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The digital revolution and the labour economics of automation: A review

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Abstract
This paper reviews the economic literature about the effects of the digital revolution on the labour market, and provides a non-technical introduction to the labour economics of automation. It conceptualizes the digital revolution and describes how recent technological trends, such as robotics, industry 4.0, artificial intelligence and the platform economy, affect specific occupations. It reviews the main economic theories and the empirical evidence of how automation affects labour demand, the occupational structure and the work task composition of occupations. It discusses the consequences of this occupational change for labour market outcomes such as wages, inequality, job quality and unemployment. The paper concludes with a discussion of the main avenues for further research.

Keywords: Automation; Labour market; Digital revolution; Occupational change

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1. Introduction

The digital revolution and recent technological trends, such as robotics, industry 4.0, artificial intelligence and the platform economy, are widely considered to bring substantial effects on labour markets and the nature of work (Brynjolfsson & McAfee, 2014; Ford, 2015; Schwab, 2017; Frey, 2020; George & Paul, 2020; Ivanov, 2020; Bornet et al., 2021). New technologies are automating some jobs, they raise the demand in other jobs, they shift the concrete tasks that workers perform on their jobs, and they alter the way we consume. The result is a restructuring of the economy in which some sectors grow and others decline, in which some occupations disappear and the task requirements of other occupations change, and in which some groups may lose and others win in terms of income, employment and job quality (Goos & Manning, 2007; Acemoglu & Restrepo, 2019; Autor, 2019).

The aim of this paper is to review the economic literature about the effects of the digital revolution on the labour market, and to provide a non-technical introduction to the labour economics of automation for both readers interested in economics, and economists looking for a concise introduction to this field. To make it as accessible as possible, the text includes many examples and it avoids the use of mathematical equations and formal models (the references point the reader to literature that contains these models). The focus of the paper is on economic theories, i.e. on the various explanations of how and why the digital revolution is affecting labour markets, but it also contains a review of the main empirical evidence. This review is not meant to be exhaustive because the literature is expanding rapidly and discussing everything would draw away the attention from the main points. Instead, the review focuses on the seminal contributions of the main scholars in the field.

The paper is structured as follows. Section 2 conceptualizes the digital revolution and describes how recent technological trends are affecting work in specific occupations. Section 3 presents the main economic theories and the empirical evidence of how automation affects labour demand, the occupational structure and the work task composition of occupations. Section 4 discusses the main consequences of this occupational change for labour market outcomes such as wages, inequality, job quality and unemployment. The final section concludes and discusses the main avenues for further research.

2. The digital revolution

Many commentators describe the current wave of technologies as a technological revolution and their effects on the economic structure as an industrial revolution, i.e. a sudden and discontinuous qualitative leap over a relatively short time-span. For example, Brynjolfsson and McAfee (2014) refer to the adoption of digital technologies as the second machine age, which follows the "first machine age" that was based on technologies such as steam engines, electricity and railroads. Schwab (2017) calls it the *4th Industrial Revolution* or *Industry 4.0*, which follows the 1st Industrial Revolution (driven by steam power), the 2nd (electrification and railroads) and the 3rd Industrial Revolution, also known as the *digital revolution* (computers and communication technologies). The 4th Industrial Revolution is distinguished from the previous (digital) revolution by being supposedly driven by the combination of digital technology and machines/products. By building sensors and computers into things that are not computers themselves (such as cars or industry robots) and by integrating hardware and software (Schwab, 2017), machine-to-machine communication improves and things become "smart" or even networked into an *Internet of Things*. Examples of Industry 4.0 include vehicle communication to allow for self-driving cars, the collection of detailed soil data in agriculture and preventive maintenance in computerized machinery (Economist, 2019). The new technologies of the digital revolution and Industry 4.0 are widely considered to be the main (but not necessarily the only) sources of automation in contemporary labour markets.

These commentators create the impression that we live in technologically revolutionary times, but the possibility must be considered that there is much more historical continuity – not discontinuity – than many suspect. Take the example of the decline of employment in agriculture. Between 1910 and 2010, agricultural employment fell by 84 percent in the US, by 77 percent in the UK and by 83 percent in Japan (Roser, 2013).

This huge shift in the occupational structure has been largely driven by technological change and increased productivity in agriculture. But although the process was painful for many involved, the economic restructuring was rather gradual and spread over many decades. Similarly, many observers fear that the development of autonomous driving could eliminate the occupation of truck drivers in the future, but they tend to be blind for the labour-saving technologies of the past that are already embodied in trucks today. For example, the adoption of the standardized container after the 1950s largely eliminated jobs related to unloading cargo from container ships and reloading it on trucks or trains. Moreover, after years of hype about autonomous driving, limitations and difficulties are becoming clear: some self-driving car companies had to close down because the current technology does not allow cars to respond safely in unusual circumstances, and the remaining firms have become less ambitious about autonomous driving (Economist, 2020).

