital, progressive tax systems redistribute wealth to limit capital accumulation.

The optimists

There are ample historical observations to support the view that mass unemployment is not a likely outcome (David, 1990; Frey, 2019; Mokyr, Vickers, & Ziebarth, 2015). Although no comprehensive and precise quantitative data exist for unemployment rates during the first industrial revolution (the data available for Britain start in 1855, when unemployment was at 3.7% (Mitchell, 1998, p. 163)), a variety of qualitative accounts suggest that although technologically induced joblessness was commonplace during the Industrial Revolution, it was temporary and dependent on craft and location. As for example hand weavers were replaced by machines, some districts and towns reported job-specific unemployment rates of

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up to 69%, prompting scholars to make the invention of the power loom responsible for "the largest case of redundancy or technological unemployment in our recent economic history" (Bythell, 1969, p. 139; Nardinelli, 1986).

Interpreting the predominantly qualitative resources, Frey (2019, p. 93) argues that the first part of the first industrial revolution was shaped by technologies of the replacing sort, resulting in technological unemployment at least for some part of the population. For many, unemployment supplanted the previously more common phenomena of underemployment, vagrancy, and landlessness as sources of poverty (Perry, 2000, p. 11). Only over time did mechanization come to impact human labour positively, which he (p. 139) attributes to a shift from replacing to augmenting technology.

During the second industrial revolution, official numbers for the US do not cover the whole transformation but are available from 1890 onwards. Although unemployment rates in the first period were very high (rising up to 18.4% in the US in 1894), the literature does not indicate large-scale technological unemployment issues for the second industrial revolution (Frey, 2019, pp. 189-199; Mitchell, 1983, p. 161). During this state there was neither grand opposition to mechanization, nor Luddites (Frey, 2019, p. 189). Research by Alexopoulos and Cohen (2016) on the aftermath of the second industrial revolution (1909-1949) found a positive relationship between technological change and employment. Frey (2019, p. 173) therefore deduces that that the technology of the second industrial revolution was largely labour enabling. Workers profited from machinery; wages increased alongside GDP. Although some workers were temporarily displaced, no large-scale technological unemployment materialized.

Historical accounts do suggest that technology affects different sectors differently. For example, the first industrial revolution engendered a fundamental shift in the means of production, and therefore a shift in the system of production from a domestic to a factory setting. This resulted in a decline of agricultural employment, within which total employment decreased from 70% (1820) to 27.5% (1917) (Bruckner et al., 2017, p. 11). In terms of occupations, skilled artisan workers were often worse off (Frey, 2019, pp. 99-135). In particular, hand spinners and weavers are named as those hit most severely by replacing machinery (Frey, 2019, pp. 99-105). In the American experience, agriculture likewise declined

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in favour of urban-based factories (Frey, 2019, p. 214). The second industrial revolution required higher skills of those working in the electrified factory (Frey, 2019, p. 215). However, no comprehensive labour displacement occurred, as rising skill requirements were met by expanding education in the American high school movement (Frey, 2019, p. 214). The third industrial revolution witnessed a significant decline of people employed in manufacturing and a further shrinkage of the agricultural sector to 2% (Autor, Dorn, & Hanson, 2018; Bruckner et al., 2017, p. 11; Charles, Hurst, & Schwartz, 2018; Hernandez, 2018); the falling numbers are however mostly offset by employment increases in the services sector (Autor, Dorn, & Hanson, 2015; Bruckner et al., 2017, p. 12).

The pessimists

Unlike the optimists and the historical reasons that do not suggest mass-unemployment from technology, Brynjolfsson and McAfee (2014, pp. 158-161) put forward three economic arguments against traditional economic theory regarding technological unemployment. First, economists tend to assume an elasticity of demand, which can adapt to increases in efficiency: If productivity increases, demand will increase at equal pace, counterbalancing potential unemployment. Only a lack of elasticity can account for technological joblessness. By contrast, based on Keynes, Brynjolfsson and McAfee assert that we cannot suppose demand to be perfectly adjustable to productivity. At some point, be it in the economy as whole or in specific sectors, demand becomes satiated and consumption stagnates. We cannot principally assume constant growth of needs and desires to be satisfied economically.

Secondly, the mismatch of technology and human skills. Common conviction has it that humans are bound to adapt to novel skill requirements, thus technological displacement is at most temporary. But, as the authors (2014, p. 160) inquire, “what if this process takes a decade?” By extension, “what if, by then, technology has changed again?” With machines rapidly growing increasingly capable, there is at least a possibility that they might permanently outrace humans.

Finally, economic theory supports – under a set of assumptions – equilibrium between supply and demand; thus, wages would fall in reply to falling demand for labour. If wages decrease too severely, those at the bottom of the income distribution might choose not to work

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(especially if there are no minimum wage precautions). Brynjolfsson and McAfee agree that the actual outcomes of increasing automation depend on the design of innovations. Adopting the notion of enabling technologies, they acknowledge that AIs could be built in a labour augmenting way, while restricting those that would replace workers.

Brynjolfsson and McAfee (2014, pp. 161-163) also offer a helpful thought experiment: imagine a company started employing all-purpose and self-improving robots, such as is the possibility of an AGI or intelligence explosion (theorized for example in Tegmark (2017) and Bostrom (2014), but also more specifically by Nordhaus (2015)). Productivity would rise dramatically, while all workers would be replaced for lacking comparative advantage: "Those with no assets would have only their labour to sell, and their labour would be worthless" (Brynjolfsson & McAfee, 2014, p. 162). Altering the experiment slightly, it becomes obvious that technological unemployment is conceivable. If humans retained comparative advantage in some jobs, but a decreasing amount of those as machines replace a significant share of labour, the competition for these 'human occupations' would intensify; increased supply would lower wages, as employers have more than enough options to fill the open positions. Job availability would lessen, while salaries would fall even for the lucky ones.

In addition, various working papers present innovative theoretical models that – at least theoretically – allow for labour immiseration (see e.g. Sachs and Kotlikoff, 2012; Berg et al., 2017; Susskind, 2017).

Technology as a task replacement or augmentation mechanism

Acemoglu and Restrepo (2016) postulate that the labour share of income depends on the rate with which technological progress replaces tasks and substitutes human workers and the rate with which endogenous technological progress creates new tasks that do demand human labour. The model suggests that a compensating general equilibrium is possible, but not a given. In general, many economists suggest that in the short run, technological change can be disruptive. Each time a new general purpose technology is diffused, we encounter a race between job destruction and job creation (Acemoglu & Restrepo, 2018c; Bruckner et al., 2017; Brynjolfsson & McAfee, 2011). While some tasks might be mechanized or automated, other tasks with the potential of absorbing the laid-off workforce appear.

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Frey (2019, p. 13), drawing from Acemoglu and Restrepo (2018a), differentiates in this regard between replacing and enabling technology. Replacing technology decreases the demand for human labour, whereas enabling technology serves humans by making them more productive or create altogether new tasks for them. These countervailing effects must neither necessarily occur simultaneously, nor have similar effect sizes, thus leaving the labour market susceptible for temporary and potentially permanent displacement effects, which depends on various factors (Acemoglu & Restrepo, 2018a, pp. 2-3). Even temporary displacement can be detrimental, because for those whose jobs are affected, temporary may mean a lifetime, as Frey (2019, p. 18) remarks.

Technology can affect production by replacing or augmenting human workers in the performance of specific job tasks, thereby boosting their productivity. By changing job tasks, technology changes the content of jobs. It can create new jobs and make some jobs redundant. Indicators thus include the substitution of humans by machines in specific job tasks or even whole jobs, the creation of new jobs, and the changing of job tasks.

For example, during the first industrial revolution due to the mechanical division of labour, tasks that previously necessitated trained manual workers were divided into its constituent parts and increasingly mechanized. Technology in the early first industrial revolution was largely labour-replacing (Frey, 2019, p. 97). An example is the mechanization of the cotton spinning process, rendering hand spinners redundant (Frey, 2019, pp. 100-103). Skilled artisan craftsmen became waged labourers in monotonous mechanized processes (Frey, 2019, p. 8). The second industrial revolution increased the demand for semi-skilled work in the form of machine operators, for example (Frey, 2019, p. 144). Technology, which previously displaced many workers, had now become labour-augmenting (Frey, 2019, p. 144). Jobs created during this period were largely routine-based (Braverman, 1998). Computer-based automation took over some routine tasks. Digital technologies were enabled to take on cognitive tasks. As Frey (2019, p. 227) notes, “before the spread of computers, machines could not operate on their own”. However, with the computer revolution, technology became able to independently perform tasks that could be reformulated into an algorithmic sequence of steps based on rule-based logic.

