ESSAYS ON ICTS, EXPECTATIONS AND SUBJECTIVE WELL-BEING

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Henrik Schwabe

Abstract

This doctoral thesis investigates how emerging ICTs affect individuals' expectations and their subjective well-being. The European Union's Digital Agenda for Europe has in the last few years led to massive investments to improve digital infrastructures and skills, in order to ensure that European nations have the necessary endowment and know-how to compete in an increasingly digital world economy. The Digital Agenda policy program includes initiatives to foster high-speed broadband network rollout, digital skills development, and the formation of public-private partnerships to stimulate innovation in emerging technologies such as high-speed internet, robotics and artificial intelligence. The ongoing digitalization process and related policies represent important structural changes that are disrupting existing social and economic activities, and represent the background and empirical setting that provide the foundations of this thesis.

Much scholarly effort has been devoted to investigating the economic effects of ICTs, such as, for instance, in the literature studying the productivity and growth effects of the internet, and the more recent strand of research on the employment effects of automation and robotics. However, extant literature has not yet investigated the possible subjective welfare effects of these emerging ICTs, and in particular the impacts on individuals' expectations and well-being. This thesis engages with this research gap by presenting novel empirical studies on how the internet and automation influences individuals' expectations and their subjective well-being. This is important because it allows a more comprehensive evaluation of the socio-economic effects of the current process of digitalization by focusing on the perspective of those who are directly exposed to this change—namely individual users and workers.

The dissertation consists of four essays that empirically investigate how ICTs affect individuals' expectations and subjective well-being, by making use of micro-level survey data for a large number of individuals and workers in European countries. Two of the papers study the effect of internet use on subjective well-being, and how these differ for individuals of different age groups. The other two papers contribute to the recent growing literature on automation and the future of work by investigating how the introduction of industrial robots in local labor markets affects workers' fear of replacement, future job prospects, and current life and job satisfaction.

These analyses highlight three main sets of findings. First, ICTs affect individuals' expectations about their personal future. Our studies of the internet show that its use is associated with optimism regarding future life conditions, work and economic prospects. Our studies of automation indicate that people working in regions with a greater historical presence of industrial robots are more likely

to anticipate that they themselves will compete with smart machines for work in the future. Second, expectations about the future informed by ICTs in turn influences individuals' current subjective well-being. Specifically, the internet and its available services provide users with information that raises aspirations about desirable outcomes, e.g. through online social networks that encourage social comparisons. However, aspirations are often overly optimistic and induce people to focus more on outcomes that will not materialize rather than those that will. Such unmet aspirations depress individuals' subjective well-being. In the case of automation, anticipating technological competition generates a fear of replacement in workers that is detrimental to their current life and job satisfaction. Third, ICT-shaped expectation formation and its effects on well-being are experienced differently for individuals depending on their age and skills. Young individuals are especially exposed: they are susceptible to developing overly optimistic expectations that are not easily satisfied later in life; and in their working life, their fear of being displaced by automation technologies depresses their present well-being. The threat of automation is also felt more strongly by workers with low education who perform repetitive tasks. These propensities become less pronounced at older ages.

The thesis lies at the intersection of two strands of research that have so far developed as separate literatures: the economics of subjective well-being and the economics of innovation and ICTs. The work contributes to the former strand of research by introducing ICTs and digitalization as new explanatory factors explaining individuals' well-being (which have so far mostly been neglected in happiness studies). And it contributes to the latter strand of studies by investigating effects of ICTs on individuals' subjective well-being (whereas most previous research has focused on the economic effects of ICTs on e.g. productivity, growth and employment).

This theme of research and the findings of this dissertation have societal relevance and potentially important policy implications. Policy makers who promote public support for digitalization must be informed of the ways in which this process affects individuals' expectations and subjective well-being. As pointed out in the thesis, the relevant effects can be positive or negative depending on whether the technology is perceived to improve or deter future prospects, and depending on individuals' personal characteristics such as age and skills. On the whole, digitalization policies should take these empirical findings into account, and seek to foster positive effects for some individuals and age groups, and at the same time limit the negative effects on others.

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PART I: INTRODUCTORY CHAPTER

1. INTRODUCTION

At present, the future is digital. Many European nations are currently making major efforts to facilitate the process of digitalization that is expected to sustain competitiveness and economic performance. In particular, the Digital Agenda for Europe (DAE) initiative coordinated by the European Union points to internet technology as central to fostering digitalization, emphasizing universal access, increasing speed and better infrastructures as key factors for improving firms' productivity and citizens' living standards. This policy agenda has motivated swift internet adoption in many European countries in recent years. Nowadays many individuals spend an increasing amount of time using digital services on their smartphones, tablets and computers. Yet, there are substantial differences in digital use and skills between people, depending in particular on their age, education and sector of occupation. Firms, meanwhile, continue to invest in automation technologies and new business models that exploit the increasing amount of digital data made available by individuals' online activities. Industrial and service robots, big data and artificial intelligence are not restricted to manufacturing firms but have also been adopted in a variety of other sectors. Developing further workers' skills and creativity is crucial to maintaining a productive workforce in the future. Digitalization is fundamentally transforming economic and societal structures, and the challenge is to ensure that such transformation benefits a great number of individuals and social groups without threatening the welfare of others.

Recent research focuses on the economic effects of digitalization. Broadband investments have contributed positively to economic growth (Czernich, Falck, Kretschmer, & Woessmann, 2011). The internet has raised the productivity of workers (Jorgenson, Ho, & Stiroh, 2008; Byrne, Oliner, & Sichel, 2013; Syverson, 2017) and firms (Brynjolfsson & Hitt, 2003; Draca, Sadun, & Van Reenen, 2009). Other recent research focuses on the effects of digital technologies such as automation and artificial intelligence for the future of labor and employment. Some believe that the ongoing process of developing and adopting advanced ICTs is a disruptive force that could lead to widespread joblessness in the future (Ford, 2015). Others argue that emerging ICTs will increase productivity and labor demand, thus leading to employment and wage growth (Bessen, 2020). Nevertheless, ICTs continue to change job tasks and skill requirements (Acemoglu & Autor, 2011; Deming & Kahn, 2018; Acemoglu & Restrepo, 2019). Because many of the new tasks require skills acquired by higher education, skilled workers have experienced superior wage growth (Autor, 2015b). Moreover, digital technologies have so far been able to carry out routine tasks that are typically performed by mid-skilled workers, who have seen their employment share diminish to the point where job creation now occurs mostly in low- and high-paying occupations (Autor & Dorn, 2013; Goos, Manning, & Salomons, 2014). In short, this recent research suggests that employment and wage prospects of workers largely depends on their skills and education credentials.

These strands of research have provided important insights regarding the economic effects of ICTs. However, information technology transforms professional *and* private domains of life and may thus also have important non-economic effects that are relevant for individuals' wealth and welfare. Specifically, in working life, automation technologies may lead individuals to experience uncertainty about future job and financial prospects. In private life, ICTs like the internet and related web services affect individuals' productivity, autonomy, and social interactions, thus contributing to welfare (Castellacci & Tveito, 2018). At the same time, though, the internet also fosters social comparisons, allowing its users to define their own peer groups which they can then compare their own outcomes against (Card, Mas, Moretti, & Saez, 2012; Sabatini & Sarracino, 2016). It is thus natural to think that the internet and automation may affect individual users' expectations about the future and their evaluations of how life outcomes compare against these expectations, or the outcomes of others.

In the economics of innovation literature, there has so far been limited attention to the study of the non-economic effects of ICTs, and particularly on their effects on individuals' well-being. Human welfare improves with economic growth and disposable income. Yet, such economically-defined welfare measures say little about the extent to which individuals may realize their potential and live satisfying lives. Nor do they tell about how digitalization impacts human emotions, aspirations, and feelings of accomplishment. The lack of research on the effects of digital technologies on individuals' well-being represents an important research gap that motivates the present dissertation.

The study of well-being is indeed the domain of a different literature, so-called *happiness economics* (Clark, Frijters, & Shields, 2008). This research studies the determinants of subjective well-being, pointing for example to the fact that people have changing preferences, care more about relative than absolute improvements, and compare their achievements with their peers. Moreover, expectations and aspirations determine both individual efforts and satisfaction with outcomes (Foster & Frijters, 2014; Schwandt, 2016). However, in spite of a few recent studies, happiness economics has not yet systematically investigated the digital dimension, i.e. how the use of ICTs may shape individuals' expectations and well-being.

In short, the economics of innovation and happiness economics are two burgeoning strands of research that investigate topics of high public interest, but so far they have developed separately and with weak interactions. This thesis is motivated by this knowledge gap, and it investigates how emerging digital technologies influence individuals' expectations and subjective well-being.

The dissertation contains four empirical essays. Two of the papers consider the recent development of high-speed internet by asking how internet use and social media shape the relationship between expectations and life satisfaction over the life cycle. The Eurobarometer survey provides rich cross-sectional data on self-reported expectations and life satisfaction and internet use frequency. To address endogeneity concerns, I draw on data that describe the regional take-up of the ongoing investments in broadband infrastructure under the DAE in a two-stage instrumental variable model. The results suggest that the internet is a source of optimism that contributes to unmet aspirations as it increases the gap between expected and subsequently realized life satisfaction over the life cycle. The two other papers rely on data from the Eurobarometer survey and the YS Employment Outlook Survey to engage with the widely discussed topic of automation by investigating the relationship between anticipated job competition with smart machines and workers' current life and job satisfaction. Historic adoption of industrial robots in local labor markets marks this relationship as workers learn from their own experiences and that of their peers when forming their expectations. As the results indicate, a substantial share of workers consider their own jobs and tasks to be automatable, and the fear of displacement is detrimental to their present well-being.

The next sections in this introductory chapter will present the relevant theoretical, empirical and methodological background of the thesis. Section 2 introduces recent developments of emerging ICTs in Europe under the Digital Agenda for Europe initiative. Sections 3 and 4 provide a synopsis of the literatures on the economics of ICTs, and on subjective well-being (SWB) and expectations, respectively. Section 5 discusses some possible ways in which ICTs may affect individuals' well-being through income, employment, education, and age-related effects. Section 6 summarizes the four papers of this thesis. Section 7 discusses the data and methods used in the analyses, and the related assumptions and possible limitations. Section 8 concludes the chapter by discussing the overall findings, their policy implications and possible future extensions.

2. EMERGING ICTS IN EUROPE

An ongoing policy program is currently transforming the European economy in anticipation of a digital future. In May 2010, the European Commission launched its Europe 2020 strategy for smart, sustainable and inclusive growth that affects employment, productivity, and social cohesion. Digitalization, business competitiveness, and building a knowledge-intensive economy are key pillars for developing a smart and sustainable economy. The EU identified innovation as the future growth engine, which in turn requires improvements in industrial technological transformation, ICT infrastructure, and human capital upskilling (European Commission, 2010). Each member state committed to formulate national plans to support the establishment of a "Digital Single Market". These plans required the member states to develop high-speed internet strategies with targeted public funding, to establish legal frameworks that facilitate cost-reduction of network rollout, and to promote deployment and usage of accessible online services (e.g. e-government and digital skills). The national broadband plans subsequently developed to promote initiatives supporting the European Commission's Digital Agenda for Europe have differed between European nations and resulted in investment and progress differentials between and within member states (European Commission, 2014b).

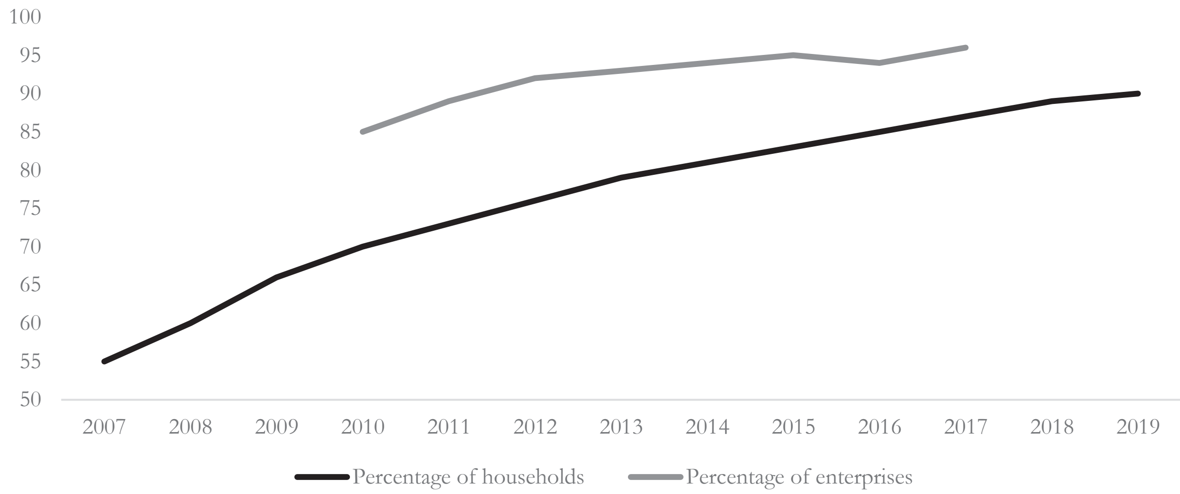
Broadband internet development has been paramount for the present trends toward digitalization. Policy makers are currently investing in infrastructure that is necessary for the next generation of technology. The digital eco-system does not develop piece by piece but rather through interdependencies and feedback loops. The European Commission, through the DAE, intends to facilitate and guide a digital transformation of society and economy. The processing capacity of information technologies and the explosion of available data create opportunities for sophisticated technologies, including cloud computing and Big Data, 3D printing, artificial intelligence, and robotics. To this end, the EU invested €6 billion in broadband infrastructure between 2014 and 2020 via the European Regional Development Fund and the European Agricultural Fund for Rural Development and has committed to invest another €9.2 billion in digital initiatives between 2021 and 2027 (European Commission, 2014b, 2019). Societal challenges related to aging, health, work, security and well-being display the intricate role of technology and place much faith in innovation as a tool to address these issues. Artificial intelligence and robotics are promising venues in this regard. The EU represents about 25 percent of the global industrial robot market, and 50 percent of the professional services robot sector (European Commission, 2014a).

The capabilities related to the adoption and use of high-speed internet, robots and AI will thus need to become increasingly sophisticated in European countries in the coming years. Human interaction, cognition and learning are qualities that these technologies should possess when venturing beyond traditional deployment in manufacturing and into other economic areas (Rajan & Saffiotti, 2017). Internet, automation and AI are indeed distinct technologies. However, it is reasonable to consider them as part of the same technological trajectory because they are so closely interrelated. The capacity of the internet is crucial for the amount of information that can be transferred across and between technologies and devices. The volume of information has exploded with the amount of digital content from the internet. Big data from technological devices and user-specific information from social media, consumption and geo-locations are increasingly available. Better hardware capacity improves the computational power necessary to run sophisticated techniques, e.g. machine learning, that utilize these data and improve the 'smartness' of machines with the ambition to create 'artificial intelligence'. Robotics is also developing with both industrial and service robots being deployed in a wide range of tasks, e.g. warehouses and cleaning services, which has made it a promising market with large potential (SPARC, 2013; Rajan & Saffiotti, 2017). It is therefore important to consider these emerging ICTs together because their pervasiveness in economic and societal structures expands as they converge. To show the rapid diffusion and wide range of applications of these digital technologies, this section will present some trends and descriptive data on the adoption and use of these emerging ICTs by individuals, firms, and national economies in Europe.

2.1. Internet use

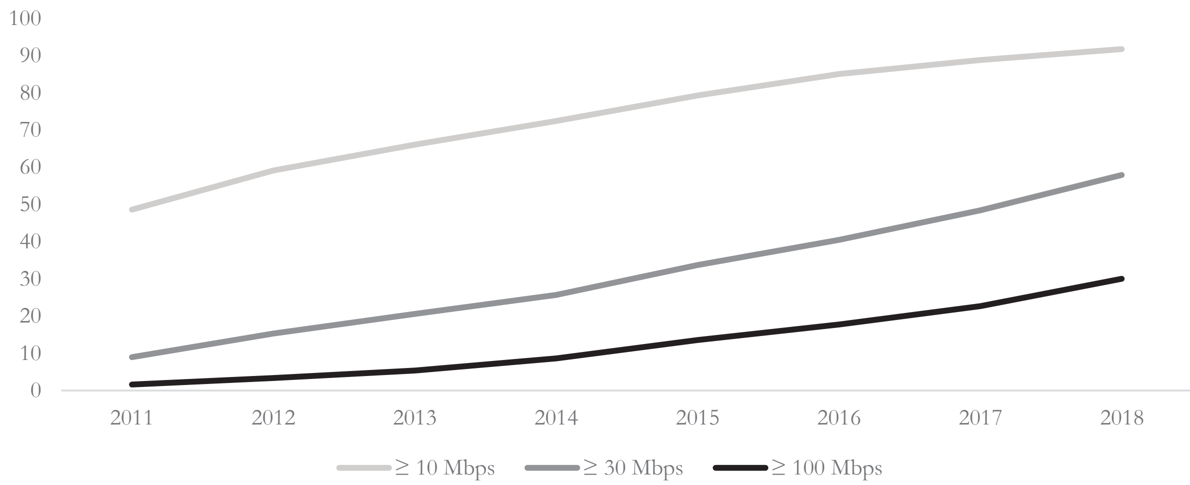
To guide the DAE, the Commission set out three main targets for broadband internet development: 1) broadband access for all by 2013; 2) access to internet speeds of 30 Mbps or more by 2020; and 3) that 50 percent or more of European households subscribing to internet connections above 100 Mbps by 2020. The first target was accomplished, and figure 1 presents broadband availability for European households between 2007 and 2019 and for European enterprises between 2010 and 2017. As for the second target, figure 2 shows that access to high-speed (30 Mbps or above) internet is becoming increasingly available to the population, representing almost 40 percent of all broadband subscriptions in 2018. Moreover, 30 percent of all broadband subscriptions in 2018 have speeds of 100 Mbps or above. This is well below the target of 50 percent by 2020 but considering that subscriptions in this category grew by more than 7 percentage points, or 32 percent, from 2017 to 2018, a similar growth over the next two years suggests that this target also is within reach. Higher broadband capacity allows more demanding and wide-ranging operations and services to be possible and is important for developing e-government and e-economy services. It is particularly interesting to see from figure 2 that speed below 10 Mbps currently represents less than 10 percent of all subscriptions. This shows market responsiveness to improved digital infrastructure and puts into context what broadband internet actually can represent in societal analyses. Studies dealing with the first rollout of broadband internet in the first decade of the 2000s used speeds of 256 Kbps (Czernich et al., 2011; Bhuller, Havnes, Leuven, & Mogstad, 2013; Akerman, Gaarder, & Mogstad, 2015). Since then, increased capacity has made the internet more powerful and capable of facilitating new services and activities. To understand the effects of these possibilities it is necessary to document how economies adopt and utilize available powerful technologies.

Figure 1: Broadband internet access (percent)



Share of European households and enterprises with access to broadband internet. Source: Eurostat, Digital Economy and Society dataset.

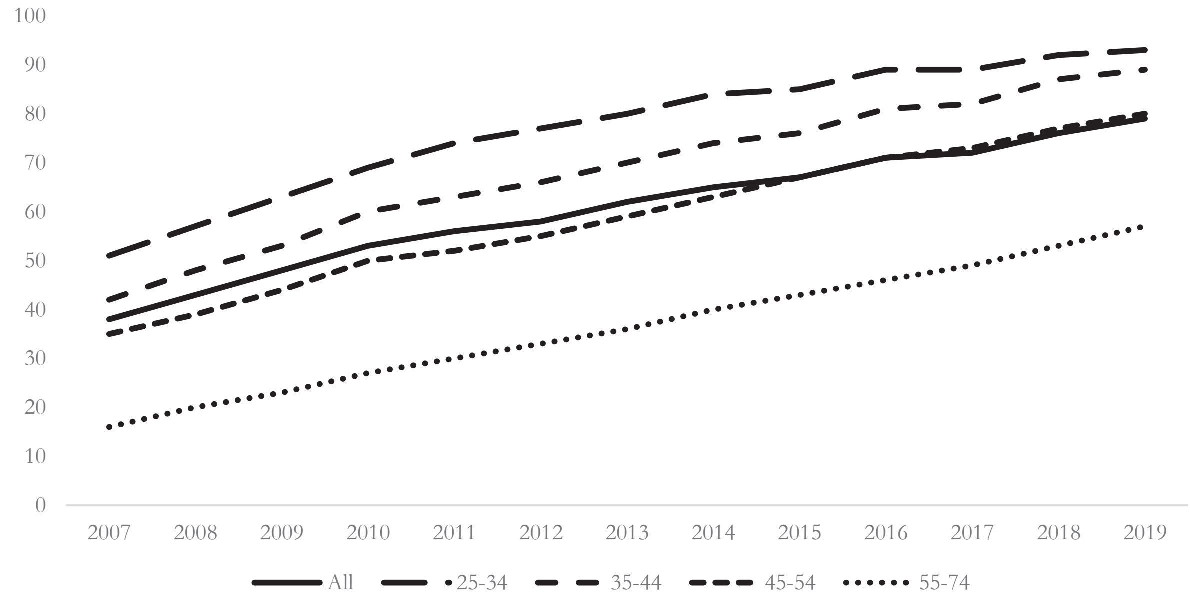
Figure 2: Broadband speed subscriptions (percent)



Share of fixed broadband subscriptions by advertised download speeds. Source: European Commission, Digital Scoreboard.

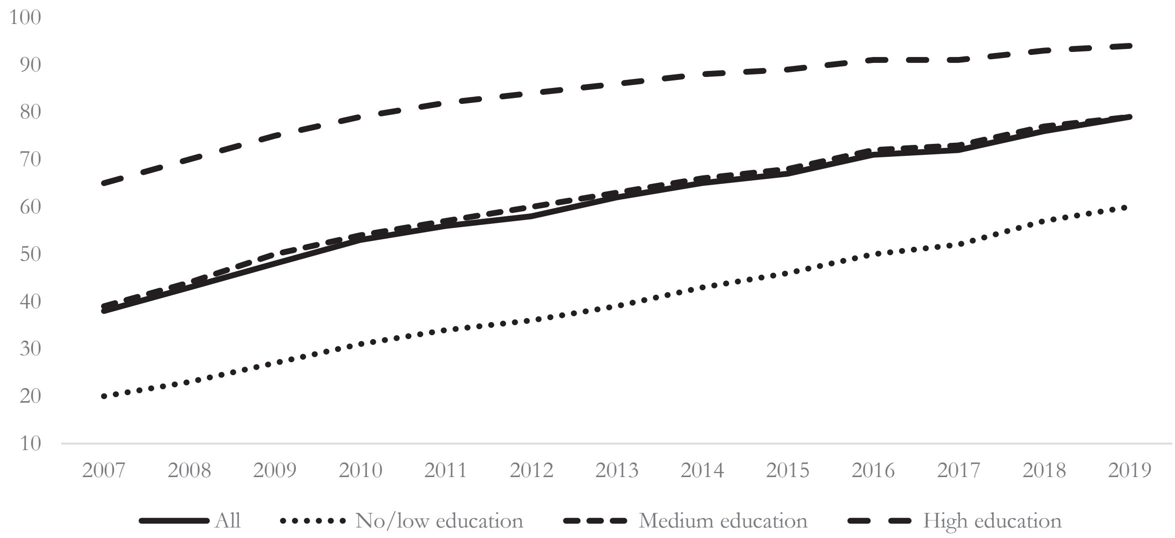
The DAE's ambition to connect the European population to the internet and improve their technological skills depends on not leaving any demographic segment behind and avoiding digital divides between exposed groups such as the young and elderly and those with low education. It is therefore important to see whether these groups have different levels of internet utilization. Figures 3 and 4 show internet use patterns for different age and education groups, respectively. Overall, internet use has become an increasingly common activity. However, while it is part of daily life for younger age groups, older individuals are still lagging behind. Moreover, internet use differs substantially between education groups. Highly educated individuals appear to be pulling the overall growth pattern in daily use, more so than those with lower education.

Figure 3: Daily internet use by age group



Source: Eurostat, Digital Economy and Society dataset.

Figure 4: Daily internet use by education level



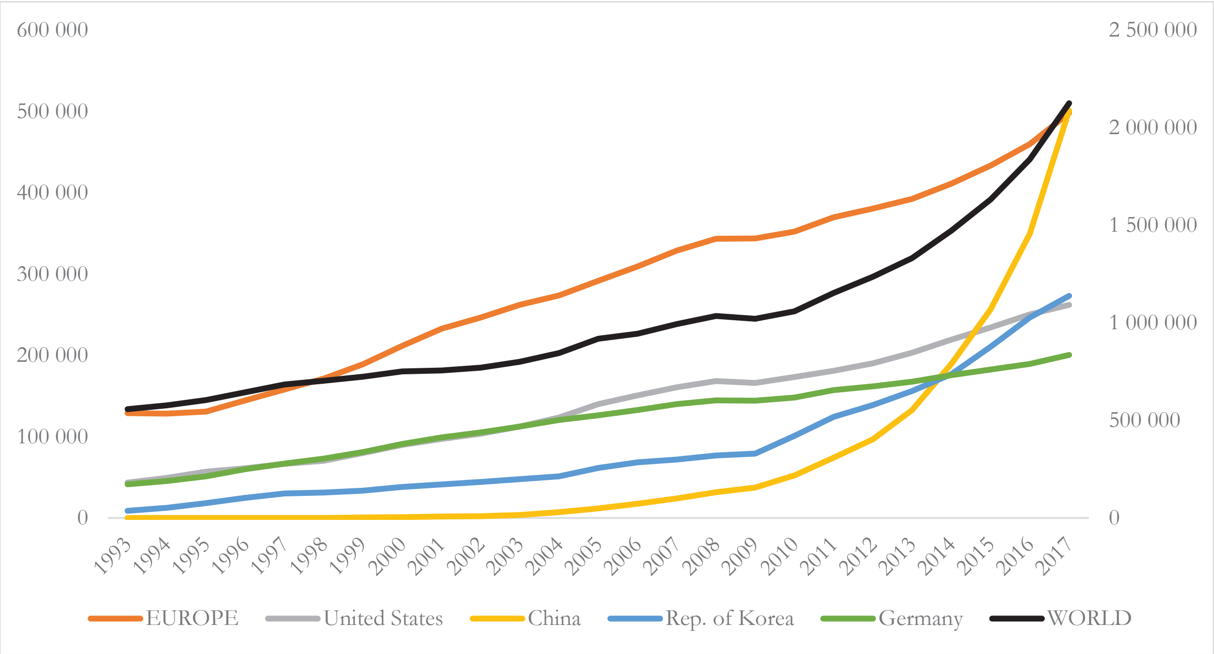
Source: Eurostat, Digital Economy and Society dataset.

2.2. Automation, Robots and Artificial Intelligence

As noted above, one of the characteristics of the internet is that it enables high-speed communication among agents and devices that are not co-located, thus increasing substantially the amount of data and information available to each. In turn, this has fostered the emergence and development of other important technological trajectories, such as automation, AI and robots. The convergence between these technologies and their future possibilities are often referred to as Industry 4.0. Globalization pressures firms and economies to innovate and new ICTs are developed to meet this competition. Economic processes have become increasingly intertwined by the internet, and robots, AI and sophisticated software are changing the production, design and consumption of new products and services (European Commission, 2018b). Individuals are consuming more digital goods and services, leaving behind traces of information (e.g. Big Data) that firms are collecting and analyzing to optimize their products and improve market reach. Because the internet, computers, software, and robots and AI are so interrelated, growth in the digital market feeds on interdependencies and feedback loops between different technologies and market adoption (Ford, 2015). In fact, the excitement about the potential of robot and AI technologies eventually converging relies on the improved computational power of hardware combined with the exponential increase in digital data from the internet that can be analyzed and incorporated into smarter technology (Rajan & Saffiotti, 2017).

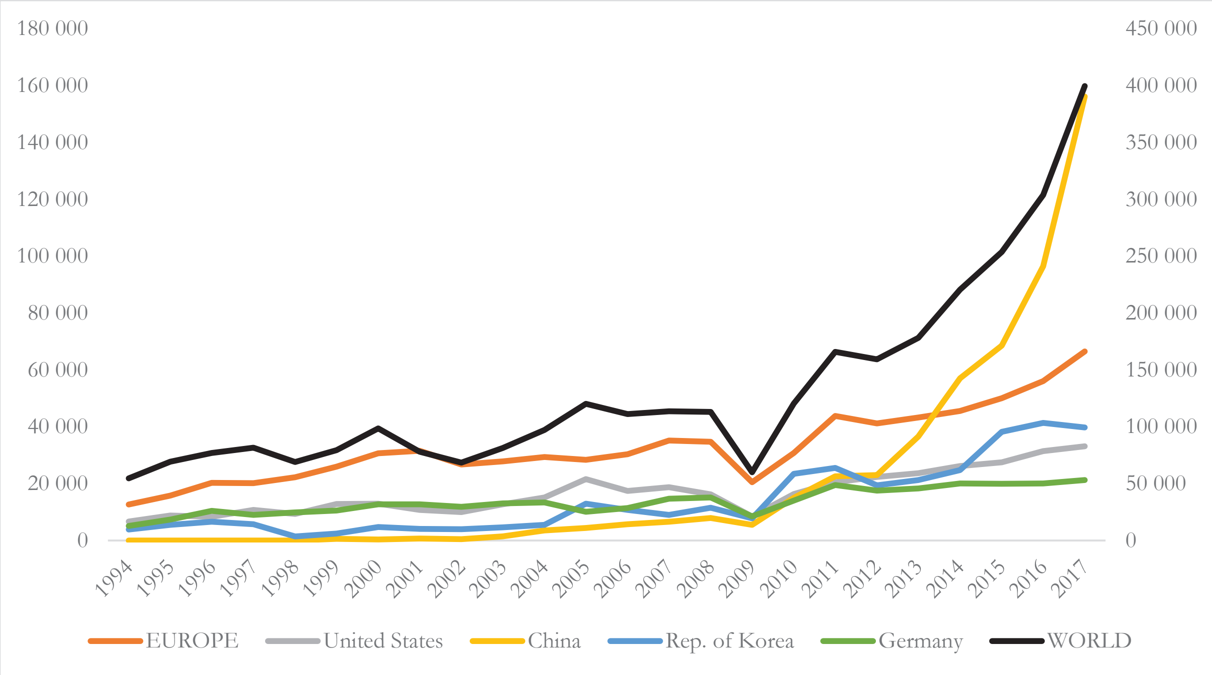
The International Federation of Robotics (IFR) provides annual data on the international robot market dating back to 1993. Figure 5 presents the deployment of robots between 1993 and 2017. Over that period, the total operational stock of industrial robots grew almost four-fold to more than 2.1 million robots worldwide. Although Europe held the largest stock of robots in that time span, China surpassed it in 2017, becoming the world's largest market according to IFR data. Germany, the US, and the Republic of Korea are the next major economies; yet the robot stock of these countries is about half that of China and Europe. Figure 6 shows robot sales over the same period, indicating that all major robot markets have grown considerably, notwithstanding a short dip around the 2008 financial crisis. Although demand for robots in Chinese firms has exploded recently and is pulling worldwide growth, Europe is still the second largest market. These markets have very different labor compositions however and the situation looks somewhat different when looking at robots per manufacturing worker. As shown in figure 7, human workers in the Republic of Korea and Europe face the stiffest competition from machines. These patterns suggest that robots have gained ground in production relative to human workers—a trend that does not look like stopping anytime soon.

Figure 5: Operational stock of industrial robots



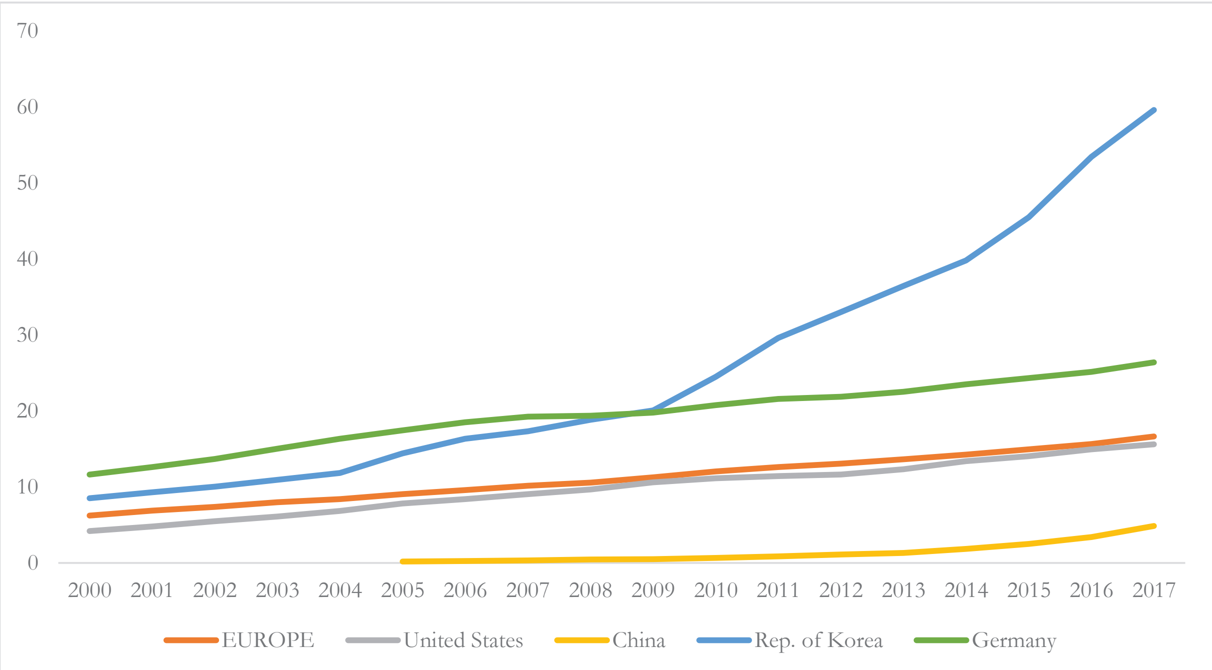
Source: International Federation of Robotics.

Figure 6: Annual deliveries of industrial robots



Source: International Federation of Robotics.

Figure 7: Industrial robots per 1,000 manufacturing workers.



Authors' calculations. Sources: Robot data are collected from International Federation of Robotics. Employment data for manufacturing workers are retrieved from different sources. Eurostat's National accounts employment data by industry provides employment figures for Europe and European countries. US and Rep. of Korea figures are collected from the International Labour Organization (ILOSTAT). Data for China are derived from the China Statistical Yearbook.

Table 1 shows data on robot adoption by sector in European countries for 2018. Not surprisingly, robots are most commonly adopted by manufacturing firms but are also beginning to spread in other sectors a well. Although these numbers might look unimpressive at first glance, they are likely disguising the employment effects because most adopting firms are large companies (Koch, Manuylov, & Smolka, 2019; Acemoglu, LeLarge, & Restrepo, 2020). In France, for example, only 1 percent of a sample of 55,000 manufacturing firms invested in robot technology between 2010 and 2015, yet these firms represented 20 percent of all employees (Acemoglu et al., 2020). The spread of robots will likely grow as service robots become more commercialized. Surveillance, transportation, cleaning, warehouse management, assembly works, clerical tasks, and construction/repair tasks represent about 90 percent of the use of service robots by adopting firms (not shown but available from Eurostat). These uses are undoubtedly relevant for many large employers, regardless of whether they represent their core business or not. Robot technology is no longer restricted to manufacturing but is making inroads into other parts of the economy as well.

Table: 1: Industrial and service robot adoption in European sectors (2018).

	Industrial robots	Service robots	3D printing	Big Data
All enterprises, without financial sector	5	2	4	12
Manufacturing	16	4	9	9
Electricity, gas, steam, air conditioning and water supply	2	2	1	20
Construction	2	1	1	11
Wholesale and retail trade; repair of motor vehicles and motorcycles	2	3	2	12
Transportation and storage	1	2	1	19
Accommodation	0	2	1	13
Information and communication	2	1	5	27
Real estate activities	1	1	2	9
Professional, scientific and technical activities	2	1	6	14
Administrative and support service activities	1	2	2	13

Data from Eurostat, ICT (Information and Communication Technologies) usage and e-commerce in enterprises 2018. Percentage of European enterprises with 10 persons employed or more.

The EU's Digital Agenda for Europe is a massive attempt to compete in the ongoing race for game-changing technology by stimulating sustainable innovation that attracts capital and fosters talent. Emerging ICTs are believed to have the disruptive power to generate economic and societal transformations (Brynjolfsson & McAfee, 2014). An optimistic take is that new sophisticated technologies can become tools to solve certain headwinds that threaten modern living standards, such as aging populations and shrinking workforces (European Commission, 2014a; EU & UN-Habitat, 2016; European Commission, 2018a). A more pessimistic viewpoint holds that emerging ICTs will improve the ability of smart machines in ways that make them capable of competing with human workers in other parts of the economy besides manufacturing. This appears to already be happening to some extent with the adoption of 3D printing, artificial intelligence, and Big Data. These technologies may complement some workers and displace others from their jobs either directly, by replacing their tasks or jobs with technology requiring skills not attainable to many, or indirectly by increasing competition between workers with different skills for fewer jobs (Ford, 2015). Governments are paying close attention to these developments and trying to incentivize firms into developing new technologies necessary to tackle economic, societal and environmental purposes, in addition to pushing innovation through R&D (OECD, 2018a, 2019). This interplay between public and private actors has also raised questions about whether the incentives for developing increasingly sophisticated and pervasive technology will align with the interests of the average person and prompts important ethical concerns regarding their use and welfare effects (Webb, 2019). For example, the mounting collection and utilization of digital data by public and private actors warrant serious discussions regarding the ownership and stakes in future capitalization of such data (Savona, 2019).