But the increase in the use of information technology is evident. The real cost of performing a standardized set of computations is estimated to have fallen by a factor of over one trillion in the six decades after 1945, which implies a speed of productivity growth that is far larger than that for other technologies (Nordhaus, 2007). Over this period, the share of information processing equipment in private investment is estimated to have risen from about 8 percent to more than 30 percent (Autor, 2014) so the use of computing has been increasing extremely rapidly and this “digital transformation” (European Commission, 2019) may rightly be coined a “digital revolution”.

The digital revolution is affecting labour markets through a great variety of technologies. The number of secretaries, an occupation that used to involve typing work and answering phones in offices, has been declining rapidly as executives started using personal computers and smartphones to write correspondence, answer phones and organize their calendars themselves and as software for business operations is automating much of the back-office work in both the private and public sectors. Since the year 2000, over 2 million of such jobs in “administrative and office support” have been lost in the US and the US Department of Labor predicts that administrative assistants, office clerks and executive secretaries will see the largest job losses of any occupation in the coming decade (Bureau of Labor Statistics, 2020).

In manufacturing, some blue-collar occupations are automated by the use of *industrial robots* (i.e. programmable devices that interact with the physical world) in a variety of routine tasks such as assembly line work in automotive production or palletizing (placing goods on a pallet for shipment or storage). In logistics, robots are increasingly used for tasks such as order picking and parcel sorting (DHL, 2016). Amazon has over 200,000 mobile robots that can pick up a shelf of goods and bring the entire shelf to a worker who then selects the needed items while staying in one spot instead of walking around the warehouse. These swarms of robots at Amazon who find their optimal routes through the warehouse, are an example of *artificial intelligence* (AI), i.e. the use of intelligent agents that perceive the environment using sensors and take actions that affect that environment (Russel & Norvig, 2020). An example of such intelligent automation (Bornet et al., 2021) is the use of an army of small mobile AI robots by STO Express, one of the largest delivery service companies in China, to sort up to 18,000 packages per hour (China Global Television Network, 2017).

Digital technologies are no longer just replacing muscle-power but also more cognitive tasks. For example, online teaching and intelligent tutoring systems have the potential to increase the productivity in higher and adult education. Recent advances in pattern recognition have led to artificial intelligence systems that, in terms of accuracy, are close to doing the work of radiologists, whose job it is to use medical imaging to diagnose diseases such as breast cancer by screening mammograms (Nature, 2019). This technology is an example of *machine learning*, i.e. the branch of artificial intelligence in which computer algorithms are automatically improved by a process of training and reinforcement – instead of being explicitly programmed as in conventional programming (Ng, 2021). Similar machine learning algorithms are increasingly used in finance to assess investment risks and compliance with regulations (Aziz & Dowling, 2019), in recruitment to assess job applicants

(Garg et al., 2021) and in health care to aid in medical decision making (Char et al., 2018). Google Translate, an online service that claims it translates over 100 billion words per day for 500 million users, has been using machine learning since 2016 by learning from millions of examples of existing translations (Turovsky, 2016).

The digital revolution is also affecting the way we consume and the demand side of the product market. New products are bought and sold such as smartphones, tablets and new software applications. As consumer demand shifts, companies in other industries struggle. Traditional retailing, such as supermarkets, book shops and fashion stores, is in decline because of the rise of e-commerce – a trend that has accelerated during the Covid-19 health crisis (OECD, 2020). Even before the Covid-19 crisis, the share of e-commerce in total turnover increased from 12% in 2008 to 18% in 2018 in the EU-28 (Eurostat, 2020), and an increasing number of shop closures is being reported and expected in the near future (Economist, 2017). In the remaining shops, the shift towards self-service by consumers is also threatening jobs: supermarkets and public libraries are introducing self-checkout machines, fast-food restaurants introduce self-ordering machines, and self-banking has become the norm for customers to manage their bank accounts and transfer money themselves. Consumer demand also shifts with the rise of *the platform economy*, in which digital platforms create markets for specific products by functioning as online matchmakers (Parker et al., 2016; Iivari et al., 2016). Uber, the largest platform for taxi rides, had 5 million drivers by the end of 2019 who do about 6 monthly trips on average (Uber, 2020). The rise of these ride-sharing platforms is disrupting the traditional taxi industry, with falling prices for taxi licenses (Economist, 2015) and protests of traditional taxi drivers against Uber in many places (Brusselstimes, 2020).