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The changing of tasks has consequences for the skills requirements of workers: they change as well. For example, as machines are able to perform routine tasks better than humans, human workers can add value by performing non-routine tasks. This implies that differently skilled workers are required, for example when technological change is skill biased. To understand the impact of AI on firms, then, it becomes crucial to understand how AI-driven automation will change job tasks and skill requirements. Thus, to observe the way in which automation affects jobs, we may observe the changing demand for skills.

Exogeneity of technological progress

Last, we also need to revisit the importance of market functions in this debate. So far, we have assumed that technologies evolve as a result of more efficient allocation of inputs and that the decline in the labour share is driven by this process. However, this is far from real. Research by Acemoglu et al (2020) has shown that there are ways that can facilitate this shift, from tax policies favouring capital over labour to the risks that firms faced with organized demands from labour unions (see Keefe, 1991). In this context, the technological transition is not necessarily exogenous with regards to labour substitution but instead, it builds on the very incentives that most economic models – making this omission – have relied on.

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3. Empirical findings

The theoretical considerations outlined in the previous chapter can be evaluated in various ways. We structure this section as follows: First we look into the the broad macroeconomic trends of the past decades and focus on the role of technology direction. Next we examine the evolution of the labour share over the past decades across countries. Third we discuss the empirical evidence related to the rate of labour replacement. Then we assess the effects on productivity growth and labour incomes. Finally we propose our suggestions for the future.

Technology direction and broader macroeconomic trends

Rise in Markups and market power, limited entry of new firms, technology direction

The driving force of technological change is that it brings significant improvements in the efficiency of production. In this section we discuss whether **technology direction** itself is not necessarily focussed on this doctrine but instead driven by other forces.

Taxes

Acemoglu (2020) makes the case that over the past decades the US tax code has significantly favoured investments in capital against labour. This means that firms were incentivised to invest in various forms of technological equipment (which differ across sectors and jurisdictions). The empirical arguments behind this process appear to be compelling: if policy-makers support this transition over labour then it is not only an efficiency consideration but a policy induced trend. The empirical evidence in from Acemoglu et al (2020) suggests that if the US tax system moved towards optimal taxation of capital and labour, employment would increase by 4.02% and the labour share by 0.78 percentage points, thus restoring the optimal level of automation. Even in modest reforms of the tax system would be beneficial for the labour share and employment. The reason behind these changes is that marginal automated tasks do not bring with them significant productivity gains but still displace workers and reduce employment below the socially optimal level. This work also makes the case of a

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separate “automation” tax as a way to restore the imperfect allocation of inputs caused by the distorted tax base. Further work in the effects of automation that has accelerated due to imperfect taxation in the US shows that income inequality will not be avoidable with the current status quo. Guerreiro et al (2022) introduce a robot tax that balances two objectives: incentives for the young generations incentives to invest in skills and become non-routine workers and a redistribution of income toward routine workers, since their wages fall as robots become cheaper. In this context, taxing robots reduces the non-routine wage premium and helps redistribute income toward routine workers. Within Europe Hoette et al (2021) look into the effects of automation on public finances and show that robot diffusion led to decreasing factor and tax income, and a shift from taxes on capital to goods.

The push towards automation

Apart from the taxes that directly favour an input over another, the role of dominant firms towards automation plays a crucial role in this transition. Increasing automation leads to more data being generated and consumed by users that are then fed to AI systems. One of the key issues with this process is that with enough data about users, data platforms would only require the detailed footprint of one of them to “predict” the habits other “similar” users. This externality implies that large benefits are appropriated by the automating firms which can then be used for advertising or other profitable purposes. In this way the plethora of data further reduces the “value” of privacy and has direct effects on shifting the AI generated surplus from users to firms (Acemoglu, 2021)

The decline of labour bargaining power

The explicit favouring of capital over labour and the intrinsic characteristics of technologies that affect this process have also been reinforced by policy was also supported by other indirect ways that affected the role and bargaining power of labour unions in the US. The decline in unionization over the past decades and the technology direction may have shaped the current situation.

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These important trends documented in the literature seem to add to a broader picture that the effects of deregulation had over the past decades, may have been affected by the adoption of automation technologies. These macro trends include the rise in markups (De Locker et al, 2019), the rise of profit share (Barkai, 2020) and the declining intervention of antitrust authorities in mergers and acquisitions. The role of internet platforms that rely on AI have featured in Lina Khan Amazon antitrust paradox (2016) and paint a picture of the role of technology in this transition along with the limits of regulation to tackle the new challenges. For our question in this report “Is this time really different” we already have some clear signs about this time favouring technology over the recent past.

The labour share of national income

A declining labour share of the national income may suggest – among many other things – that automation is increasingly labour replacing. During much of the twentieth century, the labour share of GDP was so stabile that Kaldor (1961) called it a “stylized fact” of economic growth. A large number of studies empirically assesses if technological change is reducing labour demand or stifling wage growth. From this literature it has been long supported that in many countries, the labour share of the national income has fallen steadily during the 2000s (e.g., Baker, 2007; Brynjolfsson and McAfee, 2011; Fleck, Glaser, & Sprague, 2011; Elsby, Hobijn and Sahin, 2013; Karabarbounis and Neiman, 2014; Piketty 2014; Dao et al. 2017; Autor & Salomons, 2018; Frey, 2019: p. 243). According to Autor et al. (2020), there is a general consensus among economists “that the fall is real and significant.

There are several authors that provide explanations for this trend which in some cases appear to turn this into a measurement issue. The rising spending on computer software and other forms of intellectual property (IP) has grown during the same time that the labour share has declined but the classification of IP spending as an intermediate expenditure or as investment in durable property can directly affect the denominator in a labour-share calculation (Grossman and Oberfield, 2022). For example, Koh et al (2020) attribute the decline in the labour share to the Bureau of Economic Analysis reclassification of intellectual property outlays from non-durable inputs to durable capital. Other economists suggest that measurement issues can arise because of the allocation of self-employment and

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entrepreneurial income between labour and capital (Elsby et al. 2013) and from the treatment of imputed rent on owner-occupied housing, which as Rognlie (2015) points out, can be considered to be a return to capital that accrues mostly to workers and their families.

The main issue in the context of this essay is whether this declining labour share - whether an artefact of measurement or not - is linked causally to technological change. Some authors point to relevant explanations. For example, Elsby, Hobijn and Sahin (2013) point towards outsourcing as the main explanation. Piketty (2014) points to the role of labour market institutions. Both arguments are reasonably refuted by recent empirical evidence (Autor et al., 2020).

Karabarbounis and Neiman (2014) empirically assess the evidence and conclude that the falling labour share is indeed best explained by decreased prices of technology relative to labour. This conclusion is not incompatible with a recent model that points towards the emergence of superstar firms as an explanation for the declining labour share (Autor et al., 2020), which is consistent with a plethora of empirical observations. In fact, technological advances are considered one of the driving forces of the creation of superstars (p. 649). At the same time we have recent evidence that points towards a strong measurement channel that may be driving this decline. As the role of intangible capital became more prominent over the past decades, part of the returns to labour (in the form of royalties, bonusses or other reimbursement modes) shifted outside its measured share. Koh et al (2020) suggest that re-attributing a fraction of intangible capital towards labour explains all of its decline. Further from that Barkai (2020) has suggested that it is not the decline of the labour share but predominantly the rise of the profit share that has led to this phenomenon. Acemoglu (Vox, 2021) explains that this is part of the much broader discussion in economics around the rise of markups which lead to higher profits and as a result push the labour share down. This discussion seems to diverge from the role of technology in the first place but it is likely that technology has helped this process even further.

From this literature, we can conclude that technology has – at least partially – affected the traditional measurement channels of economic activity through the increasing importance of intangible capital and new forms of work. There is no convincing evidence that the absolute

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share of income towards labour has been reduced but there is strong support that there is increasing divergence of the labour compensation within this stable or declining share.

From a historical standpoint, it is noteworthy that during the first industrial revolution, the labour share of income in Britain fell for eighty years, recovering only around 1850, while productivity was increasing (Acemoglu & Restrepo, 2018a, pp. 12-13; Piketty, 2014, p. 267). Piketty (2014, p. 267) demonstrates that the labour share of the national income has increased between 1850 and 2010, but argues that industrial revolutions do not immediately benefit labour, and seem to do so only after a considerable time lag. Autor and Salomons (2018) point out that a declining labour share in itself does not imply increased unemployment: it does so only if the direct replacement of humans by machines in certain job tasks is not compensated by rising productivity or the creation of new tasks. It is to these indicators we turn next.

Technology and labour replacement

In this section we explore whether within the labour market we observe trends that have not been observed in the previous technological revolutions. We start from the job destruction, then move to job and task creation. We then revisit the historical evidence for the changes in existing tasks and last we discuss the rate of automation.

