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THE FOURTH INDUSTRIAL REVOLUTION AND THE DISTRIBUTION OF INCOME

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Introduction

The recent stream of technological innovations, especially in the field of cognitive computing technologies, is expected to lead to significant structural changes in the economy and society – comparable to periods of technological upheaval in the past. While technology is commonly seen as a main driver of economic growth, phases of major technological change have always been accompanied by anxieties and fears associated with the possible negative effects technology may have on employment as machines have increasingly become able to substitute for human labour (Mokyr et al. 2015). Thus far, the predictions of high technological unemployment have never been fulfilled. On the contrary, innovation and new technologies have usually given rise to the creation of new jobs and industries as labour productivity and productive capacities increased, living standards improved, and new products were developed.

However, even though previous technological revolutions have had positive long-run effects, they were accompanied by significant disruptions such as rising income inequality. In fact, technological change has long been identified as one of the main drivers of income inequality (Atkinson 2015). The more recent phase of technological development, which is often referred to as the fourth industrial revolution, is no exception and might therefore exacerbate income inequalities, which are currently at historically high levels (Piketty 2014). Income inequality encompasses two different, but interconnected aspects: the personal income distribution and the functional income distribution. The former describes the distribution of wages on the individual or household level, while the latter refers to the distribution of income between the owners of the factors of production.

In economic theory new technologies are treated either as substitutes or complements of human labour depending on the skill-content of jobs or tasks. Hence, innovations affect the wage distribution between different skill groups by increasing the relative productivity of some (the high-skilled workers) while decreasing the relative productivity of others (the low-skilled workers). Based on the assumption that wages are paid according to the marginal productivity of labour, this implies that technological change increases wage dispersion. The hypothesis of skill-biased technological change and the newer concept of routine-biased technological change have been studied intensively (Acemoglu 2002; Acemoglu and Autor 2011; Autor 2013; Autor et al.
2003, 2008; Card and DiNardo 2002; Goos et al. 2009, 2014; Goos and Manning 2003, 2007) but need to be reconsidered, nonetheless. Given the progress in fields such as Artificial Intelligence, machines can perform a rising number of tasks of increasing complexity, such as driving or speech recognition (Brynjolfsson and McAfee 2014). Hence, to remain competitive, people will need to acquire new skills for the upcoming era of the fourth industrial revolution (Acemoglu and Restrepo 2020; Furman and Seamans 2019). One set of new skills can be subsumed under the term digital skills, which refer to abilities related to the use of digital technologies, encompassing a broad range of skills such as creating and editing digital media, using online services, or protecting privacy and data. It is well-known from the literature in sociology and media and communication studies on digital inequality that these skills are unequally distributed along the usual dimensions of social inequality, such as age, gender, race, or socio-economic status (DiMaggio et al. 2004; Drabowicz 2014; Robinson et al. 2015; van Deursen et al. 2017). The unequal distribution of digital skills, which can be explained by theories of social stratification, might therefore perpetuate existing wage inequalities as the demand for these skills grows in the labour market.

But technical progress may also affect the income distribution by changing market structures. The recent wave of technological innovations is characterised by the growing importance of knowledge-based capital (KBC), which gives rise to economies of scale. Due to these increasing returns to scale, KBC-intensive sectors tend to be highly concentrated and dominated by few incumbent firms that may achieve global market power and benefit from monopoly or oligopoly rents and high capital returns. These oligopolistic market structures as well as the high innovative capacity in KBC-intensive sectors increase the risk for competitors to be successful in such markets. Consequently, the risk premium is higher for investment in KBC, increasing the return on capital for successful investors. These effects may lead to rising capital shares in knowledge-based economies and thus, lower wage shares.

The goal of this chapter is to present an overview of the most popular explanations to relate income inequality with technological change in the economics literature and to discuss what this relationship may look like in the era of increasingly smart technologies, which “enable[e] intelligence, processing, communication, and networking capabilities in all products, systems, and processes, influencing all parts of society” (Beernaert and Fribourg-Blanc 2017: 567). This does by no means mean that new technologies are the only explanation for rising income inequality. Indeed, there are several important (and usually intertwined) factors explaining income inequality, for example, globalisation, redistribution policies, financialisation or the reduced bargaining power of labour. Hence, our account provides one puzzle piece for explaining social and economic inequality.

The chapter is structured as follows. First, we discuss technological revolutions from a historical perspective. In the following section, we present the key mechanisms how digitalisation may affect income inequality. Then, we discuss how product and process innovation affect labour demand and consequently the earnings distribution. Afterwards, we review recent research on the impact of digital innovations on market concentration, the functional income distribution, and the rise of the top 1% income share. The last section concludes.

**Transformative technologies: a historical perspective**

Adding a historical perspective helps to inform our understanding of the ways in which current technological changes may affect the economy and society. The use of the term fourth industrial revolution, coined by Schwab (2016), suggests that recent technological developments, often
summarised under the catchword “digitalisation”, have a similarly transformative character as technological revolutions of the past. This is also reflected in the conceptualisation provided by Lee et al. (2018: 7) who describe the fourth industrial revolution as “the broad changes in industries as well as society that are affected by the disruptive technological changes in artificial intelligence, automation, and hyper-connectivity”.

The first great industrial revolution refers to the onset of the mechanisation of production with the help of steam and waterpower at the end of the 18th century and marks the transition from an agricultural society to an industrial society – at least in those countries that are considered the most highly developed economies today. The transformative character of the general purpose technology (GPT) that drove the first industrial revolution, namely steam power, can be illustrated by two examples: firstly, the invention of the steam locomotive made it possible to bridge geographical distances at a speed never seen before. Secondly, the concept of wage labour emerged with the implementation of the industrial mode of production and, conversely, a class of capitalists was formed while for the first time in history, the workplace was separated from home. These two examples illustrate an important characteristic of a general purpose technology (GPT): they do not only change the economy by increasing productivity, but they change society as a whole (Lipsey et al. 2005). The social changes brought about by the first industrial revolution in Britain are well-studied (see for example Feinstein 1998) and the general conclusion that is drawn distinguishes between long-run and short-run effects: despite the recurring concerns that machines will make human labour redundant (see Mokyr et al. 2015), the mechanisation of production did not lead to technological unemployment at a large scale in the long run because sustained productivity growth and the emergence of new industries and occupations were able to absorb the displaced workers. However, the authors emphasise that these developments took time and, estimations suggest, longer than an average working life. In fact, the transition phase was characterised by substantial disruptions such as the worsening of working conditions as production shifted from artisan shops to factory mass production, and rising income inequality (Mokyr et al. 2015).