The automation of certain work tasks and the shifts in consumer demand affect the demand for labour in specific occupations. However, the digital revolution also affects the supply of labour and the institutions that govern labour markets. The rise of internet-based job search and recruiting is reported to have increased worker mobility and improved job matching quality (European Commission, 2019). Platforms such as Deliveroo and Uber Eats, both online food delivery companies, have reduced entry barriers into the labour market for some groups in the labour force such as students. Freelancing platforms of *the gig economy*, such as Freelancer.com or Amazon Mechanical Turk that function as online matchmakers for contractor jobs such as translation work or programming work, may increase the labour supply of some groups in the labour force because employers use these platforms to disaggregate certain jobs into separate tasks (Cook et al., 2019; European Commission, 2019). Platform-mediated work seems to be increasing and is now the main source of income for as many as 2% of adults across 14 EU member states (European Commission, 2019). On the other hand, a platform such as Airbnb, an online marketplace for renting real estate by providing lodging and homestays, has become a source of income for an increasing number of people (Business of apps, 2020) and, to the extent this is a non-labour income, this process is likely to reduce labour supply.

3. The economics of automation and occupational change

There is a growing literature on the effect of the digital revolution on labour markets (Autor et al. 2003; Frey and Osborne, 2013; Arntz et al. 2016; Acemoglu & Restrepo, 2019). Most studies focus on *automation*, which is the substitution of human labour by machines in the production process. As technology improves and machines become capable of performing certain occupations more cheaply than humans do, these occupations tend to be automated. History shows many examples of such obsolete occupations. A dramatic example in Belgian history is the rapid decline of the linen industry during the 1840s which employed a substantial part of the population in occupations such as weaving and spinning. The mechanization of the textile industry during the First Industrial Revolution created competition from cheaper textile products. By 1850, the linen industry, that only 10 years earlier had still employed over 20% of the active population in Flanders, was almost completely wiped out. As the crisis unfolded, the Belgian Parliament launched an inquiry and put forward various initiatives to save the industry – but none were successful (Winter & Deschacht, 2015). The digital revolution has made various occupations obsolete as well. For example, before the arrival of digital photography, people brought their analogue photographs to shops to have their film developed and printed to photo paper: these jobs have almost completely disappeared. Kodak, the company that had dominated the market for analogue photography during the 20th century, went bankrupt in 2012. Video rental stores, where people rented movies on VHS tapes, largely disappeared as technology created more efficient ways of delivering movies to homes. Digital payments and ATM machines have eliminated the need for cash withdrawals with bank tellers.

But the effects of automation on the occupational structure are much broader than is suggested by these examples of occupations closely related to technologies that have been replaced. An influential study by Oxford academics Frey and Osborne (2017) concluded that 47% of all US jobs have a high probability of being automated over a period of a decade or two. The study received an enormous amount of press coverage and it has led to fears of substantial job losses and unemployment in the near future. But the study has been misunderstood. The authors asked a group of experts which occupations would surely be automated in the near future and which jobs would surely not be automated. The experts came up with 70 occupations they thought they could confidently assign to one of both categories. Next, the authors constructed a model that classifies all the other occupations in the economy based on the characteristics of these occupations, such as the level of creativity or social intelligence required in the occupation. The result is, for each occupation, a predicted probability to be in the category of the occupations that are likely to be automated. The occupations with a predicted probability greater than 0.7 represent 47% of all US jobs. The aim of the analysis was to study which occupations are more susceptible to automation and not to estimate how many jobs will actually be automated – a subtle but important difference. In a reaction to the press coverage and the discussion that followed the publication of their study, one of the authors stated that their paper has been misunderstood and that it definitely does not claim that half of all jobs will be automated in a decade or two (Economist, 2019b). The more accurate conclusion of Frey and Osborne (2017) is that the least risky jobs of being automated are in occupations that require academic training and occupations such as therapy or social work that require skills such empathy or emotional awareness.

3.1. The effects of automation on labour demand

In theory, the effect of new technologies on labour demand is ambiguous: it may reduce the demand for workers in an occupation through substitution, but it may also increase the demand for workers. Focusing on substitution potentials is misleading because this ignores the *complementarities* that increase productivity and the countervailing economic forces that can compensate for the displacement of workers through automation (Autor, 2014; Vivarelli, 2015; DeCanio, 2016; Acemoglu & Restropo, 2018; Gregory et al. 2019).