3. LITERATURE I: THE ECONOMICS OF ICTS

The effects of ICTs on economic growth, innovation in firms, and worker performance have extensively been studied in the economics of innovation literature. These questions are undoubtedly important, and extant research has investigated how ICTs diffuse in the economy and the importance of innovation for economic growth. Technological change transforms the economy and affects workers. The implications of emerging ICT for workers' productivity, employment prospects, skills and wages are widely documented in the literature.

Economist and Nobel laureate Robert Solow famously noticed the paradox that "you can see the computer age everywhere but in the productivity statistics" (Solow, 1987). Along with Swan (1956), Solow (1957) is known for formulating the idea that technological change is essential to long-term economic growth. In this framework, technological progress arrives unexpectedly and can raise the productivity of workers. Unsatisfied with the neoclassical assumption that new technologies are exogenous *manna from heaven*, endogenous growth theory posits that innovation and human creativity can explain growth differentials through earlier investments in R&D and human capital (Aghion &

Howitt, 1998). Technological change thus becomes a social feedback process that is conditioned on the environment in which it occurs whilst simultaneously changing it—in other words “technological progress transforms the very economic system that creates it” (Aghion & Howitt, 1998, p. 1). This intuition derives from Schumpeterian growth theory, where the entrepreneurial spirit stimulates market competition in the search for new ideas or combinations that render competitors obsolete—a dynamic called *creative destruction* (Schumpeter, 1934). The intuition behind creative destruction is particularly relevant for understanding the implications of automation technology adoption for firms' competitiveness and labor demand.

3.1. ICT adoption, network effects and demographics

Widespread adoption of ICTs in production and consumption started in the 1970s and exploded with the diffusion of the internet (Maurseth, 2020). The internet is integrated in most production processes and organizational structures, and it is the vehicle used by governments to digitalize their public services and develop e-government (European Commission, 2014a). It is also omnipresent in the way people navigate in society, consume news, and entertain themselves (Hong, 2007; DellaVigna & La Ferrara, 2015).

An important determinant of ICT adoption is the technology's compatibility with other factors, e.g. technologies or human capital, which makes it more likely to spread as it opens up new possibilities for complementary technologies to adopt it in their product or solution (Bresnahan & Trajtenberg, 1995). Network externalities make the value of a technology dependent on how many other agents are using it, and they have been crucial in, for instance, the diffusion of home computers (Katz & Shapiro, 1986; Goolsbee & Klenow, 2002). The adoption of ICTs also depends on social incentives. Adopters of new technologies induce others to adopt as well through social learning between users and non-users (Goolsbee & Klenow, 2002). While social learning refers to the process of technological adoption through knowledge spillovers, social pressure to use ICTs and partake in their services is another incentive for individuals to invest in learning new technologies (Agarwal, Animesh, & Prasad, 2009).

Demographic composition is another important determinant of digitalization. People living in cities are more likely to adopt ICTs (Goolsbee & Klenow, 2002). This is arguably a result of both supply and demand. The European Commission assessed the national broadband plans of its members states and found substantial regional differences in the rollout of high-speed broadband infrastructure (European Commission, 2014b). Urbanization, education, and age are important factors that influence the adoption and spread of ICTs (Caselli & Coleman, 2001; Goolsbee & Klenow, 2002; Ford, Koutsky, & Spiwak, 2011; Bauernschuster, Falck, & Woessmann, 2014). Education differentials are believed to be one of the key determinants of the digital divide and persist across countries with different digitalization development (Chinn & Fairlie, 2007; Goldfarb & Prince, 2008; Cruz-Jesus, Vicente, Bacao, & Oliveira, 2016). Brandtzæg et al. (2011) analyzed survey data for a group of European countries and found age to be one of the most important factors explaining both internet adoption and use. Age of workers is an important factor for robot adoption as well. Firms in aging economies are more likely to invest in robot technology that replaces job tasks typically performed by middle-aged workers (Acemoglu & Restrepo, 2018a).

3.2. ICTs and economic growth

The effects of ICTs on economic growth have also been studied extensively, although the implications in terms of human capital and inequality are still actively debated. Emerging ICTs have stirred anxiety over their potential because they are considered to be game changers due to their wide-ranging implications. This anxiety, however, is split between those who fear that ICTs will be capable of replacing human workers with severe consequences for social inequalities, and those who believe that ICTs will contribute sufficiently to economic growth to counter headwinds such as slow productivity and population growth (Mokyr, Vickers, & Ziebarth, 2015). Some doubt whether the contribution of ICTs to economic growth is sufficient (Gordon, 2012; Acemoglu, Dorn, Hanson, & Price, 2014), whereas others are more sanguine (Jorgenson, 2005; Brynjolfsson & McAfee, 2014; for a recent survey of the literature, see Maurseth, 2020). Interestingly, recent investments in broadband internet infrastructure in Europe are a bright spot, arguably because the internet has made workers more productive, and online services such as job search, e-commerce, and new markets have increased economic activity (Evangelista, Guerrieri, & Meliciani, 2014). At the macro-level, broadband infrastructure investments stimulate growth (Koutroumpis, 2009). In an assessment of the DAE program, Gruber et al. (2014) conducted a cost-benefit analysis of broadband investments and found that the economic benefits outweighed the costs, concluding therefore that they should be subsidized by governments.

One reason that the overall effects of automation are hard to pinpoint is that productivity can be growing in some sectors and declining in others. This is known as Baumol's hypothesis of unbalanced growth—where aggregate economic productivity can appear stagnant while economic activity shifts between sectors, and rising costs in the growing sectors allow slow-growing sectors to survive (Baumol, 1967; Baumol, Blackman, & Wolff, 1985). The ambiguity concerning contributions from technological change to economic growth, and whether it displaces labor or reallocates it from one activity to another, depends on demand elasticity (Bessen, Goos, Salomons, & van den Berge, 2020; Bessen, 2020). The next section will shift the focus toward the micro-level effects of ICTs.

3.3. Effects of internet and automation for workers

> The role of labor as the dominant factor of production was not reduced but enhanced [by more complex machinery]. The control and guidance of increasingly powerful and intricate machinery require that each worker exercise mental capabilities of progressively higher and higher order. The competitive market mechanism translated this steadily increasing demand for labor into higher and higher real wage rates. […] Computers and robots [now] replace humans in the exercise of mental functions in the same way as mechanical power replaced them in performance of physical tasks. […] Any worker who now performs his task by following specific instructions can, in principle, be replaced by a machine. That means that the role of humans as the most important factor of production is bound to diminish (Leontief, 1983).

Despite being written almost four decades ago, this quote by economist Wassily Leontief captures well current debates about how ICTs are transforming present and future work. The conclusions, broadly, are: a) Technological change has had an overall positive effect on worker productivity; b) ICTs and automation have incentivized an upskilling in human labor that has resulted in higher compensation of labor-intensive jobs; and c) more sophisticated technologies will challenge cognitively demanding tasks currently undertaken by humans, especially jobs that include highly repetitive tasks.

The first point encapsulates the Solow paradox as the contribution of ICTs to productivity continues to puzzle researchers. Leading up to the Dot-com bubble in 2000, ICTs became the center of attention and were awarded a crucial role in the rising productivity of workers (Oliner & Sichel, 2000). More recent data suggest that productivity returns to ICT have stagnated (Jorgenson et al., 2008; Byrne et al., 2013; Syverson, 2017). Firm-level data add some nuance to this picture. Because general purpose technologies (GPTs) involve interaction with other complementary factors such as organizational innovations or workflow changes, computerization in firms shows that ICTs have raised productivity and output (Brynjolfsson & Hitt, 2003; Draca et al., 2009). Moreover, better economic performance motivates firms to invest further in innovation activities and ICTs (Cainelli, Evangelista, & Savona, 2005). Brynjolfsson and McAfee (2014) find evidence of productivity improvements from the adoption of IT capital by firms and the implementation of ICTs in job performance, arguing that the Solow paradox no longer exists. Despite major productivity improvements in ICT-intensive sectors, there is a worry that these improvements are caused by automation and ICT transformation of workplaces that replace, rather than complement, workers. This concern is often based on evidence showing that workers have seen their share of income decline globally over the last three decades as ICTs have incentivized firms to supplant workers with machines (Karabarbounis & Neiman, 2013). This explanation however is not straightforward. Acemoglu et al. (2014) look at industries that use, rather than produce, information technology and find that ICT-intensity is ambiguously related with productivity growth and that the Solow paradox is still unresolved.

The implications of digitalization for labor extend beyond the question of how much humans and machines produce—they also concern their relative share in production. Evidence suggests that workers are losing terrain in competition with machines, in part as a result of information technology becoming cheaper (Elsby, Hobijn, & Şahin, 2013; Karabarbounis & Neiman, 2013). While productivity has been growing, the labor share—meaning how much of GDP is represented by worker compensation—has not been able to keep up (Fleck, Glaser, & Sprague, 2011). Bessen et al. (2020) survey recent studies on employment effects from emerging ICTs, including sophisticated software, robots and artificial intelligence, and find no consistent pattern. However, individual studies have found that ICTs generate employment and wage differentials based on the skill and age of workers.

This leads us to ask whether technological change has put a premium on skill and whether ICTs compete with workers in jobs with routine-based repetitive tasks. In the literature, these effects are referred to as 'skill-biased' and 'routine-biased' technological change, respectively. A situation where technological improvement displaces human labor faster than it creates new occupations is called 'technological unemployment', and it has been compared to an economic disease (Keynes, 1930) or an invasion (Heilbroner, 1965). Schumpeterian growth models assume that creative destruction, by displacing workers who become unemployed and then available to new entrant firms, re-allocates labor (Davis & Haltiwanger, 1992). This intuition assumes, in essence, that technological unemployment is temporary for workers: when displaced they find employment elsewhere. This, in turn, requires that entrant firms employ displaced workers who become superfluous in their previous job. For this to happen, technological change must not deter labor market matching, which requires that workers either retrain or that they possess skills that are attractive to entrant firms. Empirical studies suggest that this is not necessarily the case.[1] Akerman, Gaarder and Mogstad (2015) find that the adoption of broadband internet by Norwegian firms has positive productivity and wage effects for skilled workers but negative ones for unskilled workers. Skilled workers gain from technological change because they perform non-routine tasks while unskilled workers typically occupy jobs with routine tasks that are replaced by ICTs (Autor, Levy, & Murnane, 2003). The skilled workers are assumed to have a comparative advantage in performing new tasks in technology-intensive jobs that make unskilled workers redundant. Inequality consequently rises, although standardization of ICTs has been argued to reduce inequality and benefit unskilled workers in the long run (Acemoglu & Restrepo, 2018c).

Routine-biased and skill-biased technological change thus has implications for the employment and wage prospects of workers with different skills. Acemoglu and Autor (2011) trace wage inequality to skills, showing that medium-skilled workers typically occupied in blue-collar production and white-collar repetitive jobs are more exposed to automation than low-skilled and high-skilled workers. This "hollowing out" of middle-skilled workers is reflected in employment and wage growth for low- and high-skilled workers (Autor & Dorn, 2013; Autor, 2015b). A possible explanation for this pattern is that standardization makes operating technology easier and requires less specialized skills. Jobs that involve using standardized technologies may thus make those workers replaceable, not by machines, but by other workers (Ford, 2015). Work that does not require specialization, only some basic technological skills, can be performed by different workers and causes wages to stagnate. Beaudry et al. (2016) argue that skill-biased technological change has negatively affected the market return to education and reversed the demand for cognitive skills. Moreover, they show that high-skilled workers have replaced workers in less demanding jobs, and that recent graduates are increasingly likely to start their professional life in service or routine jobs as opposed to a cognitively demanding job (Beaudry et al., 2016). This reasoning is in line with studies finding evidence of over-education, which has detrimental effects for wage outcomes and job satisfaction (Cappelli, 2015). At least in the US, the number of abstract task-intensive jobs where workers can utilize ICTs and still use their creativity and analytical capabilities has not grown sufficiently to match the number of highly educated workers (Autor, 2015a; Autor, 2015b). Whether widespread adoption of ICTs has resulted in a job shortage or if there is an over-supply of educated workers, or both, is not clear, but workers

[1] A recent study, however, finds that the rollout of broadband infrastructure in Norway improved job market matching, making it easier for firms to fill vacancies and for job seekers to find employment (Bhuller, Kostol, & Vigtel, 2020).

nevertheless face different employment and financial prospects depending on their skills, education credentials, and age.

So far, I have discussed studies on the economic effects of ICTs, which typically consider investments in information technology systems, the use of the internet at work, and the importance of technological skills for worker outcomes. Emerging ICTs, e.g. advanced software, robots and artificial intelligence, have received recent attention in the literature as these pervasive technologies arguably threaten the role of human workers to a greater extent than the introduction of computers and internet-services at workplaces. Theoretical work suggests that automation by machines or artificial intelligence does not necessarily displace workers and can even raise demand if technology reduces the cost of production using labor (Acemoglu & Restrepo, 2018c). In their task-based framework, Acemoglu and Restrepo (2018b) argue that pervasive automation will have an overall negative effect on labor if it fails to raise productivity sufficiently to offset this displacement or if the creation of new labor-intensive tasks stalls. The consequences of automation for workers will thus be determined by the tasks that can be performed by smart machines and the cost of technology in production (Zeira, 1998; Aghion, Jones, & Jones, 2017). In contrast to the adoption of the internet in workplaces, automation from robots and AI negatively affects employment for workers with both low *and* high education, although negative wage effects concentrate in the lower part of the wage distribution (Acemoglu & Restrepo, 2020).

What happens to workers at firms investing in robots? Koch et al. (2019) use data on Spanish manufacturing firms between 1990-2016 to analyze firm-level robot adoption. They find that larger and more productive firms are more likely to adopt robots than skill-intensive firms. Following adopting and non-adopting firms over time revealed significant job creation, output gains and labor cost reductions for adopters, while non-adopters experienced substantial job losses. Displaced workers re-allocated from non-adopters toward adopters. As noted above, workers face different job and income prospects depending on their education. Recent studies also show an age-effect. Studying Dutch firms over the period 2000-2016, Bessen et al. (2019) analyze the effect of automation for incumbent workers and recent hires. For incumbents, younger workers are more likely to lose their jobs than older workers and with negative wage effects. Older workers are less likely to lose their jobs but remain unemployed longer in the event that that happens. For recent hires, young workers are less likely to lose their jobs and earn higher wages than older workers. This pattern suggests that younger workers are relatively more competitive for vacant jobs than older workers, perhaps because automation has created new tasks that better fit their skillset, e.g. their social skills (Deming & Kahn, 2018). Age-effects are also visible in aggregate measures. Firms in economies with aging workforces are more likely to invest in automation that performs tasks typically carried out by middle-aged workers (Acemoglu & Restrepo, 2018a).

Emerging ICTs impact the productivity, employment opportunities and income of workers with different skills unequally and may transfer to different well-being trajectories as well. Sachs and Kotlikoff (2012) argue that smarter technologies will raise the productivity of machines and high-skilled workers with potentially damaging consequences for the future prospects of young and low-skilled workers. Technological advances can result in these exposed groups contending with fewer employment opportunities, weaker financial prospects, and the inability to capitalize on productivity improvements. It is therefore important to consider what innovation policy initiatives such as the DAE actually lead to. Focusing on the way innovation transforms economic activity is important, but it can neglect the study of the consequences that this transformation has on individual welfare and well-being (Binder, 2013; Engelbrecht, 2015; Martin, 2016).

4. LITERATURE II: SUBJECTIVE WELL-BEING AND EXPECTATIONS

A notable feature of the literature summarized in section 3 is that it has until now mostly focused on the important economic effects of ICTs, such as growth and employment. However, emerging ICT technologies like the internet, robots and automation may have both economic and non-economic effects, since they may affect wealth and welfare in a variety of direct and indirect ways. For instance, having access to information about societal developments through the internet may cause people to reflect differently to their own achievements. It is natural to think that emerging ICTs thus influence individual users' future expectations concerning job and financial prospects, but also their evaluations of how life outcomes compare against these expectations, or the outcomes of others. In other words, ICTs may have important effects on individuals' *subjective well-being*. What is subjective well-being (SWB), and what are its main determinants? Shifting the focus to the main variable of interest in this PhD thesis, the present section will briefly review some of the relevant literature on subjective well-being and its causes.

Human welfare is typically associated with income because higher income presumably means more freedom for individuals to pursue their desires and satisfy their preferences. Economists have traditionally postulated that people allocate their income and time in ways that maximizes their expected satisfaction, and from this inferred welfare effects from individual choices. This view has been increasing challenged by psychologists and a branch of economists who argue that preferences are not the only, or even the best, measure for understanding the relationship between human behavior and satisfaction (Dolan, Peasgood, & White, 2006). As measures of well-being have been collected over time and across countries, the subjective well-being of individuals has received increased attention from economists. Although the study of the subjective was for some time practically absent from economics, supplanted by the objective and observable, it has since returned in popularity, and is often referred to as *happiness economics* (MacKerron, 2012).

Economists and psychologists interpret subjective well-being differently. Psychologists typically rely on survey data to assess people's thoughts and desires (Angner, 2009). Economists questioned the reliability of subjective data that cannot be vetted or fully understood. Instead they directed their efforts at studying behavior, deducing from observable choices that people act to fulfill their wants, known as *preference satisfaction* (Clark, Frijters, et al., 2008). From a developmental perspective, it is thus important to identify basic needs, e.g. having access to institutional and societal services that enable people to make choices that improve their capability to function and thus contribute to their well-being (Sen, 1999; Nussbaum, 2001). Early economists such as Jevons, Bentham and Edgeworth used psychological concepts, e.g. sensation and pleasure, in utility theory before these were replaced by assumptions of rational choice in the mid-20th century, a shift referred to as the "Paretian turn" after the influence of Pareto (Bruni & Sugden, 2007).

The understanding of subjective well-being differs between and within fields, and we can distinguish three related notions: 'evaluative', 'hedonic', and 'eudemonic' well-being. Evaluative well-being considers individuals' cognitive evaluation of their lot and is measured by asking people about their own assessment of their life or job satisfaction (Deaton, 2008). Although much of the SWB literature uses happiness and life satisfaction interchangeably, these are distinct concepts. Asking people about their life or job satisfaction provokes a subjective assessment of those outcomes in comparison to their expectations, and is an appropriate tool for life cycle analyses (Deaton, 2018). On the other hand, happiness considers affective states, or pleasure and pain, and derives from a hedonic understanding of human experiences (Deaton, 2008). In short, happiness refers to the experienced utility of individuals (Kahneman, Wakker, & Sarin, 1997), and it is typically measured by asking people to indicate how happy they are with their lives on a given scale. Finally, eudemonic well-being refers to the extent to which people flourish and realize their potential (Ryff, 1989; Ryan & Deci, 2001). Specifically, according to this notion, individual autonomy and doing meaningful things are important for people's psychological well-being. While the evaluative and hedonic strands arguably treat well-being as an outcome, the eudemonic strand has a procedural interpretation in that humans live fulfilling lives when they are allowed to develop and express their true nature (Deci & Ryan, 2008).

Critics of SWB point to its methodological and epistemological challenges and question whether it is measurable and comparable between individuals. SWB advocates argue that it is complementary to revealed preferences and even a proxy measure of utility that offers valuable insights into the way people make sense of their surroundings and reflect on their choices (Clark, Frijters, et al., 2008). [2]

4.1. Determinants of SWB

Existing surveys of the happiness economics literature provide comprehensive overviews of the most important factors that are associated with life and job satisfaction. These include both personal characteristics and mental processes. *Personal characteristics* refer to a person's income, health, employment, age, education, marriage, family formation, trust, religious beliefs, social involvement, and ability to self-realize (Wilson & Oswald, 2005; Clark, Frijters, et al., 2008; Dolan, Peasgood, & White, 2008; MacKerron, 2012). [3] *Mental processes* describe the way people react to, and make sense of, their outcomes and achievements relative to some positive criteria, such as adaptation, social comparison, and rising aspirations (Clark, Frijters, et al., 2008).

Adaptation means that people get accustomed to levels of stimuli and react primarily to changes before these stabilize over time. The tendency to become less affected by circumstances over time is widely documented in psychology and economics and referred to as the "hedonic treadmill" (Frederick & Loewenstein, 1999; Clark, Frijters, et al., 2008). Social comparison is the tendency for people to compare their outcomes to those achieved by their peers, or to some reference point formed by their aspirations. Aspirations are, in turn, also subject to adaptation, meaning that they are updated in response to people's own past achievements or developments in their environments (Gilboa & Schmeidler, 2001). SWB can therefore be understood as a triple-counting of experiences, meaning that people derive utility from their expectations of an experience, the actual experience, and the memory

[2] One similarity between objective and evaluative subjective well-being is that both approaches share the common premise of rejecting external criteria, leaving it to the individual to decide for her- or himself about their degree of well-being (MacKerron, 2012). Section 7.1 discusses further the validity of SWB.

[3] Recent studies argue that factors that are intuitively positive to SWB such as marriage and having children are subject to adaptation and regress back to an individual's baseline disposition with time (Clark, Diener, Georgellis, & Lucas, 2008; Clark & Georgellis, 2013). Of course, it might also be the case that it is not actual SWB that adapts to events such as marriage and having children but rather that measured SWB fails to capture how these events change the idiosyncratic definitions of what is a satisfactory life.

of that experience (Elster & Loewenstein, 1992). To illustrate these distinct determinants, I discuss findings related to income, unemployment, education, and age as these are particularly relevant for the topic of this thesis.

4.1.1. Income

Perhaps the most well-known contribution of SWB in economics concerns the relationship between income and SWB documented in the seminal work by Easterlin (1974). The finding that satisfaction seems not to improve continuously with income was dubbed the "Easterlin paradox". Easterlin (2001) suggested that adaptation and social comparison, both mechanisms that affect satisfaction by influencing expectations, could explain this finding. The Easterlin paradox brought subjective well-being back into the economics discourse, and has since been a debated topic that remains unresolved (Deaton, 2008; Stevenson & Wolfers, 2008). Importantly, it provoked a discussion about whether welfare should primarily be understood in monetary terms and raised awareness of relative income effects (Clark, Frijters, et al., 2008).

4.1.2.Employment and job satisfaction

Having a job is important for people to live satisfying lives. Economists have long considered work as a trade-off with leisure for income. However, employment does not only provide income, it also involves social interactions, stress and conflict that affect life satisfaction (Erdogan, Bauer, Truxillo, & Mansfield, 2012). There has been a growing interest in the non-pecuniary dimensions of work (Nikolova & Cnossen, 2020). People derive utility directly from their work, which makes job satisfaction an important dimension in labor market studies (Freeman, 1978). Kaplan and Schulhofer-Wohl (2018) use data from the American Time Use Survey to discuss how changes in the occupational structure in the US economy since 1950 have affected the SWB of workers. In their analysis, the authors focus on different aspects of job satisfaction such as reported happiness, stress, and meaning at work. Their work indicates that the information economy has significantly changed how workers feel about their job and tasks in general, a shift most keenly felt in terms of the level of education employees have. The polarization in employment and wages for workers with low and high education discussed in section 3.3 is relevant for feelings at work as well. In a discussion of the relative importance of pecuniary and non-pecuniary dimensions of work, Cassar and Meier (2018) highlight how the modern labor market is adjusting to workers' desire to do meaningful work. Extrinsic and intrinsic motivations have implications for job design because employers are hiring people who appreciate (and perhaps expect) mission-oriented, autonomous, social, and meaningful work. Workers who are happy and have meaningful jobs are more productive and less likely to quit (Green, 2010; Chandler & Kapelner, 2013; Oswald, Proto, & Sgroi, 2015). When people are rewarded with both income and meaning, a job becomes part of their identity (Akerlof & Kranton, 2005). If work goes from being a means to an end to an end in itself, it is perhaps not surprising that becoming unemployed is a situation that people do not adapt to or fully recover from (Clark, Diener, et al., 2008; Clark & Georgellis, 2013). Unemployment is something that people have difficulty foreseeing but which changes their outlook on life afterwards (Odermatt & Stutzer, 2018). However, the effect of unemployment on SWB depends on whether people believe it will be long-term because economies with higher turnover and more innovation activities make people optimistic about their prospects (Aghion, Akcigit, Deaton, & Roulet, 2016).[4]

4.1.3. Education

Being highly educated is associated with better individual outcomes, such as family formation, employment prospects, income, and health (Acemoglu & Autor, 2011; Autor, 2015a; Case & Deaton, 2017; Binder & Bound, 2019). Empirical studies however find an ambiguous relationship between education and SWB, with both positive and negative correlations reported (Clark, Oswald, & Warr, 1996; Di Tella, MacCulloch, & Oswald, 2001). Recent work elaborates on this inconsistency by showing that education and life satisfaction are positively correlated at the lower end and negatively correlated at the upper end of the well-being distribution (Binder & Coad, 2011). This pattern is attributed to the possibility that education raises aspirations for what are satisfactory outcomes in life and that this is detrimental to life satisfaction (Foster & Frijters, 2014; Clark, Kamesaka, & Tamura, 2015; Kristoffersen, 2018). Education thus makes available a richer set of opportunities, but it also raises expectations about what those opportunities should be and their expected utility (Kahneman et al., 1997). People form expectations about what outcomes are achievable and expend effort onto reaching these, but their assessments may not be precise; highly educated people who end up with jobs for which they are overqualified report lower life and job satisfaction (Green & Zhu, 2010; Cappelli, 2015).

[4] Concerns about selection effects have been raised in response to analyses on unemployment and SWB in that unhappy people are less productive and less healthy, but these effects are likely to be small (Dolan et al., 2008).

4.1.4. Age

Extant literature has documented an empirical regularity showing a U-shaped relationship between life satisfaction and age (Blanchflower & Oswald, 2008; Frijters & Beatton, 2012; Steptoe, Deaton, & Stone, 2015; Cheng, Powdthavee, & Oswald, 2017). U-shaped patterns have been shown also for job satisfaction (Clark et al., 1996). Life cycle analyses study the development of expected and lived experiences throughout life by looking at SWB patterns over age. Age encapsulates the influences of adaptation and expectation for SWB from a temporal perspective. Using longitudinal data from the German Socioeconomic Panel (GSOEP), Schwandt (2016) shows a persistent discrepancy between expected and experienced SWB over the life cycle. While expected SWB follows a downward trajectory with age, experienced SWB reportedly forms a U-shape that turns around mid-life. Schwandt (2016) explains this pattern in terms of unmet aspirations theory: people form high expectations in early life that become detrimental to well-being if left unrealized by causing feelings of regret, which are felt most strongly in mid-life. Pessimistic expectations may not materialize in late adulthood, so that SWB improves again as people get older.

Expectations are not always excessive and can also be set too low. Bertoni and Corazzini (2018) explore the psychological effect of experiencing positive and negative mismatches against expectations, using GSOEP panel data. They find that positive affective forecasting errors, where outcomes exceed expectations are unassociated with SWB, and negative forecasting errors, where outcomes fail to meet expectations, are negatively correlated with subsequent SWB. They also show that expectations adjust to past errors in the sense that negative forecast errors lower future expectations and vice-versa. A comparison of the influences of thwarted versus unmet past expectations on life satisfaction and future expectations suggests that unmet aspirations are felt more strongly, and that people carry with them the displeasure of past letdowns. Consistent with unmet aspirations theory (Frey & Stutzer, 2010; Schwandt, 2016), Bertoni and Corazzini (2018) show that unmet expectations are more frequent in younger individuals and thwarted expectations are reported more often for older individuals.

4.2. Expectations

This literature then suggests that there is some truth to the old adage that happiness depends on the difference between expectation and realization. Expectations are subjectively held beliefs about an uncertain future (Pesaran & Weale, 2006). People form expectations based on available information that affects SWB by adaptation, social comparison, or reasoning (Gilboa & Schmeidler, 2001). Most empirical studies on expectation formation analyze subjective probabilities from survey data asking respondents to estimate the likelihood of some future event (Attanasio, 2009). Categorical questions are less popular because they are considered difficult to compare between people and are too coarse to be informative (Manski, 2004). The aversion to including subjective expectations in welfare analyses has limited the understanding of social interactions where people's choices affect the constraints, expectations, and preferences of others (Manski, 2000). In the SWB literature, however, there is less resistance to categorical questions as most studies are interested in ordinal relationships. Some argue that categorical questions are more representative of how most people consider the future through general assessments rather than assigning specific probabilities (Foster & Frijters, 2014). Modeling expectations, rather than taking them as exogenous, improves the descriptive accuracy of economic models because it compares the relative importance of different factors (Gilboa, Postlewaite, & Schmeidler, 2008). Analyses of expectation formation have revealed important relationships—for example that failing to meet expectations about future outcomes depresses SWB (Schwandt, 2016), and that people are capable of updating their beliefs by assessing existing information differently rather than by acquiring new information (Gilboa et al., 2008).

Expectations have a fundamental place in economic theory because they are considered to guide choice behavior. Neoclassical welfare economics interprets choice behavior as people trying to maximize their utility under the constraints they operate within (Von Neumann & Morgenstern, 1947). This intuition relies on the assumption of rational choice, where people are capable of assessing potential outcomes and their relative attractiveness under conditions of uncertainty, and act under the guidance of this assessment (Muth, 1961). Recent studies using SWB data challenge this interpretation. Benjamin et al. (2012, 2014) find that people do not always choose what they believe will make them more satisfied. Moreover, people are systematically unable to predict their satisfaction with future outcomes (Schwandt, 2016; Bertoni & Corazzini, 2018; Odermatt & Stutzer, 2018). The mismatch between expectations and experiences has theoretical foundations in regret theory, disappointment theory, and prospect theory, postulating that people consider the consequences of their actions relative to the alternatives and gain (or lose) utility if their choice turns out (un)favorably (Kahneman & Tversky, 1979; Loomes & Sugden, 1982, 1986).[5]

[5] So far, I have discussed evidence where expectations enter individual utility indirectly through choices, and directly by retrospection, e.g. from regret or disappointment. But expectations can also affect utility directly, through savoring or fear (Elster & Loewenstein, 1992).

5. EMERGING ICTS AND SWB

After having defined SWB and briefly discussed some of its main determinants according to extant research, it is now time to go back to the core questions and topic of this dissertation. The main idea that motivates this PhD thesis is that emerging ICTs, such as the internet, robotics and automation, do not only have important economic effects, but also have major impacts on individuals' SWB. When I began this doctoral research, this idea was rather new, and there was only a very limited number of studies investigating a similar topic.

Dolan and Metcalfe (2012) connect recent innovation policy initiatives with well-being and argue that workers in innovative jobs report greater job satisfaction and feel more imaginative and creative. This finding is important knowing how reliant economic growth is on the creation of new ideas (Aghion et al., 2017; Akcigit, 2017), and because creativity and autonomy affect employees' work-life balance and productivity (Erdogan et al., 2012; Oswald et al., 2015). A few other recent studies have found that internet use is positively associated with well-being, and more so for technologically affluent users (Kavetsos & Koutroumpis, 2011; Graham & Nikolova, 2013; Pénard, Poussing, & Suire, 2013; Ganju, Pavlou, & Banker, 2016). Workers who actively use ICTs in their job are also more productive and satisfied with their job (Martin & Omrani, 2015; Castellacci & Viñas-Bardolet, 2019).

In a survey of this literature and other related strands of research, Castellacci and Tveito (2018) argue that ICTs affect SWB by creating new activities that change the way people choose to spend their time, providing users with information, and changing the way people communicate. ICTs thus allow individuals to allocate their time in ways that improve their productivity and also save time by replacing tedious activities. On the other hand, there is also the possible downside that ICTs affect people differently depending on their experiences, abilities, and age. As ICTs continue to influence the way people work, socialize, and thrive there are possible direct and indirect effects on individual welfare that require careful consideration (Castellacci & Tveito, 2018). In the following, I will discuss possible ways that emerging ICTs, i.e. the internet and robots and AI, can influence SWB, focusing on the main factors noted in the previous section: income, employment, education, age and expectations. Some of the mechanisms noted below are later developed further in the four articles of this thesis (which will be summarized in the next section).

5.1.1. Income

The internet and online services, such as social networks, increase individual users' possibility to make social comparisons. Internet use has been found to raise material aspirations with detrimental effects on life satisfaction (Lohmann, 2015). For instance, workers who find information online that their salary is lower than their peers become less satisfied with their job and more open to changing jobs (Card et al., 2012). It is thus possible that emerging ICTs not only foster social comparisons but also reduce job satisfaction. Moreover, employment and income consequences of skill-biased technological change suggest that ICTs are disrupting the labor market leading to significant skill differentials and contrasting economic outcomes (Akerman et al., 2015; Falck, Heimisch, & Wiederhold, 2016; Falk & Biagi, 2017). The internet and emerging technologies can thus influence individual utility by affecting absolute and relative outcomes with consequences for life and job satisfaction.

5.1.2. Employment and job satisfaction

The internet, ICT investments, and computerization have changed tasks, jobs, and occupations across many sectors of the economy. The pervasiveness of emerging ICTs has spurred a debate about whether smarter machines and sophisticated technological tools will complement workers and improve the human lot (Brynjolfsson & McAfee, 2014), or whether they will make humans increasingly replaceable until the majority of the workforce is superfluous (Ford, 2015). From the literature reviewed in section 3, it is clear that the consequences of ongoing technological change have mostly been studied from the supply-side, e.g. skill and age differentials in employment and wages and changing task composition in jobs. The influence of these changes for workers' SWB and subjective expectations of future prospects has received limited attention and is not, as yet, well understood. It is however clear that the structural change in occupations since 1950 has had significant impacts on the way workers feel at work (Kaplan & Schulhofer-Wohl, 2018). People also think differently about work and prefer having a meaningful job where they can use their skills with autonomy in the service of a greater good together with other coworkers (Cassar & Meier, 2018). Technology can improve SWB by eliminating repetitive work, increasing social connectivity, offering flexible solutions, and giving people the opportunity to develop their skills. It is clear that as jobs and tasks develop with technological change, workers not only face different monetary situations but also unequal chances of finding meaningful work (Cassar & Meier, 2018). Moreover, meaningful work is also associated with the likelihood of participating in skills training (Nikolova & Cnossen, 2020). If new work requires skills unattainable to many, then technological change may deprive people of the opportunity of making a contribution, thus damaging their self-worth (Mokyr et al., 2015).

5.1.3. Education

A typical response to technological change is to invest in people's skills either by retraining displaced workers or by incentivizing and improving formal education (Autor, 2015b). Education is believed to be perhaps the most decisive factor in growing wage inequality (Autor, 2014). Another possibility is that technological complexity and a more globalized world have created significant network effects that separate a small set of workers from the rest—the superstars. Individuals with technologically inimitable skills may be sufficiently attractive to exploit bottlenecks in the market (Benzell & Brynjolfsson, 2019). Firms offering a combination of products or services with great scaling potential and that require less labor will outcompete competitors and increase market concentration (Autor, Dorn, Katz, Patterson, & Van Reenen, 2020). In combination, the two forces create an environment where highly skilled individuals can thrive in large firms operating in scalable industries, achieving income mobility (Kaplan & Rauh, 2013). Skill-biased technological change predicts that technology will reward skills by either making skilled workers more productive or capable of producing superior goods, or by generating scalable markets. A consequence of a polarizing labor market between workers with low and high education may be that more people enter higher education who may not have the ability to thrive there or are not suitable for other reasons. It can also raise the aspirations of more people who then require better outcomes to feel satisfied. If there are not enough—sufficiently challenging—jobs available to these individuals, then their SWB might suffer from disappointment or regret.

5.1.4. Age

ICTs provide a variety of new digital services that are likely to influence individuals' SWB differently depending on their age (Castellacci & Tveito, 2018). Exposed groups such as the young and the elderly may have substantially different experiences. According to recent research, for instance, the internet can make younger people less satisfied with their lives while for older people it reduces feelings of isolation and enhances well-being (Lelkes, 2013; Best, Manktelow, & Taylor, 2014; McDool, Powell, Roberts, & Taylor, 2016). ICTs increase autonomy and flexibility for working age individuals who are employed but they also trigger social comparison (Card et al., 2012). Automation has replaced many straining and repetitive tasks but also made workers feel more stressed in the jobs that have emerged from technological change (Kaplan & Schulhofer-Wohl, 2018). Some have argued that young workers, especially those less skilled, stand to lose from advanced ICTs and R&D activities that complements older skilled workers (Chiacchio, Petropoulos, & Pichler, 2018; Ciarli, Marzucchi, Salgado, & Savona, 2018). Technology diminishes their opportunities to climb the social ladder through life resulting in permanent damage to their well-being (Sachs & Kotlikoff, 2012). Whether ICTs are considered a social communication tool, a work productivity enhancing tool, or a hostile competition for human labor, it is clear that workers and individuals may face different prospects depending on their age and skills.