Job destruction

To gauge whether robots will help or hurt human employment, we start with scrutinizing the literature on aggregate employment. Literature suggests it is not clear from the empirical evidence if robots increase or decrease aggregate employment. Some studies report a negative correlation (suggesting that robots decrease human employment), including Carbonero, Ernst and Weber (2018), who study 41 countries between 2000 and 2014, Borjas and Freeman (2019) who study US data between 2004 and 2016, Acemoglu and Restrepo (2017) who study the US between 1990 and 2007, and Chiacchio et al. (2018) who study six European countries.

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Other studies, however, report positive associations, suggesting that robots can increase human employment. For example, Koch et al. (2019) study manufacturing firms in Spain between 1990 and 2016 and report a positive association between robotization and employment. Employment rates went down in firms that did not adopt robots. This positive correlation is also observed in other countries, including France (Domini, Grazzi, Moschella, & Treibich, 2019). For example, Gregory, Salomons,and Zierahn (2016) analyse data from 27 European countries between 1999 and 2010. They find that technology is negatively associated with employment in middle-skilled jobs, but that this negative effect is more than compensated by increased product demand and spill overs. The net effect is positive. Similarly, Klenert et al. (2021), studying 14 European countries between 1995 and 2015, report positive net effects.And some studies find no effects. Graetz and Michaels (2018) studied the relation between robotization and changes in employment shares in 17 countries between 1993–2007, they find that robotisation is not correlated with total employment (measured as overall labour hours), but that it does reduce the share of low-skill employment. Dauth et al. (2017) suggest that industrial employment was negatively impacted by robots in Germany between 1994 and 2014. They show that each robot destroys two manufacturing jobs. However, this is compensated by job creation in the service sector. The net effect on total employment is therefore zero. Jäger, Moll and Lerch (2016) analysed the association between industrial robots, employment and productivity in 7 European countries in 2012. The authors find that firms with robots are more productive but report no association between robots and employment.

Just as many other authors, Frey (2019, pp. 232, 246) sees no overall unemployment increase due to technology so far. He argues that the automation of routine tasks has probably been offset by the creation of new jobs; consequently, unemployment due to labour replacing technology has been mostly sectoral. Hoette et al (2021) also find limited evidence of job losses across European countries for the period 1995-2016 due to automation.

Job and task creation

Acemoglu and Restrepo (2018a) recognize that technological change may induce a displacement effect, causing the wages to detach from productivity growth, thus yielding a

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decreasing labour share. Contrastingly, subscribing to the perspective that labour will retain comparative advantages in performing certain tasks, they (Acemoglu and Restrepo, 2018a: pp. 6-10) enumerate several countervailing effects that might neutralize the displacing forces: a productivity effect, which fosters demand for non-automatable skills resulting from the lowering costs of automated tasks; a capital accumulation effect, bringing about increased demand for labour (as according to neoclassical economics); a deepening of automation effect, when previously automated tasks are 'upgraded' to more productive automation, thus yielding higher productivity and correspondingly rising labour demand (as according to standard economic theory); finally, the creation of new tasks serves to reinstate the workforce displaced elsewhere.

The first two effects hinge upon the elasticity assumption. As these economic considerations support historical ones, the latter in turn aid the economic ones. For instance, capital accumulation was observed during the first and second industrial revolution, while a deepening of automation also led to growing incomes for workers as horses were replaced by tractors (Allen, 2009; Manuelli & Seshadri, 2014; Olmstead & Rhode, 2001). These impulses, taken together, might account for balancing of job destruction and job creation (Autor & Salomons, 2018; Bruckner et al., 2017; Frey, 2019, p. 15; Levels et al., 2019).

However, displacement and counteraction might not operate simultaneously, leaving open a chance of temporary technological unemployment. Furthermore, note again that there is no law that dictates the equal compensation of job losses; Acemoglu and Restrepo (2018a, p. 34), in accordance, caution that innovation does not necessarily augment human labour, and that political economic research and design is required to direct progress adequately.

Frey (2019, p. 232) suggests that in the past, as routine tasks became increasingly automated, new tasks appeared for humans. Berger and Frey (2016) show that the creation of employment in jobs with altogether new titles (e.g., software engineers, database administrators) favoured abstract skills during the computer revolution. As Reich (1992) pointed out, a new class of symbolic analysts emerged at the detriment of the semi-skilled workers so heavily in demand during the second industrial revolution. The result is an increasing demand for high-skilled workers (Brynjolfsson & McAfee, 2011; Frey, 2019, pp. 235-243).

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Autor, Salomons and Steegmuller (2021) demonstrate this. In an attempt to "consistently measure the evolution of new work over eight decades, document its changing locus and relationship to the occupational structure of employment, and explore the forces that explain where new work appears and where old work disappears." (ibid: p. 2), they analyse the US census microdata and an inventory of 80 years of job titles and show that new job tasks are created in jobs that are augmented by technology, but not in response to automation innovations. They also document that task creation and task automation are positively related at the occupational level, but can counterbalance each other's effects on occupational labour demand.

From the empirical evidence we conclude that there are no clear signs of job destruction leading to mass unemployment so far and that the rate of new task creation has not changed dramatically compared to previous historical cycles. Job destruction can go hand in hand with the creation of new tasks and has done so in the past. However, it should be noted that there is no economic law that necessitates the equal compensation of task destruction and creation (Brynjolfsson & McAfee, 2011, p. 37).

Job automation

One of the main scholarly debates revolves around the questions how many jobs will be susceptible to automation, and what the consequences of this may be for employment. This debate was kicked off by the publication of the highly cited working paper version of the study by Frey and Osborne (2013, 2017), whose analyses found that 47% of all jobs in the United States are highly susceptible to computerization within two decades.

In response to this rather striking conclusion, a burgeoning literature of empirical studies have proposed estimations of how many of the current jobs are susceptible to automation. Their predictions depend strongly on modelling assumptions they make. In general, two broad methodologies can be distinguished: occupation-based and task-based approaches (Bruckner et al., 2017, p. 28). The former assume that entire occupations are automatable, whereas the latter presume that the variety of tasks in a single occupation are so various that a job can persist even if some of its associated tasks are automated.

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Occupation-based estimates are usually higher than task-based ones, which derives from the methodological differences. Using this approach, Frey and Osborne (2013, 2017) see 47% of US jobs as susceptible to automation; Bowles (2014) finds that 54% of jobs in the EU are at risk; for the ASEAN countries, Chang and Huynh (2016) calculate that 56% are automatable.

Alternatively, the numbers resulting from task-based methodologies go as low as 9% (Arntz, Gregory, & Zierahn, 2016), while other scholars using the same approach conclude job automation risks between 21 and 38% (Berriman & Hawksworth, 2017). A cross-national analysis that further corrects earlier models for unrealistic assumptions about task distribution and engineering bottlenecks (Nedelkolska and Quintini, 2018) concludes that about 14% of all jobs are highly automatable and reports a large cross-national variation.

A different methodology to assess the impact of robots on jobs is based on industrial robot stocks and some reasonable estimate of replacement potential. Studies in some wealthy economies using such methods found that each multipurpose robot substitutes between 2 and 3.3 jobs (Acemoglu & Restrepo, 2020; Dauth, Findeisen, Südekum, & Woessner, 2017; Prashar, 2018). Bloom et al. (2019) use such methods to calculate that automation will destroy about 60 million jobs until 2030.

One issue with many studies is that they do not consider how automation will affect employment given wider demographic and labour market trends. Taking the estimations about susceptibility to computerisation of Frey and Osborne (2017) as input and arguing that the impact of automation on work depends on innovation speed, market diffusion, the actual replacement potential, and government intervention policies (Levels et al., 2019), the Technequality consortium forecasts the potential impact of automation on jobs, taking wider demographic and labour market trends into account (Heald et al., 2019). They report that (a) between 5% and 44% of jobs will disappear in all sectors, that (b) there are large cross-national differences, and (c) that these effects are highly susceptible to implementation speed and policies. Just as other studies in this field, however they do not take the possibility of job creation into account.

In sum, different studies report varying estimates and calculations for the amount of jobs susceptible to automation. The level of ensuing technological unemployment might range from an extension of routine-biased automation, thus affecting more people but leaving in

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place those who perform non-routine labour; to all-encompassing unemployment based on the ability of modern AI systems to perform most tasks in the future, thus replacing more or all jobs.