Economic analysis regards the various types of machines and labour as production factors. Two production factors are perfect substitutes if they can be substituted at a constant rate, for example if every two workers can be substituted by one machine. Self-checkout machines in a supermarket and cashier workers are a good example of nearly perfect substitutes (although these machines also shift some of the work to clients). Profit-maximizing firms should in theory shift from using labour to using the perfect substitute machinery in a sudden and discontinuous way if the price of capital falls below that of labour as a result of technological progress. Production factors are perfect complements if they must be used in fixed proportions, for example if every truck requires a truck driver. If a new technology lowers the price of trucks, then more trucks are used for transporting goods and the demand for truck drivers increases. In this case where labour complements capital, labour demand increases as a result of technologies that lower the price of capital.

In practice, capital goods are no perfect substitutes or complements for labour, but instead they partly substitute and partly complement certain work tasks. Each pair of capital goods and work tasks is characterized by a cross-elasticity of labour demand, i.e. the percent change in the demand for that work task resulting from a one percent increase in the price of the capital good. The cross-elasticity is negative for complements and positive for substitutes, and the size of the elasticity varies. In the construction industry, an excavator substitutes for manual digging work using a shovel, but it increases the productivity of and the demand for construction workers who can operate an excavator. Even self-checkout machines in supermarkets are no perfect substitute for labour because some customers may not know how to use the machines and some workers may still be required to oversee a number of self-checkout machines to solve problems.

Even if the substitution effect of a new technology dominates so that *the first-order effect* is automation and a replacement of human labour in an occupation, the final demand for labour in that occupation could increase because the overall effect also depends on how the demand for products by consumers responds to falling prices. After all, as productivity increases with technological progress, the cost of production falls and prices are likely to fall (this assumes that product markets are competitive, which need not be the case). If consumers respond to falling prices by consuming a lot more (elastic demand), then more workers are needed and this increased demand may compensate or even exceed the employment loss that resulted from the first-order substitution effect. Economic theory predicts that labour demand increases as a result of technological progress if product demand is elastic and it falls if the elasticity of product demand is less than 1 (Neisser, 1942; Blien & Sanner, 2014; Bessen, 2018). For example, the demand for basic necessities such as food and housing is relatively inelastic: people do not buy a lot more vegetables as they become cheaper. Because of this, the productivity increase in agriculture over the 20th century and the substitution of farm labour by machinery did not lead to the type of increase in demand for agricultural products that could have off-set the substitution effect. The result was a large decrease in agricultural employment over this period. On the other hand, consider the airline industry. The demand for air travel is relatively price elastic, so that the declining price of airline tickets over the years has led to a surge in consumer demand. As a result, the demand for airline pilots has increased, even though many of their tasks have been automated and productivity in the occupation has increased. In the 19th century, employment in the textile factories did not decline although the automation by steam engines boosted productivity, because consumer demand for clothes was elastic in that period of time (Bessen, 2015). We refer to the effect of technological change in an industry on labour demand in that industry resulting from changes in prices and the scale of production in that industry, as *the second-order effect* or the scale effect.

Technological change in one occupation or in one market may also affect the demand for other occupations or the demand for products in other markets (Autor & Salomons, 2018; Caselli & Manning, 2019). These indirect effects in the economy as a whole can be referred to as the *third-order effect* of technological change, to distinguish it from the substitution and scale effects in the market where the technological change took place. The main reason why the demand in other sectors may increase, is that technological change lowers product prices so that consumers have more income to spend in other sectors. (i) Labour demand can be affected in industries that are directly related to the new technologies, such as the increased demand for workers in the production of robots. However, the workers displaced by introducing labour-saving technologies can – in theory – never be fully reabsorbed in the production of the labour-saving devices since otherwise the cost of production would not be smaller than before and there would be no economic incentive to adopt the new technology (Neisser, 1942). (ii) Labour demand may increase in a technologically advancing industry if it competes with a technologically lagging industry, as in the example of e-commerce where the number of workers delivering parcels and picking order increases rapidly. Amazon.com, one of the large e-commerce companies, employed over 1 million workers in 2020 – and this number is rising (Washington Post, 2020). (iii) But labour demand may also increase in industries that are completely unrelated to technological change. As productivity increases, real wages tend to increase – either through increasing wages or falling product prices – and consumers can spend this additional income on goods and services in any sector of the economy depending on their preferences. The way consumers spend their additional income on various products is determined by the income elasticity of the demand for each product. The demand for basic necessities such as food and housing is generally assumed to be income inelastic (as well as price inelastic as was discussed higher). An example of an income elastic product is the demand for personal coaches: employment in this type of "new wealth jobs" has been increasing substantially in recent decades (European Commission, 2019). It is hard to predict how consumers spend additional income, especially because income elasticities appear to change over time. Bessen (2018) shows that the demand for many products, such as clothes and manufacturing products, shows an inverted U pattern over time where product demand (and employment) first increases with productivity over many decades, before it starts declining with further productivity growth. The decline of manufacturing during the past decades in Europe and the US is the declining part of the inverted U curve for manufacturing. Bessen explains this general pattern by arguing that initially, i.e. at a time when product prices are still relatively high, demand is income elastic (so that rising incomes result in increasing employment in this industry) and that demand becomes inelastic as product prices fall further and consumer needs have been met (so that rising incomes result in declining employment).