The second industrial revolution is commonly dated back to the late 19th and the early 20th century when mass production caught on with the help of the GPT of that time, electricity. One example illustrating the transformative character of electricity is the electric telegraph, which was as revolutionary as the Internet in accelerating the flow of information and thus facilitating trade and commerce, among others (Mokyr 1999; Wajcman 2013). Furthermore, the electrification of the assembly line was crucial for the mass production of goods, turning former niche or luxury markets to mass markets. A classic example is the market for the automobile: the high productive efficiency translated to a massive fall in prices for cars from an average of 2,126 US-$ in 1908 to 317 US-$ (in 1908 dollars) in 1923. This drop in prices is reflected in a massive growth of annual sales from 64,000 in 1908 to 3.6 million in 1923 (Wajcman 2013). Furthermore, the organisational requirements of mass production, especially the need to plan both the product as well as the work process in advance, contributed to the emergence of new bureaucratic corporation structures, which resulted in a growing demand for white-collar workers (Lauder et al. 2018). The mass market does not only require mass production, but also mass consumers – the emergence of consumerism is therefore driven by the early industrial revolutions. Indeed, between 1870 and 1914 real wages increased considerably and standards of

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1 There is a variety of terminologies and characterisations of the on-going phase of technological change; see for example Kurz et al. (2018).

2 A general purpose technology is characterised by the following features: they are not restricted to individual industries, they are evolving and reduce costs for users, and they ease the diffusion of innovations.
The fourth industrial revolution

living, for example in terms of social insurance, working hours, nutrition, or housing, started to improve in Western industrialised countries (Mokyr 1999).

The third industrial revolution, which started in the 1970s, is characterised by the increasing usage of IT and electronics to automate production processes even further. It marks the beginning transition from the industrial to the information society. At the same time, this period is characterised by an acceleration of globalisation trends, which is closely connected to the development of information and communication technologies. The most important GPTs of this period are computers and the Internet, whose global spread increased rapidly between 1970 and 2000. While there is disagreement to what extent these technologies affected productivity, it is widely agreed upon that computerisation has altered the nature of work and the structure of employment, for example through its impact on the task composition within industries and occupations with considerable shifts towards analytical and interactive non-routine tasks (Spitz-Oener 2006; Black and Spitz-Oener 2010).

ICT and the Internet still play a dominant role for the fourth industrial revolution, but it is difficult to foresee what the next GPT will be. One candidate is Artificial Intelligence (AI), which relies heavily on the availability of enormous data stocks (big data) to improve pattern recognition and analysis (OECD 2020). Pratt (2015) estimates that global data storage is roughly equivalent to the capacity of ten million human brains. Of course, this should by no means be equated with the capacity of ten million human brains, but it is a good indicator of the scale of global information storage. Since AI benefits greatly from large amounts of data and the implementation and availability of local wireless communication as well as the increasing spread and performance of the Internet, the foundations for AI-intensification in the production of goods and services seem to have been laid. Moreover, given the efforts in various countries to promote variants of the German “Industry 4.0”, a concept of industrial production in which smart machines, production parts, and storage systems communicate with each other by autonomously exchanging data and thus automatically initiating the execution of work tasks (Brödner 2018), it is not surprising that David Ricardo’s “machinery question” has re-returned in recent years. In general, the historical evidence suggests that the impact of technological revolutions on the economy and society is positive for economic and social welfare. However, even optimistic accounts, such as the one of Mokyr et al. (2015), recognise that there are significant detrimental impacts on some parts of the society in the short and medium term, thereby increasing social inequality. Hence, it is important to study the consequences of these disruptions that will hit society as the fourth industrial revolution evolves. Especially during the first industrial revolution no measures were taken to alleviate the negative impacts of mechanisation, but the ongoing fourth industrial revolution can be shaped so that risks and opportunities are more evenly shared. “Technology is not destiny” (Brynjolfsson and McAfee 2014: 257) and neither is the impact of a technological revolution on society.

The key relationships between the fourth industrial revolution and income distribution

In the following sections we discuss the key mechanisms through which the fourth industrial revolution affects the income distribution illustrated in the conceptual diagram presented in Figure 9.1. The diagram provides a summary of the main arguments encountered in the literature on the impact of the recent wave of technological change on income inequality and guides the structure of this section. First, we describe the general macroeconomic effects of technological innovation on labour demand, illustrated as channel (1), using the compensation theory as presented in Vivarelli (1995, 2014). We then discuss the consequence of changing
skill requirements due to the employment effect induced by process and product innovations for the personal income distribution, illustrated as channel (2), based on the commonly used explanations in the economic literature, skill-biased technological change and routine-biased technological change (e.g., Acemoglu and Autor 2011). In addition, we relate the demand for “new” digital skills to wage inequality based on the digital inequality literature and the stratification hypothesis. Next, we turn to the potential effects, which the fourth industrial revolution might have on market concentration due to economies of scale, network effects, and the process of creative destruction, illustrated in channel (3). Finally, we describe how rising market concentration may affect the distribution of income due to the distribution of monopoly rents and potential superstar effects illustrated as channel (4).

The fourth industrial revolution, employment, and the distribution of wage income

Macroeconomic effects of process and product innovations on labour demand

For a simplified analysis of macroeconomic employment effects of technological change, one can distinguish between process innovations and product innovations. While the former are generally assumed to increase labour productivity by improving the production process (labour
saving technological change), the latter are assumed to enlarge product markets and, thus, tend to have positive effects on employment and aggregate income (Vivarelli 1995). Smart technologies, which play a key role in the fourth industrial revolution, are characterised by both types of innovations. On the one hand they are used in industrial production, for example in the form of robots, where they displace more costly human labour in the production process. On the other hand, some smart technologies are products that can be seen to (indirectly) expand the market while others are merely substitutes for existing goods. For example, smartphones exhibit both properties: they substitute for standard mobile phones and at the same time, they create new markets complementary to smartphones, such as the market for apps.

The productivity gains associated with process innovations can trigger compensation effects in quite distinct parts of the economic system that might mitigate or even offset their negative displacement effects (Acemoglu and Restrepo 2020; Vivarelli 1995, 2014). The following description of the compensation effects follows Vivarelli (1995: 26ff.) and Vivarelli (2014: 125ff.) who takes into account institutional and market mechanisms. One commonly used argument in favour of compensating effects assumes that, in perfectly competitive markets, falling production costs lead to lower prices for consumers which stimulates demand for products and, thus, labour demand. The effectiveness of this mechanism of compensation via decrease in prices crucially depends on competitive market structures and on the price elasticity of demand: the lower the price elasticity of demand, the weaker the compensation effect. If markets are incomplete and if there is imperfect competition, cost saving does not necessarily lead to lower product prices for consumers which weakens the compensation effect due to lower prices.

If market power prevails, cost reductions might in fact result in higher profits for companies and/or higher wages for those employed in those innovating firms. Higher profits, in turn, can be used in different ways: they can be distributed as dividends to shareholders, reinvested in the company (for example in R&D to foster further innovation), or invested in the financial market. In principle, profits that are shared with employees in the form of higher wages or if they are shared as dividends with shareholders, this may induce a compensation effect via increases in income by generating additional demand. The scale of this compensation effect via increases in income depends on factors related to bargaining power, but also the propensity of households to consume or propensity of firms to invest. This demand-driven compensation effect in the Kaldorian and Keynesian tradition stands in contrast to the neoclassical compensation effect via decrease in real wages: although it is of course possible that firms hire more workers when wages decrease, as suggested by partial labour market theory approaches, this may be offset due to potential negative impacts of lower income on effective demand.