5.1.5. Expectations

Extant literature has studied how ICTs have affected economic outcomes, neglecting so far the study of possible impacts on individuals' *expectations*. The internet presumably influences expectations in at least two ways. First, it allows users to consume information about the lives of others or societal developments that may influence the criteria for what is deemed a successful life. Internet use has been shown to encourage social comparisons that raise aspirations about what are desirable outcomes, thus making people less satisfied with their own outcomes (Card et al., 2012; Lohmann, 2015). Second, internet use represents a skill component that is increasingly sought after by employers. Skill-biased and routine-biased technological change has substantial effects on the employment and wage prospects of people and one determined by the skills of the individuals (Autor et al., 2003; Autor & Dorn, 2013; Goos et al., 2014; Michaels, Natraj, & Van Reenen, 2014; Autor, 2015b). It is thus important to understand whether individual expectations are directly affected by ICTs, e.g. high-speed internet and automation. In an original study of the psychological effects of innovation-driven economic growth, Aghion et al. (2016) find evidence that creative destruction improves SWB and future optimism about how life will turn out, especially for workers with higher education. Whether a person's expectations absorb and adjust to the consequences of pervasive ICTs for economic, financial, and overall life prospects remains an open question however. ICTs may affect expectations negatively if they trigger social comparisons or make workers fear for their jobs and prospects, or positively if people believe that economic activity creates achievable opportunities or innovative and stimulating work. The direction—negative or positive—of this effect likely depends on the age and skills of individuals, as exposed groups such as low-skilled young workers have to project the probable consequences farther into the future.

5.1.6. Objectives and research questions

The main objective of this thesis is *to investigate the relationship between ICTs and SWB*. In particular the thesis studies show how internet use and automation affect SWB by shaping individuals' expectations about the future. Whereas extant literature has focused on the economic effects of ICTs, I argue that the understanding of how these trends affect subjective welfare is still rather limited and warrants further study.

This motivation is based on the patterns and literature discussed in the previous three sections. Emerging ICTs continue to cement their position in economic activity and the daily lives of individuals. This will continue for the foreseeable future as massive investments by firms and governments are directed toward innovation and digitalization under the DAE program. A rich literature exists on the economic effects of ICTs for the productivity, employment and wages of workers. There has so far been less research directed at understanding the subjective welfare effects of emerging ICTs. The way people utilize ICTs at work and in private life arguably affects their expectations about the future, and thereby their own feelings of life and job satisfaction. This thesis is thus situated at the intersection between the economics of innovation and happiness economics. Further, as noted in previous sections, there appear to be differences in the use and effects of ICTs on individuals' well-being depending on their age and skills. Such heterogeneity has not been documented and explained so far in extant research, and this thesis will shed new light on these patterns.

In short, the RQs investigated throughout this doctoral thesis can be summarized as follows:

- RQ 1: How do recent ICT developments affect individuals' expectations and SWB?
- RQ 1.1: Do these effects differ for individuals of different ages and skill levels?

6. SUMMARY AND OVERVIEW OF ARTICLES

The thesis is composed of four articles. Before discussing in further depth how each article addresses the research questions noted above, I provide a summary overview—in table 2 below—of the four articles.

Table 2: Overview of articles

	Article 1: Internet Use and the U-Shaped Relationship Between Age and Well-Being	**Article 2: Internet use and Expectation Formation over the Life Cycle**	**Article 3: Automation, Fear of Replacement, and the Subjective Well-Being of Workers**	**Article 4: Automation, workers' skills and job satisfaction**
Article status	PLOS ONE: https://doi.org/10.1371/journal.pone.0233099	Working paper	Working paper	PLOS ONE, revised and resubmitted
Main topic	The effects of internet use on SWB	The effects of internet use on expectation formation	The effects of robots and automation on SWB	The effects of robots and automation on job satisfaction
Main sub-topic	Age heterogeneity	Age heterogeneity	Age heterogeneity	Skill heterogeneity
Data sources	Eurobarometer; Eurostat	Eurobarometer; Eurostat	Eurobarometer; IFR; Eurostat; European Working Conditions Survey	YS Employment Outlook Survey; IFR; Eurostat; Statistics Norway; NAV; Nkom
Dependent variable	SWB (Life satisfaction)	Expectations for life in general, job and financial situation	SWB (Life satisfaction)	SWB (Job satisfaction)
Main explanatory variable	Internet use intensity	Internet use intensity	Anticipated job replacement due to robot/AI	Anticipated task replacement due to automation
Instrumental variable	National/regional broadband infrastructure	National/regional broadband infrastructure	Long-term structural change in regional robot exposure	Long-term structural change in region-sector robot exposure
Empirical method	2-stage instrumental variable estimations	2-stage instrumental variable estimations	2-stage instrumental variable estimations	2-stage instrumental variable estimations
Time period	2010-2016	2010-2016	2014; 2017	2016-2019
Country sample	28 European nations	33 European nations	10 European nations	Norway
Observations	Approx. 150,000 individuals	Approx. 140,000 individuals	Approx. 8,000 workers	Approx. 10,000 workers

6.1. Article 1: Internet Use and the U-Shaped Relationship Between Age and Well-Being

Objective: A few recent studies have found a positive relationship between internet use and well-being (Kavetsos & Koutroumpis, 2011; Graham & Nikolova, 2013; Pénard et al., 2013). Less however is known about the factors and mechanisms that can explain this relationship, and whether this varies between different age groups. It is reasonable to think that the intensity and type of internet use varies for individuals of different ages. The main objective of this article is thus to investigate the effects of internet use on SWB over the life cycle.

Main idea: Empirical studies show that SWB is U-shaped with age (Blanchflower & Oswald, 2008; Cheng et al., 2017). Unmet aspirations theory proposes that this U-shape pattern occurs because people systematically err when they form aspirations about future life satisfaction, and that this mis-prediction tends to be overly optimistic at young age and overly pessimistic when people get older (Schwandt, 2016). Based on findings that internet use raises aspirations (Lohmann, 2015), this article incorporates internet use into the unmet aspirations conceptual framework, and postulates that internet use makes the U-shape steeper, i.e. exacerbating its effects through unmet aspirations for younger and older individuals.

Results: We empirically test this proposition using individual data on life satisfaction and internet use from the Eurobarometer surveys between years 2010 to 2016 and identify the causal effects of internet use on well-being for different age groups by exploiting exogenous variation in broadband internet take-up across European countries and regions. The analysis finds that the effect of internet use on SWB varies significantly with age. More intensive use of the internet predicts a steeper U-shape with an earlier turning point for active users than for those who use it less or not at all. Using country-level indicators of expectations about life satisfaction and job situation, we show that these empirical results are in line with the predictions of unmet aspirations theory.

Relevance for thesis: This paper links directly to both research questions by studying the effect of internet use on SWB over age, and by developing a theoretical framework that links internet use, aspiration formation and SWB.

6.2. Article 2: Internet use and Expectation Formation over the Life Cycle

Objective: Article 2 sets out to extend article 1 by investigating the relationship between internet use and the formation of expectations, focusing on individuals' expectations about life satisfaction as a whole, and about their job and financial expectations. The article also extends the scope of the first paper by studying how the relationship between internet use and expectation formation varies for individuals of different ages.

Main idea: There has been a growing interest in how expected well-being develops over the life cycle (Schwandt, 2016; Bertoni & Corazzini, 2018; Deaton, 2018). Less is known though about how people form job and financial expectations at different ages and how internet use affects this relationship. As previously noted, the internet provides at least two channels that can influence expectations. First, it allows people to find information about peers that influences their aspirations (Card et al., 2012). Second, ICTs have transformed the labor market in ways that reward technological skills with very different employment and wage prospects for people of low and high skills (Autor et al., 2003; Michaels et al., 2014; Akerman et al., 2015). I thus hypothesize that internet use raises expectations because it makes available aspirational information and because ICT skills are associated with better labor market prospects.

Results: I analyze the relationship between internet use and expectations empirically in a two-stage instrumental variable setup. As in article 1, I rely on the Eurobarometer surveys between years 2010 to 2016 to collect individual data on expectations and internet use and identify the causal effects of internet use on expectations for different age groups by exploiting exogenous variation in broadband internet take-up across European countries and regions. I find that internet use intensity raises expectations for life in general and for job and financial prospects, except for older adults. In light of the recent literature on skill-biased technological change, I scrutinize this effect by including measures of creative destruction to assess the psychological implications of innovation-led growth. In robustness tests, internet use remains positive and significant when including job creation and destruction as separate forces, and when I use total job turnover as an indicator of overall changing job prospects.

Relevance for thesis: Article 2 makes a twofold contribution to the questions investigated in this thesis. First, it expands on the findings of article 1 by showing that internet use affects expectation formation directly. Second, it bridges literatures on expectation formation, economics of innovation, and skill-biased technological change. Active internet users remain optimistic in the face of job turnover, which seems plausible considering how emerging ICTs have benefitted skilled workers. This raises concern that exposed groups—such as young people with unsophisticated ICT skills—might expect worse job and financial outcomes and become passive bystanders unable to keep pace with technological developments.

6.3. Article 3: Automation, Fear of Replacement, and the Subjective Well-Being of Workers

Objective: Despite the fact that much effort has been dedicated toward understanding the economic effects of automation, the implications for workers' well-being have so far been neglected. Article 3 addresses this gap by investigating whether and to what extent workers anticipate job exposure to automation, and if anticipated job replacement affects their life satisfaction.

Main idea: As noted in previous sections, there are two broad views on how future technology may impact on human labor. Workers' lifetime utility may suffer if robot and AI technologies become too pervasive and indicative of a society with more unemployment, less human interaction, and financial uncertainty. Alternatively, these technologies may improve workers' productivity in ways that bring about promising economic and occupational results in the future that may foster welfare. Automation can thus affect future well-being both positively and negatively, and this paper sets out to test empirically which of these possible effects is more prominent. The fact that workers have competed with robots for an extended period of time in the recent past allows me to develop a theoretical framework where anticipated job replacement depends on learning from past experience.

Results: I analyze the effect of anticipated job exposure from robots and AI on life satisfaction using two years of Eurobarometer survey data for a sample of countries that represent about 85 percent of the European robot market. I exploit the fact automation has grown over a long period and use data on industrial robots from the International Federation of Robotics (IFR) to introduce exogenous variation in the learning that workers in different European regions have been exposed to. I find that anticipated job displacement by smart machines is negative for well-being overall. However, the results indicate that there are substantial age discrepancies—young (old) workers derive negative (positive) utility from anticipated job replacement due to automation. The disutility of young workers is explained by the fact that they will have to compete with robots and the effects of automation over a longer time horizon during their working life, and it is therefore mainly driven by fear of unemployment and deteriorating financial prospects in the future.

Relevance for thesis: This article explicitly links the SWB dimension with the recent growing literature on the economic consequences of automation. It engages with theoretical and empirical studies showing that automation may affect the welfare of workers differently depending on their age, and that economies' age composition is an incentive to invest in robot technology (Sachs & Kotlikoff, 2012; Acemoglu & Restrepo, 2017, 2018a). Importantly, it contributes to the understanding of how workers anticipate the (discounted) utility of a future work scenario where smart machines threaten their jobs and the uncertainty that this entails.

6.4. Article 4: Automation, workers' skills and job satisfaction

Objective: The literature on automation and employment shows that high- and low-skilled workers are exposed differently to the effects of the introduction of industrial robots. This article sets out to investigate whether automation affects workers' job satisfaction, and the extent to which this relationship differs depending on workers' skill levels.

Main idea: The introduction of industrial robots and data analytics in production activities has led to the automation of many tasks that were previously carried out by humans. This development has urged some to argue that workers are primarily competing for tasks, rather than jobs, and that low- and high-skilled workers are unequally exposed. An original, and not yet used, source of information is represented by survey data on workers' own assessment of having smart technology replace their tasks. It is relevant to investigate how this assessment affects current job satisfaction considering the importance of work for well-being. To study the relationship between automation and job satisfaction, I first consider if the diffusion of industrial robots in local labor markets affects workers' expectations about having to compete with smart machines in the future for their jobs. Then, I investigate whether this fear of replacement negatively affects workers' current subjective well-being, distinguishing between workers with low and high education levels.

Results: This idea is investigated empirically by making use of a two-stage econometric model, in which fear of replacement and job satisfaction are the dependent variables of the first and the second stage, respectively. We use microdata from the Working Life Barometer for the period 2016-2019 surveying several thousand Norwegian workers, combined with information on the stock of industrial robots in Norway from the IFR dataset that allows us to exploit variation in the pace of introduction of industrial robots across regions and industries over time. The results indicate that automation has induced fear of replacement by smart machines in employed workers, and that this effect is stronger for low-skilled workers. Moreover, our findings show this fear is detrimental to workers' current job satisfaction, and more so for low-skilled workers.

Relevance for thesis: This paper studies the impact of automation on workers' job satisfaction, and it is thus positioned at the intersection of research on job satisfaction, innovation studies and labor economics (employment effects of automation). Although both consider the effects of automation on well-being, article 4 extends article 3 by shifting the focus to job satisfaction (rather than life satisfaction as a whole), and by investigating how the relationship between automation and job satisfaction differs depending on workers' skills and education level. It is important to understand the impacts of automation on workers' job satisfaction and expectations because these factors are important to people's overall subjective well-being in view of the amount of time that individuals spend at work.

7. DATA AND METHODS: A DISCUSSION

This section will present an overview and discussion of the data and methods used in the empirical analyses of the four articles included in the dissertation First, I will introduce the datasets and core variables used in the analyses, and some related issues that are important to be aware of when using these data and indicators. Second, I will present and discuss the main methodological strategy used in the econometric analyses, pointing out briefly its main advantages and possible drawbacks.

7.1. Data sources and indicators

To investigate how recent ICT developments affect SWB and expectations, I rely on survey data from the Eurobarometer and the YS Employment Outlook Survey. Table 3 presents the central variables in the analyses, indicating their source, the questions, and the various response alternatives in the questionnaires. Eurobarometer data are used in papers 1, 2 and 3 to study the effects of internet use and automation, on, respectively, expectations and life satisfaction. In paper 4, to extend research on the effects of automation and artificial intelligence, I draw on the annual YS Employment Outlook Survey data for Norwegian workers.

Table 3: Overview of data source and core variables

Source	Period	Question	Answer
SWB			
Eurobarometer	2010-2016	On the whole, [how satisfied are you] with the life you lead?	Not at all satisfied; not very satisfied; fairly satisfied; very satisfied
YS Employment Outlook Survey	2016-2019	In all how satisfied are you with your job?	Very dissatisfied; pretty dissatisfied; neither satisfied nor dissatisfied; pretty satisfied; very satisfied
Expectations			
Eurobarometer	2010-2016	What are your expectations for the next 12 months, when it comes to your [life, household financial situation, job situation]?	Worse; stay the same; better
Eurobarometer	2014, 2017	Do you think your current job could be done by a robot or artificial intelligence in the future?	Not at all; partially; mostly; entirely
YS Employment Outlook Survey	2016-2019	Do you think some of your current tasks could be done by a machine instead?	No; yes
Internet use			
Eurobarometer	2010-2016	Could you tell me to what extent you use the internet at home, at work, or elsewhere?	No access to this medium; never; less often; two or three times a month; about once a week; two or three times a week; (almost) every day

7.1.1. The Eurobarometer Survey

The Eurobarometer surveys representative samples across European nations multiple times annually, totaling about 25,000 individuals aged 15 years and older per survey. Importantly, it includes a wide range of variables that are relevant for the topic of this thesis, including information on expectations and SWB and emerging ICTs, and it is well suited to investigate the main research question (RQ 1), on how recent ICT developments affect individuals' SWB. The Eurobarometer includes questions about life satisfaction and expectations for life in general, and future job and financial situation. Moreover, it offers a wide range of demographic background variables, including age, education, financial situation, and employment that are commonly used in the SWB literature, and therefore contribute to the identification of the relevant effects (see more on this later in this section). The available data on life satisfaction, expectations, and age also makes it possible to investigate the effect of ICTs on expectations and SWB, and the extent to which these effects vary for individuals of different age groups (RQ 1.1).

The Eurobarometer datasets, though, also have some drawbacks. For instance, they do not provide a direct measure of income, but instead use a proxy categorical variable for household financial situation. Further, information on employment and education does not comply with the International Standard Classification of Occupations (ISCO) or Education (ISCED). Also, the Eurobarometer unfortunately does not have information on NACE Rev. 2 statistical classification of economic activities in the European Union. In spite of these few limitations, the Eurobarometer surveys represent a rich and comprehensive dataset that allows a systematic investigation into the topic of this thesis.

Respondents indicate their life satisfaction on a four-point scale ranging from *not at all satisfied* to *very satisfied*. The life satisfaction question is widely used in applied economics research on subjective well-being (Clark, Frijters, et al., 2008). There is a wide range of measurements in the SWB literature that rely on different scales. Although some rely on data from the Gallup survey and the German Socio-Economic Panel survey that use 10-point scales (Deaton, 2008; Schwandt, 2016), others rely on six-point scales using the American Time Use Survey (Kaplan & Schulhofer-Wohl, 2018) or four-point scales from the Eurobarometer (Stevenson & Wolfers, 2008; Kavetsos & Koutroumpis, 2011).

What makes the Eurobarometer especially well-suited for the objectives of this thesis is that it also includes a topical supplement for some of the survey years that contains information on individual expectations about life domains. As noted above, the use of ICTs does arguably affect SWB through its effects on individuals' expectations, and this is something that the Eurobarometer makes it possible to investigate empirically. I use data between 2010 and 2016 that include information about expectations where respondents indicate whether they believe that their financial situation, job situation, and life in general will become worse, stay the same, or improve in the coming year. The use of categorical subjective expectations has sometimes been criticized in applied economics because of issues with comparability and informativeness (Manski, 2004). However, there has been a recent surge of interest in these measures because they better represent how most people actually consider the future (Foster & Frijters, 2014), and because they offer important qualitative information for understanding societal and economic changes (Gilboa et al., 2008). The effect of internet use on future expectations has, to my knowledge, not been investigated yet in the literature and is the topic of article 2 in this thesis.

Regarding the main explanatory variables employed in the dissertation, internet use intensity is the central explanatory variable used in papers 1 and 2. It is measured on a seven-point scale where individuals state the frequency of their internet use at home, work, or elsewhere. Importantly, the Eurobarometer includes data on a spectrum of users, ranging from those without internet access to those who use it every day. On the other hand, papers 3 and 4 analyze the effects of automation on SWB. Questions about automation appear in surveys in 2012, 2014, and 2017, but only the last two years have information about life satisfaction. A subsample of employed individuals were asked to what extent they believed robots or artificial intelligence would be able to perform their job in the future (with answers ranging from *not at all* to *entirely*). As noted in the literature sections above, existing studies have focused on the employment and income effects of high-speed internet and automation (Autor, 2015b). It is therefore relevant to understand how individuals evaluate and anticipate the personal consequences of these disruptive technologies. The Eurobarometer, by asking this directly to individuals, does therefore provide novel information on workers' expectations related to emerging ICTs. Article 3 studies this topic of the links between SWB and anticipated replacement due to robots and automation. One limiting feature is that the data do not include standardized information on employment. This was an issue for the research for article 3, because it did not allow the matching of workers and robot exposure by industry codes. I therefore had to rely on a more aggregated indicator of robot exposure to introduce variations in the conditions under which individuals anticipate robot or AI competition.

7.1.2. The YS Employment Outlook Survey

The YS Employment Outlook Survey collects annual data on Norwegian workers (18-67 years). It includes information on workers' age, gender, education, occupation. These data specify, among other things, whether workers have a university education and which sector they work in, as well as their job satisfaction. Importantly, since 2016 they have also included questions on perceived competition with automation and other new technology. The YS Employment Outlook Survey data thus include rich individual-level information to investigate RQ 1 and RQ 1.1.

To collect data on job satisfaction, this survey asked working age individuals to assess "how satisfied are you with your job?" on a seven-point scale ranging from *very dissatisfied* to *very satisfied*. Extant literature has linked job satisfaction with a range of possible determinants such as U-shaped age effects, the likelihood of job resignations, and social comparison propensities (Clark et al., 1996; Green, 2010; Card et al., 2012) (see literature review in section 4 above). The YS Employment Outlook Survey also includes a question on anticipated competition from smart technology, which represents the main explanatory variable in our analysis. Respondents are asked whether they believe a machine could perform some of their current tasks. Since the YS Employment Outlook Survey provides data on job satisfaction, expected competition from smart machines, and information on the age and education of workers, article 4 has used these data to further investigate the SWB consequences of fearing technological replacement, and how this differs for workers of different skills and educational attainments.

7.1.3. Is SWB a valid measure?

There has been an increasing interest in the qualitative information available in survey data. This qualitative data has allowed researchers to document how people live and what they think is important. New applications are growing with the availability and richness of data and the creativity of researchers. But there are also notable criticisms that should be taken seriously if the ambition is for subjective variables such as well-being or expectations to be informative and applicable. Critics of using subjective assessments from surveys typically acknowledge that they concern interesting questions and important topics, yet doubt their ability to offer meaningful data (Bertrand & Mullainathan, 2001). This skepticism relates to epistemological and methodological issues.

Epistemological concerns involve the measurability and comparability of subjective experiences (MacKerron, 2012). Because happiness is defined and understood individually (if at all) it is possible that it might not be measurable or comparable within and between individuals (Wilkinson, 2007). However, efforts to test the validity of SWB have compared it against objective or external measures, such as heart rate and blood pressure, smiling, suicide, or reports of friends and family members, and found intuitive correlations (for a summary, see: Di Tella & MacCulloch, 2005). Another concern is whether subjective well-being can be quantified, or rather if efforts to quantify it are successful. Because well-being is subjective, the range and intensity that people experience well-being may differ and thus not translate onto an ordinal scale (Wilkinson, 2007). Like Wilkinson, Johns and Ormerod (2007) argue that the boundedness of SWB variables limits their relevance to real-world applications that often compare SWB with unbounded variables such as GDP. This is because of a ceiling effect. However, MacKerron (2012) points out that SWB responses typically are well distributed among the available categories, with a relatively small share in the lower and upper limit categories.

Beside the epistemological challenges discussed above there are also methodological concerns about the reliability of SWB variables. Overall, the challenge with reliability is whether people mean what they say (Bertrand & Mullainathan, 2001). Objections based on methodological issues point out that respondents are susceptible to forces that could bias their responses. Survey design (e.g. question ordering) is one example, while the possibility of feeling expected to answer in a certain way might influence people to respond untruthfully (e.g. social desirability) is another (Bertrand & Mullainathan, 2001). Political and economic circumstances are also important because they substantially influence the way people respond to subjective questions (Deaton, 2012). These objections are problematic for the interpretability of subjective data, which is why polling companies carefully organize questionnaires when including questions on sensitive topics (Deaton & Stone, 2016b, 2016a).

These challenges are especially relevant with the growing influence of SWB in policy making. As the body of work on SWB has grown, some advocate for SWB to be the primary goal of government policies (Layard & O'Donnell, 2015). Others argue that one should look beyond the difficulties mentioned above and acknowledge that SWB, like GDP, is an imperfect measure but still a potentially helpful indicator for policy (O'Donnell, Deaton, Durand, Halpern, & Layard, 2014). There are valid criticisms of these convictions. One is that adaptation makes the measurement of subjective experiences obsolete because they are unable to capture objective progress. This has consequences for interpreting SWB over time and across individuals because adaptation can occur both with respect to how strongly people experience changing circumstances but also to the attention people assign their experiences (Haybron, 2007; Wilkinson, 2007). Another objection is that SWB variables are sensitive in some respects (e.g. context effect) and insensitive in others (e.g. to economic growth or public spending). It is therefore a risk that researchers use findings on SWB to advocate for paternalistic policies because people are supposedly incapable of deciding what makes them happy without fully understanding the tradeoffs these decisions imply (Johns & Ormerod, 2007). The underlying question is whether 'experts' are equipped to understand the particular choices, beliefs, and motivations of people, which is also known as the 'knowledge problem' (Hayek, 1945; Ormerod, 2012). Moreover, the use and reporting of SWB can be manipulated to serve personal, political, religious or ideological interests rather than contributing to people's welfare (Frey & Stutzer, 2012).

Recognizing the limitations of subjective variables does not mean relieving them of their meaning or importance. The fact that people seem to adapt to income changes but not to unemployment is important (Clark, Frijters, et al., 2008). That education improves outcomes in life but also raises expectations about what constitutes acceptable achievements in ways that can be detrimental to a person's SWB is also important (Kristoffersen, 2018). The fact that people systematically mis-predict the likelihood and utility of future outcomes throughout their lives is relevant to most people and has substantial policy implications (Deaton, 2018). Things do not always turn out as expected but, in important life cross-roads such as education and career decisions, people also appear to make choices that diverge from what they believe will bring the most satisfaction (Benjamin et al., 2012, 2014). Many important life events, e.g. deciding on education, becoming unemployed or family formation, occur on only a few occasions in a lifetime and people may thus not have sufficient background to form realistic expectations about the utility of these outcomes (Bruni & Sugden, 2007). If subjective indicators can provide some insight into the expectations and well-being of people, then policy makers may be armed with better measures of welfare to weight policy tradeoffs (Loewenstein & Ubel, 2008). This seems pertinent in a time where pervasive ICTs can have disruptive consequences that are hard for people to anticipate, e.g. unemployment, but that are nonetheless important for their well-being.

7.2. Econometric methods

The empirical analyses presented in the four essays in this thesis rely on econometric methods. In all four articles, the dependent variables are ordinal indicators, and it is therefore appropriate to use ordered probit estimation methods. This is a standard approach in the SWB literature that typically deals with categorical dependent variables by applying ordered response (logit or probit) models for estimation. Interpreting responses to SWB questions typically invokes three increasingly restrictive assumptions (Ferrer-i-Carbonell & Frijters, 2004): 1) reported satisfaction is a positive monotonic transformation of an individual's true underlying welfare; 2) reported satisfaction can be ordinally compared between individuals; and 3) reported satisfaction can be cardinally compared between individuals. The first assumption is the basic premise for attributing meaning to SWB analyses; people are capable of truthfully translating their true welfare into different categories. The second assumption implies that particular categories, e.g. very satisfied, represent similar utility across people, which is necessary for ordered response models. The third assumption is even stricter in the sense that it assumes that the welfare difference is evenly spaced across satisfaction answers—meaning, for example, that the welfare of two individuals who report their satisfaction to be 2 and 3 are equally distant as two others who report 8 and 9 on a 10-point scale. Welfare analyses that assume cardinality often rely on the OLS estimation method.

This thesis relies on ordered probit models that assume that a latent continuous variable (e.g. well-being or expectations) can be sequenced and measured by ordinal responses in survey data (Wooldridge, 2010). More specifically, this implies that since the true satisfaction of individuals (*SWB**) cannot be directly observed, individuals instead report their satisfaction on a scale with specific categories (*SWB*). This response, *SWB*, can be compared between individuals assuming that people share a common understanding of happiness. An ordered probit model of *SWB* uses some covariates (e.g. individual characteristics) to estimate the conditional likelihoods of certain thresholds, γ, that divide the latent *SWB** into particular response categories in the questionnaire. The latent true welfare of an individual is assumed to be a linear combination of these individual characteristics, x', plus an error term, ε, that has a standard Normal distribution:

$$SWB^*{}_i \quad = \quad x'{}_i\beta + \varepsilon_i, \quad \varepsilon_i \sim N(0,1), \quad \forall\, i = 1, \dots, N$$

The observed *SWB* takes on different values, j, according to:

$$SWB_i = j \quad \Leftrightarrow \quad \gamma_{j-1} < SWB^*{}_i \leq \gamma_j$$

The ordered probit model estimates how changes in the different covariates translate into the probability of observing each ordinal value, which is defined as:

$$P(SWB_i = j) = P\left(\gamma_{j-1} < SWB^* \leq \gamma_j\right) = \Phi\left(\gamma_j - x_i\beta\right) - \Phi\left(\gamma_{j-1} - x\beta\right)$$

where Φ is the standard normal cumulative distribution function.

In this thesis, I am interested in the bivariate relationship between *SWB** and some ICT* variable. I assume that SWB* and ICT* are determined by:

$$\begin{aligned} ICT^* \quad &= \quad x'{}_1\beta_1 + \varepsilon_1 \\ SWB^* \quad &= \quad x'{}_2\beta_2 + \delta ICT^* + \varepsilon_2 \end{aligned}$$

where β_1 and β_2 are vectors of unknown parameters, δ is an unknown scaler, and ε_1 and ε_2 are the error terms.

Because neither characteristic is directly observable, I rely on responses to their proxy variables life satisfaction (LS; which has four values on a scale) and ICT (assume this variable also has four values). The likelihood that respondents answer these values is then estimated conditional on a set of covariates x. I follow the framework for bivariate ordered probit in Sajaia (2008). This framework allows *SWB** to be measured in terms of a proxy variable, life satisfaction, that takes different values to be conditional on some unknown threshold parameters that are estimated.

$$ICT_i = \begin{cases} 1 & if \quad ICT^* \leq \alpha_1 \\ 2 & if \quad \alpha_1 < ICT^* \leq \alpha_2 \\ 3 & if \quad \alpha_2 < ICT^* \leq \alpha_3 \\ 4 & if \quad ICT^* > \alpha_3 \end{cases} \qquad LS_i = \begin{cases} 1 & if \quad SWB^* \leq \gamma_1 \\ 2 & if \quad \gamma_1 < SWB^* \leq \gamma_2 \\ 3 & if \quad \gamma_2 < SWB^* \leq \gamma_3 \\ 4 & if \quad SWB^* > \gamma_3 \end{cases}$$

The unknown thresholds satisfy the condition that $\alpha_j < \ldots < \alpha_{J-1}$ and $\gamma_k < \ldots < \gamma_{K-1}$. The probability that ICT_i and LS_i take some values j and k is:

$$P(ICT_i = j, \quad LS_i = k\,) = P(\alpha_{j-1} < ICT^* \leq \alpha_j, \quad \gamma_{k-1} < SWB^* \leq \gamma_k)$$

The distributions of *ICT* and *LS* conditional on x'_1 and x'_2, respectively, are derived by computing each response probability. Assuming that ε_1 and ε_2 are distributed as bivariate standard normal with correlation ρ, then the individual contribution to the likelihood function could be expressed as:

$$\begin{aligned}(ICT_i = j, \quad LS_i = k\,) \\ &= \Phi_2(\alpha_j - x'_1\beta_1, \quad (\gamma_k - \delta x'_1\beta_1 - x'_2\beta_2)\lambda, \quad \tilde{\rho}) \\ &- \Phi_2(\alpha_{j-1} - x'_1\beta_1, \quad (\gamma_k - \delta x'_1\beta_1 - x'_2\beta_2)\lambda, \quad \tilde{\rho}) \\ &- \Phi_2(\alpha_j - x'_1\beta_1, \quad (\gamma_{k-1} - \delta x'_1\beta_1 - x'_2\beta_2)\lambda, \quad \tilde{\rho}) \\ &+ \Phi_2(\alpha_{j-1} - x'_1\beta_1, \quad (\gamma_{k-1} - \delta x'_1\beta_1 - x'_2\beta_2)\lambda, \quad \tilde{\rho})\end{aligned}$$

$\Phi 2$ is the bivariate standard normal cumulative distribution function, $\lambda = \frac{1}{\sqrt{1+2\delta\rho+\delta^2}}$ and $\tilde{\rho} = \lambda(\delta + \rho)$. The log likelihood of an observation *i* is:

$$\ln \mathcal{L} = \sum_{j=1}^{J}\sum_{k=1}^{K} I(ICT_i = j, \quad LS_i = k\,)\, lnP(ICT_i = j, \quad LS_i = k\,)$$

There are discussions about appropriate estimation methods when analyzing SWB. Some argue that ordinary least squares (OLS) estimations are preferable because they better capture fixed effects, produce signs and significance levels that typically correspond with those of ordinal response models, and are easier to interpret (Ferrer-i-Carbonell & Frijters, 2004). Studies that involve SWB dependent variables measured on 10-point scales often assume cardinality and use OLS as the estimation method (Deaton, 2008; Aghion et al., 2016; Deaton, 2018). In practice, it has been shown in the literature that the use of ordinal or cardinal methods does not have major consequences on the results. However, since the main dependent variables used in this thesis are limited to three (expectations), four (life satisfaction) or five (job satisfaction) categories, and they are estimated on repeated cross-sectional data—rather than longitudinal data with individual fixed effects—I mostly rely on ordered probit models in all four articles. These are estimated in Stata using a maximum likelihood estimation program developed by Roodman (2011). This program is designed to allow the estimation of two (or more) ordered response variables such as life (or job) satisfaction and internet use (or fear of technologies), and enable a straightforward calculation of marginal effects. By constructing a recursive set of equations, similar to a two-stage least squares (2SLS) regression, the models used in this thesis have defined stages where instrumental variables address endogeneity between the dependent and main independent variables (Monfardini & Radice, 2008; Sajaia, 2008).

7.3. Identification and instrumental variable analysis

Applied researchers are typically interested in uncovering and estimating causal relationships among the key variables of interest. A frequent concern is the potential endogeneity between the outcome variable and the main explanatory variable. Endogeneity may be due to omitted variables, measurement errors or simultaneity between variables (Angrist & Pischke, 2009; Wooldridge, 2010). In this thesis, it is possible to argue for instance that more satisfied or optimistic individuals are more likely to use the internet frequently, or to be less fearful of competition from smart machines. This possibility challenges the interpretation of a causal effect running from internet use, or anticipated job replacement, respectively, to SWB. To address endogeneity issues, the four papers in this dissertation use an overall similar identification and estimation strategy. In each study, I seek to exploit exogenous variation in some 'instrumental variables'. In papers 1 and 2, we assume and test the idea that internet use presumably increases with access to improved broadband connection (which in turn is defined by the DAE policy agenda presented in section 2 above). In papers 3 and 4, on the other hand, we posit that fear of job competition from smart machines may well be stronger for workers in local labor markets that have historically invested more heavily in industrial robots. In essence, these instrumental variables are used to draw inferences from observational data under an exclusion restriction. The exclusion restriction requires that instrumental variables affect the main explanatory variable of interest, i.e. internet use or anticipated ICT job competition, but they are presumably unrelated to the outcome variable SWB, and randomly distributed between individuals (Angrist & Pischke, 2009).

More specifically, articles 1 and 2 seek to investigate the effect of internet use on life satisfaction and expectations, respectively. The analyses are confronted with the possibility that the main explanatory variable of interest, internet use intensity, is not randomly distributed among respondents but instead depends on a set of unobserved personal characteristics. To address this concern, we apply an identification strategy that is based on two aspects. First, we control for a large set of relevant characteristics and possible confounding factors (e.g. age, education, occupation type and geographical location, etc.). Second, we exploit exogenous variation in broadband infrastructures that is correlated with internet use but not with the outcome variables. A growing body of studies use geographical differences in broadband infrastructure over time as an instrument for internet use (Bhuller et al., 2013; Bauernschuster et al., 2014; Akerman et al., 2015; Falck et al., 2016; Falk & Biagi, 2017). Our analyses adopt a similar empirical design by using high-speed broadband take-up across European countries and NUTS 1 regions. The DAE program described in section 2 has developed at different speeds across Europe, with substantial variations between nations and regions. This is due to both supply (e.g. pre-existing telecom infrastructure) and demand (e.g. diffusion of public e-services) factors (European Commission, 2014b). If those supply and demand factors remain stable over the period of study and if the DAE broadband expansion did not coincide with other circumstances that influence life satisfaction and expectations, then broadband rollout differentials can be used as a source of exogenous variation to identify the causal effect of internet use on these personal assessments (Bhuller et al., 2013, p. 1250). ICT diffusion depends on network effects and social motivation incentives (see sub-section 3.1) that improve the utility of ICTs as more people adopt them. The identification strategy thus posits that internet use intensity depends on both personal characteristics and the overall level of diffusion in the area where individuals reside through "peer effects" (Angrist & Pischke, 2009). It also assumes that these instrumental variables affect life satisfaction and expectations through their impact on internet use only, and that they are determined by dimensions uncontrollable by individuals (especially since the instruments also predate the survey data).[6]

[6] The possibility that broadband infrastructure omits important confounding variables has led other studies to use circumstantial yet not random factors such as local rainfall (Gavazza, Nardotto, & Valletti, 2018) or pre-internet telephone network infrastructure (Campante, Durante, & Sobbrio, 2017) as instruments for internet penetration. These studies differ from the analyses in articles 1 and 2 however in that they use aggregate internet penetration to predict aggregate behavior without including information about specific internet adoption asymmetries.