Changing jobs and tasks

Even if they do not lead to unemployment or destroy jobs, technological revolutions generally do change the nature of work, by changing tasks that are done by human workers (Autor, 2015, Fernández-Macías & Hurley, 2016; Barbieri, Piva, Mussida & Vivarelli, 2019). The historic examples of this mechanism in previous revolutions are well-known and often discussed, but we repeat the main arguments here, because they provide the foundation for formulating expectations about the ways in which ai will impact firms and organisations. During the first industrial revolution, the crucial change was mechanization. The creation of engines and machines enabled factory system and the division of labour, greater production efficiency and greater task specialization. To take Smith's famous example, one untrained craftsman in the pin-making business could hardly produce twenty pins a day when working independently; however, if the pin-making process was separated into up to eighteen distinct operations, ten workers could reasonably be expected to manufacture 48 thousand pins every day, equalling about 4800 pins per person (Smith, 1801: pp. 17-18). Production of many goods thus changed from a domestic system of production, within which people produced largely in a familial setting and without waged employment, to the factory system (Frey, 2019, pp. 24, 71; Perry, 2000). While factories existed prior to the first industrial revolution, the factory system was marked by mechanization based on machines (Frey, 2019, p. 94; Marx, 1867). As machines began replacing human muscles in performing of heavy, or simple repetitive tasks, the division of labour was an analogous development (Babbage, 2010; Smith, 1801, p. 18).

During the second industrial revolution, further and faster mechanization took place due to the electrification of factories (Frey, 2019, p. 142). The electrified factory propelled productivity, as the production process was organized in a continuous flow, where workers remained stationary by moving assembly lines (Frey, 2019, p. 150). As Frey argues, this demanded a significant functional re-organization of factories' value chains based on electrical power. Moreover, mass production started in this period (Frey, 2019, p. 148; Schwab, 2015). The re-organized factory focussed on producing goods from uniform and interchangeable parts, the classic example being the construction of Ford's Model T, which did not require any manual assembly (Frey, 2019, p. 150). Here, the relation between employers and employees also changed markedly. The goals and physical circumstances of mass production made scientific management possible (Taylor, 1911). By closely monitoring workers and measuring their performance, scientific management increased their productivity, but also strongly limited their autonomy in deciding how to execute tasks. The third (digital) industrial revolution was driven by computer-based automation (Frey, 2019: p. 227). Where the electrical mechanization of the second industrial revolution required machine operators, the third industrial revolution allowed for a delegation of repetitive tasks to computer-controlled machines (Frey, 2019, p. 228). For companies, this transformation meant the possibility of dividing tasks between workers and computers. As a consequence, the demand for routine jobs fell steadily with the falling costs of computers (Frey, 2019, p. 232).

Technological change during the third revolution was largely routine biased. According to Levy and Murnane (2004), tasks following pre-existing rules are indeed most easily automatable. To understand how computers affect occupations, Autor, Levy, and Murnane (2003 p. 1280) postulated the routine-biased technological change hypothesis, which maintained that computers replace workers in repetitive, routine tasks, and augment them in non-routine tasks. Consequently, computers would replace workers in jobs that consist of many routine tasks. As such jobs are often middle paying jobs, routine biased technological change would lead to job polarization. this line of reasoning provides a rather good explanation for polarization of employment and wages between the 1990s and the early 2000s in the US (Acemoglu and Autor, 2011; Autor, Katz, & Kearney, 2008) and Western Europe (Goos, Salomons and Manning, 2014).

Nordhaus (2007) calculated that the real costs of executing standardized tasks fell by 65-70% annually between 1980 and 2006. In 2004, Levy and Murnane reasoned that people would still be able to compete with technology, because computers could only operate rigidly defined tasks but humans can operate in realms where pre-set rules do not exist. The authors

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concluded such non-routine behaviour as the limits to automation. The assumption is also articulated well by Acemoglu and Autor (2011, p. 20): "Although computers are now ubiquitous, they do not do everything. Computers – or, more precisely, symbolic processors that execute stored instructions – have a very specific set of capabilities and limitations. Ultimately, their ability to accomplish a task is dependent upon the ability of a programmer to write a set of procedures or rules that appropriately direct the machine at each possible contingency. For a task to be autonomously performed by a computer, it must be sufficiently well defined (i.e., scripted) that a machine lacking flexibility or judgment can execute the task successfully by following the steps set down by the programmer. Accordingly, computers and computer-controlled equipment are highly productive and reliable at performing the tasks that programmers can script – and relatively inept at everything else." They define these rule-based algorithmic tasks as routine operations and oppose them to those tasks that require "situational adaptability, visual and language recognition, and in-person interactions" (p. 21). As examples they offer "[d]riving a truck through city traffic, preparing a meal, installing a carpet, or mowing a lawn", all of which – at the time of their writing – they held to be hardly automatable due to the limits of technological capability (p. 21).

If this assumption holds true also for current technological developments, current waves of automation should primarily change routine jobs. However, some evidence suggests this assumption no longer holds. Algorithms can potentially be applied to a "cascading variety of tasks" (Frey, 2019, p. 305). Brynjolfsson and McAfee (2011, p. 28) observe: "[C]omputers are now demonstrating skills and abilities that used to belong exclusively to human workers. This trend will only accelerate […]". Although they recognize the still prevalent bottlenecks to machine competence in areas like creativity and intuition (all ai systems operating today are narrow in scope), they (p. 26) wonder: "If, as these examples indicate, both pattern recognition and complex communication are now so amenable to automation, are any human skills immune?"

Empirical studies of the way in which ai-driven automation changes job tasks are scarce, and as a consequence, inferences about the way in which jobs will change are by definition rather speculative. One key observation from previous waves of computerization is that ICT-technologies were labour-augmenting because they replaced routine tasks. The AI-driven

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industrial revolution would be fundamentally different from the previous ones if, as a result of automation, machines would become able to also perform non-routine job tasks.

So, the question is whether AI can learn to perform non-routine tasks. An artificial general intelligence almost certainly would. Bostrom (2014, p. 19) refers to a survey conducted among expert groups, who in combination assumed a 10% probability of creating human-level ai by 2022, 50% by 2040, and 90% by 2075. According to the author, this is in line with findings from author surveys and opinions of researchers in the field. Tegmark (2017, p. 121) remarks that “there’s no fundamental reason why this progress can’t continue until AI matches human abilities on most tasks”. Indeed, he argues that there is a “non-negligible possibility that artificial general intelligence progress will proceed to human levels and beyond” (Tegmark, 2017, p. 172); a superintelligence of such sort will render all or most human labour redundant, thus restructuring the organization of companies (and the economy as a whole) entirely, with consequences predictable only in a completely hypothetical manner.[1] However, we are a long way from creating artificial general intelligence.

One key insight is that it does not take machines powered by artificial general intelligence or superintelligence to drastically automate workplaces; weaker versions of AI suffice. Frey (2019, pp. 312-313) illustrates this point by pointing towards of Amazon Go stores (autonomous supermarkets without cashiers)[2] or unmanned warehouses. Innovations of this sort necessitate a restructuring of companies without requiring general-purpose AI. Similarly, as Brynjolfsson and McAfee (2011) note, autonomously driving vehicles must perform a variety of non-routine tasks. Driving was deemed non-automatable by Levy and Murnane in 2004. Today, self-driving cars have been tested successfully in many open world settings. Second, Levy and Murnane also lacked confidence in the competence of machines to perform complex communication. Nowadays, neural machine translation systems use machine learning to quickly close the gap between human and ai performance. Similarly, although Alexa and Siri are not yet human-like communicators, their speech recognition abilities improve with every word humans speak to them.

1 For an overview of these hypotheticals, see Tegmark (2017) and Bostrom (2014).
2 For a video introduction of these Amazon Go stores, already available in many US cities, check https://www.youtube.com/watch?v=NrmMk1Myrxc .

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Frey (2019, p. 301-323) argues that AI surpasses the rule-based nature of digital automation. Indeed, the distinction between routine and non-routine tasks that Levy and Murnane discussed in 2004 were accurate then, but no longer seem to hold. Novel innovations enable machines to perform some complex and non-routine tasks better than humans. Various authors (e,g, Acemoglu & Restrepo, 2018b, p. 206; Feng & Graetz, 2016) now contend that, although the clear-cut distinction between the automatability of routine *versus* non-routine might not apply anymore, there are still various tasks in which human labour has a comparative advantage over machines and vice versa. This does justice to Moravec's paradox (Moravec, 1988), which states that some tasks, which are easy for a computer to do, are extremely difficult for humans (e.g. processing large databases into statistical models); but conversely, some tasks are easy for humans but enormously difficult for computers (say, recognizing emotions) (Frey, 2019, p. 236).

So, which tasks are not automatable? This also still a matter of controversy. For example, while some scholars doubt the possibility of automating high-skilled jobs (Frey, 2019, p. 323), others contend that even the professions exhibit an already evident trend towards replacement of tasks by machines. Examining trends in occupations like doctors, educators, lawyers, journalists, *et cetera*, Susskind and Susskind (2015, p. 2) assert that "increasingly capable systems will bring transformations to professional work that will resemble the impact of industrialization on traditional craftsmanship". Even the most prestigious of occupations already are augmented by modern technologies, such as surgeons, who lack the fine motor skills and consistency of robotics, or dermatologists and radiologists, who are being outperformed by computer programs at recognizing patterns of cancerous cells and other anomalies (Frey, 2019, p. 306).