3.2. Automation and the changing task composition of occupations

Technology does not just affect the demand for occupations as a whole – it also changes the task composition within occupations (Autor et al. 2003; Autor, 2014; Arntz et al. 2016). Any occupation is essentially a bundle of tasks, where a task is a unit of work activity that produces output such as moving an object, communicating a piece of information or organizing the work of others. Occupations are generally composed of a variety of tasks and new technologies usually allow for the automation of only some tasks of an occupation. An example of the changing task content is the occupation of office secretary work, in which the tasks have shifted away from typewriting towards more management related tasks (Khalid et al. 2002).

The literature on the effects of the digital revolution usually distinguishes between *routine tasks*, i.e. tasks that follow an exhaustive set of rules and can thus be computerized, and *non-routine tasks*, i.e. tasks that are not sufficiently well understood to be specified in computer code and executed by machines (Autor et al., 2003; Autor, 2014). Routine tasks are important in activities such as bookkeeping, clerical work and repetitive production tasks. Autor et al. (2003) further distinguish between two types of non-routine tasks: *abstract non-routine tasks*, that require problem-solving capabilities, intuition, creativity and persuasion and are characteristic of professional, technical and managerial occupations, and *manual non-routine tasks*, that require situational adaptability, visual and language recognition and in-person interactions and are characteristic of food serving jobs, cleaning work, health work and security work.

The literature that followed Autor et al. (2003) assumes that routine tasks are relatively easy to automate, so that digitalization leads to a decline in labour demand for routine tasks and to an increased demand for non-routine tasks. This is the *routine-biased technical change hypothesis*. Within occupations, the result is a shift over time from routine tasks towards more non-routine tasks as technological change lowers the price of digital capital. A recent example of changing work tasks in an occupation, is the shift to online teaching in higher education as a result of the Covid-19 crisis. Much of the teaching by university professors can be considered a routine task in the sense that the same lecture is taught every year. Video recordings of these lectures allow for a substantial automation of teaching, which is shifting the task content of university lecturers towards more non-routine tasks, such as responding to individual questions and evaluating students.

The empirical evidence largely confirms the shift over time towards non-routine labour and the increasing skill requirements in occupations. Autor et al. (2003) show that the demand for routine tasks has decreased over the past decades and they present evidence from the US Dictionary of Occupational Titles, which contains qualitative descriptions of occupations, that non-routine tasks have become more important within nominally identical occupations. A seminal study by Spitz-Oener (2006) using German survey data on the tasks done by workers going back to 1979, shows that a large part of the increased skill requirements over the past decades results from the changing tasks within occupations, rather than from changing employment shares between occupations and that the changes in skill requirements have been most pronounced in the rapidly computerizing occupations. Research also shows that the task composition within occupations not only varies across time, but also across jobs at the same moment in time (Autor and Handel, 2013): workers within a similar occupation often carry out very different tasks. Taking into account that workers adjust to new technologies by altering the tasks they do on the job, strongly nuances the alarming predictions about job loss due to automation. Arntz et al. (2016) show that, if it is assumed that machines displace certain tasks instead of whole occupations, only 9 percent of the US jobs are at risk of automation – not 47 percent as suggested by Frey and Osborne (2017) – because many workers that Frey and Osborne consider to be in the high-risk category also perform tasks that are difficult to automate.

3.3. Technological change and skills: deskilling, upskilling and job polarization

Different work tasks require different skills and as technology alters the task content of occupations, skill requirements in occupations and in the economy at large change accordingly. As an example, consider the changing task content of a construction worker when excavators were introduced to automate the digging work that used to be done using a shovel (Autor, 2014). The excavator substitutes the manual work of digging using a shovel and a construction worker who knows how to operate a shovel but not an excavator, will likely lose employment. A construction worker who does have (or learns) the skills to operate an excavator, supplies a task that complements the new technology and that is more valuable in the sense that construction work becomes more productive as the task composition of the average construction worker shifts. But the transition can be hard. Shop workers who lose their jobs as traditional retailing declines, might consider a job in the e-commerce and logistic sectors that are gaining market share. However, most jobs in e-commerce require a university degree, which most workers in conventional retailing do not have (Economist, 2017).