The compensation effects described thus far emerge due to process innovations. But an important aspect of technological progress and innovation is the invention and development of new products and services that may lead to the emergence of entirely new markets and sectors with new employment opportunities. The magnitude of this effect, compensation via new products, depends on the substitutability of new and old products as well as on the labour intensity of the production of new products. This effect is the most difficult to foresee or speculate about because it impossible to know what goods or services people will want or need in the future, but it has clearly been a highly effective compensation mechanism in the past. Just think about the vast number of jobs in all kinds of sectors of the economy created around the invention of the automobile, the computer or the Internet. Related to these effects caused by product innovation, is the creation of new tasks or the alteration of “old” tasks due to the development of new technologies that complement labour (Acemoglu and Restrepo 2018). One good example for a new task created by the Internet is web development while tasks related to social media management can be seen as a mix of new and traditional marketing tasks. Thus, if humans continue
to have a comparative advantage in performing certain tasks and if R&D efforts are directed towards labour-friendly innovations, for example assistive technologies in care, even sophisticated computer technologies will not lead to persistently high technological unemployment (Autor 2015; Acemoglu and Restrepo 2018). The interaction of the substitution and compensation effects determine the net impact of process and product innovation on the demand for labour.3 Regarding the technologies of the fourth industrial revolution, much of the literature focuses on quantifying substitution effects, or more precisely substitution potentials, without assessing possible compensation effects. Overall, these studies predict that new technologies can substitute for an increasing number of tasks and consequently jobs that rely heavily on automatable tasks. For example, Dengler and Matthes (2020) show in a recent analysis that 34% of male and 15% of female employees in Germany work in jobs with a high potential of substitution (i.e., more than 70% of the tasks could be automated). The gender differences are explained by the gender-specific segregation of the German labour market: the risk of substitution is high in male-dominated occupations, while it is low in social and cultural service jobs, which are dominated by women. They further find that employment growth between 2013 and 2016 is significantly weaker in occupations with a higher potential for substitution. This might indicate that these occupations are subject to on-going automation processes.

While Dengler and Matthes (2020) and similar research, such as Frey and Osborne (2017) or Arntz et al. (2017), study the technological potential for substitution, they leave aside the potential for compensation. So far history has shown that compensation effects always more than offset the substitution effects on the aggregate, due to sustained productivity growth and the expansion of markets following the introduction of new products as well as the creation of new tasks, as described in Acemoglu and Restrepo (2018). Moreover, technological unemployment was also avoided by dividing work between a greater number of people thereby reducing the total numbers of hours worked (Leontief 1982). For example, the quantity of annual hours worked per employees halved between 1870 and 1998 in highly industrialised Western economies (Mokyr et al. 2015).4 Nevertheless, current developments, such as the slowdown of productivity growth and in particular its decoupling from employment growth in recent years (Brynjolfsson and McAfee 2013), suggest that for the fourth industrial revolution, some compensation effects might just not be as strong as for previous industrial revolutions which might be a consequence of the different nature of the capital used in the production of goods and services today: the fourth industrial revolution is characterised by the growing importance of so-called knowledge-based capital (i.e., intangible capital goods such as software, data, but also Research & Development [R&D] and intellectual property rights). Due to the non-rivalry property of knowledge, KBC-intensive industries are characterised by increasing returns to scale giving rise to growing market concentration (Guellec and Paunov 2017). This may reduce the size of the compensation effects significantly if innovating firms do not share innovation rents with their employees or invest them to expand production, but rather engage in rent-seeking, or use the rents to invest in (unproductive) financial capital.

3 This is discussed in a similar way in Acemoglu and Restrepo (2018, 2020). However, the account of Vivarelli (2014) presented here gives a more general overview as it also discusses substitution and compensation effects in terms of how institutional and market structures can affect the overall labour demand outcomes.

4 Even though it is reasonable to assume that humankind will never actually run out of work, the unequal distribution of work will remain one of the most pressing issues for modern societies. For example, in recent years a polarisation of hours worked can be observed; the share of people working many hours and the share of people working no or few hours have both been increasing, which contributes to the polarisation of employment (Wajcman 2013).
Labour demand and wage inequality: skill-biased technological change, routine-biased technological change, and digital inequality

The dominant view in economics is that technological change is expected to increase income inequality because new technologies complement high-skilled workers while they substitute for low-skilled workers and thus raise the demand for high skills relative to the demand for low skills (Atkinson 2015). The argument is rooted in human capital theory and it relies on the assumption that wages reflect a worker’s marginal productivity of labour. Consequently, according to the skill-biased technological change hypothesis, new technologies increase the productivity of high-skilled workers who receive higher wages as they are remunerated according to their marginal product of labour. An early contribution fuelling the idea of biased technological change is the paper of Atkinson and Stiglitz (1969) in which they argue that technological change does not affect workers’ productivity in general but is often specific to certain production activities. Atkinson and Stiglitz (1969) deviate from the then-orthodoxy by recognising that technological change is not neutral, but that the localisation of technological change in the work process matters. Ideas of the model proposed by Atkinson and Stiglitz (1969) found application in the literature on skill-biased technological change but even more so in the literature on task-biased technological change. In this section we discuss both, as they are still the dominant explanations of rising wage inequality due to technological change.

SKILL-BIASED AND ROUTINE-BIASED TECHNOLOGICAL CHANGE

The textbook model relating wage dispersion to technological change in economics draws on the hypothesis that modern technologies are essentially skill-biased in favour of highly skilled workers (Acemoglu and Autor 2011). According to the hypothesis of skill-biased technological change (SBTC), technological change affects the wage distribution between different skill groups by increasing the productivity of high-skilled workers relative to that of low-skilled workers. This was extensively studied regarding the computer revolution: at least since Krueger (1993) economists argue that the use of computers increases the productivity of employees and they are thus rewarded higher for their computer skills. The computer wage premium therefore contributes to rising earnings inequality between those who have these skills and those who do not.

While the idea that new technologies are pre-dominantly upskilling seems to receive empirical support, they fail to explain more recent developments such as the polarisation of labour markets with growing employment shares at the top and at the bottom of the skill or income distribution at the cost of middle-income jobs, or the rising share of top 1% income earners. While the former has been addressed by economists through shifting the focus from skills, or rather formal education, to tasks (Autor et al. 2003), the latter, and we will return to this in

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5 Kristal and Edler (2019) briefly discuss status distinction as an alternative reason for why computer use at work is rewarded. The general idea is that computer use at work can help to “generate resources that workers can use in making claims on starting salary and pay raises” (4). This goes back to DiMaggio and Bonikowski (2008) who argue that computer savviness may signal competence or greater skills and employers might therefore be inclined to pay them higher wages. Furthermore, apt Internet users can access a greater range of labour market information, increasing their bargaining power, and they can expand their social network and may therefore benefit from wage effects due to greater social capital.