In articles 3 and 4, the endogeneity issue concerns the possibility that individuals have idiosyncratic characteristics that influence both their well-being and their anticipations about the future. The extent to which workers make subjective assessments about the possibility of being displaced from their jobs by robots or AI in the future does arguably depend on their own ability, tolerance of uncertainty, and technological or digital competencies. These are all important unobservable factors that potentially influence both their life or job satisfaction and their anticipated exposure to technological replacement. To exploit exogenous variation that correlates with workers' anticipations but not their SWB, these papers use the (lagged) pace of robot adoption in local labor markets. The identification strategy assumes that workers who are employed in labor markets with a more pronounced history of adopting robot technology have experienced greater exposure to automation. This exposure has presumably allowed workers to learn about the potential and consequence of automation from competing with technology in the past and makes them more likely to consider it a threat. Data from the International Federation of Robotics, used in the figures presented in section 2.2, are used to introduce exogenous variation in regional automation exposure that workers are faced with in their local labor markets. I follow existing work and construct long term adoption intensities by allocating industrial robots per thousand workers according to regional and region-industry shares of employment (Acemoglu & Restrepo, 2018a; Chiacchio et al., 2018; Dauth, Findeisen, Suedekum, & Woessner, 2018; Abeliansky & Beulmann, 2019). As in the diffusion and incentive to adopt the internet (see discussion of papers 1 and 2 above), this instrument captures *peer effects* (Angrist & Pischke, 2009). Network effects and social motivations are important also for robot adoption, as studies show investment spillovers in robot technology between economies (Chiacchio et al., 2018; Dauth et al., 2018; Acemoglu & Restrepo, 2020). Peer effects in employment expectations are documented in micro-level studies showing that unemployment brings uncertainty to the prospects of employed workers as well (Di Tella, MacCulloch, & Oswald, 2003; Luechinger, Meier, & Stutzer, 2010). Furthermore, firms' decision to invest in automation technology is assumed to be out of the control of most employees and the introduction of industrial robots is thus arguably exogenous. Investment in automation is however influenced by demographics, e.g. the age and production tasks performed by workers (Acemoglu & Restrepo, 2017, 2018a). Workers in robot-intensive regions and industries thus learn from their own or others' past experience of automation and are presumably more inclined to believe that smart machines may either perform their tasks or replace either their job entirely.

This identification strategy is also complemented further by controlling for important factors that can be thought to influence the life and job satisfaction of workers such as the unemployment rate and benefit generosity, economic growth, education level and ICT utilization. There are still potential factors that are not accounted for and that might correlate with robot adoption and SWB and violate the exclusion restriction—for example regional industry characteristics or the presence of automation in the respondent's workplace. The Eurobarometer does not include information on standardized occupation or sector employment to control for this possibility. It does however contain information about how comfortable workers are in working with robots, and this was included as a robustness control variable from two years prior to the survey data, used to partial out geographical differences in familiarity with robots in the workplace.

The use of aggregate variables to identify individual responses (i.e. based on the idea of *peer effects* noted above) raises at least three issues. First, it is possible that regional measures are too coarse and that a narrower geographical scope would improve precision. However, the internet and automation are subject to network effects and diffuse across economies as the value of adoption increases with the number of users (Agarwal et al., 2009; Acemoglu & Restrepo, 2020). Individuals' propensity to respond to network effects depends on both peer behavior and external developments that improve the welfare benefits that the internet and automation technologies represent. Although the extent to which social connectedness is local depends on socio-economic factors, recent findings suggest that online social networks have made social connectedness a reality even at substantial distances (Bailey, Cao, Kuchler, Stroebel, & Wong, 2018). The DAE initiated a coordinated digitalization effort that involves legislation, development of e-public services and e-commerce, as well as establishing public-private initiatives and investments in robotics and AI (SPARC, 2013; European Commission, 2014a). These initiatives have wide effects and coordinate a change in population behavior that extends beyond local transmission (Young, 2011). Second, this strategy potentially misses the effect of distance between households and network nodes that is found to predict broadband access (Geraci, Nardotto, Reggiani, & Sabatini, 2018). Third, it is likely correlated with other developments such as the quality of public services, environmental factors, and existing infrastructure. The articles in this thesis have controlled for regional differences in important confounders such as economic activity, unemployment, education level and competing technology to mitigate this problem. But other factors that we are unable to measure arguably remain unaccounted for.

In more general terms, the use of econometric designs based on instrumental variables is not without its critics. Deaton (2010) argues that econometric techniques exploiting variation from policy intervention or from some other source have changed the focus of economic analysis from theoretical models to empirical analyses of various programs. Estimating the average effect of a program or project in this transaction, he claims, misses the chance to understand better the underlying mechanisms at work. The concern is that results based on these techniques at best show *what happened*, leaving out the mechanisms of *why it happened*, and the prevailing conditions which lead the *what* and *why* to consistently produce the same results. At worst, they give a misleading impression of the latent relationship (Heckman & Urzúa, 2010). In response to these concerns, Imbens (2010) advocates that the use of (quasi-)experimental methods may not only bring about new insights but also provoke important discussions among researchers and policy makers.

8. RESULTS, DISCUSSION AND CONCLUSIONS

8.1. Overall results, interpretation and discussion

Each of the four articles included in this dissertation can be read separately and represents an individual contribution to existing literature. The four articles are nevertheless linked to the same overall theme of how emerging ICTs affect SWB and expectations. The main endeavor of this thesis is to investigate effects of digitalization from the bottom-up perspective of individuals' well-being. Despite the significant attention devoted to understanding the economic consequences of recent ICT developments, the effects of these factors on subjective well-being have not been investigated yet. Overall, the main findings that cut across the four articles can be summarized and discussed under the following three general points: 1) ICTs affect individual expectations; 2) Expectations affect SWB; and 3) the effects noted in 1) and 2) are heterogeneous and largely depend on the age and skills of individuals. I will now briefly elaborate on each of these three points.

8.1.1.ICTs affect expectations

Individuals form expectations to assess the future and navigate under conditions of uncertainty. Expectations are based on past experiences, peer outcomes, and reasoning from external circumstances to inform opinions about what represents justifiable outcomes (Gilboa & Schmeidler, 2001). The pervasiveness of ICTs in work and daily life can affect individual expectations both directly—by providing relevant information—and indirectly as they change economic and social structures. The first finding of this thesis is that ICTs indeed affect individual expectations. The internet makes available all sorts of information that people can use in their assessment of possible future outcomes and use to form expectations about the future. In line with a few recent studies (Card et al., 2012; Lohmann, 2015; Sabatini & Sarracino, 2016), I find, in particular, that the use of internet and online social networks raises an individual's aspirations.

The introduction of high-speed broadband in local labor markets affects people's economic expectations as well. Those who spend more time online are more likely to be optimistic about their future job and financial situation. Section 3 above discussed how emerging ICTs have influenced the labor market in ways that improve employment opportunities and the earnings potential of skilled workers (Autor et al., 2003; Acemoglu & Autor, 2011; Michaels et al., 2014; Akerman et al., 2015; Falck et al., 2016; Falk & Biagi, 2017). Taking these developments together it seems that internet use affects expectations through both an information channel and a skill component that makes its users optimistic about their future economic situation. The key risk associated with increasing aspirations induced by internet use is that that individuals will have to deal with unmet aspirations if their life circumstances and achievements do not turn out to match the high expectations they had previously established (see articles 1 and 2 in the thesis).

But what about potentially 'hostile' ICTs, such as robots and AI; do they also affect expectations? Articles 3 and 4 in this thesis find that the introduction of industrial robots in local labor markets leads workers to fear that they could be replaced by smart technology in the future. Workers in regions with a recent history of intensive robot adoption are more likely to consider their own jobs and tasks replaceable. The increasing presence of ICTs in economic production thus directly affects how exposed workers see their job prospects in relation to future automation. The future will reveal if workers' trepidations are unsubstantiated or prophetic. However, there are two main developments suggesting that advancing technology is worsening job prospects for many workers. First, automation technologies are increasingly being adopted by firms. Industrial and service robots are now adopted across industries and no longer restricted to manufacturing. Moreover, automation is challenging mid-skilled workers for routine-based jobs and tasks and has shifted job creation towards low- and high-skilled jobs (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Goos et al., 2014). At the same time, data-driven AI technologies will likely become capable of performing an increasing set of tasks and challenge a variety of jobs in the future (Brynjolfsson & McAfee, 2014; Ford, 2015). Second, economic recessions have been shown to incentivize employers to both invest further in ICTs and raise their requirements for future hires (Hershbein & Kahn, 2018). Future competition may thus come in the form of physical machines, smarter software, or better skilled human beings. Regardless, many workers do currently anticipate a future associated with job uncertainty.

8.1.2. Expectations affect SWB

The finding that the introduction of ICTs has affected individual expectations about future outcomes makes it relevant to investigate what this means for subjective well-being. Unmet aspirations, and the mismatch between aspirations and outcomes, is the crux of a recent theory that has been used to explain why life satisfaction is U-shaped over the life cycle (Schwandt, 2016). Since internet use raises expectations, it is reasonable to argue that this may contribute to individuals' unmet aspirations, thereby depressing their SWB. To consider this question, article 1 proceeds in two steps. First, I examine whether internet use affects expectations differently at young and old ages, and show that optimism bias is more evident for younger adults. Second, the article finds that the U-shape of life satisfaction becomes steeper the more time people spend online, and that the turning point of the curve arrives on average at an earlier age. Taken together, these patterns indicate that internet users are more prone to experience unmet aspirations that affect their SWB. Schwandt (2016) argues that unmet aspirations reduce current life satisfaction because they lead to frustration and regret about failing to fulfil desired objectives and hopes. Interestingly, Bertoni and Corazzini (2018) point out that regret appears to be felt more acutely when expectations surpass experiences than vice-versa, which lends support to there being a more rapid decline in well-being for internet users leading up to mid-life. The information economy is often pointed to as a great opportunity for individuals as it may increase their autonomy and lower barriers to participating in economic and societal activity. However, greater opportunities also lead to greater expectations, and with increased choice comes personal responsibility that can improve individuals' self-esteem when things go well, but also generate regret when things do not work out as expected. The internet and online social networks also motivate social comparisons that can reduce satisfaction with one's own achievements (Lohmann, 2015; Sabatini & Sarracino, 2016). This online social transparency may thus generate a focusing illusion where individuals fail to appreciate their own accomplishments because they are so focused on those of others (Kahneman, Krueger, Schkade, Schwarz, & Stone, 2006).

However, people's quality of life also depends on available job and financial prospects. The internet has contributed substantially to increased productivity and economic growth. Automation technologies, on the other hand, represent a threat because they can potentially displace workers from their jobs and replace some of their working tasks. Automation thus introduces uncertainty about future job and financial prospects, posing a risk to individuals' SWB. Studies also show that skill requirements elevate after economic downturns, and more so in areas with higher automation investment, which means that workers appear to be even more exposed to automation during economic recoveries (Hershbein & Kahn, 2018; Jaimovich & Siu, 2020). Moreover, the psychological cost of being unemployed increases when social norms place great importance on work (Akerlof, 1980; Stutzer & Lalive, 2004). Nowadays, people derive utility from doing meaningful collaborative work which allows personal autonomy (Cassar & Meier, 2018; Kaplan & Schulhofer-Wohl, 2018). Mokyr et al. (2015) discuss how work provides individuals with feelings of accomplishment and argue that automation, by reallocating job opportunities and hours at work, may further diverge the welfare of high-skilled and employed workers from those who become unemployed or underemployed.

There are thus economic and social motivations and costs associated with employment in the new information economy. The possibility of becoming displaced from work is so undesirable that it is detrimental to workers' current well-being. This is the case regardless of whether people believe that their tasks can be performed by machines or if their entire jobs are susceptible to future technology.

8.1.3. Heterogeneous effects of ICTs on SWB

The two sets of findings discussed above indicate that both internet and automation technology affect individuals' expectations and aspirations with consequences for their subjective well-being. Now, shifting the focus to research question 1.1, I will briefly point to and discuss a third set of results that cuts across the articles in this thesis—namely that the effects of ICTs on SWB are quite heterogeneous, and they largely depend on individuals' age and skills.

The empirical analyses in articles 1 and 2 show that young adults use the internet in ways that make them optimistic about their future prospects. However, reported life satisfaction of this age group indicates that aspirations are often set too high and fail to produce the expected satisfaction. Due to data restrictions, the empirical analyses were not able to test directly the particular reasons why young internet users experience unmet aspirations more intently than less active users. Nevertheless, the fact that many important life decisions are made at a young age arguably plays a role. Young individuals might experience perfectionism and meritocracy more keenly today than before and this may be intensified by social media (Curran & Hill, 2019). Such social norms are evident in the professional domain of life as well where young adults might feel expected to pursue educational and professional accomplishments. Many who graduate are discouraged by finding themselves underemployed in entry-level jobs that typically do not require their education and offer stagnating wages in areas with high living costs (Moretti, 2013; Abel, Deitz, & Su, 2014; Beaudry et al., 2016). While life is certainly full of unpleasant surprises, it is also possible that people make decisions based on other motivations than anticipated SWB (Benjamin et al., 2012). Due to status concerns, young internet users might be more inclined to deprioritize things that will make them happier in favor of benefits that they imagine will materialize later in life (Benjamin et al., 2014), and then go on to experience unmet aspirations more harshly.

Since expectations tend to become less optimistic with age, unmet aspirations imply that the surge in SWB after mid-life occurs because experiences surpass expectations (Schwandt, 2016). In this thesis, older adults appear to be less affected by the internet when forming their expectations, yet still their life satisfaction is enhanced by internet use. Digital services provide social communication tools that reduce loneliness for the elderly (Lelkes, 2013), which may bring about an unexpected joy. However, the specific reasons remain an open question for future research.

Shifting the focus to the articles in the thesis that investigate age disparities between expectations and subjective well-being with respect to automation, I find overall similar patterns and results. Fear of automation negatively (positively) affects the subjective well-being of younger (older) workers. There are both theoretical and empirical arguments suggesting that automation may have favorable effects for older workers and entail greater risks for younger workers (Sachs & Kotlikoff, 2012; Chiacchio et al., 2018). In articles 3 and 4, I propose that older workers have learned from past automation and consider it to have positively contributed to their welfare by replacing heavy and repetitive tasks. This interpretation however relies on the responses of *employed* workers who have survived automation so far, to which our survey datasets refer. The perspectives of displaced workers would in principle be useful in order to get a broader understanding of how automation affects the well-being of workers of different ages. This information is unfortunately not included in the datasets that articles 3 and 4 made use of. Anyway, it is reasonable to conclude that the consequences for younger workers are arguably more severe and carry a greater cost to future welfare. Not only can technological change raise entry barriers for young workers but it also stands to automate many of the entry level jobs that graduates have traditionally occupied (Beaudry et al., 2016; OECD, 2018b). Younger workers also have to consider the implications of competition from smart technology farther into the future and the discounted utility of those prospects is detrimental to their well-being at present.

Another important result that is pointed out in article 4 of the thesis relates to the effects of automation on SWB for workers who have different education and skills. According to the work on task-based automation (Acemoglu & Restrepo, 2019), the impact of automation for workers will depend, among other things, on the creation of new tasks beyond those automated by emerging ICTs. Of the workers considered in the dataset used in article 4 of the thesis, about 40 percent report that they believe that their job tasks can be automated (while about 35 percent of respondents in the dataset used in article 3 believe that robots or AI are capable of performing their job). It is clear that fear of automation occupies the minds of workers and it is no longer seen as part of a dystopian future, but a present threat that is detrimental to their future job prospects and subjective well-being. Workers with low education performing routine tasks are particularly exposed to the risks of automation (Goos et al., 2014; Akerman et al., 2015). This is reflected in workers' anticipations about future technological competition as well—workers with high education are less threatened by automation than those with low education. The thesis finds that the current job satisfaction of low-skilled workers is more negatively affected by this fear than that of high-skilled workers. Fear of automation is important *per se*, and it can also generate anxiety that impedes workers' productivity and creativity. This scenario, in turn, could further incentivize firms to invest in 'hostile' ICTs in order to offset the productivity loss: there is presumably no more replaceable worker than one who is unproductive, apathetic and unhappy.

8.2. Academic contributions

The main ambition of this thesis is to illustrate how the inclusion of subjective well-being variables can complement traditional welfare analyses in light of recent ICT developments. To this end, the themes investigated in this thesis lie at the intersection of two strands of literature that have so far developed as two separate lines of research: happiness economics and the economics of innovation. Specifically, I draw on both these literatures to extend a new line of inquiry into the well-being effects of innovation (Aghion et al., 2016) and ICTs (Castellacci & Tveito, 2018) by investigating how emerging ICTs influence SWB through expectations.

The thesis contributes to the literature on SWB by introducing the internet and automation as new dimensions of technological change that have so far received limited attention in happiness economics research. A few recent studies have found an overall positive relationship between internet use and SWB (Kavetsos & Koutroumpis, 2011; Graham & Nikolova, 2013; Pénard et al., 2013; Ganju et al., 2016). However, as discussed in sections 2 and 4, there are significant differences in the adoption and use of the internet between people of different ages and education. These patterns suggest that studies involving internet use are likely to miss important nuances if they focus only on its overall relationship with SWB. Indeed, a main finding in this thesis is that internet use has opposite effects for young and old individuals. The internet negatively (positively) affects life satisfaction of young (old) individuals. To make sense of this finding, I point to expectations as a particular mechanism through which ICTs influence SWB. Others have found that internet and social media use negatively affect people's financial satisfaction and suggest that social comparisons raise aspirations (Card et al., 2012; Lohmann, 2015; Sabatini & Sarracino, 2016). To the best of my knowledge, this thesis is a novel contribution in respect of its analysis of the direct effect of internet use on individuals' expectations and future well-being. By linking ICTs with SWB through expectations over the life cycle, this thesis has particular relevance for the way unmet aspirations can explain that life satisfaction is U-shaped over age—one of the most widely discussed findings in the recent happiness economics literature (Schwandt, 2016).

On the other hand, the economic effects of ICTs have been thoroughly studied in the economics of innovation literature. While this strand of research has focused on economic effects, the well-being consequences of ICT use for individuals have not yet been studied in the economics of innovation literature (Sachs & Kotlikoff, 2012; Abeliansky & Beulmann, 2019). Investigating how automation influences subjective well-being is a promising avenue for economic research given the rapid development and integration of robot and AI technology in economic activities. The way pervasive ICTs continue to integrate in daily lives will have direct and indirect influences on people's well-being. Further, recent work has discussed the various ways that automation can perform tasks and replace jobs (Autor, 2015b; Acemoglu & Restrepo, 2018b, 2019). However, the perspectives of workers themselves are often neglected despite the fact that workers are continuously exposed to new technologies at work. One can imagine that individuals' experiences could potentially play the role of 'a canary in the coal mine'—giving indications of what is to come. It is also possible that, combined with objective measurements of creative destruction, subjective expectations can detect if certain groups are walking blindfolded into the future. In these respects, the work of this thesis contributes with a novel perspective to individual anticipations of competition with future technology and the effect of that scenario for life and job satisfaction at present.

8.3. Policy implications

Survey data on subjective well-being and expectations provide valuable information to policy makers. The various ways that such data can be used to investigate relationships that are hard to understand ex ante have been demonstrated throughout this thesis. Hence, a first general policy implication of this work relates to the need to intensify policy efforts and commit public funding to the collection of survey data that can provide reliable and thorough measures of how individuals' well-being is affected by ICTs and digitalization. Applied economics research often studies individual behavior by exploiting economic discontinuities, i.e. specific events or shocks that may help to identify changes in patterns or behaviors of interest. Given the current rapid pace of digitalization, it is paramount to have good quality data on subjective welfare in order to understand its effect on the way people reflect on their life and form expectations about the future. To understand the subjective dimensions of digitalization, the collection of survey data should ideally follow the same individuals over time and include questions on ICT-related behavior and competencies that reflect how people use it and their thoughts on possible implications. Although it is impossible to predict with certainty how the future will turn out, it is surely important to grasp how people anticipate and react to both sudden and long-term implications of current ICT developments.

Second, a careful evaluation of the capacity of public institutions to produce competent workers to meet the needs of automation and digitalization is necessary to better satisfy future needs. Emerging ICTs will automate some tasks and create others that require human labor and advanced skills. In this process of creative destruction, some industries will experience sluggish demand and higher unemployment. New industries or sectors will arguably arise and offset this effect—partly or completely. The crucial question to ask about this process is whether the new activities are as labor intensive as the ones they replace. Governments should provide timely new labor market and training policies that incentivize firms to hire human workers and provide opportunities for existing employees to develop new skills that are relevant for the future of work. Governments may soon find themselves forced to develop incentives and practices that motivate businesses and individuals to develop their capabilities and skills. What is clear from this thesis is that workers already perceive smarter technology to be a possible threat to their jobs; a scenario that negatively affects their current life and job satisfaction. Education and training policies will thus become all the more relevant in the coming years.

Third, specific attention should be directed at young individuals in general, and those who lack the necessary qualifications to capitalize on the opportunities in the digital economy in particular. Being able to utilize ICTs is an important gauge of optimism in young adults. People who believe that great achievements are possible are motivated to invest in education or entrepreneurial activities that are important for individual and societal welfare. There are many costs of becoming detached from economic prosperity—the loss of family structure, crime, and deaths of despair. The lives of those 'left behind' are difficult to turn around and often accompanied by a sense of hopelessness. It is therefore important to ensure that young adults develop professional and social skills that are attractive for the future of work and avoid that their aspirations are set below their true potential. Moreover, since young individuals have much to lose under the threat of automation, it is important to ensure that the public debate does not only highlight the future threats but also reflects the many opportunities that lie ahead to make certain that these people are motivated to invest in their own futures.

Fourth, efforts should be made to ensure that ICTs are available and accessible to the elderly. Many economies in Europe and elsewhere are experiencing aging populations that will put pressure on public spending, e.g. from pensions and healthcare. Considering the positive impact of ICTs on the well-being of older adults that is found in this thesis and elsewhere, a more diffused use of ICTs among the elderly is an important and seemingly effective measure against the problems of loneliness and social isolation that are often experienced at older stages of life.

Fifth, policies and guidelines for digitalization should reflect the experiences of those who live with its consequences. Evaluations of public investment programs such as the EU's Digital Agenda that direct substantial funds toward improving digital infrastructure and skills often measure success in the form of market adoption or economic growth. However, recent literature on responsible innovation asks for ethical, social and legal requirements to guide future ICT developments (von Schomberg, 2011; Stahl, Eden, & Jirotka, 2013). In this effort, academic and policy discussions should not overlook how public investments and market regulations affect individual well-being. People's sensitivity to technological change gives a valuable indication of their ability to utilize technology and thrive in the digital economy. The DAE's ambition is to generate economic growth to tackle societal challenges such as demographic change and corresponding needs in the future. Including expectations and subjective well-being in evaluations of public strategies would allow policy makers to understand not only how much economies grow but also in what ways they are growing, and what the social effects of this are. Public policy should thus supplement supply-side interventions with user-oriented initiatives to assess and limit the negative effects of digitalization (e.g. privacy concerns and ensuring equal opportunity to participate in societal activities), as well as ways to govern and assess the value of digital data (Savona, 2019). Such considerations lie at the heart of happiness economics, exemplified by the debate on whether governments should direct their efforts at improving subjective well-being or enhancing objective measures of progress. In a sense, ICTs resemble education in how they improve life outcomes but also in how they raise people's expectations about what constitutes acceptable achievements in ways that can depress subsequent life satisfaction. Besides the moral and ideological question of how far governments should intervene in people's lives and experiences, there is an obvious tradeoff between whether "*the capacities that come with greater freedom are as or more important than what we report about our feelings having been granted that freedom*" (Deaton & Stone, 2013, p. 596). While unquestionably important, such considerations are beyond the scope of this thesis, and lie in the realm of policy analysis.

These suggestions are particularly relevant in order to help individuals thrive in the new information economy. I have focused on specific efforts that policy makers should consider when working toward ensuring equal opportunities for people to succeed in life. While the majority of this thesis concerns the subjective welfare effects of ICTs, there is a simultaneous challenge regarding the societal cost of being unprepared for the future of work. Becoming disconnected from modern way of living and working with limited future prospects severely diminishes the quality of life for those left behind (Case & Deaton, 2017; Binder & Bound, 2019; Coile & Duggan, 2019). Perhaps the most important takeaway is that the consequences of technological advances will challenge institutions and require experimentation with new policies (Brynjolfsson & McAfee, 2014). Economic growth relies on productive workers and creativity to stimulate innovation. Greater broadband capacity and adoption of the internet and its services contributes to economic growth and individual optimism. Giving people the opportunity to develop necessary skills and attitudes might inhibit feelings of 'technological anxiety' that can demotivate people from realizing their potential. SWB indicators provide researchers with important tools to measure important non-pecuniary dimensions of economic growth (Nikolova, 2016).

8.4. Limitations and future extensions

Many open questions remain concerning the effects of digitalization, and some of the most interesting potential for future research lies in combining subjective and objective perspectives in welfare analyses. During the work on this thesis I was confronted with certain restrictions that limited the scope of possible interpretations and conclusions. These restrictions were related to available data, which forced me to take some methodological decisions. I will briefly mention some of these in the concluding notes of this chapter.

A first limitation is that the use of cross-sectional survey data in my analyses prevented me from tracking intrapersonal changes over time. Consequently, I have been unable to trace how individuals have adopted or been exposed to ICTs as these develop. To assess the rigor of the relationships identified in this thesis, future work should prioritize longitudinal data to the greatest extent possible. One promising initiative is that the German Socio-Economic Panel has recently begun collecting information about whether workers have experienced new technologies being introduced in their workplace. The workers are also asked about how they expect such technologies will influence their work over the coming two years with respect to their health and productivity, as well as the demand for their skills and work performance and the risk of losing their job. Moreover, the survey asks workers to indicate changes in their labor intensity from year to year. This information provides researchers with the opportunity to analyze the effect of new technologies across industries and sectors on self-reported attitudes, experiences and reflections of individuals and how they fare in life. One caveat of these data that also applies to those used in this thesis is the crude definition of technology. Digitalization is developing at racing speeds, and while indications about technology adoption are useful, qualitative information about the type and use of particular technologies would allow for more detailed analyses. For this thesis in particular, access to information about the type of content that individuals consume over the internet or how they identify peers would have allowed a more far-reaching understanding of their aspiration formation. And knowing that workers anticipate that competition with smart machines in the future of work will be detrimental to their well-being, it would be interesting to extend this line of research by investigating the type of tasks that people expect to be automated and which new ones might occur. These are interesting avenues for future research.

Another limitation concerns econometric identification issues. To be able to fully utilize available data to understand the effects of emerging ICTs on individual welfare and well-being it is necessary to find valid instruments or other types of study designs that identify causal relationships. More detailed survey data that includes information necessary to properly match individuals (or firms) with geographical, educational, occupational, or employment identifiers would allow researchers to better exploit exogenous variations as experimental settings. Being able to combine panel data with information on structural disruptions could improve identification in each of the four papers. Facilitating proper matching between different data sources would enable future research to engage with the individual and technological impacts of external shocks such as the 2008 financial crisis and the current Covid-19 pandemic. Major events that have structural impacts on economic activity often appear in the form of shifts in aggregate measurements, e.g. unemployment or technology investments. These events impact widely across the economy and make it difficult to identify control groups. Instead, the way exogenous shocks affect different groups can become visible in the particular trajectories they later take. For example, one worrying tendency is that economic recessions seem to accelerate technological change. Many laid-off workers never find their way back into the labor market when economic activity resumes because job descriptions and skill requirements have changed. This jobless recovery is often attributed to technological change as firms invest in new technologies and reorganize their workflows to automate routine tasks and ensure new hires have the requisite skills to complement these changes (Hershbein & Kahn, 2018; Jaimovich & Siu, 2020). What this observation illustrates is that technological change affects displaced workers both directly through competition with ICTs but also by competition from better skilled workers. If individuals are able to anticipate the possible consequences of such future developments, as suggested by this thesis, then future work should be directed toward studying the behavioral responses to these anticipations.

This points to a third limitation of this thesis: since technology influences expectations it would also be relevant to consider if and how this information guides individual decisions. Discrepancies between the expected and experienced satisfaction of outcomes make it challenging to draw firm conclusions from empirical evidence using survey data. However, promising recent efforts have engaged with this issue by studying choice behavior and SWB in order to understand how people anticipate the likelihood and utility of future events (Benjamin et al., 2012, 2014). Although this thesis finds that individuals utilize ICTs when forming their expectations, still many important questions remain open. For example, how do people act on the optimism they derive from using the internet? And does fear of becoming replaced by technology motivate people to pursue further training? There is great potential in understanding the relationship between ICTs and decision making, especially given the massive investments that are committed to digitalization under the DAE and the large potential costs for individuals, firms, and economies who are not able to keep up with these developments.

The fourth and final limitation is that human well-being extends beyond measures of life and job satisfaction that are used in this thesis. I focused on life satisfaction because it is suitable for life cycle analyses and can be used as an (imperfect) proxy for (discounted) past and future utility (Clark, Frijters, et al., 2008; Benjamin et al., 2012). However, eudemonic well-being is another relevant dimension that could be pursued in further work. The way ICTs encourage the formation of impressions about life outcomes and whether or not they enable people to fulfill their potential is a promising area for future research. Feelings of stress, meaningfulness, and happiness in workers have changed with the emergence of the information economy (Kaplan & Schulhofer-Wohl, 2018). Workers now place greater importance on performing meaningful work with autonomy (Cassar & Meier, 2018). These are dimensions of work that emerging ICTs presumably influence, either directly by offering the necessary tools, or indirectly in the sense that employers may differ in their ability to provide them. In either case an intensification of social comparison is the likely result. Moreover, workers with meaningful jobs are more likely to engage in skills training and would prefer to retire at older ages (Nikolova & Cnossen, 2020). The study of the emotional well-being of individuals is thus a promising theme for further research in the light of recent ICT developments and the future of work.

9. REFERENCES

Abel, J. R., Deitz, R. & Su, Y. (2014). Are recent college graduates finding good jobs? *Current issues in economics and finance, 20*(1).

Abeliansky, A. L. & Beulmann, M. (2019). *Are they coming for us? Industrial robots and the mental health of workers*. cege Discussion Papers, No. 379. University of Göttingen, Center for European, Governance and Economic Development Research (cege), Göttingen.

Acemoglu, D. & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics* (Vol. 4, pp. 1043-1171): Elsevier.

Acemoglu, D., Dorn, D., Hanson, G. H. & Price, B. (2014). Return of the Solow paradox? IT, productivity, and employment in US manufacturing. *American Economic Review, 104*(5), 394-399. doi:10.1257/aer.104.5.394

Acemoglu, D., LeLarge, C. & Restrepo, P. (2020). Competing with Robots: Firm-Level Evidence from France. *AEA Papers and Proceedings, 110*, 383-388. doi:10.1257/pandp.20201003

Acemoglu, D. & Restrepo, P. (2017). Secular stagnation? The effect of aging on economic growth in the age of automation. *American Economic Review, 107*(5), 174-179. doi:10.1257/aer.p20171101

Acemoglu, D. & Restrepo, P. (2018a). Demographics and Automation. *NBER Working Paper (No. w24421)*. doi:10.3386/w24421

Acemoglu, D. & Restrepo, P. (2018b). Modeling Automation. *AEA Papers and Proceedings, 108*, 48-53. doi:10.1257/pandp.20181020

Acemoglu, D. & Restrepo, P. (2018c). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review, 108*(6), 1488-1542. doi:10.1257/aer.20160696

Acemoglu, D. & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives, 33*(2), 3-30. doi:10.1257/jep.33.2.3

Acemoglu, D. & Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy, 128*(6), 2188-2244. doi:10.1086/705716

Agarwal, R., Animesh, A. & Prasad, K. (2009). Social Interactions and the "Digital Divide": Explaining Variations in Internet Use. *Information Systems Research, 20*(2), 277-294. doi: 10.1287/isre.1080.0194

Aghion, P., Akcigit, U., Deaton, A. & Roulet, A. (2016). Creative destruction and subjective well-being. *American Economic Review, 106*(12), 3869-3897. doi:10.1257/aer.20150338

Aghion, P. & Howitt, P. (1998). *Endogenous growth theory*: MIT press.

Aghion, P., Jones, B. F. & Jones, C. I. (2017). *Artificial intelligence and economic growth*. National Bureau of Economic Research. NBER Working Paper (No. w23928).

Akcigit, U. (2017). Economic Growth: The Past, the Present, and the Future. *Journal of Political Economy, 125*(6), 1736-1747. doi:10.1086/694617

Akerlof, G. A. (1980). A Theory of Social Custom, of which Unemployment may be One Consequence. *The quarterly journal of economics, 94*(4), 749-775. doi:10.2307/1885667

Akerlof, G. A. & Kranton, R. E. (2005). Identity and the Economics of Organizations. *Journal of Economic Perspectives, 19*(1), 9-32. doi:10.1257/0895330053147930

Akerman, A., Gaarder, I. & Mogstad, M. (2015). The skill complementarity of broadband internet. *The quarterly journal of economics, 130*(4), 1781-1824. doi:10.1093/qje/qjv028

Angner, E. (2009). Subjective Measures of Well-Being: Philosophical Perspectives. In D. Ross & H. Kincaid (Eds.), *The Oxford Handbook of Philosophy of Economics*. New York: Oxford University Press.

Angrist, J. D. & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion* (Vol.). Princeton, NJ.: Princeton university press.

Attanasio, O. P. (2009). Expectations and perceptions in developing countries: their measurement and their use. *American Economic Review, 99*(2), 87-92. doi:10.1257/aer.99.2.87

Autor, D. (2014). Skills, education, and the rise of earnings inequality among the "other 99 percent". *Science, 344*(6186), 843-851. doi:10.1126/science.1251868

Autor, D. (2015a). Polayi's Paradox and the Shape of Employment Growth. In *Re-Evaluating Labor Market Dynamics* (pp. 129-179): Federal Reserve Bank of Kansas City.

Autor, D., Dorn, D., Katz, L. F., Patterson, C. & Van Reenen, J. (2020). The Fall of the Labor Share and the Rise of Superstar Firms. *The quarterly journal of economics, 135*(2), 645-709. doi:10.1093/qje/qjaa004

Autor, D. H. (2015b). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives, 29*(3), 3-30. doi:10.1257/jep.29.3.3

Autor, D. H. & Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *The American economic review, 103*(5), 1553-1597. doi:10.1257/aer.103.5.1553

Autor, D. H., Levy, F. & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The quarterly journal of economics, 118*(4), 1279-1333. doi:10.1162/003355303322552801

Bailey, M., Cao, R., Kuchler, T., Stroebel, J. & Wong, A. (2018). Social Connectedness: Measurement, Determinants, and Effects. *Journal of Economic Perspectives, 32*(3), 259-280. doi:10.1257/jep.32.3.259

Bauernschuster, S., Falck, O. & Woessmann, L. (2014). Surfing alone? The internet and social capital: Evidence from an unforeseeable technological mistake. *Journal of Public Economics, 117*(C), 73-89. doi:10.1016/j.jpubeco.2014.05.007

Baumol, W. J. (1967). Macroeconomics of unbalanced growth: the anatomy of urban crisis. *The American economic review, 57*(3), 415-426.

Baumol, W. J., Blackman, S. A. B. & Wolff, E. N. (1985). Unbalanced growth revisited: asymptotic stagnancy and new evidence. *The American economic review*, 806-817.

Beaudry, P., Green, D. A. & Sand, B. M. (2016). The great reversal in the demand for skill and cognitive tasks. *Journal of Labor Economics, 34*(S1), S199-S247. doi:10.1086/682347

Benjamin, D. J., Heffetz, O., Kimball, M. S. & Rees-Jones, A. (2012). What Do You Think Would Make You Happier? What Do You Think You Would Choose? *The American economic review, 102*(5), 2083-2110. doi:10.1257/aer.102.5.2083

Benjamin, D. J., Heffetz, O., Kimball, M. S. & Rees-Jones, A. (2014). Can Marginal Rates of Substitution Be Inferred from Happiness Data? Evidence from Residency Choices. *American Economic Review, 104*(11), 3498-3528. doi:10.1257/aer.104.11.3498

Benzell, S. G. & Brynjolfsson, E. (2019). *Digital Abundance and Scarce Genius: Implications for Wages, Interest Rates, and Growth*. National Bureau of Economic Research.

Bertoni, M. & Corazzini, L. (2018). Asymmetric affective forecasting errors and their correlation with subjective well-being. *PloS one, 13*(3), e0192941. doi:10.1371/journal.pone.0192941

Bertrand, M. & Mullainathan, S. (2001). Do People Mean What They Say? Implications for Subjective Survey Data. *The American economic review, 91*(2), 67-72. doi:10.1257/aer.91.2.67

Bessen, J., Goos, M., Salomons, A. & van den Berge, W. (2020). *Automation: A Guide for Policymakers*. Retrieved from https://www.brookings.edu/wp-content/uploads/2020/01/Bessen-et-al_Full-report.pdf

Bessen, J. E. (2020). Automation and Jobs: When Technology Boosts Employment. *Economic Policy, eiaa001*(17-09). doi:10.1093/epolic/eiaa001

Bessen, J. E., Goos, M., Salomons, A. & Van den Berge, W. (2019). *Automatic Reaction - What Happens to Workers at Firms that Automate?* Boston Univ. School of Law, Law and Economics Research Paper Retrieved from https://ssrn.com/abstract=3328877

Best, P., Manktelow, R. & Taylor, B. (2014). Online communication, social media and adolescent wellbeing: A systematic narrative review. *Children and Youth Services Review, 41*, 27-36. doi:10.1016/j.childyouth.2014.03.001

Bhuller, M., Havnes, T., Leuven, E. & Mogstad, M. (2013). Broadband internet: An information superhighway to sex crime? *Review of Economic Studies, 80*(4), 1237-1266. doi:10.1093/restud/rdt013

Bhuller, M., Kostol, A. R. & Vigtel, T. C. (2020). *How Broadband Internet Affects Labor Market Matching*. IZA Discussion Papers, No. 12895. Institute of Labor Economics (IZA), Bonn. Retrieved from http://hdl.handle.net/10419/215291.