Theoretically, the effect of technological change on the demand for skills, and higher levels of education, is not straightforward. New technologies could lead to *deskilling*, i.e. the substitution of skilled labour by machines that are operated by unskilled labour (Braverman, 1974; Katz & Margo, 2013; Kunst, 2019). The replacement of artisans by mechanization and the factory system in the 18th and 19th centuries, and the division of labour into simple steps that could be carried out by unskilled workers using special purpose machines, was regarded as a process of deskilling by the classical economists such as Adam Smith and Karl Marx. The workers who operated the machines were less skilled than the artisans they replaced in the sense that the artisan could make a product from start to finish whereas the operator only needed to perform a small set of relatively simple tasks. On the other hand, new technologies could lead to *upskilling* if machines substitute unskilled labour and require more skilled labour to operate them (Griliches, 1969; Autor et al., 1998). This latter theory is referred to as the skill-biased technological change hypothesis.

Empirical evidence supports the hypothesis that new technologies complement, rather than substitute, more-skilled workers and that technological progress has raised the demand for educated workers. Educational levels have increased a lot over the past decades and over this period the wages of higher educated workers have not fallen (on the contrary), which implies that the demand for higher educated workers must have increased over time with technological change (Autor et al., 1998). Although upskilling appears to be the main result of technological change, there is evidence of deskilling among some groups of workers (Autor, 2019; Kunst, 2019). Autor (2019) argues that technology has been deskilling for less-skilled workers in the sense that non-college workers today perform less-skilled work than they did five decades ago. Non-college workers used to do a lot of middle-skills jobs, such as production work in manufacturing or white-collar office and administrative work, but employment in these occupations has declined because of automation which forced these workers into occupations that are less-skilled and pay lower wages.

However, empirical evidence also shows that technological change is routine-biased, rather than skill-biased. The evidence shows a process of *job polarization* that has occurred in the past decades, i.e. the simultaneous growth of high-education and low-education jobs and the fall in employment in the middle of the skill distribution (Autor et al., 2006; Goos & Manning, 2007; Goos et al., 2014). The routine-biased technological change hypothesis states that the routine tasks that tend to be automated are common in middle-skill occupations, whereas non-routine tasks dominate in both low-skilled jobs (with manual non-routine tasks as in cleaning occupations) and high-skilled jobs (abstract non-routine tasks as in management jobs). The employment growth at the lower end of the skill distribution is almost entirely in service occupations, involving assisting or caring for others, such as food service workers, security guards, gardeners, cleaners, home health aides, child care workers, personal coaches, hairdressers and beauticians. Autor and Dorn (2013) argue that this growth in service occupations results from growing consumer demand for these services as productivity in other sectors and incomes increase. This has increased the wages in service occupations so that low-skill workers are reallocating their labour supply away from routine tasks and toward these service occupations.

Perhaps more important than the skill level, is the type of skills that workers have. The work of a radiologist may be highly skilled but if it can be automated as AI technology improves, then these skills offer little protection. What counts is the extent to which specific skills complement new technologies. Skills that allow workers to use new technologies or operate new machinery strengthen the labour market position of workers. A related dilemma for policy makers, and students, is whether to invest in general skills, that are useful over a broad range of occupations, or in vocational skills acquired through work-placed learning. Theory and empirical evidence suggest that vocational training may be more effective in the short-run for workers, whereas general training may be more effective in the long-run because specific vocational skills tend to become obsolete as technologies change over time (Hanushek et al., 2017).

3.4. Effect heterogeneity: which workers are affected?

The effects of the digital revolution on labour market outcomes depend on the characteristics of the workers involved. Skills are probably the most important worker characteristic for determining whether the worker will be competing with or complementing new technologies. But other characteristics matter too, such as gender, race, age and geography (OECD, 2018; Black & Spitz-Oener, 2010). The increase of telework may strengthen the position of women, compared to men, as it allows for a better combination of their careers with the roles they continue to adopt in the family. Men and women also continue to work in very different occupations in most countries, so the challenges posed by technology may differ by gender. Women more often work in occupations that require in-person interactions, such as health workers, that are less likely to be substituted by new technologies. However, Autor and Handel (2013) find that females are substantially more likely than males to do repetitive tasks. The fact that in most countries many more girls than boys currently graduate from university, could strengthen the labour market position of women, but girls participate less in STEM fields, which are more likely to complement new technologies. In any case, the substantial declines of manual routine jobs in manufacturing (a male dominated occupation) and secretary office jobs (a female dominated occupation) show that no gender is immune for the challenges posed by the digital revolution.