6 See for instance Acemoglu (2002) for a review and Card and DiNardo (2002), Lauder et al. (2018), and Bogliacino (2014) for critical discussions of SBTC.
the following section, is related to “superstar” economics and rising returns to capital and the unequal distribution of capital ownership.

To explain the phenomenon of polarisation of labour markets, Autor et al. (2003) develop a task model which recognises that jobs consist of different tasks that can be categorised along the dimension’s routine/non-routine and manual/cognitive tasks. The distinction of skill and task is the most important difference between the canonical model and the task model (Acemoglu and Autor 2011): while a task is defined as a unit of work activity which produces output, skills refer to a worker’s general stock of capabilities to perform different tasks. This implies that workers of a given skill level, which has been acquired by formal education and experience, can reallocate their skills towards different sets of tasks in response to needs and wants. In other words, within the defined skill groups workers are essentially free to change the set of tasks they perform and consequently, they can adapt to changing labour market conditions. The main argument put forward in Autor et al. (2003) is that technologies can replace specific, codifiable routine tasks while they cannot perform non-routine manual and cognitive tasks. Whether a job is prone to substitution depends on the mix of codifiable routine tasks and more complex, non-routine tasks. The routine-intensive jobs do not necessarily have to be low-skill and low-paying jobs. In fact, many low-paying jobs in personal services are non-routine intensive while some typical middle-paying occupations, such as administrative work or bank tellers, are routine intensive (Autor 2013, 2015).

Since the introduction of the task model, numerous empirical studies confirm its prediction of a shift away from jobs with a high-routine task content towards jobs with a low-routine task content and corresponding wage dispersion (for example Autor 2015; Autor et al. 2008; Goos et al. 2014) or put differently, the past decades were characterised by the dual growth of what Goos and Manning (2003) call good MacJobs and lousy McJobs (Wajcman 2013). In addition, Black and Spitz-Oener (2010) show that the task content within occupations changed considerably because of computerisation between 1979 and 1999. They observe a significant increase of the share of non-routine analytical tasks.7

Considering the fourth industrial revolution the question arises to what extent new smart technologies such as AI will change the demand for skills and therefore wage differentials. It is difficult to foresee which tasks will become routine in the future – for example, the initial work of Autor et al. (2003) considered driving a car as a non-routine task. Nowadays autonomous driving is not fiction anymore from a technical point of view. This highlights how difficult it is to predict which skills will be needed to perform which tasks in the future. While high skills are needed to develop, design, and programme smart technologies, medium skills are needed to supervise, maintain, and manage the production processes (in manufacturing as well as in services). Low skills to perform, for example, non-routine manual tasks that require responsive reactions, such as the tasks carried out by click-workers, will also be demanded in the future. Deming (2017), on the other hand, highlights the growing importance of social and interpersonal skills since the 1980s. One explanation, following Autor (2015) is that tasks which require such skills cannot easily be carried out by machines – not even by very smart ones. Nevertheless, although precise estimates of future skill demand are not feasible, there is broad consensus that the task content of occupations has already been subject to significant changes and that the demand for (more or less) new digital skills and other technology-complementing skills will

7 This development was particularly pronounced for women and Black and Spitz-Oener (2010) argue that this was a main driver of the declining gender wage gap. While we believe that gender equality in the fourth industrial revolution is a very important topic, the literature is too large to discuss it here but Howcroft and Rubery (2018) provide an informative overview of gender equality issues in the fourth industrial revolution.
increase (Deming 2017; Ferrari 2013; Furman and Seamans 2019). Furman and Seamans (2019) specifically point to machine-learning skills for the era of AI while Deming (2017) emphasises social and so-called “soft” skills as important complementary skills. Moreover, Acemoglu and Restrepo (2018) highlight the problem of workers acquiring the “wrong” set of skills for the upcoming era of technologies such as AI. They further argue that a shortage of certain skills might have significant negative effects with far-reaching implications for inequality. Since economic research shows that there is a wage premium for digital skills (Falck et al. 2016; Grundke et al. 2018; Hanushek et al. 2015), rising demand for digital skills will affect wage inequality between those who possess these skills and those who do not.

### DIGITAL SKILLS

Digital skills are understood as skills which are necessary to perform activities and meet the requirements of digital technologies. The range of activities that require a certain level of digital skills is manifold and differ regarding their levels of complexity: using a smartphone, using a self-service cash register, maintaining an industrial robot, using spreadsheets to prepare budget plans and various forms of Internet use for research purposes, programming a search engine algorithm, etc. In short, digital technologies already permeate all areas of life and digital skills are therefore not only becoming increasingly important for (finding and keeping) work, but also increasingly determine the extent of social participation in everyday life (e.g., to use online services provided by the government).

It is often assumed that as the fourth industrial revolution progresses, relative demand for (new) digital skills will continue to rise (Berger and Frey 2016) and consequently their value, which results in higher wages for jobs requiring those skills intensively. However, these jobs will most likely be filled by people who already possess digital skills since it is more costly to acquire new skills than to “update” skills that already exist. As a result, the gap between people who are more comfortable using digital technologies and those who are not will widen. The crucial question is what causes this gap. From an economist’s perspective, people possess different digital skills, a specific form of human capital, due to a variety of individual factors such as personal characteristics (e.g., innate abilities), acquired knowledge through formal and informal learning processes, and selection mechanisms following considerations of comparative advantage (Rosen 2008). Human capital formation is essentially assumed to follow the same logic as any other investment decision, but socio-economic inequalities mediate the returns to these investments. This is not too different from research in sociology that emphasises how existing structural social inequalities determine and shape the patterns of digital inequality and the distribution of digital skills (Robinson et al. 2015). However, scholars of social stratification and social exclusion are particularly interested in understanding the interplay of social structures (e.g., class, status group, or power) and digital inequality (Ragnedda 2017).

In this section we switch to the sociological perspective and discuss how wage inequality in the digital age is related to digital inequality, which can be described as the unequal access to and the differentiated use of digital technologies across different social strata of the society (e.g., Helsper 2012; DiMaggio et al. 2004; Robinson et al. 2015). The theoretical basis for digital inequality research is provided by Helsper (2012) who develops a corresponding field model to explain differences in ICT use as a complex interplay of economic, cultural, social, and personal factors in the offline and the digital world, which reinforce each other. In this model, social inclusion is restricted by economic constraints (e.g., lack of income, joblessness), cultural constraints (e.g., gender or other stereotypes), social constraints (e.g., networks of friends and family), or personal constraints (e.g., physical/mental well-being or psychological
traits). Helsper (2012) argues that exclusion from these offline fields corresponds to exclusion in digital economic, cultural, social, and personal fields – and vice versa. In the context of this model, digital skills are an important mediator of the influence of offline social exclusion on digital exclusion (Helsper 2012). Consequently, their distribution determines to what extent offline social inequality is reproduced, amplified, or might even be reduced. However, the vast body of literature on the digital divide and digital inequality indicates that the distribution of those skills is characterised by existing patterns of social inequality and reveals the structural differences in the access to digital technologies (first-level divide) and in the use of digital technologies (second-level divide) along the usual dimensions of social inequality, such as gender, socio-economic background, age, ethnicity, etc. (DiMaggio et al. 2004; Robinson et al. 2015; van Deursen and van Dijk 2014; Zilian and Zilian 2020; Zillien and Hargittai 2009). Over the past years, the concept of the third-level digital divide, which focuses on inequalities in outcomes related to ICT use, gained attention (Ragnedda 2017; van Deursen et al. 2017).