Binder, A. J. & Bound, J. (2019). The Declining Labor Market Prospects of Less-Educated Men. *Journal of Economic Perspectives, 33*(2), 163-190. doi:10.1257/jep.33.2.163

Binder, M. (2013). Innovativeness and subjective well-being. *Social Indicators Research, 111*(2), 561-578. doi:10.1007/s11205-012-0020-1

Binder, M. & Coad, A. (2011). From Average Joe's happiness to Miserable Jane and Cheerful John: using quantile regressions to analyze the full subjective well-being distribution. *Journal of Economic Behavior & Organization, 79*(3), 275-290. doi:10.1016/j.jebo.2011.02.005

Blanchflower, D. G. & Oswald, A. J. (2008). Is well-being U-shaped over the life cycle? *Social Science & Medicine, 66*(8), 1733-1749. doi:10.1016/j.socscimed.2008.01.030

Brandtzæg, P. B., Heim, J. & Karahasanović, A. (2011). Understanding the new digital divide—A typology of Internet users in Europe. *International Journal of Human-Computer Studies, 69*(3), 123-138. doi:10.1016/j.ijhcs.2010.11.004

Bresnahan, T. F. & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth'? *Journal of Econometrics, 65*(1), 83-108.

Bruni, L. & Sugden, R. (2007). The Road not Taken: How Psychology was Removed from Economics, and How it Might be Brought Back. *The Economic Journal, 117*(516), 146-173. doi:10.1111/j.1468-0297.2007.02005.x

Brynjolfsson, E. & Hitt, L. M. (2003). Computing productivity: Firm-level evidence. *Review of Economics and Statistics, 85*(4), 793-808. doi:10.1162/003465303772815736

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

Byrne, D., Oliner, S. D. & Sichel, D. (2013). Is the Information Technology Revolution Over? *International Productivity Monitor, 25*, 20-36.

Cainelli, G., Evangelista, R. & Savona, M. (2005). Innovation and economic performance in services: a firm-level analysis. *Cambridge Journal of Economics, 30*(3), 435-458. doi:10.1093/cje/bei067

Campante, F., Durante, R. & Sobbrio, F. (2017). Politics 2.0: The Multifaceted Effect of Broadband Internet on Political Participation. *Journal of the European Economic Association, 16*(4), 1094-1136. doi:10.1093/jeea/jvx044

Cappelli, P. H. (2015). Skill Gaps, Skill Shortages, and Skill Mismatches:Evidence and Arguments for the United States. *ILR Review, 68*(2), 251-290. doi:10.1177/0019793914564961

Card, D., Mas, A., Moretti, E. & Saez, E. (2012). Inequality at work: The effect of peer salaries on job satisfaction. *American Economic Review, 102*(6), 2981-3003. doi:10.1257/aer.102.6.2981

Case, A. & Deaton, A. (2017). Mortality and Morbidity in the 21st Century. *Brookings Papers on Economic Activity, 2017*(1), 397-476.

Caselli, F. & Coleman, W. J. (2001). Cross-Country Technology Diffusion: The Case of Computers. *American Economic Review, 91*(2), 328-335. doi:10.1257/aer.91.2.328

Cassar, L. & Meier, S. (2018). Nonmonetary Incentives and the Implications of Work as a Source of Meaning. *Journal of Economic Perspectives, 32*(3), 215-238. doi:10.1257/jep.32.3.215

Castellacci, F. & Tveito, V. (2018). Internet use and well-being: A survey and a theoretical framework. *Research Policy, 47*(1), 308-325. doi:10.1016/j.respol.2017.11.007

Castellacci, F. & Viñas-Bardolet, C. (2019). Internet use and job satisfaction. *Computers in Human Behavior, 90*, 141-152. doi:10.1016/j.chb.2018.09.001

Chandler, D. & Kapelner, A. (2013). Breaking monotony with meaning: Motivation in crowdsourcing markets. *Journal of Economic Behavior & Organization, 90*, 123-133. doi:10.1016/j.jebo.2013.03.003

Cheng, T. C., Powdthavee, N. & Oswald, A. J. (2017). Longitudinal Evidence for a Midlife Nadir in Human Well-being: Results from Four Data Sets. *127*(599), 126-142. doi:10.1111/ecoj.12256

Chiacchio, F., Petropoulos, G. & Pichler, D. (2018). The impact of industrial robots on EU employment and wages: A local labour market approach. *Bruegel Working Papers (02).*

Chinn, M. D. & Fairlie, R. W. (2007). The determinants of the global digital divide: a cross-country analysis of computer and internet penetration. *Oxford Economic Papers, 59*(1), 16-44. doi:10.1093/oep/gpl024

Ciarli, T., Marzucchi, A., Salgado, E. & Savona, M. (2018). The Impact of R&D Growth on Employment and Self-Employment Composition in Local Labour Markets.

Clark, A., Oswald, A. & Warr, P. (1996). Is job satisfaction U-shaped in age? *Journal of occupational and organizational psychology, 69*(1), 57-81. doi:10.1111/j.2044-8325.1996.tb00600.x

Clark, A. E., Diener, E., Georgellis, Y. & Lucas, R. E. (2008). Lags and leads in life satisfaction: A test of the baseline hypothesis. *The Economic Journal, 118*(529), F222-F243. doi:10.1111/j.1468-0297.2008.02150.x

Clark, A. E., Frijters, P. & Shields, M. A. (2008). Relative Income, Happiness, and Utility: An Explanation for the Easterlin Paradox and Other Puzzles. *Journal of Economic Literature, 46*(1), 95-144. doi:10.1257/jel.46.1.95

Clark, A. E. & Georgellis, Y. (2013). Back to Baseline in Britain: Adaptation in the British Household Panel Survey. *Economica, 80*(319), 496-512. doi:10.1111/ecca.12007

Clark, A. E., Kamesaka, A. & Tamura, T. (2015). Rising aspirations dampen satisfaction. *Education Economics, 23*(5), 515-531. doi:10.1080/09645292.2015.1042960

Coile, C. C. & Duggan, M. G. (2019). When Labor's Lost: Health, Family Life, Incarceration, and Education in a Time of Declining Economic Opportunity for Low-Skilled Men. *Journal of Economic Perspectives, 33*(2), 191-210. doi:10.1257/jep.33.2.191

Cruz-Jesus, F., Vicente, María R., Bacao, F. & Oliveira, T. (2016). The education-related digital divide: An analysis for the EU-28. *Computers in Human Behavior, 56*, 72-82. doi:10.1016/j.chb.2015.11.027

Curran, T. & Hill, A. P. (2019). Perfectionism is increasing over time: A meta-analysis of birth cohort differences from 1989 to 2016. *Psychological Bulletin, 145*(4), 410. doi:10.1037/bul0000138

Czernich, N., Falck, O., Kretschmer, T. & Woessmann, L. (2011). Broadband infrastructure and economic growth. *The Economic Journal, 121*(552), 505-532. doi:10.1111/j.1468-0297.2011.02420.x

Dauth, W., Findeisen, S., Suedekum, J. & Woessner, N. (2018). Adjusting to Robots: Worker-Level Evidence. *Opportunity and Inclusive Growth Institute Working Paper (13).*

Davis, S. J. & Haltiwanger, J. (1992). Gross Job Creation, Gross Job Destruction, and Employment Reallocation. *The quarterly journal of economics, 107*(3), 819-863. doi:10.2307/2118365

Deaton, A. (2008). Income, Health, and Well-Being around the World: Evidence from the Gallup World Poll. *Journal of Economic Perspectives, 22*(2), 53-72. doi:10.1257/jep.22.2.53

Deaton, A. (2010). Instruments, Randomization, and Learning about Development. *Journal of Economic Literature, 48*(2), 424-455. doi:10.1257/jel.48.2.424

Deaton, A. (2012). The financial crisis and the well-being of Americans 2011 OEP Hicks Lecture *. *Oxford Economic Papers, 64*(1), 1-26. doi:10.1093/oep/gpr051

Deaton, A. (2018). What do self-reports of wellbeing say about life-cycle theory and policy? *Journal of Public Economics, 162*, 18-25. doi:10.1016/j.jpubeco.2018.02.014

Deaton, A. & Stone, A. A. (2013). Two Happiness Puzzles. *American Economic Review, 103*(3), 591-597. doi:10.1257/aer.103.3.591

Deaton, A. & Stone, A. A. (2016a). Response to Lucas, Oishi, and Diener. *Oxford Economic Papers, 68*(4), 877-878. doi:10.1093/oep/gpw024

Deaton, A. & Stone, A. A. (2016b). Understanding context effects for a measure of life evaluation: how responses matter. *Oxford Economic Papers, 68*(4), 861-870. doi:10.1093/oep/gpw022

Deci, E. L. & Ryan, R. M. (2008). Hedonia, eudaimonia, and well-being: an introduction. *Journal of Happiness Studies, 9*(1), 1-11. doi:10.1007/s10902-006-9018-1

DellaVigna, S. & La Ferrara, E. (2015). Economic and social impacts of the media. In *Handbook of media economics* (Vol. 1, pp. 723-768): Elsevier.

Deming, D. & Kahn, L. B. (2018). Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals. *Journal of Labor Economics, 36*(S1), S337-S369. doi:10.1086/694106

Di Tella, R. & MacCulloch, R. (2005). Partisan Social Happiness. *The Review of Economic Studies, 72*(2), 367-393. doi:10.1111/j.1467-937X.2005.00336.x

Di Tella, R., MacCulloch, R. J. & Oswald, A. J. (2001). Preferences over Inflation and Unemployment: Evidence from Surveys of Happiness. *American Economic Review, 91*(1), 335-341. doi:10.1257/aer.91.1.335

Di Tella, R., MacCulloch, R. J. & Oswald, A. J. (2003). The Macroeconomics of Happiness. *The Review of Economics and Statistics, 85*(4), 809-827. doi:10.1162/003465303772815745

Dolan, P. & Metcalfe, R. (2012). The relationship between innovation and subjective wellbeing. *Research Policy, 41*(8), 1489-1498. doi:10.1016/j.respol.2012.04.001

Dolan, P., Peasgood, T. & White, M. (2006). Review of research on the influences on personal well-being and application to policy making. *London: Defra*.

Dolan, P., Peasgood, T. & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology, 29*(1), 94-122. doi:10.1016/j.joep.2007.09.001

Draca, M., Sadun, R. & Van Reenen, J. (2009). Productivity and ICTs: A Review of the Evidence. In C. Avgerou, R. Mansell, D. Quah, & R. Silverstone (Eds.), *The Oxford Handbook of Information and Communication Technologies* Oxford University Press.

Easterlin, R. A. (1974). Does Economic Growth Improve the Human Lot? Some Empirical Evidence. In *Nations and households in economic growth* (pp. 89-125): Elsevier.

Easterlin, R. A. (2001). Income and Happiness: Towards a Unified Theory. *The Economic Journal, 111*(473), 465-484. doi:10.1111/1468-0297.00646

Elsby, M. W., Hobijn, B. & Şahin, A. (2013). The decline of the US labor share. *Brookings Papers on Economic Activity, 2013*(2), 1-63. doi:10.1353/eca.2013.0016.

Elster, J. & Loewenstein, G. (1992). Utility from memory and anticipation. In G. Loewenstein & J. Elster (Eds.), *Choice over time* (pp. 213-234). New York: Russel Sage Foundation.

Engelbrecht, H.-J. (2015). A general model of the innovation-subjective well-being nexus. In *The Evolution of Economic and Innovation Systems* (pp. 69-90): Springer.

Erdogan, B., Bauer, T. N., Truxillo, D. M. & Mansfield, L. R. (2012). Whistle While You Work: A Review of the Life Satisfaction Literature. *Journal of management, 38*(4), 1038-1083. doi:10.1177/0149206311429379

EU & UN-Habitat. (2016). *The State ofEuropean Cities 2016 - Cities leading the way to a better future*. Retrieved from https://ec.europa.eu/regional_policy/sources/policy/themes/cities-report/state_eu_cities2016_en.pdf

European Commission. (2010). A Digital Agenda for Europe Retrieved from http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52010DC0245R(01)&from=EN

European Commission. (2014a). Digital Single Market. Retrieved from https://europa.eu/european-union/file/1497/

European Commission. (2014b). Study on National Broadband Plans in the EU-28. Retrieved from https://op.europa.eu/en/publication-detail/-/publication/b6e8b5ee-4edb-11ea-aece-01aa75ed71a1/language-en/format-PDF

European Commission. (2018a). The 2018 ageing report economic & budgetary projections for the 28 EU member states (2016-2070). Retrieved from https://ec.europa.eu/info/sites/info/files/economy-finance/ip079_en.pdf

European Commission. (2018b). Employment and Social Developments in Europe 2018. Retrieved from https://ec.europa.eu/social/main.jsp?catId=738&langId=en&pubId=8110

European Commission. (2019). Digital Europe Program Factsheet. Retrieved from https://ec.europa.eu/digital-single-market/en/news/digital-europe-programme-proposed-eu92-billion-funding-2021-2027

Evangelista, R., Guerrieri, P. & Meliciani, V. (2014). The economic impact of digital technologies in Europe. *Economics of Innovation and New Technology, 23*(8), 802-824. doi:10.1080/10438599.2014.918438

Falck, O., Heimisch, A. & Wiederhold, S. (2016). *Returns to ICT skills*. IEB Working Paper N. 2016/05.

Falk, M. & Biagi, F. (2017). Relative demand for highly skilled workers and use of different ICT technologies. *Applied Economics, 49*(9), 903-914. doi:10.1080/00036846.2016.1208357

Ferrer-i-Carbonell, A. & Frijters, P. (2004). How Important is Methodology for the estimates of the determinants of Happiness?*. *The Economic Journal, 114*(497), 641-659. doi:10.1111/j.1468-0297.2004.00235.x

Fleck, S., Glaser, J. & Sprague, S. (2011). The compensation-productivity gap: a visual essay. *Monthly Labor Review, 134*(1), 57-69.

Ford, G. S., Koutsky, T. M. & Spiwak, L. W. (2011). The Frontier of Broadband Adoption Across the OECD: A Comparison of Performance. *International Economic Journal, 25*(1), 111-123. doi:10.1080/10168737.2010.487540

Ford, M. (2015). *Rise of the Robots: Technology and the Threat of a Jobless Future*: Basic Books.

Foster, G. & Frijters, P. (2014). The formation of expectations: Competing theories and new evidence. *Journal of Behavioral and Experimental Economics, 53*, 66-81. doi:10.1016/j.socec.2014.08.001

Frederick, S. & Loewenstein, G. (1999). 16 Hedonic Adaptation. In D. Kahneman, Diener, E., & Schwarz, N. (Ed.), *Well-being: The foundations of hedonic psychology* (pp. 302-329): Russell Sage Foundation.

Freeman, R. (1978). Job Satisfaction as an Economic Variable. *American Economic Review, 68*(2).

Frey, B. S. & Stutzer, A. (2010). *Happiness and economics: How the economy and institutions affect human well-being*: Princeton University Press.

Frey, B. S. & Stutzer, A. (2012). The use of happiness research for public policy. *Social Choice and Welfare, 38*(4), 659-674. doi:10.1007/s00355-011-0629-z

Frijters, P. & Beatton, T. (2012). The mystery of the U-shaped relationship between happiness and age. *Journal of Economic Behavior & Organization, 82*(2), 525-542. doi:10.1016/j.jebo.2012.03.008

Ganju, K. K., Pavlou, P. A. & Banker, R. D. (2016). Does Information and Communication Technology Lead to the Well-Being of Nations? A Country-Level Empirical Investigation. *MIS Quarterly, 40*(2), 417-430.

Gavazza, A., Nardotto, M. & Valletti, T. (2018). Internet and Politics: Evidence from U.K. Local Elections and Local Government Policies. *The Review of Economic Studies, 86*(5), 2092-2135. doi:10.1093/restud/rdy028

Geraci, A., Nardotto, M., Reggiani, T. & Sabatini, F. (2018). *Broadband internet and social capital*. arXiv:1810.04575 [cs.CY].

Gilboa, I., Postlewaite, A. W. & Schmeidler, D. (2008). Probability and Uncertainty in Economic Modeling. *Journal of Economic Perspectives, 22*(3), 173-188. doi:10.1257/jep.22.3.173

Gilboa, I. & Schmeidler, D. (2001). A cognitive model of individual well-being. *Social Choice and Welfare, 18*(2), 269-288. doi:10.1007/s003550100103

Goldfarb, A. & Prince, J. (2008). Internet adoption and usage patterns are different: Implications for the digital divide. *Information Economics and Policy, 20*(1), 2-15. doi:10.1016/j.infoecopol.2007.05.001

Goolsbee, A. & Klenow, P. J. (2002). Evidence on Learning and Network Externalities in the Diffusion of Home Computers. *The Journal of Law and Economics, 45*(2), 317-343. doi:10.1086/344399

Goos, M., Manning, A. & Salomons, A. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *American Economic Review, 104*(8), 2509-2526. doi:10.1257/aer.104.8.2509

Gordon, R. J. (2012). *Is US Economic Growth Over? Faltering Innovation Confronts the Six Headwinds*. National Bureau of Economic Research. NBER Working Paper (No. 18315).

Graham, C. & Nikolova, M. (2013). Does access to information technology make people happier? Insights from well-being surveys from around the world. *The Journal of Socio-Economics, 44*, 126-139. doi:10.1016/j.socec.2013.02.025

Green, F. (2010). Well-being, job satisfaction and labour mobility. *Labour Economics, 17*(6), 897-903. doi:10.1016/j.labeco.2010.04.002

Green, F. & Zhu, Y. (2010). Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. *Oxford Economic Papers, 62*(4), 740-763. doi:10.1093/oep/gpq002

Gruber, H., Hätönen, J. & Koutroumpis, P. (2014). Broadband access in the EU: An assessment of future economic benefits. *Telecommunications Policy, 38*(11), 1046-1058. doi:10.1016/j.telpol.2014.06.007

Haybron, D. M. (2007). Do We Know How Happy We Are? On Some Limits of Affective Introspection and Recall. *Nous, 41*(3), 394-428. doi:10.1111/j.1468-0068.2007.00653.x

Hayek, F. A. (1945). The Use of Knowledge in Society. *The American economic review*, 519-530.

Heckman, J. J. & Urzúa, S. (2010). Comparing IV with structural models: What simple IV can and cannot identify. *Journal of Econometrics, 156*(1), 27-37. doi:https://doi.org/10.1016/j.jeconom.2009.09.006

Heilbroner, R. L. (1965). Men and Machines in Perspective. *The Public Interest, 1*, 27.

Hershbein, B. & Kahn, L. B. (2018). Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings. *American Economic Review, 108*(7), 1737-1772. doi:10.1257/aer.20161570

Hong, S.-H. (2007). The recent growth of the internet and changes in household-level demand for entertainment. *Information Economics and Policy, 19*(3-4), 304-318. doi:10.1016/j.infoecopol.2007.06.004

Imbens, G. W. (2010). Better LATE Than Nothing: Some Comments on Deaton (2009) and Heckman and Urzua (2009). *Journal of Economic Literature, 48*(2), 399-423. doi:10.1257/jel.48.2.399

Jaimovich, N. & Siu, H. E. (2020). Job Polarization and Jobless Recoveries. *Review of Economics and Statistics, 102*(1), 129-147. doi:10.1162/rest_a_00875

Johns, H. & Ormerod, P. (2007). *Happiness, Economics and Public Policy*. London: The Institute of Economic Affairs.

Jorgenson, D. W. (2005). Chapter 10 Accounting for Growth in the Information Age. In P. Aghion & S. N. Durlauf (Eds.), *Handbook of economic growth* (Vol. 1, Part A, pp. 743-815): Elsevier.

Jorgenson, D. W., Ho, M. S. & Stiroh, K. J. (2008). A Retrospective Look at the U.S. Productivity Growth Resurgence. *Journal of Economic Perspectives, 22*(1), 3-24. doi:10.1257/jep.22.1.3

Kahneman, D., Krueger, A. B., Schkade, D., Schwarz, N. & Stone, A. A. (2006). Would You Be Happier If You Were Richer? A Focusing Illusion. *Science, 312*(5782), 1908-1910. doi:10.1126/science.1129688

Kahneman, D. & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica, 47*(2), 263-291. doi:10.2307/1914185

Kahneman, D., Wakker, P. P. & Sarin, R. (1997). Back to Bentham? Explorations of Experienced Utility. *The quarterly journal of economics, 112*(2), 375-406. doi:10.1162/003355397555235

Kaplan, G. & Schulhofer-Wohl, S. (2018). The Changing (Dis-)Utility of Work. *Journal of Economic Perspectives, 32*(3), 239-258. doi:10.1257/jep.32.3.239

Kaplan, S. N. & Rauh, J. (2013). It's the Market: The Broad-Based Rise in the Return to Top Talent. *Journal of Economic Perspectives, 27*(3), 35-56. doi:10.1257/jep.27.3.35

Karabarbounis, L. & Neiman, B. (2013). The Global Decline of the Labor Share. *The quarterly journal of economics, 129*(1), 61-103. doi:10.1093/qje/qjt032

Katz, M. L. & Shapiro, C. (1986). Technology Adoption in the Presence of Network Externalities. *Journal of Political Economy, 94*(4), 822-841. doi:10.1086/261409

Kavetsos, G. & Koutroumpis, P. (2011). Technological affluence and subjective well-being. *Journal of Economic Psychology, 32*(5), 742-753. doi:10.1016/j.joep.2011.05.004

Keynes, J. M. (1930). Economic Possibilities for Our Grandchildren. S. 321-332 in: Essays in Persuasion. The Collected Writings of John Maynard Keynes, IX. In: London: MacMillan.

Koch, M., Manuylov, I. & Smolka, M. (2019). *Robots and firms*. CESifo Working Paper No. 7608. Retrieved from https://ssrn.com/abstract=3377705.

Koutroumpis, P. (2009). The economic impact of broadband on growth: A simultaneous approach. *Telecommunications Policy, 33*(9), 471-485. doi:10.1016/j.telpol.2009.07.004

Kristoffersen, I. (2018). Great expectations: Education and subjective wellbeing. *Journal of Economic Psychology, 66*, 64-78. doi:10.1016/j.joep.2018.04.005

Layard, R. & O'Donnell, G. (2015). How to Make Policy When Happiness is the Goal. In J. F. Helliwell, R. Layard, & J. Sachs (Eds.), *World happiness report* (pp. 76-87). New York: Sustainable Development Solutions Network.

Lelkes, O. (2013). Happier and less isolated: Internet use in old age. *Journal of Poverty and Social Justice, 21*(1), 33-46. doi:10.1332/175982713X664047

Leontief, W. (1983). National perspective: The definition of problems and opportunities. *The long-term impact of technology on employment and unemployment*, 3-7.

Loewenstein, G. & Ubel, P. A. (2008). Hedonic adaptation and the role of decision and experience utility in public policy. *Journal of Public Economics, 92*(8), 1795-1810. doi:10.1016/j.jpubeco.2007.12.011

Lohmann, S. (2015). Information technologies and subjective well-being: does the Internet raise material aspirations? *Oxford Economic Papers, 67*(3), 740-759. doi:10.1093/oep/gpv032

Loomes, G. & Sugden, R. (1982). Regret Theory: An Alternative Theory of Rational Choice Under Uncertainty. *The Economic Journal, 92*(368), 805-824. doi:10.2307/2232669

Loomes, G. & Sugden, R. (1986). Disappointment and Dynamic Consistency in Choice Under Uncertainty. *The Review of Economic Studies, 53*(2), 271-282. doi:10.2307/2297651

Luechinger, S., Meier, S. & Stutzer, A. (2010). Why Does Unemployment Hurt the Employed? Evidence from the Life Satisfaction Gap Between the Public and the Private Sector. *Journal of Human Resources, 45*(4), 998-1045. doi:10.3368/jhr.45.4.998

MacKerron, G. (2012). Happiness Economics from 35 000 Feet. *Journal of Economic Surveys, 26*(4), 705-735. doi:10.1111/j.1467-6419.2010.00672.x

Manski, C. F. (2000). Economic Analysis of Social Interactions. *Journal of Economic Perspectives, 14*(3), 115-136. doi:10.1257/jep.14.3.115

Manski, C. F. (2004). Measuring Expectations. *Econometrica, 72*(5), 1329-1376. doi:10.1111/j.1468-0262.2004.00537.x

Martin, B. R. (2016). Twenty challenges for innovation studies. *Science and Public Policy, 43*(3), 432-450. doi:10.1093/scipol/scv077

Martin, L. & Omrani, N. (2015). An assessment of trends in technology use, innovative work practices and employees' attitudes in Europe. *Applied Economics, 47*(6), 623-638. doi:10.1080/00036846.2014.978072

Maurseth, P. B. (2020). ICT, Growth and Happiness. In D. Maiti, F. Castellacci, & A. Melchior (Eds.), *Digitalisation and Development* (pp. 31-86). Singapore: Springer Singapore.

McDool, E., Powell, P., Roberts, J. & Taylor, K. (2016). *Social Media Use and Children's Wellbeing*. IZA Discussion Paper No. 10412.

Michaels, G., Natraj, A. & Van Reenen, J. (2014). Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years. *Review of Economics and Statistics, 96*(1), 60-77. doi:10.1162/REST_a_00366

Mokyr, J., Vickers, C. & Ziebarth, N. L. (2015). The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different? *Journal of Economic Perspectives, 29*(3), 31-50. doi:10.1257/jep.29.3.31

Monfardini, C. & Radice, R. (2008). Testing exogeneity in the bivariate probit model: A Monte Carlo study. *oxford Bulletin of Economics and Statistics, 70*(2), 271-282. doi:10.1111/j.1468-0084.2007.00486.x

Moretti, E. (2013). Real Wage Inequality. *American Economic Journal: Applied Economics, 5*(1), 65-103. doi:10.1257/app.5.1.65

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica*, 315-335. doi:10.2307/1909635

Nikolova, M. (2016). *Happiness and Development*. Institute of Labor Economics (IZA), Bonn. IZA Discussion Papers, No. 10088 Retrieved from http://ftp.iza.org/dp10088.pdf.

Nikolova, M. & Cnossen, F. (2020). What makes work meaningful and why economists should care about it. *Labour Economics, 65*, 101847. doi:10.1016/j.labeco.2020.101847

Nussbaum, M. C. (2001). Symposium on Amartya Sen's philosophy: 5 Adaptive preferences and women's options. *Economics & Philosophy, 17*(1), 67-88. doi:10.1017/S0266267101000153

O'Donnell, G., Deaton, A., Durand, M., Halpern, D. & Layard, R. (2014). *Wellbeing and Policy*. London: Legatum Institute.

Odermatt, R. & Stutzer, A. (2018). (Mis-)Predicted Subjective Well-Being Following Life Events. *Journal of the European Economic Association*, 245–283. doi:10.1093/jeea/jvy005

OECD. (2018a). *OECD Science, Technology and Innovation Outlook 2018*. OECD Publishing.

OECD. (2018b). *Putting Faces to the Jobs at Risk of Automation*. OECD Publishing.

OECD. (2019). *Artificial Intelligence in Society*. Paris: OECD Publishing Retrieved from https://www.oecd-ilibrary.org/content/publication/eedfee77-en.

Oliner, S. D. & Sichel, D. E. (2000). The Resurgence of Growth in the Late 1990s: Is Information Technology the Story? *Journal of Economic Perspectives, 14*(4), 3-22. doi:10.1257/jep.14.4.3

Ormerod, P. (2012). The folly of wellbeing in public policy. In P. Booth (Ed.), *... and the Pursuit of Happiness: Well-Being and the Role of Government* (pp. 39-58). London: The Institute of Economic Affairs.

Oswald, A. J., Proto, E. & Sgroi, D. (2015). Happiness and Productivity. *Journal of Labor Economics, 33*(4), 789-822. doi:10.1086/681096

Pénard, T., Poussing, N. & Suire, R. (2013). Does the Internet make people happier? *The Journal of Socio-Economics, 46*, 105-116. doi:10.1016/j.socec.2013.08.004

Pesaran, H. M. & Weale, M. (2006). Chapter 14 Survey Expectations. In G. Elliott, C. W. J. Granger, & A. Timmermann (Eds.), *Handbook of economic forecasting* (Vol. 1, pp. 715-776). Amsterdam: North-Holland.

Rajan, K. & Saffiotti, A. (2017). Towards a science of integrated AI and Robotics. *Artificial Intelligence: Special Issue on AI and Robotics, 247*, 1-9. doi:10.1016/j.artint.2017.03.003

Roodman, D. (2011). Fitting fully observed recursive mixed-process models with cmp. *Stata Journal, 11*(2), 159-206. doi:10.1177/1536867X1101100202

Ryan, R. M. & Deci, E. L. (2001). On Happiness and Human Potentials: A Review of Research on Hedonic and Eudaimonic Well-Being. *Annual review of psychology, 52*(1), 141-166. doi:10.1146/annurev.psych.52.1.141

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of personality and social psychology, 57*(6), 1069.

Sabatini, F. & Sarracino, F. (2016). *Keeping Up with the E-Joneses: Do Online Social Networks Raise Social Comparisons?* FEEM Working Paper 2016.32.

Sachs, J. D. & Kotlikoff, L. J. (2012). *Smart Machines and Long-Term Misery*. NBER Working Paper (No. w18629). National Bureau of Economic Research.

Sajaia, Z. (2008). Maximum likelihood estimation of a bivariate ordered probit model: implementation and Monte Carlo simulations. *The Stata Journal, 4*(2), 1-18. doi:10.1177/1536867X0400400306

Savona, M. (2019). *The Value of Data: Towards a Framework to Redistribute It*. Science Policy Research Unit. SWPS 21.

Schumpeter, J. A. (1934). *The Theory of Economic Development: An Inquiry Into Profits, Capital, Credit, Interest, and the Business Cycle*: Harvard University Press.

Schwandt, H. (2016). Unmet aspirations as an explanation for the age U-shape in wellbeing. *Journal of Economic Behavior & Organization, 122*, 75-87. doi:10.1016/j.jebo.2015.11.011

Sen, A. (1999). *Commodities and capabilities*. India: Oxford University Press.

Solow, R. M. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics, 39*(3), 312-320. doi:10.2307/1926047

Solow, R. M. (1987, July 12). We'd Better Watch Out. *New York Times,* p. 36.

SPARC. (2013). *Robotics 2020 - Strategic Research Agenda for Robotics in Europe*. Retrieved from https://www.eu-robotics.net/cms/upload/topic_groups/SRA2020_SPARC.pdf

Stahl, B. C., Eden, G. & Jirotka, M. (2013). Chapter 11 Responsible Research and Innovation in Information and Communication Technology: Identifying and Engaging with the Ethical Implications of ICTs. In R. Owen, J. Bessant, & M. H eintz (Eds.), *Responsible innovation* (pp. 199-218). Chichester: Wiley & Sons.

Steptoe, A., Deaton, A. & Stone, A. A. (2015). Subjective wellbeing, health, and ageing. *The Lancet, 385*(9968), 640-648. doi:10.1016/S0140-6736(13)61489-0

Stevenson, B. & Wolfers, J. (2008). Economic Growth and Subjective Well-Being: Reassessing the Easterlin Paradox. *Brookings Papers on Economic Activity, Spring 2008*, 1-87.

Stutzer, A. & Lalive, R. (2004). The Role of Social Work Norms in Job Searching and Subjective Well-Being. *Journal of the European Economic Association, 2*(4), 696-719. doi:10.1162/1542476041423331

Swan, T. W. (1956). Economic Growth and Capital Accumulation. *Economic Record, 32*(2), 334-361. doi:10.1111/j.1475-4932.1956.tb00434.x

Syverson, C. (2017). Challenges to Mismeasurement Explanations for the US Productivity Slowdown. *Journal of Economic Perspectives, 31*(2), 165-186. doi:10.1257/jep.31.2.165

Von Neumann, J. & Morgenstern, O. (1947). *Theory of games and economic behavior, 2nd rev*. Princeton University Press.

von Schomberg, R. (2011). *Towards Responsible Research and Innovation in the Information and Communication Technologies and Security Technologies Fields*. Luxembourg: Publications Office of the European Union.

Webb, A. (2019). *The Big Nine: How the Tech Titans and Their Thinking Machines Could Warp Humanity*. New York: Hachette UK.

Wilkinson, W. (2007). *In pursuit of happiness research: Is it reliable? What does it imply for policy?* Retrieved from Washington: Cato Institute:

Wilson, C. M. & Oswald, A. J. (2005). *How Does Marriage Affect Physical and Psychological Health? A Survey of the Longitudinal Evidence*. IZA Discussion Paper No. 1619. Retrieved from https://ssrn.com/abstract=735205.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*: MIT press.

Young, H. P. (2011). The dynamics of social innovation. *Proceedings of the National Academy of Sciences, 108*(Supplement 4), 21285-21291. doi:10.1073/pnas.1100973108

Zeira, J. (1998). Workers, Machines, and Economic Growth. *The quarterly journal of economics, 113*(4), 1091-1117. doi:10.1162/003355398555847

PART II: ESSAYS ON ICTS, EXPECTATIONS AND SUBJECTIVE WELL-BEING

First paper

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RESEARCH ARTICLE

Internet, unmet aspirations and the U-shape of life

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Abstract

The relationship between age and well-being is U-shaped. One recent explanation for this empirical pattern is related to unmet aspirations theory, pointing out that optimism bias decreases life satisfaction at younger ages, whereas pessimism bias increases it at later stages of life. This paper investigates the effects of Internet use on subjective well-being over the life cycle. Our model investigates the proposition that Internet use affects aspirations, and that this effect is relatively stronger at younger and older ages. To investigate moderation effects of Internet use on the U-shape of life, we use the Eurobarometer annual surveys for the years 2010 to 2016, which provide rich information for around 150,000 individuals in all European countries. We focus on the *EU Digital Agenda* policy program, and exploit exogenous variation in broadband Internet take-up across European countries to identify the causal effects of Internet on life satisfaction for different age groups. The results of 2SLS estimations for a recursive bivariate ordered probit model show that active Internet users have a different well-being pattern over the life cycle compared to less active users. Specifically, we find that Internet use makes the U-shape of life steeper. Country-level evidence on aspiration levels for different demographic and Internet user groups indicates that our empirical results are consistent with unmet aspirations theory.

1. Introduction

The literature on subjective well-being has pointed out a variety of factors that explain differences in happiness conditions reported by individuals [1–7]. A new strand of research has recently extended this literature and started to investigate what effects Internet may have on individuals' well-being. The introduction of the Internet variable in the study of subjective well-being is warranted. Digital technologies are pervasive, and nowadays most individuals use the Internet to access information and communicate with each other. It is reasonable to think that online information and communication patterns may affect individuals' aspirations and their perceived well-being [8].

A small number of studies have recently presented first empirical investigations of this question. Some of these works have analyzed the overall relationship between Internet adoption and life satisfaction using survey data for several countries, and pointed out an overall

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Eurobarometer survey 82.3: https://dbk.gesis.org/dbksearch/SDesc2.asp?ll=10¬abs=1&af=&nf=&search=&search2=&db=E&no=5932
Eurobarometer survey 84.3: https://dbk.gesis.org/dbksearch/SDesc2.asp?ll=10¬abs=1&af=&nf=&search=&search2=&db=E&no=6643
Eurobarometer survey 85.3: https://dbk.gesis.org/dbksearch/SDesc2.asp?ll=10¬abs=1&af=&nf=&search=&search2=&db=E&no=6695.

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positive correlation between the two variables for large samples of individuals [9–11]. Other papers have made use of country-specific surveys to investigate more specific hypotheses, such as Internet effects related to material aspirations and social comparisons [12, 13], and those related to the use of social media and communication patterns [14–16].

Overall, the main endeavor of this recent strand of research has been to uncover a general relationship between Internet use and well-being for large samples of individuals, but there has until now been more limited effort to investigate the extent to which this relationship varies for different groups of individuals. Specifically, it is reasonable to postulate that individuals of different ages use the Internet to a varying extent and for distinct purposes. The effects of online digital technologies on well-being may indeed vary substantially with age.