The digital revolution poses specific challenges for older workers, a group that has increased rapidly in size as retirement ages are increasing. Older workers invest less in human capital (and organizations invest less in older workers), so older workers are more likely to lack the skills to adjust to the changing work tasks in their job resulting from the digital revolution. If older workers are less flexible to adapt to new task requirements in their jobs, then the changing task structure in the economy may be forced upon them through unemployment and transitions to other jobs and occupations – instead of via task change within the job. Evidence shows that companies that fail to innovate, employ more older workers (Aubert et al., 2006). Moreover, older job seekers are less likely to find a job than younger job seekers, which at least to some extent is related to skill obsolescence and adaptability problems (Vansteenkiste et al., 2015). The rise of the gig economy is sometimes seen as a promising way to increase the labour supply of older workers by allowing them to choose more flexibly the working hours and work intensity they need, but it could imply earnings losses for older workers. For example, a study among Uber drivers suggests that earnings decline with age, whereas earnings increase with age for workers in traditional jobs (Cook et al., 2019).

The spatial structure and the way jobs and workers are located geographically also matters. Empirical research shows there is a large geographic variation in the risk of automation. A cross-country comparison in Europe suggests that jobs in Nordic countries are less automatable than jobs in South European countries, which is largely explained by country differences in the occupational mix within sectors and the task mix within occupations (OECD, 2018b). The effects of automation are likely to differ between cities and rural areas as well: evidence for the U.S. shows that job growth is mainly concentrated in cities and their peripheries, whereas rural areas are declining (McKinsey, 2019).

4. Consequences of the changing occupational structure

4.1. Income and inequality

The most important consequence of automation and the changing occupational structure is that the associated productivity increase tends to increase incomes and consumer welfare. As occupations shift and economies grow, so does total income. Both economic theory and empirical evidence also demonstrate a strong relation between productivity and the wages earned by workers (Stansbury & Summers, 2017; Caselli & Manning, 2019). In competitive markets, productivity puts downward pressure on product prices, so that real wages and purchasing power increase. Productivity also pushes wages up because the higher benefits from additional hiring causes firms to increase their demand for labour. The digital revolution also leads to entirely new products, such as smartphones and Wikipedia, and more product variation, such as more TV channels and customized products, that have increased welfare in ways that are hard to measure in traditional GDP indicators.

Income inequality, which has risen strongly in rich countries since 1980 (Nolan et al., 2019), is often considered to be another consequence of technological change. Even when average incomes grow, income inequality may widen and the incomes of some occupations or groups – such as low-skilled workers – might fall. Mobility, either geographical or occupational, is crucial for workers to seize opportunities in other jobs. As an extreme example, consider a hypothetical group of workers whose skills only allow them to do cashier work in a supermarket. As supermarkets introduce self-checkout machines and the demand for cashier workers falls, the wage in this market will inevitably fall as workers compete for the remaining jobs. On the other side of the skills spectrum, the wage of high-skilled workers tends to rise as new machines increase the demand for skilled workers to operate them. This skill-biased technological change is considered to be the main driver of the increase in income inequality in many countries – next to other factors such as declining union power and import competition (Autor et al., 1998). Job polarization also increases income inequality if it is assumed that the wages of low-skilled jobs do not rise because it is relatively easy to enter these jobs, and that the wages of high-skilled do rise because labour supply responds slowly to the increased demand in these jobs (Autor, 2014). This reasoning illustrates the fact that the impact of automation on the wages of specific occupations is not straightforward, because wages do not just depend on labour demand in the occupation – of which the effects of automation are relatively straightforward – but also on how labour supply responds in this occupation and on the price elasticity in the product market.

Income inequality could also have risen as a result of technological change if capital owners managed to turn the productivity gains into higher profits. In standard economic models competition drives prices down so that profits are competed away, but research shows that the market power of firms and profit rates have substantially increased over the past decades (Economist, 2016; De Loecker & Eeckhout, 2020). New technologies have also given rise to the "superstar phenomenon", i.e. the fact that in some professions a few persons earn astronomically high salaries because technology allows the very talented to reach very large markets (Rosen, 1981; Krueger, 2019). More and more markets exhibit this type of winner-take-all results, which widens the gap between the earnings of the top and those of the rest.

4.2. Job quality and wellbeing

The quality of a job is not just determined by the wage but by the entire job package that includes various dimensions of non-wage attributes (Munoz-Bustillo et al., 2009; Vandenbrande et al., 2012): job content (the intensity of work, task variety, repetitive work, autonomy in how to organize the work, etc.), working conditions (risk of injuries, hard physical work, etc.), employment conditions (job security, working times, promotion chances, on-the-job learning, etc.), and social relationships (participation in decision making).