When the digital divide research first appeared in the 1990s, it was mainly concerned with differences in Internet access, both in a comparative and intra-country context (van Dijk 2005; Zillien and Hargittai 2009) and many studies confirm the hypothesis that socio-economic inequalities are reflected in access to the Internet (for overviews, see DiMaggio et al. 2004; van Dijk 2005; Robinson et al. 2015). With the on-going process of digitalisation of an increasing number of different aspects of economic, social, and political life, the first-level digital divide lays the foundation for further digital inequalities. This idea is well summarised in van Dijk (2005: 15) who puts forward that the digital divide is driven by the unequal distribution of resources leading to “unequal access to digital technology [that] brings about unequal participation in society”.

Thus, as digital technologies and the Internet have become more widespread, the focus of research has shifted from access to the Internet, to analysing differences in the way people use computer technologies and how this affects their success in different life domains (Ragnedda 2017). For example, Zillien and Hargittai (2009) find that people with a higher socio-economic status are more likely to use the Internet for informing themselves about politics, economics, or about stock markets than people with a lower socio-economic status. More recently, van Deursen et al. (2017) study the sequential and compound pattern of digital inequality based on a representative survey of Dutch Internet users. They find that digital exclusion starts with differences in skills (not only technical but also social and creative skills), followed by differences regarding the purpose of Internet use and finally differences in tangible outcomes in the offline world. The authors therefore provide evidence for the hypothesis that the Internet exacerbates offline inequalities. For Austria, Zilian and Zilian (2020) demonstrate that being female and having a low socio-economic background have a negative impact on digital problem-solving skills, as measured by the PIAAC8 survey in 2011/12. However, the degree of ICT engagement in everyday life absorbs these differences suggesting that the acquisition of digital problem-solving skills is characterised by “learning-by-doing”, which is in line with van Dijk (2005). Hence, enabling the integration of ICT use in everyday life may help to reduce digital inequality but to what extent does not only depend on the quantity of ICT use, but ultimately on the quality – and this is primarily a question of the distribution of financial resources: despite the shifting focus towards the second-level and third-level digital divide, the first-level divide regarding access to the Internet and hardware still matters, even in developed countries. A notebook provides different features and possibilities to develop digital skills than a smartphone or a tablet. An old and slow computer or a bad and slow Internet connection may negatively affect

8 The OECD Programme for the International Assessment of Adult Competencies.
The fourth industrial revolution affects wage income inequality mainly because of its impact on skill requirements. The literature on routine-biased technological change shows that significant changes of employment and occupational structures have been taking place since the beginning of the 1990s and polarisation patterns can be observed in many Western industrialised countries. It is reasonable to expect that technology-driven transformations of the task content and organisation of work will continue. While it is impossible to predict which skills will be demanded in the future, there is broad consensus that the importance of digital skills but also of social and interpersonal skills will rise. But as the extensive, mainly sociological, literature on digital inequality shows, the distribution of digital skills is characterised by social stratification. This may well lead to rising income inequality between the digitally skilled and the digitally unskilled or even to the digital exclusion of those people, who are already socially excluded.

The fourth industrial revolution, market concentration, and the functional income distribution

At a general level, two important developments can be observed regarding the distribution of income between the production factors labour and capital: firstly, the importance of the factor capital in relation to gross domestic product (GDP) has increased significantly over the past three decades (Piketty 2014; Atkinson 2015) and a persistent decline in the wage share has been recorded in (almost) all OECD countries since the end of the 1980s (Autor et al. 2020; Karabarbounis and Neiman 2014; OECD 2011). Technological progress is assumed to be important for this development because it induces firms to switch to more capital-intensive production processes as the relative price for capital decreases, which in turn reduces the labour share (Dao et al. 2017; Karabarbounis and Neiman 2014). Secondly, increasing evidence indicates that rising market concentration, the emergence of “winner-takes-all markets” and “superstar firms” is closely connected to digitalisation, which has not only contributed to a fall of the labour share but also to the rise of income concentration at the very top (Autor et al. 2020; Furman and Orszag 2018; Guellec and Paunov 2017).

In this section we start by discussing the connection between the growing importance of intangible capital goods, which lie at the heart of smart technologies and the fourth industrial revolution, and rising market concentration before turning to the distributional effects associated with these changing market structures.

Digitalisation and market concentration

The literature on the impact of the fourth industrial revolution, or rather its driving technological innovations, on market concentration often focuses on two counteracting mechanisms, which are both related to the nature of knowledge-based capital that has been becoming increasingly important as a factor of production and should not be equated with the physical capital stock (OECD 2013). Firstly, digital innovations enable the incumbents to strengthen and defend their market power due to economies of scale, perpetuated by network and lock-in effects, which are associated with knowledge-based capital. Secondly, there is significant potential for high business dynamism due to “creative destruction” processes since entry barriers are low in
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KBC-intensive markets if the process of imitation and diffusion is unrestricted. Knowledge-based capital subsumes intangible capital goods such as R&D, software, databases, algorithms, or intellectual property rights. The non-rivalrous nature of knowledge is associated with increasing returns to scale – once knowledge has been produced, mostly through costly R&D, it can be used and reproduced at (almost) no costs (Guelllec and Paunov 2017). Thus, economies of scale arise due to the possibility to produce at low to zero marginal costs; for example, large profits can be generated through the licensing of software products without imposing any additional production costs. The economies of scale are reinforced by network and lock-in effects (Guelllec and Paunov 2017; Krämer 2019). Network effects, well known from the literature on public goods, occur when the benefit of a good increases with the number of users, which is the case for social networks or digital platforms that offer services, such as Uber or Airbnb (Allen 2017). Lock-in effects are related to network effects and they arise as it becomes more costly for consumers to switch between different products. However, incumbents can use lock-in effects, for example by restricting compatibility with similar products from competitors (e.g., Apple), to defend their market position (Krämer 2019). These mechanisms are well described in Shapiro and Varian (1999: 77) who identify the positive feedback effects related to network effects as a main determinant for the emergence of monopolistic market structures in the knowledge economy and may, in its “most extreme form” lead to the establishment of a “winner-takes-all-market, in which a single firm or technology vanquishes all others”. As prominent examples, the authors cite the triumph of Microsoft and Intel in the PC sector and the penetration of VHS over Betamax. Nowadays, the importance of network effects is even more evident. Facebook and the acquired services WhatsApp and Instagram, which connect billions of users worldwide, dominate social media and competitors can hardly assert themselves or, as in the case of WhatsApp, strong start-ups are bought up (Makridakis 2017).