This is the point that we seek to investigate in the present paper. The work presents an empirical analysis of the relationships between Internet use intensity and subjective well-being, and its specific objective is to study how this relationship varies over the life cycle. The investigation of this question is closely related to extant research on the U-shaped relationship between age and well-being [17, 18]. According to this literature, subjective well-being over the life cycle is characterized by a remarkable empirical regularity, with a progressive decline in life satisfaction until late adult life, followed by a steady recovery and growth in subsequent years.

Recent research has put forward a new explanation of the U-shape relationship based on "unmet aspirations theory" [19]. This argues that individuals make systematic forecast errors when they form expectations about future life satisfaction, and that these errors indicate optimism bias at early stages of life, and pessimism bias at older ages [20–22]. Since unmet aspirations depress life satisfaction for younger individuals, and, by contrast, unanticipated well-being fosters life satisfaction for older people, this theory can explain the U-shape pattern that has been observed and confirmed in previous empirical studies.

We take this theory as a conceptual framework for our analysis, and we extend it by investigating the effects of Internet use. We present a simple model, extending Schwandt [19], in which Internet use increases individuals' aspirations, and relatively more so for more vulnerable age groups, such as younger and older individuals [23]. Our model predicts that Internet use makes the U-shape relationship between age and well-being steeper, i.e. exacerbating optimism bias for the younger and pessimism bias for the older.

To empirically investigate this hypothesis, we make use of the Eurobarometer survey, a large survey that covers several thousand individuals in all European countries. We use the six annual surveys that refer to the years 2010 to 2016, which provide a rich dataset for about 150,000 individuals. Our identification strategy is based on the *EU Digital Agenda* policy program, which was initiated in the late 2000s to foster digitalization and Internet access in member countries [24]. The EU Digital Agenda provides an exogenous source of variation in broadband Internet take-up across European countries and regions. In fact, as we will show in the paper, the implementation of the EU policy program in different countries and regions in Europe during the period 2010–2016 was characterized by substantial spatial and temporal variation, and the timing of the roll-out was not related to other factors driving life satisfaction and its correlates.

We exploit this exogenous variation to identify the causal effects of Internet on life satisfaction for different age groups. Our instrumental variables–lagged fixed broadband take-up–measures *peer effects* in Internet adoption, based on the idea that the intensity of Internet use of each individual will partly depend on the overall level of diffusion of broadband Internet in the country or region [11, 25, 26]. The econometric analysis estimates a 2SLS recursive bivariate ordered probit model, which simultaneously estimates a treatment and an outcome equation using the CMP procedure developed by Roodman [27].

The main result of this analysis is that the effects of Internet use on subjective well-being are heterogeneous, varying significantly with age. The econometric findings point out that active Internet users have a more pronounced decrease in reported life satisfaction in their younger adult life, an earlier and stronger recovery after the turning point of the U-shape, and steady growth throughout older adult life. In short, we find that Internet use makes the U-shape of life steeper. We then provide empirical evidence that illustrates that this empirical result is consistent with the predictions of unmet aspirations theory, and the model presented in this paper.

On the whole, the contribution of this paper to the literature is twofold. First, we contribute to the recent strand of research on Internet and well-being by showing that the effects of Internet are remarkably heterogeneous among individuals of different ages. This means that age-specific characteristics must be taken into account when analyzing benefits and risks that the Internet leads to. Second, we contribute to the literature on the U-shaped relationship between age and well-being by introducing a new conceptual dimension, the Internet, and by formally testing its moderation effects on the age-well-being relationship.

2. Literature

A new strand of research has recently begun to investigate the effects of Internet use on life satisfaction and subjective well-being, carrying out econometric analyses of large survey datasets (see overview in Castellacci and Tveito [8]). Two groups of studies contribute to this emerging literature. In the first group, papers typically make use of cross-country surveys (e.g. European Social Survey, Eurobarometer, Gallup World Poll) to provide estimates of the average correlation between Internet use and life satisfaction for a large sample of individuals in different countries.

Kavetsos and Koutrompis [28] analyze the relationships between mobile phones, computers with Internet connection and life satisfaction using the Eurobarometer dataset for all European countries for the years 2005–2008. OLS estimates point out a positive correlation between computers with Internet connection and life satisfaction. Penard et al. [11], using data from the European Value Survey for Luxembourg in 2008, study the effects of Internet use on life satisfaction. The 2SLS cross-sectional estimates reported in this paper do not find any significant effect when other relevant control variables are included in the regressions. Graham and Nikolova [10] carry out a cross-country study of the relationship between Internet access and life satisfaction, using data from the Gallup World Poll for a large number of world economies in the period 2009–2011. Ordered logit cross-sectional correlation coefficients reported in this paper are positive and significant, and they vary substantially across world regions.

The second group of studies comprises papers that analyze large national household surveys, which often provide more specific variables to measure different types of online activities and Internet-related use, and thus enable to test more elaborated hypotheses. As noted below, many of these studies point out negative (or moderating) effects that Internet use has on well-being through its interactions with income and relational factors.

Focusing first on the relational dimension, Rotondi et al. [15] study the effects of smartphone use on relational patterns and social life, employing data from the Italian Multipurpose Survey on Households. 2SLS estimates point out a positive effect of smartphone use on life satisfaction, but they also show that this effect is weaker for those individuals that use the smartphone in combination with face-to-face social activities. Sabatini and Sarracino [16] investigate the relationships between social media use, social capital and well-being, using the Italian Multipurpose Survey on Households. 2SLS and SEM results reported in this article point out a significant negative effect of social media use on subjective well-being.

Regarding income-related effects, Lohmann [12] analyzes the hypothesis that Internet has negative effects on well-being by raising individuals' material aspirations. The work uses data from various sources, and specifically the German Socio-Economic Panel, the EU-SILC survey and the World Value Survey. OLS and ordered probit cross-sectional estimates reported in this paper indicate a positive and significant correlation between Internet use and life satisfaction, but also corroborate the hypothesis that Internet raises material aspirations and so weakens the positive effect of income on subjective well-being. Finally, Sabatini and Sarracino [13] investigate a similar mechanism using the Italian Multipurpose Survey on Households. The study finds in particular that use of social media spurs social comparisons and raises income aspirations, thus moderating income-related effects on subjective well-being.

In short, this recent strand of research points out a variety of different results regarding the impact of Internet use on subjective well-being, some emphasizing positive effects and others suggesting negative impacts. A common characteristic of this literature is that nearly all papers seek to uncover a general relationship between Internet use and well-being for the whole sample of individuals in the dataset, but they do not investigate the extent to which this relationship may vary for different groups of individuals. In other words, extant research has until now had limited interest in the study of the heterogeneity of effects of Internet.

In this paper, we seek to study heterogeneous effects of Internet with respect to age. A few previous studies on this topic provide mixed evidence. Research focusing on Internet use of younger adults (and particularly on the use of social media and video games) point out both positive and negative effects [8, 29, 30]. Kross et al. [23] present evidence from experience-sampling analysis of a small group of Facebook users in the US, showing the negative effects that this has on the users' well-being. McDool et al. [14] study the effects of social media use and children's well-being, using the Household Longitudinal Survey for the UK, and find negative effects for their sample of British children. Arad et al. [31] focuses on Facebook users in a security-related organization, and point out that social media increases social comparison and weakens subjective well-being for the younger half of their sample. Arampatzi et al. [32]) study a large sample of Dutch social media users, and show that the negative effects on well-being is particularly strong for SNS users who also report to be feel socially disconnected and lonely.

On the other hand, research focusing on Internet use of older adults is still scant, and it so far indicates that Internet use has mostly positive effects on well-being by facilitating social contacts and communication, and thus decreasing isolation and depression [33–36].

In order to provide a more systematic understanding of Internet effects for individuals of different age groups, we turn to the literature on the U-shaped relationship between age and well-being. Blanchflower and Oswald [17, 18] point out the existence of a U-shape relationship between age and life satisfaction, a remarkable regularity that holds for a large number of countries worldwide. According to these studies, the turning point of the U-shape–i.e. the year at which individuals face a so-called midlife crisis–is between 35 and 65 years (depending on countries, sample, and model specifications). Some studies argue that the U-shape is a methodological artefact that can be explained by cohort effects, and/or by the use of inappropriate control variables [37, 38], and Frijters and Beatton [39] point out that the U-shape may be affected by the omission of fixed effects in pooled cross-country regressions. In spite of these methodological remarks, the empirical evidence in support of the U-shaped relationship between age and life satisfaction is strong.

The literature has recently advanced a possible explanation of this empirical regularity. This is related to "unmet aspirations" [19]. A variety of empirical studies within psychology, neuroscience and behavioral economics has provided evidence that individuals make systematic forecast errors when they form expectations about the future, and that these prediction errors change along the life cycle. Optimism bias prevails at younger ages, whereas pessimism bias is more common at older life stages [20–22] (p. 123). According to this theory, the mismatch between expectations and realized life satisfaction may explain the observed decrease in well-being during the first part of life, and the corresponding increase at older ages. A relevant related study is Proto and Rustichini (2015), which show that life satisfaction depends on the gap between aspired and realized income, and that this relationship is moderated by individuals' personality traits such as neuroticism.

3. Theoretical framework

The simple model presented in this section provides the theoretical framework for the empirical analysis. The model is based upon a generalization of Schwandt's [19] recent study of life satisfaction and unmet aspirations, and it extends his framework to investigate the effects of Internet use. In line with the literature on the determinants of well-being, we assume that individuals derive life satisfaction from different *domains of life* (e.g. working life, consumption, social life). Individual *i*'s life satisfaction at time *t* is given by the following equation:

$$LS_t = \sum_{d=1}^{D} d_t[x(d,t)] - \lambda_t \bullet \sum_{\tau=0}^{t-t_0} \{E_{t-\tau-1}[LS_{t-\tau}] - LS_{t-\tau}\} \tag{1}$$

The first term on the RHS of the equation is the sum of life satisfaction derived from all domains of life *d* at time *t*. Each domain of life's satisfaction is achieved by means of the vector of commodities (or life achievements) $x(d,t)$. The function d_t can in principle change over the life cycle, because individuals can change their preferences over time and may therefore derive different life satisfaction levels from the same vector of commodities at different ages.

The second term represents a forecast error that individuals make in their expectation formation about future life satisfaction. According to Schwandt [19], individuals expect their future life satisfaction to be a function of their current satisfaction level. If this expectation is wrong, the resulting forecast error (unmet aspiration) will affect their current life satisfaction level. Specifically, when forecast errors are positive (negative), individuals systematically predict that their future life satisfaction will be higher (lower) than it will actually prove to be. In other words, at any given period *t*, an individual makes expectations about her future life satisfaction level at time *t+1*. Then, at time *t+1*, the individual will compare her expectations with the actual realized life satisfaction level. Unmet aspirations are given by the sum of all past (positive) forecast errors, starting from early life (t0–1; in the notation adopted in Eq 1), until the current period.

Such unmet aspirations will have a negative effect on the individual's current level of well-being, because they will lead to frustration and regret about unrealized objectives and achievements that the individual had previously hoped to realize. In the second term of Eq 1, λ_t is a so-called *regret* parameter, representing the negative effect of forecast error on current life satisfaction. The parameter ranges between 0 and 1; the higher it is, the stronger is the regret for past failures (or unmet aspirations). For simplicity, we assume here that the regret parameter is fixed and it does not vary with age. Bertoni and Corazzini [21] interestingly point out that regret might actually be asymmetric, tending to be stronger when people make negative forecast errors (optimism bias) than when they make positive errors (pessimism bias). This refinement would however not change qualitatively the main properties and predictions of this model, which we discuss below.

The expectation that an individual forms at time *t-τ-1* about her life satisfaction at time *t-τ* is given by the expression:

$$E_{t-\tau-1}[LS_{t-\tau}] = [1 + \beta_{t-\tau-1}] \bullet LS_{t-\tau-1} \tag{2}$$

Future expectations are positively affected by the variable β_t, which represents individuals' *aspirations* about the future. In line with recent empirical evidence [19, 21, 22], we postulate that aspirations will decrease over the life cycle, and that they will be positive (*optimism bias*) at younger ages until midlife ($t < t(M)$), and become negative (*pessimism bias*) at later stages of life (beyond midlife; $t > t(M)$).

$$\frac{\partial\beta(t)}{\partial t} < 0; \beta(t) = \begin{cases} \beta > 0, \ t < t(M) \\ \beta < 0, \ t > t(M) \end{cases} \tag{3}$$

Introducing this expectation term in Eq 1 yields:

$$LS_t = \sum_{d=1}^{D} d_t[x(d,t)] - \lambda_t \bullet \sum_{\tau=0}^{t-t_0} \{[1 + \beta_{t-\tau-1}] \bullet LS_{t-\tau-1} - LS_{t-\tau}\} \tag{4}$$

Writing the extended form for all periods, and solving for LS_t gives the following expression:

$$LS_t = \frac{\sum_{d=1}^{D} d_t[x(d,t)]}{1-\lambda_t} - \frac{\lambda_t}{1-\lambda_t} \bullet \sum_{\tau=1}^{t-t_0} \beta_{t-\tau} \bullet LS_{t-\tau} \tag{5}$$

The first term on the RHS of this equation is the sum of life satisfaction that an individual derives from the set of commodities and achievements that she has available from all domains of life d, divided by the complement to 1 of the regret parameter. This term is hence magnified by the regret parameter: the higher the regret for past failures, the more important current satisfaction with domains of life will become for an individual's well-being (i.e. an individual with high regret must compensate these unmet aspirations with current life status). The second term on the RHS is the *optimism bias* term. As noted above, this term is affected by aspirations and it decreases over the life cycle.

This simple model can generate a U-shaped relationship between age and well-being in two ways. The first is related to the second term on the RHS of Eq 5, namely through optimism bias and unmet aspirations. As shown by Schwandt [19], if the aspiration variable β decreases over the life cycle–so that younger (older) people systematically overestimate (underestimate) their future life satisfaction–then the life satisfaction variable would follow a U-shape, because unmet aspirations would depress well-being at young ages, whereas the opposite mechanism would foster well-being later in life.

A second way in which this model could generate a U-shaped relationship arises if life satisfaction related to one given domain of life changes over the life cycle following a non-monotonic relationship. Specifically, assuming for simplicity that the forecast error term is 0, this happens if the function $d(t)$ is U-shaped, i.e. because individuals derive a satisfaction level from domain of life d that decreases until midlife, and then rises again at older ages. For instance, this would be the case if individuals change some of their preferences over the life cycle, e.g. valuing differently the importance of their social life. This could be regarded as an important dimension of life satisfaction at younger ages, less important during midlife (when many individuals shift their focus to working life and career objectives), and then becoming again more important at later stages of life.

In both of the cases noted here (decreasing aspirations or changing preferences over the life cycle), the resulting relationship between life satisfaction and age would be U-shaped.

Effects of Internet use on aspirations

To investigate the effects of Internet use in this framework, suppose now that we have two types of individuals, one that is a high (active) Internet user (HI), and the other that is low (sporadic) Internet user (LI). Based on extant literature, we argue that the different intensity of Internet use between these individuals may affect the U-shaped relationship between age and well-being. Active Internet use will expose individuals to a variety of online content that will foster social comparison mechanisms, and thereby affect individuals' expectation formation and raise their aspiration levels [12, 13]. According to extant literature on the effects of Internet on well-being, such online comparison mechanisms and the related aspiration effects will be different for distinct age groups. Aspiration effects may in fact be relatively stronger for more vulnerable age groups.

In particular, in line with recent empirical evidence from various studies, we posit that younger individuals using the Internet are highly exposed to social comparisons and peer effects through the use of social media, which will tend to foster their material aspirations [13, 14, 23, 31, 32]. On the other hand, to the extent that older adults have more pessimistic expectations about the future, exposure to online content about bad news and threats (criminality, political and economic crises, terrorism, climate change) will end up exacerbating such pessimism bias [40, 41]. If this is the case, the aspiration variable β_t will have a steeper (negative) trend for the group of active Internet users than for sporadic users:

$$|\beta_t^{HI}| > |\beta_t^{LI}| \tag{6}$$

Further, it may also be argued that digital communication technologies will make the elderly more socially connected and less isolated than they had previously expected to be, and this may lead to a realized life satisfaction that exceeds the one that was previously expected [35, 42]. Under these conditions, it follows that Internet use will make the U-shape relationship between life satisfaction and age steeper. This means that the decrease in life satisfaction at early stages of life (before the turning point $t(M)$) would become more pronounced for active Internet users due to stronger optimism bias, and that, correspondingly, the increase in life satisfaction after midlife ($t > t(M)$) would also become swifter because of stronger pessimism bias:

Proposition 1

$$\beta_t = \begin{cases} \dfrac{\partial LS(t)^{HI}}{\partial t} < \dfrac{\partial LS(t)^{LI}}{\partial t}, & t < t(M) \\ \dfrac{\partial LS(t)^{HI}}{\partial t} > \dfrac{\partial LS(t)^{LI}}{\partial t}, & t > t(M) \end{cases}$$

This is the proposition that will be empirically tested and discussed in the subsequent sections.

4. Data and methods

The empirical analysis makes use of the Eurobarometer survey, a large survey that covers several thousand individuals in all European countries. We use the annual surveys that refer to the years 2010 to 2016, which provide a pooled cross-sectional dataset for around 150,000 individuals. These surveys provide harmonized data for the main variables of interest, so that we can analyze variables that have the exact same formulation in the Eurobarometer questionnaire. The Eurobarometer surveys are representative of the country population. They collect data by carrying out face-to-face interviews in people's home and in the national language". Life satisfaction is measured by asking respondents to indicate their level of satisfaction on a four-point scale ranging from not very satisfied to very satisfied. The internet use variable is based on responses to the following question: "How often do you use the internet?". Responses are given on a seven-point scale (no internet access: 7%; never: 21%; less often: 2%; two or three times a month: 1%; about once a week: 3%; two or three times a week: 9%; everyday/almost everyday: 57%). A1 Table presents a list of the variables we use in the empirical analysis, and some descriptive statistics for the whole dataset.

The econometric analysis seeks to investigate the effect of Internet use on life satisfaction for individuals of different age groups. An important issue that has to be taken into account is that the main explanatory variable of interest, Internet use intensity, is arguably not an exogenous and randomly assigned variable, but it is in turn dependent on a set of personal characteristics that define individuals' willingness and capability to use the Internet. Some of these personal characteristics may be unobserved, and they may in principle affect both the treatment variable Internet use and the outcome variable life satisfaction.

To take this issue into account, we adopt a two-equation instrumental variable approach. The first step is a selection equation that investigates the factors explaining why some individuals have higher Internet use intensity than others, whereas the second equation studies the relationship between life satisfaction and Internet use (plus a set of control factors). The econometric model (baseline specification) is the following:

$$\mathrm{LS}_{ict} = \alpha + \gamma \mathrm{INT}_{ict} + \delta \mathbf{X}_{ict} + \eta_c + \theta_t + \varepsilon_{ict} \tag{7}$$

$$\mathrm{INT}_{ict} = \lambda + \rho \mathbf{X}_{ict} + \mu \mathrm{Z}_{ict} + \sigma_{ict} \tag{8}$$

where LS stands for life satisfaction, INT is internet use intensity, and **X** is a vector of covariates (control variables). The sub-indexes *i*, *c* and *t* indicate individuals, countries and years respectively. η_c is a set of country-specific effects, and θ_t is a set of time dummies. The variable Z in Eq (8) is an exogenous instrumental variable that is correlated with INT but not correlated with the error term of the outcome equation, as explained further below.

An identification strategy for this model has to consider two aspects. The first one is to formulate a comprehensive specification of Eq 8, and in particular include in the vector **X** all variables that are known to affect Internet use intensity according to extant literature on the subject. We thus include the following factors previously pointed out in studies of the determinants of Internet adoption and use: age, gender, occupation type, education level, civil status, and geographical location (urban vs. rural area), along with a set of country-specific effects and time dummies. This is a comprehensive set of variables that are supposedly able to account for a substantial part of the variability of Internet use intensity [43, 44]. The second aspect is to find an instrumental variable Z that provides exogenous variation correlated with the treatment variable Internet use intensity but uncorrelated with the error term of the outcome equation. For this purpose, we exploit cross-country differences in broadband take-up among European nations and regions as a source of exogenous variation.

In the late 2000s, the EU initiated a new policy to foster access and use of broadband Internet in European countries. The *EU Digital Agenda*, introduced in May 2010, formulated a set of objectives that national Member States have to achieve to increase their degree of digitalization, and particularly their Broadband Internet take-up [45]. However, *National Broadband Plans* that have subsequently been developed by Member States to implement the Digital Agenda have been quite different among European nations [24], and policy targets have been met at different speeds. Cross-country differences have been substantial on both the supply- and the demand-side. On the one hand, the supply of broadband infrastructures is affected by national regulation and competition policies that define entry costs and investment rates of telecommunication firms [46]. Supply-side factors are also related to geographical factors and pre-existing phone and Internet infrastructures, which affect the pace at which broadband transmission centrals and local access points are built up in different regions and countries. Recent papers have adopted an econometric identification strategy centered on supply-side factors, and in particular on the availability of broadband infrastructures, and its differences across municipalities and regions within a given country [16, 47–51] [15]. On the other hand, demand-side factors are also characterized by marked cross-country differences, linked for instance to different rates of diffusion of e- public services, as well as institutional differences in national education systems and public investments in e-skills [24].

Fig 1 shows the distribution of broadband Internet take-up across countries and regions in Europe, and its evolution during the time span considered in this paper. The graphs show that spatial and temporal variation in broadband coverage is substantial. Using this source of variation to identify the causal effects of Internet use on life satisfaction relies upon two features of the EU digital policy program [48] (p. 1250). First, that the supply and demand factors that affected the development of broadband Internet take up during this period did not vary substantially over time; second, that the timing of the broadband Internet expansion does not co-vary with other factors that are correlated with the outcome variable life satisfaction. We will empirically assess these two assumptions in the next sub-section.

Based on this exogenous source of variation, we make use of two instrumental variables that measure the diffusion of broadband Internet (fixed broadband take-up per 100 people) in European countries and regions during the period: one is defined at the country-level, and the other is defined at the regional level. We take lagged values of these variables (one year before each survey period) in order to ensure that they predate the outcome variable and they are thus uncorrelated with common country- or region-year shocks [52] (p. 192–197). We carried out all estimations and robustness tests using the two instruments in separate exercises. The baseline results we present in the manuscript are those for the fixed broadband take-up at the country-level, and the additional results reported in the appendix are those for the corresponding variable measured at the regional level.

Note that our instrumental variables are "peer effects" [52], based on the idea that the intensity of Internet use of each individual will not only depend on the set of personal characteristics specified in equation 10, but also on the overall level of diffusion of broadband Internet in the country (or region). The idea that peer effects affect Internet use intensity is in line with standard models of diffusion of ICTs (see e.g.) [42]. These models argue that an individual is more likely to adopt and actively use new digital technologies if many other individuals have previously adopted and used the same technology. The reason is threefold: (1) *social learning*: adoption is easier if individuals can learn from other peers about the potential of the new technology; (2) *social pressure*: if most other peers are using a new digital technology (e.g. for communication purposes), it is hard for an individual not to use the same digital tool; (3) *network externalities*: since adoption and use costs depend on the size of users' network, the larger the number of peers using a digital technology the cheaper this will be for a given user [11, 26, 53].

The key assumption of this identification strategy is that these instrumental variables affect individual life satisfaction only through their impact on Internet use intensity, and that they are therefore uncorrelated with any possible unobserved determinant of life satisfaction. This is a reasonable assumption, since for each individual *i* in our dataset, the extent of the diffusion of broadband Internet in the country, or region, in which *i* lives is determined by a set of dimensions that cannot be affected by each individual (and particularly so since our instruments *predate* the individual-level outcome variable). The next sub-sections will empirically assess the validity of this assumption for our dataset.

After clarifying the identification strategy, we now briefly point out the methods that we will use to estimate the effects of Internet use for individuals of different age groups, and in

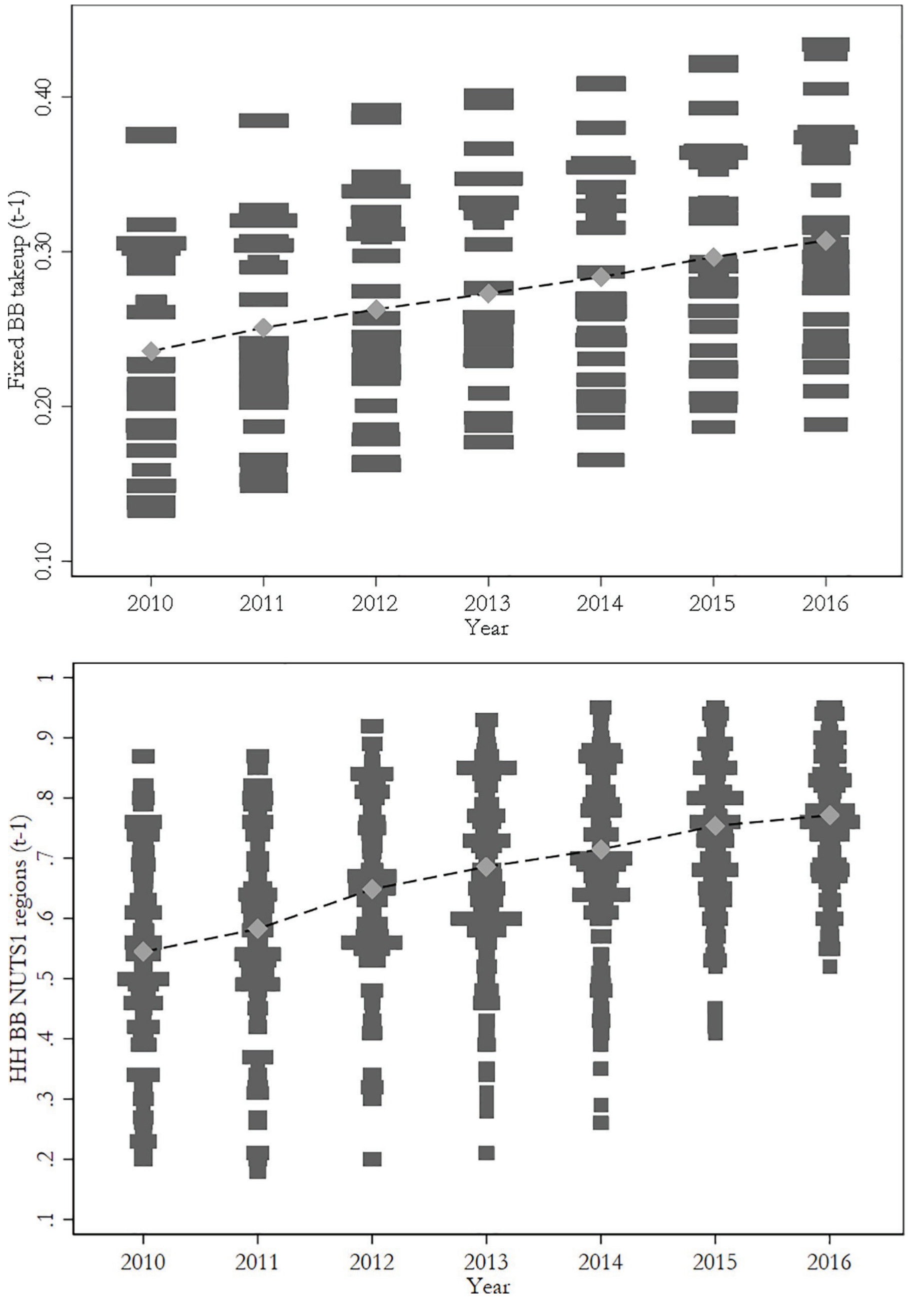

Fig 1. Distribution of fixed broadband across EU countries (above) and regions (below).

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particular to test moderation effects of Internet on the U-shaped relationship between age and well-being. We expect the use of Internet may affect (1) the turning point of the U-shape (i.e. the time at which the midlife crisis sets in on average), and/or (2) the slope of the U-shaped curve (i.e. the speed at which the midlife crisis is met, and the subsequent recovery phase for older adults). We test these hypotheses by inserting two interaction terms in the regressions:

one is an interaction between age and Internet use, and the other is an interaction between age-squared and Internet use. When we include such interaction variables in the regressions, we instrument them by using the corresponding interactions between the instrument and the age and age-squared variables, respectively. The interaction between age-squared and Internet use is the variable of our interest, using which we can test the two distinct moderation effects noted above (for further details on how to test moderation effects of U-shaped relationships, see 53: 1187).

We estimate Eqs (7) and (8) through a 2SLS recursive bivariate ordered probit model, which simultaneously estimates the two equations adopting an ordered probit approach, given the categorical nature of both the outcome and treatment variables [54, 55]. The recursive bivariate probit is a seemingly unrelated regression model with correlated disturbances, in which the dependent variable of the first equation appears on the right-hand-side of the second equation. The model is estimated by MLE. Greene [56] (p. 715–716) points out that in such a model the endogeneity of the RHS variable of the second equation could in principle be neglected because this term does not affect the maximization of the log-likelihood (differently from what it would be the case in a linear recursive model not estimated by MLE). We estimate this 2SLS recursive bivariate ordered probit model using the CMP procedure developed by Roodman [27] All our regressions are weighted, using a combined post-stratification and population size weight specified by the Eurobarometer for each respondent.

Since our instrument is measured at the national (or regional) level, the estimations are exposed to grouped structures [52] (p. 308–315). We therefore cluster our standard errors at the regional level when the instrumental variable is defined at this level of aggregation (see results in the appendix). On the other hand, when the instrumental variable is defined at the country level, it is more appropriate not to cluster standard errors due to the limited number of national groups in our data [57].

5. Results

First stage results and LATE analysis

Before presenting the estimation results for the first stage, we seek to shed further light on the variability of our instrumental variables. First, we further assess the assumption that the timing of the broadband Internet expansion does not co-vary with other factors that are correlated with the outcome variable life satisfaction. A2 Table presents the results of regressions in which the dependent variable is the annual growth rate of the instrumental variable, and the RHS variables are the country average of the control variables at the beginning of the period. A2 Table shows that the timing of broadband Internet expansion is uncorrelated with the set of control variables that supposedly affect life satisfaction (e.g. education, occupation type, gender, age, marital status, financial situation, unemployment).

In A3 Table, we report the results of some balancing regressions (OLS), in which the dependent variables are the main socio-economic control variables in the model (income status, education, unemployment), and on the RHS we include future broadband take-up (in addition to lagged take-up and other control variables). The results indicate that the estimated coefficient for future take-up is not significant, ruling out further the possibility that broadband Internet expansion co-varies with other determinants of life satisfaction.

A4 Table presents the results of the first stage estimations (Eq 8), in which the dependent variable is the intensity of Internet use of each individual. The baseline results presented in the first column of A4 Table show that the control variables take the sign as expected based on previous literature on the determinants of adoption and use of the Internet [43, 44]. The table indicates that Internet use intensity decreases with age. It is higher for people in the workforce that have higher education level and white-collar occupations, and that report a good financial situation. Unemployed workers have lower Internet use intensity than average, arguably because they do not use the Internet for professional activities. Further, Internet use is on average higher for individuals that live in a large town as opposed to those in a rural area.

The most important finding in A4 Table is that the instrumental variable–lagged value of the country's fixed broadband take-up–is as expected positively and significantly related to Internet use intensity. We obtain the same result when the instrumental variable is defined at the regional level (see A2 Table). As explained in the previous section, this finding corroborates the importance of "peer effects" as a determinant of Internet use, i.e. based on the idea that an individual is more likely to adopt and actively use Internet if many other individuals in the same country (or region) have previously adopted and used it, due to social learning, social pressure and/or network externality effects [11, 25, 26].

Our first stage estimates have a local average treatment effects (LATE) interpretation [52]. They represent the effect of fixed broadband take-up on the sub-population of *compliers* in each country, i.e. individuals that intensify their Internet use when a larger number of individuals in that country have actively been using Internet in the previous two years. Following the approach used in recent papers [48, 50], we carry out an analysis of the characteristics of the complier group. In A5 Table, we report the estimated coefficients of the effect of the instrumental variable on Internet use intensity (first stage regressions using a linear IV model) for different age sub-groups.

The table shows that individuals that respond more actively to increases in fixed broadband infrastructures are middle-aged adults (between 25 and 54), and less so younger and older Internet users. The pattern for middle-aged age groups is reasonable, since individuals in this stage of life typically use fixed broadband Internet as a professional tool in their working life, as well as for a variety of different uses related to their family and social life. On the other hand, the result that younger individuals (15–24 years old) increase their Internet use only marginally when their peers do is somewhat surprising. A possible explanation of this pattern is that younger people in our sample are those that in the period 2010–2016 increasingly begun to use wireless mobile broadband, which gradually substituted the use of fixed broadband. Hence, it may simply be the case that our instrument (based on fixed broadband development) underestimates compliers effects for adolescents and young Internet users because it neglects the early phase of diffusion of mobile broadband.

Second stage results

A6 Table presents the results of the second stage (Eq 7), in which the dependent variable is the life satisfaction reported by each individual. We briefly discuss the results for the control variables first, before turning to the effect of the main variables of interest. The estimated results for the control variables are in line with extant research on the determinants of subjective well-being [1, 2, 4, 6]. A6 Table indicates that the relationship between age and life satisfaction is U-shaped, with lowest reported subjective well-being for middle-aged individuals. We will elaborate further on this U-shaped relationship later in this section. Among other control variables, highly educated individuals report higher life satisfaction than less educated people; unemployed individuals substantially lower satisfaction levels than employed people; and life satisfaction is higher for those individuals that have a good financial situation.

The top part of A6 Table reports the estimation results for the main variable of interest: Internet use intensity. This has a positive and significant effect on life satisfaction. Marginal effects of the Internet use variable, not reported here, are positive and significant too. The next columns in the table report some additional tests in order to assess the robustness of this result and the validity of our identification strategy. First, the second column of A6 Table includes an additional control variable–the country-level time trend of life satisfaction in the period before the broadband Internet expansion. The inclusion of this additional regressor does not change the result for the Internet use variable, which is still positive and significant. This rules out the possibility that the positive effect of Internet use on life satisfaction is driven by pre-existing trends in outcome (we have carried out the same test and obtained the same result for region-specific life satisfaction time trends).

Second, the third column reports the results of a placebo test, which tests whether Internet take-up at *t+1* affects current life satisfaction at time *t*. In this placebo regression, we exclude the Internet use variable and correspondingly include the lead value of the instrumental variable (i.e. measured one year *after* the life satisfaction and other control variables). The future broadband take-up variable is not significant in the estimations, ruling out the possibility that our results are driven by some omitted variables that are related to both life satisfaction and broadband Internet expansion.

Third, the fourth column of A6 Table includes an additional set of control variables, cohort effects, in order to test whether the U-shape relationship between age and well-being is a methodological artefact driven by the omission of cohort effects in life satisfaction regressions [38, 58]. The estimation results, though, are in line with the other findings in the Table: life satisfaction is U-shaped in age, and Internet has a direct positive effect on the dependent variable.

Finally, after presenting these robustness tests, we shift the focus to the point of our main interest: the moderation effects of Internet on the U-shaped relationship between age and well-being. We test these moderation effects by introducing two interaction terms in the regression model: (1) *Internet * age*; and (2) *Internet * age-squared*. The latter is the main interaction variable of our interest, providing a direct test of moderation effects of Internet use on the U-shape of life [53]. The fifth column of A6 Table reports the full model specification that includes such interaction terms. The estimated coefficient of the variable *Internet * age-squared* is positive and significant, confirming our hypothesis that Internet use moderates the U-shaped relationship between age and well-being. We also computed marginal effects of this interaction variable by comparing predicted probabilities for the two polar cases of Internet use (everyday vs. never) for different values of the age squared variable. In line with the estimated coefficient reported in A6 Table, the marginal effect of the interaction variable is positive and significant. The slope analysis reported below in this section will elaborate further on this result. A7 Table provides similar evidence by running the same 2SLS oprobit regressions separately for four sub-groups of individuals (15–24; 25–39; 40–54; 55+). The results confirm that the effects of Internet use on life satisfaction are positive and significant, but they vary substantially with age.

Moderation effects of Internet on the age-well-being relationship can have two forms: (1) Internet use can affect the location of the turning point of the U-shape–i.e. changing the time at which, on average, individuals begin to experience a recovery period after midlife crisis; and/or (2) Internet use can change the curvature of the U-shape, making it flatter or steeper–i.e. changing the speed at which individuals fall into midlife crisis and recover thereafter. From a conceptual point of view, the latter effect is more interesting and relevant than the former. However, the two effects are obviously related to each other, and we will therefore analyze them both.

A8, A9 and A10 Tables report the results of tests of these moderation effects. First, A8 Table presents the results of second-stage estimations for seven sub-samples, each defined by a distinct Internet use intensity (i.e. sub-sample 1 (sub-sample 7) only refers to those individuals that report no Internet use (highest Internet use)). The estimated coefficients for the age and age-squared variables in A8 Table indicate that the slope and curvature of the U-shape of life change as we move from lower to higher levels of Internet use intensity.

We calculated the turning points of the U-shape (i.e. age of midlife crisis) for the seven regressions reported in A8 Table. A9 Table reports the turning point for different levels of the Internet use intensity, and it shows that this moves towards the left as Internet use intensity increases (from around 53 to 50 years old), meaning that active Internet users, on average, begin a recovery period after the midlife crisis somewhat *earlier* than individuals who use Internet less actively.