Furthermore, some contend that tasks might be relatively hard to automate because they are in the emotional, affective, or interpersonal domain (Brynjolfsson and McAfee, 2014; World Economic Forum, 2020). Creativity is another domain in which many (Brynjolfsson and McAfee, 2014; Frey,2019) see a lack of competence in ai. While algorithms are very capable of producing a novel piece of art, for example, is necessarily does so by drawing from a database of existing art, thus rendering the artificially created work a mixed replica, at best.

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Finally, some tasks that are in principle automatable, can in practice not be automated. For example, scholars are concerned whether AI can and should be enabled to make moral judgments. Although algorithms might be proficient at formal logic theoretically, we might still demand a human decision-maker in critical situations. Arguing this point, scholars like philosopher Richard David Precht (2020) defend that an AI system like an autonomous vehicle should never be authorized to decide about life and death. In the event of inevitable accident, choosing to either run over an elderly person or two children (a modernized version of the trolley problem) conflicts with the categorical pre-eminence of human dignity as codified in many constitutions.

We conclude that although it is highly likely that AI-driven automation will change tasks within jobs, it is still highly unclear how it will do so.

The real income effects of automation

If automation affects productivity of workers and economies, that would become evident in income effects. In this section we look into the real income effects of automation through the changes in productivity or incomes.

Productivity growth

The broad macroeconomic evidence suggests that labour productivity growth has been slowing down since the 1980s across most economies. With the exception of the ICT induced rise in the US (1995-2005) this trend appears to still hold (Goldin et al, 2021) in spite of the AI revolution that has been going on for the past decade. Mismeasurement has been a prominent explanation for this slowdown but still not enough to explain the decline of the growth rates. As the broader macroeconomic observations suggest, the decline in allocative efficiency through market concentration, declining competition and rising markups seems to explain half of this effect. If anything, technology has not helped to balance this trend although there are several studies suggesting that AI and robots can increase productivity at the plant or firm level. We discuss some of these below along with the historical parallels on productivity:

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Economic growth is intrinsically tied to technological progress (Comin & Ferrer, 2013; Frey, 2019, p. 4; Solow, 1956). This is arguably explained by productivity gains technology makes possible: technological advances and the organisational changes they required can make production much more efficient, increasing productivity. For example, Clark (2007a p.232) shows that production efficiency in England was stagnant until about 1790, but steadily rose afterwards. He also showed that the average production efficiency has increased exponentially ever since (Clark 2007a p.240).

Will AI-driven automation boost average productivity and increase labour? Historical examples indeed suggest that technological innovations can increase productivity and foster economic growth. Indeed, the first industrial revolution is commonly considered the root of modern economic growth and prosperity (Clark, 2007a; Mokyr, 2009: p. 349). Before industrialization, economic growth was almost stagnant for most of recorded history. The average yearly growth of world GDP was less than 0.1% between year 0 and 1700s. It grew rapidly ever since (1.6% between 1700 and 2012, exponentially), leading to the “impressive results” of modern economic productivity (Bostrom, 2014, p. 2; Piketty, 2014, pp. 106-107).

Productivity grew at a steady pace during the first industrial revolution, further increased during the second industrial revolution, but has slowed since the 1960s (Bruckner et al., 2017, p. 10; Brynjolfsson, Rock, & Syverson, 2017; David, 1990). Although technology progresses rapidly, productivity growth remains rather stagnant. Some productivity gains related to technologies of the digital revolution from the 90s until the beginning of the Great Recession have been observed (Bruckner et al., 2017, p. 10; Brynjolfsson & McAfee, 2011; Brynjolfsson & McAfee, 2014), but productivity growth is generally modest. For example, Bruckner et al. (2017, p. 10) show that the in the UK and the US, GDP per capita increased steadily from 1700 until about 2000, but then steeply declined. Similarly, labour productivity and output per hours worked grew roughly until the 1960s, decreased until 2000, but after that started to steeply decrease until 2016. Similar trends are observed in countries with vastly different labour market regimes, such as Japan and Germany, (Bruckner et al., 2017)

Empirical studies on the relation between robotization and productivity (Graetz & Michaels, 2018; Jungmittag & Pesole, 2019; Kromann, Malchow-Møller, Skaksen & Sørensen, 2019), suggests that robots can indeed boost productivity**.** Kromann et al. (2019) study industry-level

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panel data for 9 countries between 2004 and 2007 and report that during that period in these countries, an increase of one standard deviation in robot intensity is associated with more than 6% higher total factor productivity. Jungmittag and Pesole (2019) analyse data for manufacturing industries in 12 EU countries from 1995 to 2015 and report that relative robot stock was associated positively with labour productivity growth in that period.

This may suggest that artificial intelligence (or its combination with other technologies) can, boost productivity growth, but that the effects do not necessarily translate into aggregate growth. The question is how to interpret this. Some scholars argue that we have reached a point of stagnation, where technological innovation becomes too slow to account for sustained productivity growth (Cowen, 2011; Phelps & Tilman, 2010). But this may also just be a matter of time (Brynjolfsson et al., 2017; Levels et al., 2019). Studies on the first industrial revolution suggest that it can take some time for technological advancements to affect growth. There appear to be considerable time lags between the initial technological innovations and the upsurge of GDP and productivity growth. In the early stages of industrialisation, economic growth and industrial output was slow and income growth per person was not significantly faster than before (Crafts, 1985; Crafts & Harley, 1992; Frey, 2019, p. 94; Phyllis & Cole, 1962). Some attribute this phenomenon to the time it takes for the functional diffusion and adoption of novel technologies into comprehensive utilization, as well as the development of associated infrastructure and skills (Bruckner et al., 2017, p. 10; David, 1990; Eichengreen, 2015; Frey, 2019; Levels et al., 2019).

This may be illustrated by the observation that the first industrial revolution was limited to specific sectors at first and was only later impacting across the economy (Frey, 2019, p. 95). The steam engine predominantly benefitted productivity roughly eighty years after its invention (Crafts, 2004). When American factories were electrified, productivity took twenty years to increase significantly (see Brynjolfsson and McAfee, 2014: p. 92). As David (1990) illuminates using the example of the electrification of factories during the second industrial revolution, diffusion time lags and mismeasurement components account for a delayed rise of productivity in times of technological transformation. Frey (2019, p. 323) alludes to Amara's Law in this regard, who wrote that "[w]e tend to overestimate the effect of a technology in the short run and underestimate the effect in the long run."

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However, Acemoglu and Resptrepo (2019: p.5) contend that the assumption that technologies by definition increase aggregate labour demand simply because they raise productivity is incorrect. They argue that automation technologies can actually reduce labour demand because they displace large groups of workers but only offer modest productivity gains. They argue this is especially the case when workers who are being substituted by machines are cheap (i.e. have relatively low income) and the automated technology "is only marginally better than them".

Income effects

So this brings the argument to the price of labour. Will automation boost personal incomes? Historical examples again suggest this may be the case. For example, although it took considerable time, the first industrial revolution significantly contributed to increasing general welfare. As Clark (2007b, p. 2) remarks, "even according to the broadest measures of material life, average welfare, if anything, declined from the Stone Age to 1800". Since then, average incomes per person were boosted dramatically and real prices declined (Clark, 2007a, p. 237).

However, the historic link between economic and wage growth appears to have been severed. Since the 1970s, median wages have hardly grown. Median incomes barely grew since 1979 and is on a downwards trend since 1999; median hourly income between 1979 and 2011 only totalled an increase by 0.1%, as productivity continued to rise considerably (Brynjolfsson & McAfee, 2014, p. 119). While aggregate productivity grew steadily, per capita gdp and income have remained stagnant or even declined. Brynjolfsson and McAfee (2011, p. 30) interpret this as evidence of a "growing mismatch between rapidly advancing digital technologies and slow-changing humans".

So how then, can this be explained? Acemoglu and Restrepo (2019) argue that displacement effects logically imply that automation does not by definition create wage increases on par with productivity growth. Alternatively, they argue that automation by definition implies that human workers add less value to industries relative to capital, and that as a result of that, reduces the labour share in the economy. They argue that this implies that wages increase slower at a slower pace than productivity. They also provide an alternative explanation for

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the wage growth and stabile labour shares observed in the past: other technological changes created new tasks for human workers, which compensated for the fact that automation displaced workers in tasks. The net effect was that human workers remained an important production factors.