At the same time, the low or zero marginal cost property of KBC in combination with trends such as rapidly falling prices of, for example, cloud computing, implies that the growing importance of KBC reduces entry barriers to many markets by lowering innovation costs thereby driving the process of “creative destruction” (Guelllec and Paunov 2017). Creative destruction in the sense of Schumpeter (1912) describes the dynamic development of a capitalist economy in which the “old” is permanently displaced by the “new”. The “new” is defined as innovations produced by entrepreneurs who are eager to experiment. Schumpeter is often interpreted in the sense that for innovation-driven growth, entrepreneurs must have monopoly power that allows them to generate innovation rents to compensate them for bearing the risks associated with innovation activities. The time to skim off these Schumpeterian rents is limited: as soon as innovations diffuse due to imitation by competitors, they cannot be generated anymore. Consequently, the establishment of persistent dominant monopoly positions is assumed to be restricted by the continuous process of imitation and diffusion.

Even though there seems to be great potential for processes of creative destruction in the fourth industrial revolution, the empirical literature on recent developments, especially on the US economy, points towards a slowdown of business dynamism and the emergence of monopolistic or oligopolistic market structures (Autor et al. 2020; Council of Economic Advisers 2016; Decker et al. 2014). For example, Decker et al. (2014) show that the annual start-up rate, measured as the share of new companies in all companies, has fallen in the US from an average of 12% at the end of the 1980s to an average of 10.6% just before the financial crisis, only to fall to below 8% during the recession. They further show that while the survival rate of start-ups is low, those that do survive are characterised by high growth and they contribute disproportionately to job creation in the US. Furthermore, recent evidence suggests that large players tend to acquire small start-ups: Google, Apple, Amazon, and Facebook acquired more than 400
companies up to 2016 (Makridakis 2017). According to a report by the Council of Economic Advisors (CEA) from 2016, rising market concentration and decreasing intensity of competition in many sectors of the US economy is driven by a sharp rise in Merger & Acquisitions. The report also shows that the profit rate between firms has become much more heterogeneous since 1995, which is reflected in the observation that the profit rates of the top companies have increasingly moved away from the average. This heterogeneity between firms is largely traced back to differences in productivity driven by managerial and technological capabilities (Decker et al. 2017; Van Reenen 2018; Autor et al. 2020). Digital innovations are expected to facilitate the emergence of “superstar” firms, which are characterised by particularly large market shares and high rates of return. For example, Autor et al. (2020) argue that the most productive firms can attract most of the revenues in their sectors because of scale effects associated with the growth of KBC, growing platform competition, and greater possibilities for consumers to compare prices due to the Internet and search engines.

To sum up, the documented decline in start-up rates in the US indicates that the role of entrepreneurs has been becoming less important. Moreover, empirical evidence suggests a positive link between digitalisation and market concentration and the rise of superstar firms. Makridakis (2017) illustrates this with the four big American IT giants Apple, Google, Amazon, and Facebook, for whose success the efficient use of the Internet to offer their services and products is a decisive factor. In addition, the network effects already mentioned contribute significantly to the fact that digital companies can capture and defend high market shares. Finally, especially regarding the development and use of one of the most important technologies, namely AI, the digital superstars already have a considerable head start over their competitors.

Market concentration and the distribution of income

As discussed in the previous section, the tendency towards monopolisation and concentration of market power may weaken some of the compensation effects associated with new technologies such as the mechanism of compensation via decrease in prices (monopolistic firms can act as price-setters), and the effect via increase in income as the latter depends crucially on the rent-sharing behaviour of firms and the balance of power between employers and workers. Hence, monopolistic market structures and the rise of superstar firms have several potential implications for the income distribution. Firstly, the low labour intensity and low wage share in superstar firms affects the functional income distribution by pushing down the aggregate wage share (Autor et al. 2020). Secondly, the growing heterogeneity between firms with superstars extracting super-normal returns on capital due to their market dominance directly affects the personal income distribution since capital ownership is highly concentrated at the top of the income distribution (Atkinson 2015; Dao et al. 2017; Piketty 2014). Thirdly, the distribution of monopoly rents can theoretically increase or decrease income inequality depending on with whom the rents are shared or, if invested, on the type of investment. However, recent research suggest that monopoly rents are largely shared with shareholders, investors, and the management, thus increasing income inequality between the top-income earners and the average workers (Furman and Orszag 2018; Guillec and Paunov 2017).

SUPERSTAR FIRMS

In their influential paper, Autor et al. (2020) examine, both theoretically and empirically, the implications of the phenomenon of superstars for the development of the wage share. They show that the worldwide fall in the wage share (i.e., the reduced share of labour income in
total income) since the 1970s can be explained by the rising dominance of superstar firms as they are characterised by low within-firm wage shares. Due to their size, superstar firms have lower fixed costs per output and because of their market power, they can achieve higher profit margins and therefore generate higher profits – both factors contribute to the reduction of the wage share in favour of the profit share. As superstar firms increase their share in the total economy, they disproportionately affect the overall development of the wage share. Autor et al. (2020) show for the US that there has been a concentration of turnover within many industries (excluding the public sector) over the last 30 years. At the same time, there has been a decline in the wage share within all industries, which has been particularly pronounced in industries that have experienced a relatively high increase in market concentration. From the shift in turnover between firms within sectors it can be concluded that superstar firms are partly responsible for this development: the extent of the fall in the wage share within firms within a sector varied considerably but since superstar firms with lower wage shares gained more weight within their sectors, the sector-specific wage shares decreased.

Another contributing factor to the fall in the wage share relates to the textbook notion of capital-enhancing technological change. In particular, production processes of digital or KBC-intensive superstar firms are less labour intensive than those of traditional firms. For example, Karabarbounis and Neiman (2014) identify the low labour intensity of production in ICT-intensive industries as one key factor driving the global decline in the wage share since 1975. They argue that technological change in the form of improvements of ICT led to falling capital user costs and this induced firms to increasingly shift away from labour as a factor of production. Indeed, comparing employment and profitability figures of digital and traditional firms reveals significant differences. While the digital superstars Apple, Google, Amazon, and Facebook employed a total of 458,000 people in 2016, the traditional superstar companies Walmart, Johnson and Johnson, Berkshire, and Toyota employ a total of 3.004 million people. Unsurprisingly this reflects in other key figures such as market capitalisation per employee ($4.13 million in digital vs. $0.38 million in traditional firms) and revenue per employee ($950,000 vs. $310,000) (Makridakis 2017).