A10 Table shifts the focus to the second type of moderation effect, which is the one of our main interest. The table reports the estimated slope of the U-shape at six different ages (25, 35, 45, 55, 65, 75 and 85) and for each Internet use intensity level (1 to 7). We also tested the slope difference for four different years around the turning point (following the method described in Haans et al. [53]: 1195). The slopes reported in A10 Table show a clear and consistent pattern. First, the slopes are as expected negative before the turning point and positive thereafter. Second, and more relevant, a comparison of the magnitudes of slopes between different Internet user groups shows that Internet use intensity makes the U-shaped relationship between age and life satisfaction *steeper*. This finding is also consistent with the positive sign of the estimated interaction effect *Internet * age-squared* previously reported in A6 Table. This means that Internet use accelerates the decline in life satisfaction that characterizes young adults and middle-aged individuals until the midlife crisis; and that it strengthens the subsequent growth and recovery period for older adults. After the turning point of the U-shape, active Internet users turn out to experience a much more pronounced and rapid recovery from the midlife crisis, reporting steadily increasing levels of life satisfaction.

6. Discussion

What can explain these empirical results? The simple theoretical framework outlined in section 3 points to the role of unmet aspirations [19, 22], and how these are affected by Internet use for different age groups. The main idea put forward in the model is twofold. First, the framework assumes that aspirations decrease over the life cycle, leading to optimism bias in the first part of life, and pessimism bias at older ages [21]. It is such decreasing trend of aspirations that explains a U-shaped relationship between age and well-being. Second, our model points out that if aspirations decline over time more rapidly for Internet users than non-users, Internet use would make the U-shape of life steeper (which is precisely the main empirical result that has been shown by the regression analysis above).

In our dataset, we are not able to empirically test these two properties of the model at the individual level (differently from Schwandt [19] who had available a panel dataset that enabled the test of this assumption). However, the Eurobarometer survey dataset has a few questions about individuals' expectations on their future life satisfaction that can be used to provide aggregate evidence on the relevance of unmet aspirations theory. Specifically, we have used the following four variables that can be constructed based on survey questions about individuals' expectations on how their life will be in the following 12 months: (1) life as a whole; (2) working life; (3) financial situation; (4) social life. Each variable is defined on a 1–3 scale (1: worse than today; 2: same as today; 3: better than today). Since our dataset is not a panel, we are not able to match individuals' responses to the life satisfaction and expectations questions at time t (which would provide a direct measure of unmet aspirations at the individual level). Instead, we have collapsed these four expectation variables at the country-level, and calculated their average for different age groups and different Internet users groups, in order to provide aggregate evidence on the relationships between expectations, life satisfaction and Internet use.

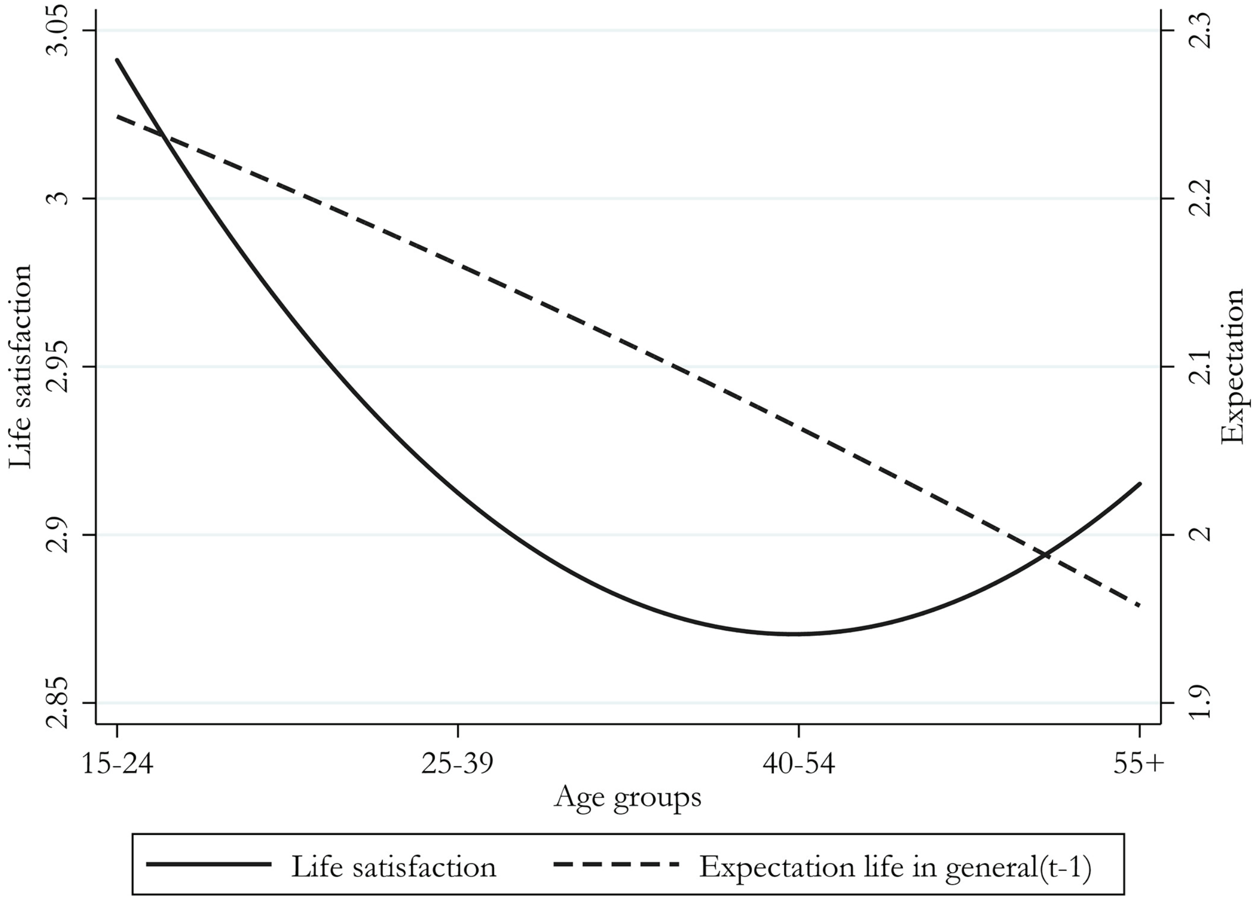

Fig 2. Aggregate life satisfaction and expectations, by age group.

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Fig 2 shows the trend of life satisfaction and expectations about life as a whole for four different age groups. The graph shows that expectations are on average higher for younger age groups, and decrease progressively for older age groups. The expectation line is above 2 (indicating that individuals do on average expect a better life in the future) until about the age group 40–54, and it then goes below 2 thereafter (indicating expectations of a worse future). This evidence is in line with the model's main assumption that the aspiration variable (here proxied by expectations about the future) decreases over time, shifting from optimism bias to pessimism bias throughout the life cycle (see Eq 3, in section 3). This pattern is consistent with the main idea and recent empirical evidence on unmet aspiration theory [19, 21, 59].

Fig 3 depicts the trends of expectations for different age groups, and comparing active Internet users to less active (or sporadic) users. The four panels in Fig 3 focus on expectations about life as a whole, working life, financial situation and social life, respectively. These figures consistently illustrate two patterns. The first is that, for all age groups, Internet users have on average higher expectations than non-users. This is in line with recent literature suggesting that Internet increases aspirations [12, 13, 60]. The second pattern is that in all four figures the expectation variable decreases with age, and this decline is relatively steeper for active Internet users than for sporadic users. This is consistent with the main property of our model that

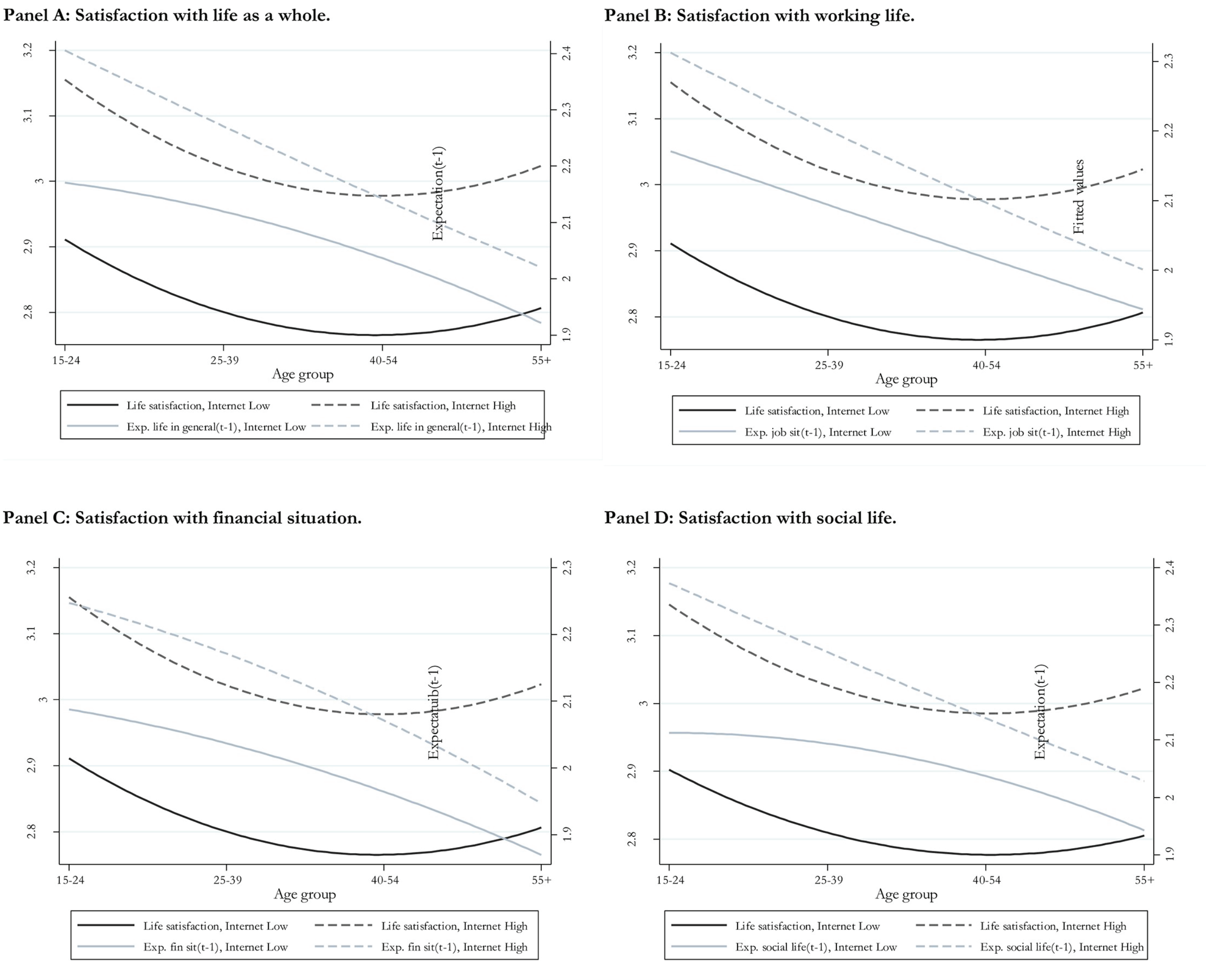

Fig 3. Aggregate life satisfaction and expectations, by age group and Internet users group. Panel A: Satisfaction with life as a whole. Panel B: Satisfaction with working life. Panel C: Satisfaction with financial situation. Panel D: Satisfaction with social life.

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Internet use affects aspirations more strongly for individuals in younger and in older age groups (see Eq 8, in section 3).

Further, the figures also show that the point at which the life satisfaction curve meets the expectation line comes earlier for Internet users than for non-users. This point indicates the stage at which expectations begin to be lower than realized life satisfaction, and hence when optimism bias of younger ages is substituted by pessimism bias typical of older life stages. On the whole, this evidence is consistent with the main properties of the model presented in section 3, suggesting that the effects of Internet on the U-shape of life can be explained in terms of aspiration effects and their evolution over the life cycle. Further, comparing the four panels in Fig 3, it is interesting to observe the remarkable similarities between the patterns for life satisfaction as a whole, working life, financial conditions and social life. The latter domain (Fig 3, panel D) is the one for which Internet use seems to have stronger effects on aspiration levels. However, the overall pattern emerging from these four diagrams is basically the same.

To corroborate this interpretation, it would be interesting to analyze more specifically the type of activities that individuals carry out on the Internet, and the extent to which these are related to their aspirations and subjective well-being. In our econometric analysis, we are not able to investigate this point because information about different types of Internet activities is not available for the Eurobarometer surveys that we have used to construct our dataset. However, we can provide some descriptive evidence based on only some of the Eurobarometer surveys, which asked individuals the extent to which they use Internet to communicate through social networks, and to watch TV online. Previous research suggests that these two online activities can affect individuals' aspirations. A11 Table shows the share of respondents that use social networks and TV streaming, and the expectations that these respondents report about their life satisfaction in the future. In line with our theoretical framework, the table indicates that active users of online social networks and of TV streaming are much more likely to have higher aspirations about their life satisfaction in the future than to expect a worsening of their life satisfaction.

Other explanations

Could our empirical result of a moderation effect of Internet on life satisfaction be explained by a different mechanism that is not related to unmet aspirations? According to the model presented in section 3, this is theoretically possible. As noted above in relation to Eq 6, it would in fact be possible to assume that life satisfaction related to one given domain of life changes over the life cycle following a non-monotonic relationship, thus generating a U-shaped relationship between age and well-being (even in the absence of forecast errors and unmet aspirations).

Let us consider three main domains of life and three possible alternative explanations of our empirical results. First, let us consider income conditions and the consumption domain. Can consumption patterns explain the U-shape of life? According to extant research, the answer is no. Empirical research consistently shows that lifetime consumption patterns follow an *inverted* U-shape, with a maximum around midlife [61]. Internet may facilitate financial transactions and foster online consumption, but it is not reasonable to think that the utility derived from digital consumption may be such to generate a U-shape of life for active Internet users (other things being equal). Hence, we think that this first explanation is not plausible.

Second, shifting the focus to the social life domain, it would be possible to think that individuals value this differently throughout the life cycle. Social life could be regarded as an important dimension of life satisfaction at younger ages, less important during midlife (when many individuals shift their focus to working life and career objectives), and then becoming again more important at later stages of life. If the use of Internet facilitates social life activities (e.g. through social media and online communication platforms), this mechanism would be consistent with the empirical pattern that we have pointed out in the previous section, namely a steeper U-shape of life for active Internet users.

Third, focusing on working life, one could assume that this domain is a source of stress and responsibilities for individuals, and that these unpleasant effects are relatively stronger during midlife than at earlier and later phases of life. Further, an intensive working life does by definition reduce leisure time devoted to social life. This argument would also generate a U-shape between age and well-being. The empirical evidence available up to date indicates that Internet use for professional purposes leads to time-saving effects at work, and that it may also increase employees' autonomy and flexibility [8]. Hence, this argument would also be consistent with our main empirical result, since the use of Internet at work may potentially improve life satisfaction and free time to be devoted to more rewarding leisure and social activities.

We think that the two possible explanations noted here (focusing on social life and working life respectively) are both consistent with the empirical result pointed out in this paper, and that they may arguably represent additional mechanisms that can explain moderation effects of Internet on the U-shape of life–in addition to the main explanation that we have focused on in this paper based on unmet aspirations theory. These possible mechanisms explaining the effects of Internet on the U-shape of life should be analyzed further and empirically tested in future research.

7. Conclusions

Empirical research has consistently shown that the relationship between age and life satisfaction is U-shaped. The present study has investigated whether, and the extent to which, Internet use moderates the U-shape of life. According to recent research [19, 22], one possible explanation of the U-shape relationship is related to unmet aspirations, pointing out that individuals make systematic forecast errors when they form expectations about future life satisfaction, and that these errors indicate optimism bias at early stages of life, and pessimism bias at older ages. Since unmet aspirations depress life satisfaction for younger individuals, and, by contrast, unexpected well-being fosters life satisfaction for older people, this theory can explain the U-shape pattern that has been observed and confirmed in previous empirical studies.

The present paper takes this theory as a conceptual framework, and it extends it by investigating the effects of Internet use. Our main proposition is that Internet tends to increase aspirations, and that this effect will be stronger for more vulnerable age groups, such as younger individuals and older adults. Internet use would thus make the U-shape relationship steeper, i.e. exacerbating optimism bias for the younger and pessimism bias for the older.

To empirically investigate this proposition, we used the Eurobarometer surveys for the years 2010 to 2016, and exploited exogenous variation in broadband Internet take-up across European countries and regions to identify the causal effects of Internet use on well-being for different age groups. The results of 2SLS bivariate ordered probit estimations are twofold. First, Internet use has a positive and significant effect on subjective well-being. Second, Internet use does also moderate the U-shaped relationship between age and well-being by making it steeper. Specifically, we find that Internet users experience a more pronounced decrease in reported life satisfaction in their younger adult life, and then an earlier and stronger recovery after the turning point (midlife crisis).

According to our model, the interpretation of this result is related to the effects of Internet on individuals' aspirations, and how these effects differ for distinct age groups. As noted above, our dataset does not enable to carry out a proper empirical test of unmet aspirations theory at the individual level. However, we have reported aggregate (country-level) evidence showing that our empirical results are consistent with the main predictions of the unmet aspirations model. This evidence shows in fact that: (1) aspirations decline over the life cycle; (2) active Internet users have on average higher aspirations than less active users; (3) the effect of Internet use on aspirations is stronger for younger and older groups. In short, this aggregate evidence corroborates an unmet aspirations explanation of our econometric results.

However, as discussed above, it is also important to acknowledge that the U-shape of life could in principle be explained by other mechanisms, such as e.g. changing preferences and values over the life cycle. Therefore, we cannot rule out the possibility that our econometric results on the moderation effects of Internet may be explained not only by aspiration-related patterns, but also by age-specific effects of Internet in specific domains of life. This calls for further research investigating how the effects of Internet on well-being vary with age, employing individual-level data and variables that enable a test of different possible explanations.

Although the focus of this paper has been on age-specific patterns of Internet use and well-being, our findings may in principle also have relevance for the study of income-specific patterns, which affect the relationship between aspirations and well-being [62]. In particular, our study may be related to the emerging literature on aspirations and poverty. Dalton et al. [63] shows that poverty strengthens the effects of the behavioral bias that leads to aspirations failure. It is reasonable to think that poor people, which have now increasing access to internet, may for this reason raise their aspirations, and therefore increase their aspiration failure even further. The study of Internet use may thus be a relevant dimension to extend the literature on aspirations and poverty in future research.

By empirically showing that the effects of Internet are remarkably heterogeneous among individuals of different ages, the present work has also some important implications for policy. Digitalization is currently a recurrent theme of societal debate, and an important objective for policy. Many countries are actively investing large amounts of public resources to foster digitalization through Internet access and infrastructures (see e.g. the EU Digital Agenda program that has been considered in this paper). However, research-based evidence on how these policies affect different socio-demographic groups of the population is still limited. Our empirical findings indicate that the effects of increased access to Internet may be particularly positive for the well-being of older adults, and much less so for younger age individuals. For the latter, it is therefore important that digital infrastructures policies are combined with the development of appropriate regulations, ethical standards and education policies that may mitigate the risks for younger Internet users.

Supporting information

S1 File. Online appendix: Results for region-level instrument.
(DOCX)

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References

1. Frey B. S., & Stutzer A. (2002). What can economists learn from happiness research? *Journal of Economic Literature*, 40(2): 402–435.
2. Senik C. (2005). Income distribution and well-being: what can we learn from subjective data? *Journal of Economic Surveys*, 19(1): 43–63.
3. Clark A. E., Frijters P., & Shields M. A. (2008). Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles. *Journal of Economic Literature*, 95–144.
4. Dolan P., Peasgood T., & White M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology*, 29(1): 94–122.
5. Kahneman D. and Deaton A. (2010). High income improves evaluation of life but not emotional well-being. *Proceedings of the National Academy of Sciences*, 107(38): 16489–16493.
6. MacKerron G. (2012). Happiness economics from 35 000 feet. *Journal of Economic Surveys*, 26(4): 705–735.
7. Algan Y., Murtin F., Beasley H., Higa K. and Senik K. (2019). Well-being through the lens of the internet. *PLOS ONE*, 14(1): e0209562. https://doi.org/10.1371/journal.pone.0209562 PMID: 30633759
8. Castellacci F. and Tveito V. (2018). Internet Use and Well-being: A Survey and a Theoretical Framework. *Research Policy*, 47: 308–325.
9. Kavetsos G. and Koutroumpis P. (2011). Technological affluence and subjective well-being. *Journal of Economic Psychology*, 32(5): 742–753.
10. Graham C., & Nikolova M. (2013). Does access to information technology make people happier? Insights from well-being surveys from around the world. *Journal of Socio-Economics*, 44: 126–139.
11. Pénard T., Poussing N., and Suire R. (2013). Does the Internet make people happier?. *The Journal of Socio-Economics*, 46: 105–116.
12. Lohmann S. (2015). Information technologies and subjective well-being: does the Internet raise material aspirations? *Oxford Economic Papers*, 67(3): 740–759.
13. Sabatini, F. and Sarracino, F. (2016). Keeping up with the e-Joneses: Do online social networks raise social comparisons?. MPRA Working Paper 69201.
14. McDool, E., Powell, P., Roberts, J. and Taylor, K. (2016). Social Media Use and Children's Wellbeing. IZA Discussion Paper 10412.
15. Rotondi, V., Stanca, L., & Tomasuolo, M. (2016). Connecting Alone: Smartphone Use, Quality of Social Interactions and Well-being. DEMS Working Paper 357.
16. Sabatini F. and Sarracino F. (2017). Online networks and subjective well-being. *Kyklos*, 70(3): 456–480.
17. Blanchflower D. and Oswald A. (2004). Well-being over time in Britain and the USA. *Journal of Public Economics*, 88: 1359–1386.
18. Blanchflower D. and Oswald A. (2008). Is well-being U-shaped over the life cycle? *Social Science & Medicine*, 66: 1733–1749.
19. Schwandt H. (2016). Unmet aspirations as an explanation for the age U-shape in wellbeing. *Journal of Economic Behavior and Organization*, 122: 75–87.
20. Sharot T., Riccardi A., Raio M.C. and Phelps E.A. (2007). Neural mechanisms mediating optimism bias. *Nature*, 450 (1): 102–106.
21. Bertoni M. and Corazzini L. (2018). Asymmetric affective forecasting errors and their correlation with subjective well-being. *PLOS ONE*, March 2018: 1–22.
22. Deaton A. (2018). What do self-reports of wellbeing say about life-cycle theory and policy? *Journal of Public Economics*, 162: 18–25. https://doi.org/10.1016/j.jpubeco.2018.02.014 PMID: 30220744
23. Kross E., Verduyn P., Park J., Lee D.S., Lin N., Shablack H., et al. (2013). Facebook use predicts declines in subjective well-being in young adults. *PLOS ONE*, 8: 1–6.
24. EC (2014). Study on National Broadband Plans in the EU-28. Final Report, European Commission.
25. Goolsbee A. and Klenow P. (2002). Evidence on learning and network externalities in the diffusion of home computers. *Journal of Law and Economics*, XLV: 317–343.
26. Agarwal R., Animesh A. and Prasad K. (2009). Social Interactions and the "Digital Divide": Explaining Variations in Internet Use. *Information Systems Research*, 20(2): 277–294.
27. Roodman D. (2011). Fitting fully observed recursive mixed-process models with cmp. *The Stata Journal*, 11(2): 159–206.

28. Jackson L.A., Fitzgerald H.E., Zhao Y., Kolenic A., Von Eye A., Harold R. (2008), Information Technology (IT) use and children's psychological well-being. *Cyberpsychology Behavior*, 11(6): 755–757. https://doi.org/10.1089/cpb.2008.0035 PMID: 18991532

29. Radovic A., Gmelin T., Stein B. and Miller E. (2017). Depressed adolescents' positive and negative use of social media. *Journal of Adolescence*, 55: 5–15. https://doi.org/10.1016/j.adolescence.2016.12.002 PMID: 27997851

30. Arad, A., Barzilay, O. and Perchick, M. (2017). The impact of Facebook on social comparison and happiness: Evidence from a natural experiment. SSRN paper.

31. Arampatzi E., Burger M. and Novik N. (2018). Social network sites, individual social capital and happiness. *Journal of Happiness Studies*, 19: 99–122.

32. Chen Y., Persson A. (2002). Internet use among young and older adults: relation to psychological well-being. *Educational Gerontology*, 28(9): 731–744.

33. Ford G.S., Ford S.G. (2009). Internet use and depression among the elderly. Phoenix Center Policy Paper.

34. Lelkes O. (2013). Happier and less isolated: internet use in old age. *Journal of Poverty and Social Justice*, 21: 33–46.

35. Ahmed R., Kesavayuth D. and Zikos V. (2018). Does being smarter make you happier? Evidence from Europe. *Journal of Behavioral and Experimental Economics*, 76: 55–67.

36. Blanchflower D. and Oswald A. (2009). The U-shape without controls: A response to Glenn. *Social Science & Medicine*, 69: 486–488.

37. Hellevik O. (2017). The U-shaped age-happiness relationship: real or methodological artifact? *Quality and Quantity*, 51: 177–197.

38. Frijters P. and Beatton T. (2012). The mystery of the U-shaped relationship between happiness and age. *Journal of Economic Behavior & Organization*, 82: 525–542.

39. Soroka S. (2006). Good news and bad news: Asymmetric responses to economic information. *Journal of Politics*, 68 (2): 372–385.

40. Garz M. (2013). Unemployment expectations, excessive pessimism, and news coverage. *Journal of Economic Psychology*, 34: 156–168.

41. Castellacci F. (2010). Structural change and the growth of industrial sectors: Empirical test of a GPT model. *Review of Income and Wealth*, 56(3): 449–482.

42. Kiiski S. and Pohjola M. (2002). Cross-country diffusion of the Internet. *Information Economics and Policy*: 297–310.

43. Chinn M. and Fairlie R. (2006). The determinants of the global digital divide: A cross-country analysis of computer and internet penetration. *Oxford Economic Papers*, 59: 16–44.

44. Gruber H., Hatonen J. and Koutrompis P. (2014). Broadband access in the EU: An assessment of future economic benefits. *Telecommunications Policy*, 38: 1046–1058.

45. Cambini C. and Jiang Y. (2009). Broadband investment and regulation: A literature review. *Telecommunications Policy*, 33: 559–574.

46. Czernich N., Falck O., Kretschmer T. and Woessmann L. (2011). Broadband infrastructure and economic growth. *Economic Journal*, 121: 502–532.

47. Bhuller M., Havnes T., Leuven E. and Mogstad M. (2013). Broadband Internet: An Information Superhighway to Sex Crime? *Review of Economic Studies*, 80: 1237–1266.

48. Bauernschuster S., Falck O. and Woessmann L. (2014). Surfing alone? The internet and social capital: Evidence from an unforesseable technological mistake. *Journal of Public Economics*, 117: 73–89.

49. Falck O., Gold R. and Heblich S. (2014). E-lections: Voting Behavior and the Internet. *American Economic Review*, 104(7): 2238–2265.

50. Akerman A., Gaarder I. and Mogstad M. (2015). The skill complementarity of broadband Internet. *Quarterly Journal of Economics*, 1781–1824.

51. Angrist J. and Pischke J. (2009). *Mostly Harmless Econometrics*: *An Empiricist's Companion*, Princeton University Press, Princeton and Oxford.

52. Haans R., Pieters C. and He Z-L. (2016). Thinking About U: Theorizing and Testing U- and Inverted U-Shaped Relationships in Strategy Research. *Strategic Management Journal*, 37: 1177–1195.

53. Monfardini C. and Radice R. (2008). Testing Exogeneity in the Bivariate Probit Model: A Monte Carlo Study. *Oxford Bulletin of Economics and Statistics*, 70 (2): 271–282.

54. Sajaia Z. (2008). Maximum likelihood estimation of a bivariate ordered probit model: Implementation and Monte Carlo simulations. *The Stata Journal*, 4(2): 1–18.

55. Greene W. (2003). Econometric Analysis. Fifth Edition, Upper Saddle River, N.J., Prentice Hall.
56. Cameron A. and Miller D. (2015). A Practitioner's Guide to Cluster- Robust Inference. *The Journal of Human Resources*, 50(2): 317–372.
57. De Ree J. and Alessie R. (2011): Life satisfaction and age: Dealing with underidentification in age-period-cohort models. *Social Science and Medicine*, 73: 177–182. https://doi.org/10.1016/j.socscimed.2011.04.008 PMID: 21664739
58. Deaton A. (2013). Through the darkness to a brighter future. In Palacios-Huerta I. (ed.), 100 Years: Leading Economists Predict the Future, MIT Press, London.
59. Schwabe, H. (2018). Internet use and expectation formation over the life cycle, TIK Working Paper.
60. Ponthiere G. (2016). Lifetime Well-Being, Mortality Risk, and Public Policy. In Adler M. and Fleurbaey Marc (eds.), *Oxford Handbook of Well-being and Public Policy*, Oxford University Press.
61. Proto E., and Rustichini A. (2015). Life satisfaction, income and personality. *Journal of Economic Psychology*, 48: 17–32.
62. Dalton P. S., Ghosal S., and Mani A. (2016). Poverty and aspirations failure. *The Economic Journal*, 126(590): 165–188.
63. Kahneman D. and Krueger A. B. (2006). Developments in the measurement of subjective well-being. *Journal of Economic Perspectives*, 20(1): 3–24.

Internet, unmet aspirations and the U-shape of life

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Supporting information.

Online appendix: Results for region-level instrument

Table A.1. Descriptive statistics.

	Mean	St.dev.	Min	Max	Obs
Life satisfaction	2.92	0.81	1	4	139,865
Internet use	5.46	2.25	1	7	139,865
Age	47.18	18.15	15	99	139,865
Women	0.52	0.50	0	1	139,865
House/apartment ownership	0.74	0.44	0	1	139,865
Up to 15 years of education	0.25	0.43	0	1	139,865
16-19 years of education	0.43	0.50	0	1	139,865
20+ years of education	0.32	0.47	0	1	139,865
Unemployment	0.10	0.30	0	1	139,865
Divorced	0.07	0.26	0	1	139,865
Widow	0.08	0.28	0	1	139,865
Living in a rural area or village	0.33	0.47	0	1	139,865
Living in a small/middle sized town	0.39	0.49	0	1	139,865
Living in a large town	0.28	0.45	0	1	139,865
White-collar	0.36	0.48	0	1	139,865
Blue-collar	0.14	0.35	0	1	139,865
HH broadband connection	0.72	0.13	0.20	0.95	139,865

Table A.2. Timing of broadband Internet variation.

	2012	2013	2014	2015	2016
Education level	0.017	-0.028	-0.006	-0.051*	0.015
Women	0.014	0.088	0.032	-0.005	-0.009
Urbanization	0.002	0.022	-0.008	0.011	0.012
Unemployment	-0.254	0.105	0.045	-0.003	0.131
Age	-0.000	0.004*	0.000	0.003	0.002
House/apartment ownership	0.004	-0.051	-0.074	-0.016	-0.062*
Divorces	-0.149	-0.356**	-0.440**	-0.312**	-0.155
Widowers	-0.060	0.069	0.093	-0.222	0.172
Blue-collar jobs	-0.027	0.096	-0.004	0.036	-0.030
White-collar jobs	-0.229	0.240**	0.100	-0.062	0.037

Note: The table reports estimated coefficients from regressions of the annual growth rate of broadband Internet for the years 2012 to 2016 on the level of covariates. The regression is based on a panel of 598 region-year observations.
* p<0.10; ** p<0.05; *** p<0.01

Table A.3. Balancing regressions.

	Financial situation	Education	Unemployment
HH broadband connection t-1	-0.014	-0.099	-0.036
	(0.072)	(0.107)	(0.037)
HH broadband connection t+1	0.113	0.064	-0.173***
	(0.105)	(0.110)	(0.049)

The table reports the estimated coefficients of lagged and lead broadband Internet take-up in three balancing regressions. These regress the dependent variables financial situation, education and unemployment, respectively, on the set of covariates included in the model plus the lead and lagged instruments. Heteroskedasticity-robust standard errors in parentheses. All regressions include a full set of control variables, time dummies and country fixed effects. * p<0.10; ** p<0.05; *** p<0.01.

Table A.4. First stage results. Baseline estimations and balancing tests.

	Baseline	Balancing test
HH broadband connection t-1	0.789***	0.792***
	(0.217)	(0.214)
Age	-0.045***	-0.045***
	(0.008)	(0.008)
Age squared	-0.000***	-0.000***
	(0.000)	(0.000)
Women	-0.096***	-0.095***
	(0.020)	(0.020)
House/apartment ownership	0.209***	0.211***
	(0.022)	(0.022)
16-19 years of education	0.638***	0.639***
	(0.070)	(0.070)
20+ years of education	1.177***	1.178***
	(0.069)	(0.069)
Unemployment	-0.308***	-0.308***
	(0.039)	(0.039)
White-collar job	0.501***	0.499***
	(0.068)	(0.068)
Blue-collar job	-0.083*	-0.082
	(0.049)	(0.049)
Divorced	-0.000	-0.000
	(0.036)	(0.036)
Widowed	-0.558***	-0.558***
	(0.047)	(0.047)
Living in a rural area or village	-0.182***	-0.183***
	(0.023)	(0.023)
Living in a large town	0.165***	0.166***
	(0.021)	(0.021)
_cons	6.518***	6.519***
	(0.214)	(0.218)
N	139,865	139,865
F-value (instrument)	13.22	

Robust standard errors clustered at the NUTS1 level in parentheses. The second column include a full set of controls that was averaged and lagged over region-years (i.e. $\overline{x'_{r,t}}$, and $\overline{x'_{r,t-1}}$) time dummies and region fixed effects. In additional regressions not reported here, we have also added country-level growth rates of all covariates. In additional regressions not reported here, we have also added country-level growth rates of all covariates. In additional regressions not reported here, we have also added country-level growth rates of all covariates. * p<0.10; ** p<0.05; *** p<0.01.

Table A.5. LATE results: compliers for different age groups.

		P[X=x]	Coefficient of HH broadband connection
Age groups			
	Young (15-24)	0.092	1.205**
	Younger adults (25-39)	0.226	1.900***
	Middle-aged (40-54)	0.259	1.721***
	Older adults (55+)	0.423	0.194

Note: Column 1 reports the relative shares of each age group of the total sample. The second column reports the first stage coefficients on our instrument. The regressions include time and region dummies. * p<0.10; ** p<0.05; *** p<0.01.

Table A.6. Second stage results. Baseline estimations.

	Baseline	Pre-reform trend	Placebo	Cohort	Full model
Internet use	0.059***	0.059***		0.072***	0.120***
	(0.006)	(0.006)		(0.007)	(0.029)
Internet use X age					-0.004
					(0.003)
Internet use X age squared					0.000**
					(0.000)
Age	-0.043***	-0.043***	-0.045***	-0.042***	-0.047***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.012)
Age squared	0.000***	0.000***	0.000***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Women	0.029***	0.029***	0.024***	0.033***	0.049***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.009)
House/apartment ownership	0.198***	0.198***	0.208***	0.189***	0.163***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.025)
16-19 years of education	0.022	0.022	0.060***	0.024	-0.075
	(0.016)	(0.016)	(0.019)	(0.016)	(0.048)
20+ years of education	0.179***	0.179***	0.249***	0.182***	0.016
	(0.019)	(0.019)	(0.022)	(0.020)	(0.087)
Unemployment	-0.518***	-0.518***	-0.532***	-0.486***	-0.445***
	(0.021)	(0.021)	(0.022)	(0.020)	(0.030)
White-collar job	0.077***	0.078***	0.108***	0.109***	0.103**
	(0.015)	(0.015)	(0.015)	(0.016)	(0.052)
Blue-collar job	-0.091***	-0.091***	-0.097***	-0.054***	-0.034
	(0.017)	(0.017)	(0.017)	(0.018)	(0.021)
Divorced	-0.285***	-0.285***	-0.285***	-0.287***	-0.291***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
Widowed	-0.251***	-0.251***	-0.281***	-0.238***	-0.101**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.040)
Living in a rural area or village	0.017	0.018	0.006	0.014	0.036**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.018)
Living in a large town	-0.002	-0.002	0.007	-0.009	-0.021
	(0.016)	(0.016)	(0.017)	(0.016)	(0.018)
Pre-reform trend in life satisfaction (linear)		-0.022			
		(0.064)			
HH broadband connection t-1			0.013		
			(0.261)		

HH broadband connection t+1			0.672 (0.419)		
N	139,865	139,865	137,978	139,865	139,865
Atanhrho	0.016 (0.015)			-0.007 (0.015)	

Robust standard errors clustered at the NUTS1 level in parentheses. All regressions include time dummies and region fixed effects. * p<0.10; ** p<0.05; *** p<0.01.

Table A.7. Second stage results. Separate estimations for different age groups.