In addition, median income may not be the most informative measure of how technology impacts us. Technological advancements tend to benefit some more than others. Indeed, technological developments have always played a crucial role in driving social inequalities (Lenski, 1966; Lenski and Nolan, 1970; Clark, 2007b, p. 3). During the early stages of the first industrial revolution, while factory owners were getting rich, the conditions of workers famously deteriorated in multiple ways. Between 1780 and 1840, average productivity per worker rose by 46%, while weekly wages only grew by 12% (Allen, 2009; Clark, 2005; Feinstein, 1998). Since working hours also increased during this time period by 20%, Frey (2019, p. 113) argues that hourly income actually decreased. In addition, child labour was common, and children were paid between a third and a sixth of an adult worker's salary (Frey, 2019, p. 123; Mantoux, 1961, p. 410). Only after 1840 did wages grow at a faster pace than output per worker; this trend continued throughout the second industrial revolution in Britain (Frey, 2019, p. 132).

Conditions for workers were famously ghastly during thar period. In some cases, workers in factories had a life expectancy of thirty years, which was ten years shorter than the British average (Frey, 2019, p. 113); consumption of food and non-essentials by workers stagnated or even decreased (Clark, Huberman, & Lindert, 1995; Horrell, 1996); perhaps due to an definitive degeneration of health and nutrition, there even is some evidence that those born during the industrial revolution are shorter on average than those born before and after (Floud, Wachter, & Gregory, 1990; Komlos, 1998; Mokyr, 2011). Additionally, women and children were used as a cheap supply of labour, with machines particularly designed for small workers; especially children suffered numerous hardships in the factories (Humphries, 2013). For capital owners, on the other hand, the rate of profit doubled (Allen, 2009). Peter Lindert (2000) has demonstrated that the earnings of the top five percent grew from 21% to 37% of national income between 1759 and 1867.

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Wages increased in appropriate relation to productivity gains during the second wave. The period has been called the 'Great Levelling' by virtue of its economically and socially equalizing effects (Lindert & Williamson, 2016). As mass production rendered prices for end-user technology affordable for the majority, and as wages for the lower income population rose even faster than for the rest while the share of national income accumulated by the top earners fell in the aftermath, the Gini coefficient to measure inequality remained constant and even decreased between 1870 and 1929 (Frey, 2019, pp. 159, 206-207; Kuznets, 1955; Lindert & Williamson, 2016). This equalizing effect continued long after the second industrial revolution (Frey, 2019, p. 246).

Although the labour market transformation of the second industrial revolution was skill-biased, inequality did not widen. This is explained by Jan Tinbergen (1975), who models inequality as arising out of a race between technology (raising skill demands) and education (addressing skill demands). Apparently, the grand-scale education of the American people during that time period outpaced the rising skill requirements (Frey, 2019, p. 213).

So, measures of inequality may be required to fully capture the effects of technological revolutions on people's purchasing power. The trend towards increasing equality that started during the second industrial revolution was reversed during the digital revolution (Frey, 2019, pp. 243-248; Katz & Margo, 2013). Brynjolfsson and McAfee, as well as Frey (2019, p. 224), argue that the technological advances in question should be interpreted as labour replacing for employees in routine jobs, but labour augmenting for those in skilled occupations. Technological change, in other words, was skill biased (Acemoglu and Autor, 2011). In consequence, semi-skilled workers increasingly flocked into service jobs which to this point remained hard to automate (e.g. janitors, gardeners, child-care), yielding a decline of wages by virtue of the increase in worker supply (Frey, 2019, p. 237).

In addition, recent economic developments as tending towards "winner-take-all or winner-take-most competitions", where "superstars" profit above everyone else (Brynjolfsson and McAfee, 2011; Autor, Dorn, Katz, Patterson, & Van Reenen, 2017; Bruckner et al., 2017). Digitalization has made possible the cheap replication of products and services, making it available for single competitors to comfortably absorb the whole market. The superstar logic is evident statistically. Brynjolfsson and McAfee point out that the top 10% of income earners

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have outpaced the rest; the top 1% incomes have grown even faster, as well as the top 0.1% and 0.01%, in increasing order. The relation of CEO to average employee salary has shifted from 70/1 in 1990 to 300/1 in 2005 (Kim & Brynjolfsson, 2009). Finally, the share of national income generated by top 0.01% of household has been increasing severely (Saez, 2016).

Inequality, as measured by the Gini coefficient, decreased drastically before the digital revolution, it then recorded a comparably sharp rise in inequality. Many authors report a hollowing of the middle class akin to the one of the original Industrial Revolution (Acemoglu & Autor, 2011; Autor, Katz, & Kearney, 2006; Bruckner et al., 2017, p. 20; Brynjolfsson & McAfee, 2011; Brynjolfsson & McAfee, 2014; Frey, 2019, p. 237; Goos, Manning, & Salomons, 2014).

Brynjolfsson and McAfee (2014) note that from 1973 until 2011, median hourly salary grew by 0.1% annually (indeed actually falling since 1999), while productivity increased by 1.56% with accelerating tendency (2014, p. 120). As the total wealth of US citizens increased, the bottom eighty percent saw their wealth decline (p. 119). These clear indicators for a detachment of income from productivity are coupled with the growing annexation of tasks by steadily and exponentially improving AI technologies, resulting in a real possibility of sustained income deficits. Its actualization depends on the institutional and political context (Brynjolfsson & McAfee, 2011, p. 29).

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4. Conclusion and Discussion

Is this time really different?

It may very well be. In terms of technological capabilities this time is certainly different. New automation technologies appear to be ready to replace a wide range of routine tasks. The game changer appears to be the possibility that machines can also perform non-routine tasks. We are not quite there yet. In fact only very recently have researchers made efforts to make ML models explain the range of the classifiers and the way the models interpret their inputs (Lang et al 2022) but there is still a long way for their mass use in several scientific domains and research where identification plays a crucial role.

What is also different is that the direction towards automation has been supported by tax policies and firms, in spite of the insignificant automation efficiencies that these technologies have brought. These forces have pushed automation beyond the socially optimal levels and have created an environment where the benefits of automation accrue to the wrong economic agents (platforms as gatekeepers). Although there is little if any evidence that robots will take our jobs, we do believe that this trend is worrying and that AI technologies can cause more harm than benefit of this is continued without change.

The Fourth Industrial Revolution likely brings challenges and opportunities, the relative realization of which depends heavily on the kinds of technology and technological progress we encounter, the policies adopted to address them, and the attitudes which shape these policies. Thus, by necessity, an evaluation of prospective developments remains bound by the unintelligibility of future knowledge, as philosopher of science Karl Popper (1959) pointed out. The task demands an extrapolation from current trends, contexts, experiences, for which we must assume a certain stability. For now, note that all argumentative accounts mentioned in the following involve at least a minimum number of assumptions about future developments. Since we cannot predict future knowledge, a study of potential scenarios of technology adoption is valuable, as we have done elsewhere (Levels et al., 2019). Here, however, it is our purpose to discuss argumentations that fall within specific boundaries.

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We thought it helpful to interpret the current industrial revolution from a historical perspective. To do so, we discussed the impacts of the British Industrial Revolution (1IR), the Second Industrial Revolution (2IR) and the Digital Revolution (3IR). Glossing over various details thematized above, we explicated the following. (1) In response to technology shocks, the economy has fared well in the long term, with some slightly more ambiguous developments ensuing in the digital revolution. (2) The organization of companies shifted as the 1IR brought the factory system, the 2IR electrified the factory, and automation of the 3IR yielded the opportunity to divide tasks between humans and computers. (3) Concerning task performance, the first two industrial transformations lessened the burden of physical labour, while computers initiated the possibility to automate mental tasks; concerning unemployment, no long-term deterioration of employment occurred over the course of industrial history: The 1IR incited significant technological joblessness of only temporary and sector-specific nature, the 2IR saw employment grow alongside productivity, and the 3IR featured ambiguous results, with some authors arguing that employment has detached from productivity while others note no significant decline in employment; concerning wages, the conditions of the working class of industrial England deteriorated considerably, the incomes of ordinary American grew according to economic growth during the 2IR, whereas the wages have been stagnant since the Digital Revolution. (4) Sectoral worker displacements occurred with severe consequences during the 1IR, were tackled successfully in the 2IR, and have ongoing negative impacts on semi-skilled workers since the 3IR. (5) Inter-country inequalities widened globally since industrialization; intra-country inequalities aggravated between capital and labour in the 1IR, whereas the 2IR saw a Great Levelling, but the 3IR yielded a polarization between different sets of winners and losers and a consequent decline of the middle class.