The growing productivity dispersion between firms can also partly explain the growing earnings dispersion between employees. For instance, Song et al. (2019) show that there is an agglomeration of higher-paid workers in highly productive firms that pay better than other firms, or as they put it, one can observe a sorting of the labour force. In addition, high-paid workers often work together with other high-paid workers and low-paid workers work together with other low-paid workers. The latter phenomenon of segregation between high-paid and low-paid workers is partly due to the increasing possibilities of outsourcing a higher proportion of services or tasks. This often concerns low-paid workers, such as those providing cleaning services, but also higher-paid accounting and IT services are increasingly being outsourced, which is facilitated by digitalisation. This results in rising inequalities both within and between industries. Moreover, Song et al. (2019) demonstrate that the part of rising inequality due to within-firm inequality can primarily be traced back to growing within-firm earnings dispersion in very large companies with more than 1,000 employees, and even more so, the growing concentration of top incomes at mega companies with more than 10,000 employees. Considering the findings of Autor et al. (2020), the evidence provided by Song et al. (2019) could be interpreted as an indication that superstar firms do not only drive inequality at the aggregate, but also at the individual level.

Finally, recent research on monopsony in the labour market – a situation in which employers can exert considerable market power over workers because workers cannot instantaneously find or switch jobs – indicates that the impact of firm heterogeneity on wage inequality is increased.
in the presence of asymmetric power relations (Manning 2021). Monopsony power often prevails in low-wage segments of the labour markets but in recent years different forms of online work have attracted attention. For example, Dube et al. (2020) provide a thorough analysis of Amazon Mechanical Turk (AMT), a platform where mostly low-skilled human intelligence tasks are posted by requesters (employers) who set the wage ex ante and workers can then decide to do the task or not. The requesters then review the work but only pay workers whose submitted work they approve of. Dube et al. (2020) find evidence for significant monopsony power in terms of a low elasticity of labour supply. Although some research in labour economics suggests that monopsony power contributes to rising inequality, the evidence is still inconclusive (see Manning 2021 for a recent literature review) and there is significant scope for future research – especially as new forms of work organisation, such as platform work, become more widespread.

**Distribution of monopoly rents**

An economic rent is defined as “the return to a factor of production in excess of what would be needed to keep it in the market” (Furman and Orszag 2018: 2). In a Schumpeterian framework temporary innovation rents are necessary to incite further innovative activities. Moreover, the process of creative destruction increases social mobility as “new” market entrants may become the next winners while the “old” incumbents might become the future losers (Guellec and Paunov 2017). The impact of creative destruction and innovation on top income inequality on an aggregate level is examined in Aghion et al. (2019) for the US. Their empirical findings confirm the predictions of their Schumpeterian model: the rate of innovation is positively correlated with the top 1% income share – reflecting innovation rents – while no such relationship can be established for broader inequality measures, such as the Gini coefficient. In addition, they find a positive correlation between the rate of innovation and social mobility between 1996 and 2010 which is primarily driven by new market entrants. This is interpreted as the confirmation of the effect of creative destruction on social mobility.

While Aghion et al. (2019) argue that the innovation rents are only temporary because the positive correlation weakens when lagged effects are considered, the discussion in this chapter has shown that the accumulation of KBC facilitates the emergence of highly concentrated industries. It follows that digital innovations are associated with more permanent monopoly rents that go beyond the Schumpeterian innovation rents. This ultimately leads to the question of the distribution of these rents which is determined by the bargaining power of various actors, such as inventors, shareholders, investors, different workers, and management (Atkinson 2015; Guellec and Paunov 2017). Empirical evidence suggest that the economic rents are disproportionately shared with capital owners, management, and shareholders, hence contributing to the fall of the labour share as well as to the rise of income concentration at the very top (Furman and Orszag 2018; Guellec and Paunov 2017). Furman and Orszag (2018) argue that returns on invested capital (ROIC), reflecting rents accruing to capital owners, differ greatly between firms; especially firms in the IT and health sector enjoyed very high ROIC of more than 45% on average between 2010 and 2014. Similarly, according to Guellec and Paunov (2017), the observed diverging movement of rising corporate profits and decreasing interest rates indicate

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9 Aghion et al. (2019) slightly touch on this issue by introducing the distinction between productive and defensive innovations. While the former increase productivity and are carried out by new market entrants, the latter are used by incumbents to raise entry barriers and defend their market power. Since the share of defensive innovations are rising, the imitation and diffusion part of the creative destruction process may be distorted leading to the establishment of more persistent monopoly positions and consequently monopoly rents.
that rents are to large extents captured by investors and/or capital owners. Moreover, the growth of profits strongly correlates with the growth of top 1% incomes but not with the growth of the middling 40% of incomes between 1992 and 2013 thereby increasing income inequality.

Guellec and Paunov (2017) further emphasise the increasing market instability associated with digital innovations, which leads to rising risk premia for investors and entrepreneurs: winner-takes-all markets are not only characterised by higher market concentration, but also by a high degree of volatility since successful innovations can easily result in gaining very large market shares almost instantaneously and consequently investors, business owners, and executives are compensated for taking this risk.

To sum up, digital innovations seem to foster higher market concentration, superstar dynamics, and the emergence of winner-takes-all structures, which potentially contribute to rising income inequality in terms of the functional as well as the personal income distribution. While the presented evidence does not necessarily imply that these trends of the recent past will continue as the fourth industrial revolution develops, it nevertheless sheds light on the potential risks associated with an economy that increasingly relies on KBC as a factor of production as well as a consumption good. Since many empirical studies use US data, future research should focus more on international comparisons which may help to inform about the role institutional settings play in mediating the described effects of digital innovation on market concentration and income inequality.

Conclusion

In this chapter we highlighted potential effects of technological change on the personal and functional income distribution in the context of the fourth industrial revolution. To help inform our understanding of these effects, we started by summarising how previous industrial revolutions affected economy and society, where negative effects were counterbalanced by positive effects. In particular, the recurring fears of persistent technological unemployment were unfounded, as the long-run effects on employment, income, and standards-of-living were positive. However, the short run, especially in the first industrial revolution, was characterised by rising inequality and deterioration of working conditions. The key insight from the historical perspective is therefore that processes of rapid technological change and their implications for the society need to be continuously studied to inform policy makers about potential measures that can be taken to counterbalance the negative effects from the short-run disruptions associated with industrial revolutions. Therefore, we present the main mechanisms identified in the recent economics literature relating income inequality and technological change against the background of the innovations, which drive the fourth industrial revolution.

We used compensation theory to discuss macroeconomic employment effects of technological change. The main idea of the compensation theory is that unemployment arising from process innovations which lead to the substitution of human labour by machines, is offset by several key mechanisms related to indirect effects on real income and investment, among others. Furthermore, product innovations induce the emergence of new markets, such as the app economy, increasing the demand for goods and creating new employment opportunities. In the history of economic thought, the compensation effects, especially those related to new products, were usually underestimated while the displacements effects were overestimated (Mokyr et al. 2015).