The digital revolution and occupational change pose both opportunities and threats for the quality of jobs (Peña-Casas et al., 2018). Since technology is routine-biased, it is mostly the routine and repetitive jobs that are automated so that job quality in that dimension could be expected to improve. New technologies may reduce the risk of injuries on the job and the need for hard physical work, as is clear in the use of industrial robots for welding (joining metals using high heat), the use of robots to assist in lifting heavy objects, the use of sensors by workers to detect gas or the monitoring of traffic control to improve safety in the air and railways. But other types of risks and illnesses may increase. The digital revolution has allowed for a better monitoring of workers by management, which may increase effort levels, the intensity of work and mental stress (Gallie, 2017). As occupations shift towards more tasks as operators of computer capital, more workers are spending more hours behind their laptops, which poses health risks in terms of musculoskeletal disorders (Wahlström, 2005). Telework presents opportunities for more flexible working hours, a better work-life balance and more autonomy for workers, but it also isolates workers and it blurs the boundaries between work and non-work time which may make it harder for workers to disconnect from work, increase stress and complicate the regulation of working times through collective bargaining (Daniels et al, 2001). Platform work and the gig economy present similar opportunities for more flexible working hours, but the fact that many workers in these jobs are self-employed poses risks in employment protection, such as social insurance and the lack of trade union representation (Drahokoupil & Piasna, 2019).

4.3. Unemployment

Although some commentators speculate that automation will result in massive unemployment and "the end of work" (Rifkin, 1995; Ford, 2015), the general view in the economic literature is that technological change does not substantially reduce employment in the economy as a whole (Autor, 2014; Vivarelli, 2015; Caselli & Manning, 2019; European Commission, 2019). New technologies have produced fears about widespread unemployment both today (Ivanov et al., 2020) and in the past, and most famously in the Luddite movement in the 19th century. Yet, unemployment has never risen secularly with automation over the past decades and centuries, and unemployment today is not substantially higher in technologically more advanced countries than in other countries. The main mechanisms that compensate for the automation of specific job tasks are falling product prices that increase real incomes and the demand in other sectors of the economy, and the fact that automation increases the demand for labour complementing these technologies.

However, there are a number of theoretical reasons why a wave of automation could increase the unemployment rate temporarily – at least for some groups in the labour market. First, structural unemployment may arise from skill mismatch if the workers who lose their jobs in the declining occupations lack the necessary skills to find jobs in rising occupations. Second, if the job losses are concentrated in one region, for example the Rust Belt region in the US where many manufacturing jobs were lost over the past decades, and if the employment growth is concentrated in another region, for example in Silicon Valley, then a type of inter-regional spatial mismatch arises with high unemployment rates in the declining regions that may persist for decades (Moretti, 2012; Amior & Manning, 2018; Theys et al., 2019). Third, frictional unemployment may increase if a wave of automation results in higher levels of job destruction and job creation. More turnover in the labour market implies that more workers are in between jobs at any moment in time (Aghion & Howitt, 1994). Fourth, unemployment may arise if automation results in weak aggregate demand across the economy when the returns from automation flow to profitable firms or high income earners who save (Economist, 2017b; European Commission, 2019). The increased labour demand that can compensate for job losses from automation depends on aggregate demand in the economy, so policies that sustain aggregate demand and reduce inequality may support labour demand.

5. Conclusion

Recent technological trends, such as Industry 4.0, artificial intelligence and the platform economy, suggest that the digital revolution is far from over. As the digital revolution unfolds, the occupational structure adjusts as new technologies automate certain works tasks and shift consumer demand. Occupations rise and decline, and the task composition within occupations shifts. The changing occupational structure in turn affects labour market outcomes in terms of income, inequality, job quality and unemployment – and these effects depend strongly on the characteristics of the workers involved. Empirical research on the effects of the digital revolution on labour markets are complicated by intrinsic problems of measurement and identification. Both the adoption of new technologies and changing occupations and work tasks are hard to measure accurately. Identification of the effects of new technologies or the changing occupational structure requires exogenous variations in these variables, which are hard to find. The macro-effects of new technologies, via changing prices and incomes, cannot be ignored and this further complicates the identification problem. Given the importance of the digital revolution for labour markets, further research is needed to improve the measurement and the methods required for identifying the effects of technological and occupational change. These would allow research to disentangle the various channels via which technologies affect the occupational structure, to study the heterogeneous effects on labour market outcomes and to determine the policies and institutions required to accommodate the digital revolution.

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