Since these developments, some potentially transformative innovations have sparked diverse discourses. Arguably the most important technological advance is artificial intelligence, particularly in combination with robotics and IoT-technology. Once more neglecting numerous distinctions thematized above, the following broad argumentations emerged concerning current technological impacts on the labour market. (1) Regarding current and future economic growth, some scholars recognize productivity as declining despite technological progress, whereas others see the economy as set for take-off, with temporary

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slumps explainable by technology diffusion time lags. (2) The impacts on work are a focal point of contemporary scholarly debate. Will technological unemployment occurring in one sector be offset be increased employment in others, like it did in the past? Some remark that the negative impacts of technological change occurring in some sectors will persist and will not be neutralized by other jobs and sectors in the long run. By contrast, others consider current problems as precedented by the 1IR, which eventually balanced out: The negative impacts of technological change occurring in some sectors will not persist and will be neutralized by other jobs and sectors in the long run.

However, one crucial assumption in many of the more well-behaving models is that technological change is routine biased, and the question is whether this is the case. One important caveat to this entire literature is that most of the effects of ai are potentially not yet observable. As the philosopher Roberto Unger contemplates, we have not yet unleashed the full potential of ai (Life Itself, 2019). Much of contemporary debate considers the level of autonomy of ai as its defining feature. In this regard, it is worth noting the terms 'narrow AI' and 'general AI' (alternatively: weak versus strong AI), which describe the variety of domains in which an artificially intelligent agent can operate independently, or without further human input. Narrow or weak AIs can only manoeuvre specific and well-defined tasks, but would be lost when applied to a different problem. General or strong AIs, in its ideal, could direct itself towards and learn any kind of task: it would have general autonomy. As Bostrom (2014, p. 16) remarks, all AIs constructed so far are narrow. Nonetheless, some progress has been made by means of ML. For instance, the company DeepMind Technologies developed an ai system which learned to play up to 49 Atari video games, surpassing human level performance in 29 of them, using the very same algorithm (Tegmark, 2017, p. 110). Thus, although still a long way from an AGI in its ideal sense, ai technology is trending towards more general applicability.

As measured by specific tasks, AIs have already exceeded human performance in many domains; consider the much-quoted examples of an ai outplaying the world's best Go player, largely held to be the most complex game in existence. However, superintelligence more often alludes to dystopian sci-fi scenarios in which an ai becomes so generally powerful that it subjugates humanity, or at least performs all tasks better than humans. Since all currently existing algorithms require clear input and output dimensions, the notion of a superintelligent AGI is entirely hypothetical.

AI necessitates two crucial things to improve (of course, besides well-designed algorithms): Computing power and the availability of data. As for the former, various authors refer to Moore's Law to underscore the rate of improvement of computing power, which has thus far been predominantly exponential (according to current accounts, a doubling occurs every 18 month) (Brynjolfsson & McAfee, 2011; Tegmark, 2017). More precisely, the law refers to advances in in chip design, namely the number of transistors on a circuit board, which translate into processing speed and power (Schneider & Gersting, 2019, p. 211). Moore's Law has been applied to the evolution of various other technological measurements, such as computations per second and memory space, as visualized in figure 15 (Brynjolfsson & McAfee, 2011; Levels et al., 2019; Tegmark, 2017, p. 92). But importantly, experts expect an end point or cap for Moore's Law in ten to twenty years, as the size of transistors in processors trends towards its physical limits, reaching the subatomic sizes; further improvement would then require an altogether new approach to processing (Schneider & Gersting, 2019, p. 182). In fact, the rate of computer speed enhancement has already been declining for several decades (p. 266). This may imply that the potential of ai may have natural limits. Conversely, computer chips may only be one hardware solution which will eventually reach its limits; it may be superseded by another one, just as transistors replaced vacuum tubes when their limit was reached (Tegmark, 2017, pp. 93-94). Writers refer to parallel processing and quantum computing as the hardware solution of the 4IR, which might occasion further growth in computing power (Levels et al., 2019, p. 14; Tegmark, 2017).

Numbers for the availability of data to train ai likewise show a significant upwards trend. Recent reports, for example by the International Data Corporation (IDC), Cisco, or Hewlett Packard, analyze that data growth has been exponential, and will continue to rise (Cisco, 2020; Ffoulkes, 2017; Reinsel, Gantz, & Rydning, 2018). According to IDC, the collective world's data will increase from 33 Zettabytes in 2018 to 175 Zettabytes by 2025, which represents a yearly growth of 61%. Such growth is powered by increasing exposure to the internet, rising diffusion of devices like mobile phones, cloud storage, and the development of the Internet of Things. Here, no slowdown is in sight. Nonetheless, it ought to be noted

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that data availability may be low in specific fields regardless, for instance in domains where other factors inhibit the access to data (e.g. in psychiatry and legal cases) (Levels et al., 2019, p. 14). Privacy and data protection legislation play an important role here, and will continue to shape the advances of data dispersion substantially. Yet, critical authors suspect that the speed of progression of data-driven companies will easily outpace government regulation, because technology powerhouses like Google are not only market leaders but also at the vanguard of scientific research, rendering public authorities reactionary at best (Zuboff, 2019, p. 406).

Intellectual and scientific interest in ai has been increasing since the development of the machine learning paradigm, as evidenced by the amount of funding dedicated to research (Bruckner, 2019). In total, then, and although some bottlenecks and difficulties remain, there is no indication for an endpoint of ai improvement; at most, evidence suggests a potential slowdown of the rate of improvement due to the physical limits of computer chip design in ten to twenty years, if no other solution (like quantum computing) is available by then. Brynjolfsson and McAfee (2011) hypothesize that technological advances may be embarking upon exponential progress. They (p. 51) remark: “In the 21st century, technological change is both faster and more pervasive. While the steam engine, electric motor, and internal combustion engine were each impressive technologies, they were not subject to an ongoing level of continuous improvement anywhere near the pace seen in digital technologies.”

The potential of ai to perform tasks we now consider non-routine is revealed in those cases where the combination of self-learning algorithms, sufficient training data and sufficient computing power has already allowed machines to master tasks that require more than just brute force computing. According to Tegmark (2017, p. 114), the 2016 victory of DeepMind ai AlphaGo over one of the greatest Go player in the world, Lee Sedol, is an important signal of AI’s potential. The ancient board game of Go has more legally playable positions than there are atoms in the observable universe, making an exhaustive analysis of all possible moves utterly impossible for humans and computers alike. Human players generally rely on their intuition guided by passed-down wisdoms. AlphaGO, in contrast to older ai systems, did not attempt to map out all possible moves, but instead accumulated statistical data on what positions are most powerful. At times even coming up with majorly unconventional decisions,

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the ai overcame its expert human adversary. It thus mimicked intuition and creativeness by means of statistics.

This example is worth noting, as it not only demonstrates the capability of ai to sometimes outperform humans in what we thought to be uniquely human skills, but also proves a different point. Similar to the early pioneers of AI, it is sometimes assumes that an artificially intelligent agent, if it is to acquire human-like abilities, it necessarily has to replicate the processes of the human brain. Susskind and Susskind (2015, p. 45) name this the 'ai fallacy'. It posits multiple problems, for instance the fact that we do not understand the human brain fully, and the philosophical problem of other minds, which maintains that since we can only observe other people's behaviour externally, we cannot know whether they are actually conscious. Because, in the case of machine intelligence, we cannot even draw on our subjective experience as conscious human beings to assume consciousness in others, this problem in aggravated with the advent of ai.

But the main conclusion we may draw from this review is how little we actually know, despite all the available studies. Frank et al. (2019) discuss the bottlenecks that prevent researchers from observing the true effects of ai and automation on the future of work. They lament the lack of high-quality data about skill requirement in occupations and other data on the nature of work, the lack of empirical tests of key assumptions about skill substitution and complementarity between humans and machines, and lacking research on the way in which the impact of technologies on labour markets is shaped by wider economic dynamics and institutions. They make a strong argument for further research, most notably to collect and longitudinal and spatial data, and data on workplace skills.

How to govern automation in an uncertain world?

In this context our suggestions for the future are concrete: The first is to try and address any regulatory issues that affect the rate of automation, be it through taxes for capital vs labour, redistribution policies (taxes included) and investments towards efficient use of automation. This includes the distribution of the gains from data analysis (for AI or other purposes) in a more equitable manner. In this domain the Digital Markets Act and the Digital Services Act from the EU, along with the ongoing antitrust legal battles in the US suggest we are moving towards the right direction. For market concentration and the effects of unregulated merger

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activity there is an exploding literature on blocking mergers, splitting behemoths and opening up access to data for entrants. Parker, Petropoulis and Van Alstyn (2021) provide a nice summary of key papers.