For example, the market for mobile phones was dominated by Nokia until Apple introduced its iPhone and Samsung followed suit with its Samsung Galaxy. In recent years, Huawei and Xiaomi have established themselves as serious competitors.
However, due to certain characteristics of the innovations driving the fourth industrial revolution related to their negative impact on market competition, we argue that the magnitude of compensation effects might be weakened as the balance of power between employers and workers gets distorted. Our discussion shows that digital innovations, which rely heavily on intangible knowledge-based capital, seem to drive increased market concentration, enable superstar dynamics, and contribute to the emergence of winner-takes-all structures. We identify several explanations discussed in the recent economics literature for how these technology-driven monopolistic market structures might affect the distribution of income. Firstly, since KBC-intensive superstar firms are characterised by low labour intensities of production and low labour shares, their rising importance in the economy affects the distribution between labour and capital by pushing down the aggregate wage share (Autor et al. 2020). Secondly, Furman and Orszag (2018) show that these superstar firms can also extract super-normal returns on capital and given that capital ownership is highly concentrated at the top of the income distribution (Atkinson 2015) this contributes to rising income inequality between the rich and the poor. Thirdly, growing heterogeneity between firms in terms of productivity and the agglomeration of high-skilled workers in high-productivity firms and vice versa increases income inequality between people working in highly and lowly productive firms since firms act as wage-setters rather than wage-takers (Song et al. 2019). Finally, the results from recent empirical research suggests that monopoly rents are mostly shared with shareholders, investors, and the management rather than with the average employee. This increases income inequality between the top-income earners and the average workers (Guellec and Paunov 2017). While the presented evidence does not necessarily imply that these trends of the recent past will continue as the fourth industrial revolution develops, it nevertheless sheds light on the potential risks associated with an economy that increasingly relies on KBC as a factor of production as well as a consumption good. However, as many empirical studies use US data, there is significant scope for future research to place a focus on international comparisons. This may help to inform about the role of institutional settings in mediating the described effects of digital innovation on market concentration and income inequality.

While the discussed economic research on the relationship between digital technologies, market concentration and the distribution of income has grown over the past five years, the impact of digital technologies on wage inequality has been studied extensively since the third industrial revolution. Economists usually assume that technological change in general increases wage income inequality due to the skill-bias or routine-bias of new technologies. The fourth industrial revolution and the technologies driving it are also expected to considerably increase the demand for high skills and more specifically, for digital skills while at the same time social and interpersonal skills become increasingly important. Since economic research shows that there is a wage premium for these “new” digital skills (Falck et al. 2016; Hanushek et al. 2015), rising relative demand for them will affect wage inequality between those who possess digital skills and those who do not.

The popularity and persistency of the hypotheses of skill-biased technological and routine-biased technological change may partly be attributed to their implicit message that wage inequality arising from technological change simply is a logical consequence of the technology’s skill-biased or routine-biased nature. This is convenient for policy makers as the strategy to battle this form of inequality is to turn to the panacea of more and better education – a political request that will hardly ever encounter any resistance. However, a mere quantitative increase of formal education is unlikely to help fighting wage inequality that may arise due to increasingly smart technologies if the distribution of the skills of the future, digital skills, and competencies, is itself shaped by existing social stratification. The unequal distribution of digital skills is
well-studied in the literature on the digital divide and, more recently, digital inequality and many studies confirm that existing inequalities along socio-demographic characteristics such as age, ethnicity, gender, educational background, or social status influence the use of digital technologies and the development of digital skills (van Dijk 2005, Helsper 2012; DiMaggio et al. 2004; Drabowicz 2014; Robinson et al. 2015; Hargittai 2010; Zillien and Hargittai 2009; van Deursen et al. 2017; Zilian and Zilian 2020). So even though digital inequality seems to be a new phenomenon, it in fact simply mirrors the well-known structural inequalities with the inherent danger of exacerbating them as the fourth industrial revolution progresses. Research on the relationship between digital competencies, which captures a variety of skills beyond the mere usage of ICT at work, and wage differentials is still scarce but due to the increasing availability of new and internationally comparable data, such as the OECD Programme for the International Assessment of Adult Competencies, digital inequality and its consequence for wage income inequality provides a fruitful path for future research.

Finally, the role of (labour market) institutions is neglected in most of the literature on SBTC and RBTC and it is assumed that the impact of technological change on wage inequality is more or less the same across countries. An exception is Kristal and Edler (2019) who show that there are significant differences regarding the size of the computer wage premium and consequently the computer wage gap across different varieties of capitalism. A higher degree of central market coordination, which is characteristic for Nordic coordinated countries, is associated with lower computer wage gaps, ergo lower wage inequality, compared to liberal countries. Moreover, as the recent research on platform work shows, this new form of work organisation is characterised by considerable monopsony power and may affect income inequality. Thus, the research agenda on wage inequality in the fourth industrial revolution should be expanded by considering explicitly the interaction of politics and technology and how they affect the wage distribution. To fight inequality arising from digital innovations, traditional redistributive policies through labour taxation is stretched to its limits. Although it remains a suitable instrument to reduce inequality arising from between-firm differences in average wages, it does not affect income derived from capital ownership or other sources of income aside from labour. To address top income inequality, Atkinson (2015) proposes to introduce a progressive lifetime capital receipts tax, similar to the Capital Acquisitions Tax in the Republic of Ireland, to tax receipts of inheritance and gifts. In addition, he argues in favour of an increase of the top personal income tax rate (e.g., 65% for the UK). Concerning inequality arising from technological change, he supports Mazzucato (2013: 119) and her endorsement of a more active role of the state to guide the direction of technological change by “encouraging innovation in a form that increases the employability of workers and emphasises the human dimension of service provision”.

The active role of the state is particularly important considering the rising influence of superstar firms. While the superstar firms are undoubtedly among the most successful companies in their respective industries, they also use very successfully so-called “dark” business practices such as excessive tax avoidance and political influence via lobbying activities to further entrench their own supremacy (The Economist 2016). Nobel laureate Joseph E. Stiglitz estimates the extent of tax avoidance in a contribution for The Nation:

Just five American firms, Apple, Microsoft, Google, Cisco, and Oracle, collectively have more than a half trillion dollars stashed abroad as they achieve tax rates in some cases well under 1% of profits. We can debate what a “fair share” of taxes is, but what these companies pay is below any reasonable standard.

(Stiglitz 2017)
Declining wage shares in combination with successful tax avoidance practices, rising earnings dispersion, and political influence exercised by superstars are questionable in terms of democracy, the future of the welfare state, and, consequently, social cohesion. Hence, restoring the distorted balance of power must be addressed by public policy and with regard to rising market concentration, one means to this end carved out by Atkinson (2015) seems to be of particular urgency: competition policy needs to explicitly take into account the distributional dimension of monopolistic and oligopolistic market structures.

References


The fourth industrial revolution