The second angle we support is the reskilling and upskilling of workers and the sound education of the younger generations. As workers will soon have to work in a more automated environment it is essential that policy-makers invest their time and effort to prepare them for the changes that they will face. Our message is that we should not fear automation but regulate it to support societies to do more. Rethinking education, the main question is what skills are likely to be required. To be employable in tomorrow's labour market, humans must learn skills that will enable them to compete with machines, work with machines, build machines, or be complementary to machines (Brynjolfsson and McAfee, 2014). Which concrete skills will become crucial remains a matter of conjecture. For example, there is a strong focus on digital skills, while it can be expected that these skills will not be decisive for the employability of a large proportion of workers (Brynjolfsson and McAfee, 2014; Bahski et al., 2017; World Economic Forum, 2018). Good empirical research on skills requirements in different economic sectors in different countries is scarce. Moreover, knowledge about skills demanded or needed rarely finds its way efficiently from employers to training curricula. This is particularly poignant in education systems with a relatively high level of vocational orientation. But other issues arise as well, particularly in the field of adult education. To prepare European countries for the skills demands on the labour market of the future, we need to retrain large groups of workers. Policy makers should not underestimate issues with upskilling and reskilling workers, and provide answers to the most pressing issues. First, upskilling and reskilling are in many countries not seen as a matter of any urgency by the general populace. Illustratively, Janssen et al. (2020) show that in the Netherlands, most adults do not think their job is automatable, and as a consequence do not plan to partake in adult education to remain productive and employable. Another issue is access: not all workers have equal access to training opportunities. A third issue is trainability. Policymakers must recognize that retraining is difficult, if not impossible, for many people. For example, older workers are generally less likely to learn new skills (Lustig et al., 2010; Salthouse, 2011). The ability to relearn should also not be overestimated. For example, about a third of the Dutch

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workforce has too low a numeracy skill to be retrained for a profession in the digital sector (Levels, 2020). Retraining pathways must also take into account people who have difficulty, or even no ability, to learn. A social re-skilling agenda must also provide opportunities for the most vulnerable.

The third part of our suggestions includes the strengthening of policies aiming to address rising inequality that is partly attributed to automation but not entirely. These include the efforts to impose global minimum corporate taxes (OECD, 2021).

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Appendix: Methodology and Conceptual Framework

This review aims to provide an overview of contemporary debates regarding the effects of the current technological developments on labour markets. As such, we take on an objective standpoint. However, our research is conceptually framed by the assumption that modern technology is at least potentially disruptive in a manner akin to previous industrial revolutions. We accept the definition of 'industrial revolution' of the United Nations Department of Economic and Social Affairs: While technological progress is usually gradual, at certain historical times it is marked by radical change (Bruckner, LaFleur, & Pitterle, 2017, p. 4). These transformations occur largely due to the widespread diffusion and adoption of novel general purpose technologies (GPTs) (Bruckner et al., 2017, p. 5). Accounts of recent economic history generally feature three to four of these industrial revolutions. Of note, the year indications in the following are of the broadest sort and are dated differently by various scholars.

The First Industrial Revolution (1IR) took place roughly between 1760 and 1840, initially in Britain, but also – in differing time periods – in Belgium, France, Germany, Sweden, Japan, and the United States (Bruckner et al., 2017, pp. 8-9; Frey, 2019, p. 22). Key characteristic of this transformation was the replacement of manual labour with machines, particularly the steam engine, and the division of labour organized in the machine-based factory system (Bruckner et al., 2017, p. 5; Frey, 2019, p. 94; Marx, 1867).

Known somewhat ambiguously as the Technological Revolution, the Second Industrial Revolution (2IR) is dated broadly from 1850 to 1910 (Bruckner et al., 2017, p. 9). The United States took centre stage (Bruckner et al., 2017, p. 8; Frey, 2019, p. 143). The crucial developments here were the electrification of factories and the advent of the combustion engine (Frey, 2019, p. 142).

The Third Industrial Revolution (3IR), or Digital Revolution, began approximately around 1960 and ended around 2000 (Bruckner et al., 2017, p. 9). Some authors hold that this transformation is still ongoing (Brynjolfsson & McAfee, 2014; Garbee, 2016; Rifkin, 2016; Usher, 2017). Characteristic was digitalization based on the invention and diffusion of information and communication technology (ICT) in general, and the computer in particular (Bruckner et al., 2017, p. 5; Frey, 2019, p. 227).

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The terminology 'Fourth Industrial Revolution' (4IR) was first introduced in 2015 by the founder of the World Economic Forum, Klaus Schwab. It derives from the term 'Industrie 4.0' of the 2011 German Strategy, the German government's high-tech strategy (*Germany: Industrie 4.0*, 2017; "Industrie 4.0," n.d.). Grounded in an expansion of ICT, yet coined by "qualitatively different technologies and capabilities" (Bruckner et al., 2017, p. 5), Schwab (2015) argues that 4IR features breakthroughs in and the combination of various technologies, for example robotics, AI, nanotechnology, quantum computing, 3D printing, and others, into cyber-physical systems. Most other scholars name intelligence as the cornerstone of current technological advances (Bostrom, 2014; Bruckner et al., 2017; Frey, 2019; Susskind & Susskind, 2015; Tegmark, 2017).

Whether the 4IR constitutes a separate industrial revolution or merely represents a continuation of 3IR is debated. Our utilization of the term does not imply a judgment regarding this query. We utilize the term for the sake of simplicity, as well as for the purpose of this literature review, which is to compare the effects of previous technological changes to current ones.

Various search queries we employed prompted an abundance of *a priori* irrelevant results. For instance, in one test search, the query 'ts=(industr* 4.0)' yielded 11,098 hits, roughly 9000 of which were from technical fields like (software or electrical) engineering. To limit the findings to strictly relevant sources, we formulated a number of inclusion criteria. First, we restricted the search to English-language publications by virtue of the authors' language abilities. Second, we excluded all results from technical and natural scientific disciplines; in light of our research question, we are interested in the socio-economic effects of the technology transformation, not its technical realization. Finally, to manage the sheer amount of available resources, only publications in the TOP 20 journals in the SSCI database for each field were included; to minimize the consequent bias, publications in lower ranking journals were included if they were well-cited (97th percentile in its discipline).

To obtain relevant literature, we firstly searched the Web of Science Core Collection using a set of rigorously defined search queries, constructed to cover the entirety of the field from interdisciplinary perspectives. A complete overview of the queries is available on request. In order to further reduce top-journal bias, Google Scholar was consulted using the same search

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terms (adjusted to the database). After cross-comparison to the results generated from Web of Science, additional publications were added to the literature list.

The methodology adopted is augmented by the following conceptual considerations. Based on the discourses treated in the literature, we developed a working list of dimensions, or categories, according to which we structured and conducted our further research. The dimensions are:

- Impact on the economy
- Impact on companies
- Impact on work
- Impact on workers in specific jobs and sectors
- Impact on different social groups

Note that these dimensions are dynamic and interrelated. For example, if a technological development alters the organizational structure of companies, the workers in these companies are necessarily also affected. Essentially, we are scrutinizing the same phenomena from different perspectives.

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Appendix

Appendix A: List of search queries for Web of Science, incl. initial number of results

(Indexes=SSCI, A&HCI, CPCI-SSH Timespan=All years; English language) [14.02.2021]:

1. ts=("*th Industrial Revolution") → **607 results**
2. ts=("Industr* 4.0") → **1500 results**
3. ts=("skill$ biased techn* change" OR "routine biased techn* chance") → **269 results**
4. ts=("techn* shock$") → **653 results**
5. ts=((technolog*) AND (labo$r market$ OR *employment OR *skilling OR retrain* OR skill$ OR education OR training)) → **87,498 results**
6. ts=((technolog*) AND (growth OR productivity OR GDP)) → **39,887 results**
7. ts=((technolog*) AND (*equalit* OR income OR wage$ OR "social mobility")) → **14,629 results**
8. ts=(("artificial intelligence" OR "AI" OR "machine intelligence" OR "artificial general intelligence" OR "AGI" OR "machine learning") AND (labo$r market$ OR *employment OR *skilling OR retrain* OR skill$ OR education OR training)) → **5197 results**
9. ts=(("artificial intelligence" OR "AI" OR "machine intelligence" OR "artificial general intelligence" OR "AGI" OR "machine learning") AND (growth OR productivity OR GDP)) → **1041 results**
10. ts=(("artificial intelligence" OR "AI" OR "machine intelligence" OR "artificial general intelligence" OR "AGI" OR "machine learning") AND (*equalit* OR income OR wage$ OR "social mobility")) → **522 results**
11. ts=((automation OR digiti?ation OR computeri?ation) AND (labo$r market$ OR *employment OR *skilling OR retrain* OR skill$ OR education OR training)) → **2529 results**
12. ts=((automation OR digiti?ation OR computeri?ation) AND (growth OR productivity OR GDP)) → **830 results**
13. ts=((automation OR digiti?ation OR computeri?ation) AND (*equalit* OR income OR wage$ OR "social mobility")) → **334 results**

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