	15-24	*25-39*	*40-54*	*55+*
Internet use	0.087***	0.033***	0.016	0.038***
	(0.023)	(0.013)	(0.010)	(0.009)
Women	-0.023	0.065***	0.058***	0.012
	(0.024)	(0.015)	(0.014)	(0.012)
House/apartment ownership	0.185***	0.164***	0.208***	0.211***
	(0.030)	(0.023)	(0.026)	(0.021)
16-19 years of education	-0.048	0.029	0.077**	0.098***
	(0.050)	(0.038)	(0.030)	(0.021)
20+ years of education	-0.049	0.218***	0.260***	0.276***
	(0.066)	(0.041)	(0.042)	(0.031)
Unemployment	-0.606***	-0.461***	-0.377***	-0.511***
	(0.064)	(0.038)	(0.030)	(0.030)
White-collar job	-0.114**	0.139***	0.322***	0.035
	(0.056)	(0.032)	(0.034)	(0.027)
Blue-collar job	-0.183***	-0.054	0.120***	-0.138***
	(0.067)	(0.035)	(0.029)	(0.021)
Divorced	-0.235*	-0.371***	-0.292***	-0.286***
	(0.136)	(0.034)	(0.023)	(0.019)
Widowed	0.154	-0.353***	-0.321***	-0.151***
	(0.212)	(0.102)	(0.040)	(0.016)
Living in a rural area or village	0.077***	0.033	0.001	-0.008
	(0.029)	(0.021)	(0.016)	(0.016)
Living in a large town	0.009	0.022	-0.032	-0.012
	(0.030)	(0.022)	(0.028)	(0.019)
N	12863	31645	36210	59147

Robust errors clustered at the NUTS1 level in parentheses. All regressions include time dummies and region fixed effects. * p<0.10; ** p<0.05; *** p<0.01.

Table A.8. Second stage results. Separate estimations for different Internet use groups.

	No access	*Never use*	*Less often*	*2-3 times a month*	*About once a week*	*2-3 times a week*	*Every day*
Age	-0.029***	-0.024***	-0.036***	-0.045***	-0.041***	-0.047***	-0.051***
	(0.007)	(0.005)	(0.012)	(0.017)	(0.010)	(0.005)	(0.003)
Age squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Women	0.051	0.035**	0.077*	0.051	0.130***	0.017	0.030***
	(0.032)	(0.018)	(0.046)	(0.066)	(0.044)	(0.020)	(0.009)
Financial situation	0.251***	0.173***	0.054	0.149*	0.130**	0.186***	0.210***
	(0.037)	(0.025)	(0.058)	(0.084)	(0.054)	(0.034)	(0.021)
16-19 years of education	0.175***	0.110***	0.105*	0.102	0.023	0.073**	-0.068***
	(0.034)	(0.021)	(0.062)	(0.079)	(0.060)	(0.031)	(0.024)
20+ years of education	0.385***	0.275***	0.239**	0.205**	0.047	0.177***	0.104***
	(0.042)	(0.029)	(0.094)	(0.103)	(0.077)	(0.039)	(0.027)
Unemployment	-0.436***	-0.411***	-0.522***	-0.431***	-0.265***	-0.559***	-0.504***
	(0.043)	(0.034)	(0.077)	(0.123)	(0.084)	(0.055)	(0.028)
White-collar job	0.146**	0.176***	0.276***	0.087	0.175***	0.086**	0.106***
	(0.063)	(0.041)	(0.071)	(0.101)	(0.063)	(0.039)	(0.023)
Blue-collar job	0.026	0.004	-0.026	0.060	0.024	-0.111***	-0.075***
	(0.055)	(0.029)	(0.067)	(0.109)	(0.079)	(0.034)	(0.027)
Divorced	-0.223***	-0.282***	-0.358***	-0.183	-0.342***	-0.314***	-0.299***
	(0.044)	(0.029)	(0.075)	(0.113)	(0.075)	(0.033)	(0.020)
Widowed	-0.140***	-0.176***	-0.208**	-0.166	-0.255***	-0.253***	-0.337***
	(0.031)	(0.020)	(0.094)	(0.104)	(0.067)	(0.053)	(0.028)
Living in a rural area or village	0.031	0.038	0.084	0.024	-0.004	0.027	0.015
	(0.041)	(0.025)	(0.054)	(0.092)	(0.060)	(0.030)	(0.013)
Living in a large town	-0.025	-0.050**	-0.136*	-0.042	-0.126*	-0.017	0.012
	(0.055)	(0.024)	(0.081)	(0.104)	(0.072)	(0.034)	(0.017)
N	9237	28738	2972	1697	3816	12418	80987

Heteroskedasticity-robust standard errors in parentheses. All regressions include time dummies and country fixed effects.
* p<0.10; ** p<0.05; *** p<0.01.

Table A.9. Moderation effects of Internet use on the location of turning point of U-shape.

Internet use intensity	Turning point of U-shape
No Internet access	50.76
Never use Internet	47.83
Less than 2-3 times per month	45.05
2-3 times per month	42.41
About once a week	39.91
2-3 times per week	37.52
Everyday	35.25

Table A.10. Moderation effects of Internet use on the U-shape curvature.

	Internet use category						
	1	*2*	*3*	*4*	*5*	*6*	*7*
Age							
25	-0.014	-0.012	-0.016	-0.021	-0.018	-0.023	-0.025
35	-0.009	-0.007	-0.009	-0.011	-0.008	-0.013	-0.014
45	-0.003	-0.002	-0.001	-0.001	0.001	-0.003	-0.004
55	0.003	0.003	0.007	0.009	0.010	0.007	0.007
65	0.009	0.008	0.015	0.019	0.020	0.017	0.018
85	0.020	0.018	0.030	0.038	0.039	0.036	0.039

A11 Table. Internet use activities (social networks; TV streaming) and expectations about future life satisfaction.

	Social networks			TV streaming		
Expectation: Life in general	*Worse*	*Same*	*Better*	*Worse*	*Same*	*Better*
Non-users	58 %	48 %	25 %	74 %	67 %	50 %
Active users	42 %	52 %	75 %	26 %	33 %	50 %

Second paper

Third paper

Fourth paper

Automation, workers' skills and job satisfaction

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Abstract

When industrial robots are adopted by firms in a local labor market, some workers are displaced and become unemployed. Other workers that are not directly affected by automation may however fear that these new technologies might replace their working tasks in the future. This fear of a possible future replacement is important because it negatively affects workers' job satisfaction at present. This paper studies the extent to which automation affects workers' job satisfaction, and whether this effect differs for high- versus low-skilled workers. The empirical analysis uses microdata for several thousand workers in Norway from the *Working Life Barometer* survey for the period 2016-2019, combined with information on the introduction of industrial robots in Norway from the International Federation of Robotics. Our identification strategy exploits variation in the pace of introduction of industrial robots in Norwegian regions and industries since 2007 to instrument workers' fear of replacement. The results indicate that automation in industrial firms in recent years have induced 40% of the workers that are currently in employment to fear that their work might be replaced by a smart machine in the future. Such fear of future replacement does negatively affect workers' job satisfaction at present. This negative effect is stronger for low-skilled workers, which are those carrying out routine-based tasks, and who are therefore more exposed to the risks of automation.

Key words: Automation; industrial robots; skills; fear of replacement; job satisfaction

1. Introduction

Industrial robotics and artificial intelligence (AI) have in the last few years increasingly been used in production activities. This has led to the automation of many tasks that were previously carried out by workers, and that can now be performed by smart machines. The fear that these technological advances may have dramatic consequences on the future of labor has fostered the recent development of new economics research studying the effects of automation on employment [1, 2]. Recent models and empirical evidence on this topic show that automation can have negative effects on employment demand and wages, and particularly so for workers that perform routine-based tasks that can more easily be displaced [3, 4]. On the other hand, however, these new technologies may also have positive effects by increasing productivity [5].

This recent research has so far focused on the effects of automation, industrial robots and artificial intelligence on labor demand and wages. However, while employment and wages are two central dimensions shaping individual workers' well-being, it is also important to point out that other non-pecuniary aspects do contribute to shape workers' well-being, and that automation may potentially have important impacts on these [6]. Specifically, if workers fear that their occupation might be replaced by a smart machine in the future, such prospect and uncertainty about future working conditions may arguably affect their job satisfaction at present [7, 8].

Why should we care about the impacts of automation on workers' job satisfaction? The reason is twofold. First, since individuals spend a substantial part of their life at work, job satisfaction experienced in working life does indeed represent an important component of individuals' overall subjective well-being [9]. Second, workers that are not happy and experience dissatisfaction with their job have typically lower motivation and efforts [10], and higher turnover rates. Therefore, if a large number of workers in the economy fear to be replaced by smart machines in the future, this fear may lead to mental stress and anxiety at present, as well as hamper productivity and innovation in the economy.

In spite of the relevance of this topic, to the best of our knowledge only two papers have recently explored the relationship between automation and workers' well-being. Abeliansky and Beulmann [11] focuses on workers' mental health in Germany; and Schwabe [12] studies workers' life satisfaction in a sample of European countries. Neither of these studies, though, investigates explicitly the impacts of automation on job satisfaction.

Further, these recent works do not study the role of workers' skills, and how these may affect the relationship between automation and well-being. The literature on automation and employment clearly shows that the effects of the introduction of industrial robots largely differ for high-skilled and low-skilled workers. It is therefore paramount to investigate whether the effects of automation on job satisfaction can have different effects on workers' well-being depending on their skill levels. In short, the question investigated in the present paper is the following: *Does automation affect workers' job satisfaction – and how does this effect differ for high- versus low-skilled workers?*

To study this question, it is useful to distinguish two related dimensions. The first side of the link between automation and job satisfaction is that the introduction of industrial robots in local labor markets will affect workers' expectations about their future jobs, i.e. it will lead some workers to fear that part of their working tasks might be replaced by a smart machine in the future. The second dimension is that these expectations about the future, and particularly the anticipated fear of replacement, will negatively affect workers' subjective well-being at present.

Empirically, we operationalize this idea by making use of a two-stage econometric model, in which fear of replacement and job satisfaction are the dependent variables of the first and the second stage, respectively. The empirical analysis uses microdata for several thousand workers in Norway from the *Working Life Barometer* survey (*Arbeidslivsbarometer*) (four annual surveys for the period 2016-2019), combined with information on the introduction of industrial robots in Norway from the *International Federation of Robotics* (IFR) dataset. Our identification strategy exploits variation in the pace of introduction of industrial robots in Norwegian regions and industries between 2007 and *t* (i.e. the time at which each of the four surveys was carried out).

The results indicate that automation in industrial firms in recent years has induced workers that are currently in employment to fear that their work might be replaced by a smart machine in the future, and that this effect is stronger for low-skilled workers. Further, our findings show that fear of future replacement does negatively affect workers' job satisfaction at present, and that such negative effect is stronger for low-skilled workers, which are those carrying out routine-based tasks, and who are therefore more exposed to the risks of automation.

On the whole, these results contribute to, and extend, the recent literature on automation and employment by shifting the focus to important nonpecuniary impacts that are reflected in workers' expectations, fears and job satisfaction, and showing that workers' skills is an important variable moderating the effects of automation on subjective well-being.

The paper is organized as followed. Section 2 reviews the literature on automation and employment. Section 3 points out the conceptual mechanisms that are relevant to explain the effects of automation on job satisfaction. Section 4 presents the data and indicators. Section 5 discusses the empirical methods. Section 6 presents the results. Section 7 concludes and discusses the main contributions and implications.

2. Literature

Effects of automation on employment and wages

Automation, industrial robotics and artificial intelligence have in the last few years experienced substantial advances and found an increasing number of applications in production activities. Artificial intelligence and robotics have developed as two distinct scientific and technological fields for a long time, and only recently they have converged and cross-fertilized [13]. Frank et al. [2] presents relevant illustrations of this recent convergence, and it discusses challenges for research on the economic effects of AI and automation. This has spurred the recent development of a strand of scholarly research studying the effects of these new technologies on employment.

A starting point of this literature is the canonical model of skilled bias [14], according to which new skilled-bias technologies lead to polarization and increasing differences in employment opportunities and wages between skilled and unskilled workers. Sachs and Kotlikoff [15] present a simple framework in which smart machines substitute directly for young unskilled labor, whereas they are complementary to older skilled workers. Young unskilled workers experience lower wages, which in turn lead to lower saving and investments in human and physical capital – thus perpetuating and strengthening the gap between young unskilled and older skilled workers over time.

Such pessimistic prediction on the future of employment is however not shared by other works in this field. Taking a long-run historical perspective, Autor [16] and Mokyr et al. [1] argue that, as in other times in history, technological progress will lead to major structural changes in the quantity and content of work, but it will arguably not lead to a complete substitution of capital for labor. Houseman [17] provides empirical evidence that, although manufacturing employment in the US has declined since early 2000s, this is mainly explained by international trade and global competition effects, and there is weak support in the data for the argument that such decrease in employment is due to automation. More recently, McGuinness et al. [18] and Klenert et al. [19] present empirical studies that indicate that automation technologies and industrial robots have actually positive effects on employment. On the one hand, automation leads to a creative destruction process that may on the whole increase the overall demand for labor. On the other hand, it may contribute to reduce routine-based working tasks, which are typically monotonous and physically straining, thus improving the quality of work.

A more nuanced perspective that considers both negative and positive effects of automation on employment is presented by studies of the job polarization hypothesis. In short, the main idea of this research is that automation technologies complement highly skilled labor, explaining its expansion and wage growth in recent years in most advanced countries. On the other hand, middle-skilled workers are those more negatively affected by routine-biased technical change, because their tasks are relatively easier to automate. As for low-skilled workers, and particularly those employed in personal services occupations, these often perform manual and personal communication tasks that are not that easy to automate yet. Hence, the resulting pattern is that middle-skilled workers have in recent years shifted towards low-skilled employment occupations, which have consequently grown and experienced higher wages. All in all, this explains the observed increasing polarization in the job market, with the growth of employment and wages for high- and low-skilled workers, and a corresponding decline for middle-skilled occupations [3, 4, 16, 20]. Beaudry et al. [21] argue however that the demand for high-skilled workers has declined after 2000 due to decreasing returns to investments in information and communication technologies (ICTs), and that high-skilled have then begun to compete for lower-skilled jobs. This study, though, is based on empirical evidence on ICT investments in general, and it does not focus specifically on the effects of AI and automation.

Acemoglu and Restrepo [22] present a theoretical framework that is useful to study both negative and positive effects of industrial robots on employment and wages. The model points out two contrasting effects of industrial automation: a *displacement* effect that negatively affects the demand for employment and the wages of workers that perform routine-based tasks; and a *productivity* effect that creates benefits for workers that perform non-routine tasks (in the automated sector as well as in other sectors and occupations of the economy). This study also presents empirical evidence that corroborates the model's predictions on the effects of industrial robots on employment and wages in US manufacturing industries between 1990 and 2007. In line with evidence presented by other recent works [5, 23, 24], their results show that overall the displacement (negative) effect of the introduction of industrial robots has until now been stronger than the productivity (positive) effect.

Effects of automation on job satisfaction

This recent strand of research has so far focused on the effects of automation, industrial robots and artificial intelligence on aggregate patterns of labor demand and wages for different countries and industries. However, research has not investigated yet the impacts that these new technologies may have on individual workers' subjective well-being. Do workers fear that their occupation might be replaced by a smart machine in the future, and if so how does that prospect affect their current job satisfaction?

Job satisfaction is the subjective well-being of workers (i.e. their own assessment of the well-being they experience at work). This is an obviously crucial dimension for economic analysis and policy. First, since individuals spend a substantial part of their life at work, job satisfaction experienced in working life represents an important component of individuals' overall subjective well-being. Second, workers that are not happy and experience dissatisfaction with their job have typically lower motivation and efforts, and higher turnover rates. This, in turn, weakens productivity and innovation in the economy.

The literature on job satisfaction is wide-ranging, and it has extensively investigated a variety of factors that explain why some individuals report higher subjective well-being than others [7, 8]. However, only a few studies have so far explicitly investigated the relationships between the widespread diffusion and application of digital technologies and job satisfaction [25]. Kaplan and Schulhofer-Wohl [6], using data from the American Time Use survey, discusses the nonpecuniary implications of changes in the occupational structure in the US in recent decades, i.e. the effects of these structural changes on different aspects of job satisfaction such as reported happiness, stress and meaning at work. The work indicates that the changing occupational structure has not only led to polarization in terms of skills and wages, but it has also determined substantial changes in workers' feelings about the job they have and the tasks they perform.

Two recent papers explore the relationship between automation and workers' well-being. Abeliansky and Beulmann [11] present an empirical study on the impact of automation on the mental health of workers (which is one important dimension reflecting stress and weak job satisfaction). The analysis uses individual-level data from the German Socioeconomic Panel for the period 2002-2014 linked to industry-level data on use of industrial robots in 21 manufacturing sectors in Germany. The results indicate that automation negatively affects workers' mental health, and this effect is related to the fear of having lower wages and worse economic conditions in the future.

Schwabe [12] makes use of worker-level data from the Eurobarometer survey for European countries (period 2012-2017) to investigate the relationships between fear of replacement and workers' subjective well-being (measured by life satisfaction, which is as well-known an evaluative dimension of individuals' well-being). The results of this study find that fear of replacement affects life satisfaction, but the direction of this effect does largely depend on age. In line with models of skill-bias and job polarization (see section 2.1), younger workers regard replacement as a possible threat to their job opportunities in the future, whereas older workers look at it as a positive technological development that is not likely to affect them directly, and that will arguably enhance well-being and prosperity in the society.

These two studies provide an important starting point for the present work. None of them, though, investigates explicitly the role of workers' skills, which is however a key dimension in the literature on the employment effects of automation briefly reviewed in section 2.1. In the job satisfaction literature too, education and skill levels represent one of the central factors affecting the job satisfaction of workers [26].

Two contrasting mechanisms link education and job satisfaction. On the one hand, a higher skill level increases the chances that an employee will have a higher wage level and a more interesting and rewarding job, which enhance job satisfaction. On the other hand, however, various empirical studies have found that – after controlling for income earnings – the correlation between education level and subjective well-being at work is negative [8, 27, 28]. This can be explained in the light of prospect theory [29]. When an individual invests more time in education and human capital formation, her expectations about the desired job will also be higher, and it will therefore be more likely that the worker will feel more critical and less satisfied with her actual working conditions if these high expectations are unmet. In particular, empirical research indicates that overqualified workers report significant lower levels of job satisfaction than others [26, 30].

3. Question and propositions

The question investigated in the present paper is the following: *Does automation affect workers' job satisfaction – and how does this effect differ for high- versus low-skilled workers?* The first part of the question refers to the main impact of automation on job satisfaction, which as noted above has not been analyzed in previous research yet. The second part of the question suggests that fear of replacement can have different effects on workers' well-being depending on their skill levels, and it seeks to investigate these moderation effects.

Conceptually, the link between automation and job satisfaction can be analyzed in two steps. The first is that the introduction of industrial robots in local labor markets will arguably affect workers' expectations about their future jobs, which means that some workers will fear that some of their tasks, or even their whole job, might be replaced by a smart machine in the future. The second step is that these expectations about the future, and particularly the anticipated fear of replacement, will affect workers' job satisfaction at present.

Our empirical analysis will consider both of these conceptual steps in a two-stage empirical model, and investigate whether the related impacts are stronger for high-skilled or for low-skilled workers. We point out below here the main effects that we expect to find in the empirical analysis, and how these can be explained in the light of the literature reviewed in this section. As noted below, some of the effects of interest are stronger for high-skilled workers, whereas others are more relevant for low-skilled workers, so that the overall net moderation effect cannot be pointed out *ex-ante*, but it will have to be established based on the empirical evidence.

I. Fear of replacement. The introduction of industrial robots in the local labor market increases the likelihood that some workers will be replaced by smart machines in the future. These technological changes and their applications in firms in local labor markets will therefore induce some workers that are currently employed to fear that they might be replaced in the future (or at least that some of their tasks might be).

Moderation effects. The introduction of industrial robots will arguably have different impacts for high- *versus* low-skilled workers. We envisage two contrasting effects.

Fear of replacement is stronger for the low-skilled. These workers are more exposed to the risks of displacement from automation because they typically carry out routine tasks that can more easily be automated (see literature in section 2.1).

Fear of replacement is stronger for the high-skilled. High-skilled workers are typically also more educated individuals who read more and follow media debates on robots, automation and their negative consequences for employment. Hence, high skilled workers are arguably more exposed to peer effects, which may translate in a greater fear about the future of employment. Contrary to this argument, we may however posit that workers of higher education typically have a better ability to understand and anticipate that these new technologies will also have positive effects for their future tasks and wages, as well as for the overall productivity of the economy – i.e. they are arguably be more forward-looking [31].

Proposition 1: The introduction of industrial robots in the local labor market will negatively affect low-skilled workers more than high-skilled workers if the former effect is stronger than the latter.

II. Job satisfaction. The second aspect of our conceptual analysis refers to the impacts that fear of replacement will have for workers' subjective well-being. The main expectation is that fear of replacement in the future will negatively affect job satisfaction at present. The main reason is that the prospect to become unemployed, or to be taken away some of the current working tasks, will negatively affect wage and financial conditions expected for the future, thus creating uncertainty about future job prospects and personal finance, and hence lower job satisfaction.

Moderation effects. Fear of replacement will arguably have different impacts on job satisfaction for high- versus low-skilled workers. We posit the following contrasting effects.

The negative effects on job satisfaction will be stronger for the low-skilled. If replaced, these workers will on average have fewer possibilities to find another occupation in the labor market. Acemoglu and Restrepo [22] and Blanas et al. [20] document in fact that displacement effects of industrial robots on employment and wages are stronger and more significant for low-education workers. On the other hand, as noted in section 2.1, extant research suggests that automation technologies can have more positive effects on high-skilled workers, increasing the demand for labor, wages and the complexity and interest of their tasks [18].

The negative effects on job satisfaction will be stronger for the high-skilled. According to prospect theory [29], individuals that invest more time in education and human capital formation will also have higher expectations about the working conditions that they desire and expect to have in the future, and be less satisfied with their job if this does not match the high expectations the individual has. Hence, highly educated workers, when facing the prospect of changing jobs and tasks in the future, may be those that have more to lose from automation, precisely because they are the individuals who have invested more in their human capital formation, and they have therefore higher expectations about the working conditions that they feel they deserve.

Proposition 2: Fear of replacement will negatively affect the job satisfaction of low-skilled workers more than that of high-skilled workers if the former effect is stronger than the latter.

4. Data

Individual-level data

We use the *Working Life Barometer* survey (*Arbeidslivsbarometer*), which provides annual microdata for several thousand Norwegian workers. The survey is provided by the Confederation of Vocational Unions (YS), a politically independent umbrella organization for labor unions, and organized by the Work Research Institute in Norway. TNS Gallup collects the data targeting a large random sample of Norwegian workers aged 18-67 years. Our analysis makes use of the four surveys carried out in the years 2016 to 2019, which include information on the main variables of interest for this study, and particularly workers' subjective assessments of the threats of automation, and their job satisfaction.

The main target variable in the study is job satisfaction, which is measured by means of responses to the survey question: "*How satisfied are you with your job?"*. Respondents indicate their satisfaction level on a 1-5 scale ("Very dissatisfied"; "Pretty dissatisfied"; "Neither satisfied nor dissatisfied"; "Pretty satisfied"; "Very satisfied"). The main explanatory variable is fear of replacement. This is measured by means of responses to the following survey question: "*Do you think some of your current tasks could be done by machine instead?*". Fear of replacement is a dummy variable: respondents who answer yes to this question take value 1, whereas workers who do not think that their tasks could be replaced by a machine take value 0. It is important to observe that this survey question measures workers' assessment of the possibility that their tasks could be replaced by machines (cognitive reaction), and not directly the fear to lose their job as a consequence of automation (emotional reaction). However, as we will show later in the results section, this survey question is closely related to other survey questions that measure workers' fear of losing their job, and it is therefore reasonable to use it as a proxy measure of fear of replacement. It is also worthwhile to note that only workers who are currently employed are asked to answer the question on fear of replacement, whereas unemployed individuals must skip this part of the questionnaire. Hence, our analysis focuses on the beliefs of workers who are potentially exposed to automation, but it does not consider those individuals that have already been laid off due to automation.

Next, another important variable in our study is the skill-level of workers, which is measured by their education level, distinguishing workers with a completed University degree *versus* those without tertiary education. In terms of control variables, the *Working Life Barometer* survey also provides employee-level demographic and socio-economic information such as age, gender, income, union membership, and occupation type. In total, we analyze responses from 10,051 workers aged 19-68 years. Table 1 presents a list of the variables used in the analysis, and table 2 reports some descriptive statistics.

< Tables 1 and 2 here >

Robot data

To measure the introduction of industrial robots in local labor markets in Norway, we make use of a dataset provided by the International Federation of Robotics (IFR), which contains information on robot stock and deliveries in Norwegian industrial firms since 1993. The IFR defines an industrial robot as an "*automatically controlled, reprogrammable multipurpose [stationary or mobile machine]*" [32]. Robot stock for years 2018 and 2019 are extrapolated assuming a 9 percent annual growth in operational stock as projected by IFR [33]. Following this definition, industrial robots are autonomous machines capable of operating without human intervention and that could potentially substitute or complement human labor. The IFR provides detailed data on robot stock and deliveries for the period 1993-2017, which can be broken down by application or industry. Robot stock for years 2018 and 2019 are extrapolated assuming a 9 percent annual growth in operational stock as projected by IFR [33]. IFR data have recently been used to analyze the impact of automation on employment and wages [22, 34, 35], as well as on workers' well-being [11, 12].

We allocate robots in regional labor markets following extant research [22, 34, 36], assuming that robots are distributed across region and industries by their respective employment shares. Employment shares are calculated based on Eurostat's Labor Force Survey data dating back to 2008. The long-term change in robot adoption occurs between years 2008 and *t* based on initial regional employment composition in each industrial category (industry, agriculture, construction, and services), with the change in robot adoption per 1,000 workers fixed at the starting level in year 2008.

$$\Delta robot\ exposure_{r,t} = \sum_{r \in C} \frac{emp_{r,s,2008}}{emp_{r,2008}} * \left(\frac{robots_{r,s,t} - robots_{r,s,2008}}{emp_{c,2007}} \right) \qquad (1)$$

In this setup, robot exposure is measured as national robot adoption allocated at the region-industry level *(r,s)*. Each regional labor market *r* is scaled by the nation's total employment emp_c. In short, the variable that we will use in our empirical analysis is the long-term change in the adoption of industrial robots by Norwegian firms in each local labor market *(r,s)*, which measures the extent to which workers have been exposed to automation from 2007 onwards (see a further discussion of the empirical identification strategy in section 3.2 below).

Regional-level control variables

We use the Eurostat's Labor Force Survey to obtain regional-level variables on GDP per capita, population share with tertiary education, and population size. From Statistics Norway, we retrieve data on firms by size for each region. Further, we collect data on unemployment benefit recipients as a share of total population from the Norwegian Labour and Welfare Administration (NAV), for each region and each year of our dataset.

To avoid omitting the possible conflating influence of ICTs when analyzing automation, previous studies have included ICT capital or investment as an additional control variable [34, 37]. However, others argue that more specific measures of ICT utilization are necessary for micro-level studies [38]. Unlike existing studies that have analyzed the impact of high-speed broadband developments in Norway [39, 40], we use as additional control variable the broadband internet availability in office buildings instead of households in each region. Data on office buildings with at least 8/8 Mbit/s speeds are provided by the Norwegian Communications Authority (Nkom), and matched against individuals through regional identifiers.

5. Empirical methods

The econometric analysis sets out to study the relationship between fear of replacement and job satisfaction. Fear of replacement is the subjective assessment that each worker does on the possibility that her working tasks will be replaced by a smart machine in the future. Such subjective assessment may arguably depend on unobserved and idiosyncratic factors such as e.g. ability, attitude towards risk, and technological / digital competencies. Therefore, unobserved individual factors might possibly influence both the outcome variable (job satisfaction) and the main explanatory variable (fear of replacement).

To address endogeneity concerns, we follow recent research and use the lagged introduction of robots in local labor markets as an instrument for individual workers' fear of replacement [11, 12]. Existing studies on robot implications for labor markets where robot adoption is the main explanatory variable address endogeneity issues by incorporating spillover effects from robot adoption across industries in other countries as an instrument in a 2SLS setup [22, 34, 36]. Unlike these studies, we approach subjective responses to structural inroads of robot technology in regional labor markets to identify learning effects from past automation. Specifically, our instrumental variable is the one defined in (1) above, i.e. the change in the adoption of industrial robots by Norwegian firms in each local labor market (region-industry) between 2008 and year *t* (i.e. one of the survey years 2016-2019). This variable measures the extent to which workers have been *exposed* to automation in recent years. We thus exploit (lagged) regional variations in robot adoption to instrument for individual fear of replacement at time *t*. The underlying idea of this identification strategy is that workers that are employed in local labor markets that have more rapidly been exposed to automation (i.e. in region-industries where firms have increasingly used industrial robots) will be more likely to consider automation as a possible threat, and therefore fear that some of their working tasks could be replaced by a machine in the future. In other words, we posit that workers learn from past robot adoption in their local labor markets, because they are subject to *peer effects* [41].

Norwegian firms have invested in sophisticated robotics and automation technologies to keep pace with the Digital Single Market strategy [42], and our empirical analysis exploits this exogenous source of tempo-spatial variations to identify the effects of automation on workers' job satisfaction. Figure 1 illustrates the dynamics of industrial robots adoption in Norway in the last decades, showing a much faster pace since 2014. Table 3 shows that most robots have so far been used by firms within manufacturing, and less so in other branches such as agriculture, construction and services. However, table 3 also shows that the introduction of robots by service firms has been quite rapid in the last decade.

To get a further overview of the diffusion and use of industrial robots in Norway, it is also useful to get some descriptive figures from Eurostat' survey on "ICT usage and e-commerce in enterprises (2018)" (see tables A1 to A4 in the online appendix). Large firms are the main adopters of both industrial and service robot technologies, and capital-intensive firms appear to invest in and integrate both technologies in their operations. Operating machines represent about 60% of all industrial robots in Norwegian firms in 2017. Whereas large firms use service robots for mostly logistics and transportation purposes, small and medium enterprises (SMEs) deploy robots in more product-related purposes, such as inspection, assembly or construction works.

Although our paper focuses on industrial automation, workers in knowledge-intensive service occupations may rather fear competition from new artificial intelligence technologies. Table A4 in the appendix presents some descriptives on Norwegian firms' use of Big Data in their business operations. Large firms are more likely to use Big Data than SMEs. Large firms use smart sensors (e.g. Internet of Things) and geo-data to a greater extent than SMEs. On the other hand, SMEs more actively collect data from social media for marketing purposes. In sum, smart machines are swiftly making inroads in the Norwegian economy, and this pace has accelerated in the last five years.

< Figure 1 and table 3 here >

Based on the identification strategy noted above, we estimate a two-stage instrumental variables (IV) model: the first stage (3) investigates how robot exposure and other control factors explain variations in workers' fear of replacement, whereas the second stage (2) estimates the relationship between job satisfaction and anticipated replacement:

$$JS_{irt} = a_1 + \gamma machine\ replacement_{irt} + \delta x'_{irt} + \eta_r + \theta_t + \varepsilon_{irt} \qquad (2)$$

$$machine\ replacement_{irt} = a_2 + \mu z_{rt} + \varrho x'_{irt} + \tau_r + \varphi_t + \epsilon_{irt} \qquad (3)$$

JS is reported job satisfaction, *machine replacement* is the dummy variable indicating whether the respondent believes a machine can perform her/his job tasks, z is the instrumental variable (region-industry lagged pace of robot adoption), and x is a set of covariates (measured for individuals in each survey wave). The subscript r denotes the geographical region of residence of each worker i, and the subscript t refers to survey year. Among the set of covariates, the skill variable is particularly relevant for the present study, as we seek to investigate whether the relationship between fear of replacement and job satisfaction differs for high- *versus* low-skilled workers. To test these moderation effects, we interact the skill variable with the robots variable in the first stage equation, and with the fear of replacement variable in the second stage equation.

For model identification, the vector x in equations (2) and (3) does also include detailed demographic and socio-economic characteristics expected to correlate with job satisfaction and anticipated replacement, such as age, gender, income, union membership, and occupation type. According to previous studies, these factors are relevant to explain variation in job satisfaction, labor dynamics and technological automation diffusion [8, 22, 31, 34, 37, 43-45]. Finally, both equations also include a full set of regional dummies and time dummies that control for unobservable determinants of job satisfaction within each region over time.

The econometric model is estimated as a two-stage bivariate recursive ordered probit maximum likelihood setup, which accommodates the ordinal character of the outcome and main explanatory variable [46, 47]. This model estimates response probabilities of two variables, one ordered and one dichotomous, and the exogenous variable robot exposure is included in the first stage [48, 49]. Estimations are performed with Roodman's [50] conditional mixed process (CMP) program. Because the instrument is measured at the regional level, estimations are likely to contain grouped structures [41, 51]. However, since the number of region-industry groups is limited (16), standard errors should not be clustered [52].

6. Results

First stage results

Table 4 presents the estimation results of the first stage (equation 3), in which the dependent variable is machine replacement (i.e. workers' self-reported assessment of the possibility that some of their working tasks will be replaced by a smart machine in the future). Table 4 reports estimation results for both the model without control variables and the one including the full set of controls, in order to assess whether the inclusion of controls affect the results [53, 54]. The results for the two models are however very close to each other. We begin by briefly looking at the results for the set of control variables, before turning attention to the main variables of our interest. Among the controls, table 4 shows that fear of replacement is stronger for younger workers. These have a longer time horizon remaining in their working life, and they are therefore more likely to expect that automation will replace some of their working tasks in the future [12]. Employees that belong to a trade union are less likely to fear replacement, arguably because their employment and working conditions are partly protected by the trade union membership (we elaborate further on this in section 6.3 below). Regarding wage levels, fear of replacement is stronger for workers that have higher income. A possible interpretation of this finding is that, after controlling for education and skill levels (that are correlated with wages and that also affect fear of replacement), workers with higher income have more to lose *vis-à-vis* workers with lower income, since automation of tasks may lead, in absolute terms, to a stronger wage decrease for them. Further, we control for gender and sector of occupation, which are two standard control variables in studies of workers' subjective well-being.

Shifting the focus to the main variables of interest for this study, the instrumental variable (changes in robot adoption in local labor markets between 2008 and year *t*) is as expected positively correlated with the dependent variable (workers' fear of replacement). As explained in section 5, the underlying idea is that when individuals work in region-industries in which firms have increasingly been using robots in the last few years, they are more *exposed* to automation (e.g. because some of their peers or acquaintances in the same region have lost their job due to automation). These peer effects translate into fear of replacement even for workers that are still employed and not directly touched by automation technologies yet. Table A5 in the appendix corroborates this interpretation by presenting first stage regressions in which we use two additional control variables that measure *fear of job loss*: (1) job loss worry ("To what extent are you worried about losing your job?"); (2) unemployed in five years ("Do you expect to be unemployed within the next five years?"). Both of these control variables are positive and significant in the regressions, indicating that fear of job loss (emotional reaction) and machine replacement (cognitive reaction) are closely related dimensions. Further, the inclusion of these additional control variables does not affect the size and significance of the estimated effect of the instrumental variable robot adoption on machine replacement.

Next, we look at the results for the other important variable considered in this study: workers' skills. Table 4 shows that individuals with tertiary education have on average a greater fear that some of their working tasks could be replaced by a machine in the future. As discussed in section 3, this might be explained by the fact that high-skilled workers are typically more educated individuals who read more and follow societal debates on the media about robots, AI and automation, and their negative consequences for employment. Hence, high skilled workers are arguably more exposed to peer effects, which may translate in a greater fear about the future of employment.

Relatedly, how do workers' skills affect the positive relationship between automation and fear of replacement? To test this moderation effect, table 5 reports estimation results of the first stage equation by workers' skill level. While the estimated coefficient of the robot adoption variable is positive and significant for both workers with tertiary education and those without a college degree, the size of this effect is larger for the latter group. This moderation effect is in line with the recent literature on the effects of automation on employment, which shows that low-skilled workers are more exposed to the risks of displacement from automation because they typically carry out routine tasks that can more easily be automated [3, 4, 16, 20].

< Tables 4 and 5 here >

Second stage results

Table 6 reports estimation results for the second stage of the model (equation 2), in which job satisfaction is the dependent variable. The table reports first the results for the model without control variables and then those for the model including the full set of controls. The results for the two models are very close to each other, indicating that the inclusion of controls does not affect the results on the main explanatory variables [53, 54]. The control variables that we use are commonly used in the job satisfaction literature. Income is positively correlated with job satisfaction, in line with extant literature showing that wage is one of the factors that enhance workers' subjective well-being [7, 8]. Female workers report on average higher job satisfaction than males; and individuals employed in manufacturing (industry) have lower satisfaction than average, a finding that is explained in the subjective well-being literature by the fact that factory workers typically carry out routine and monotonous working tasks and have a lower degree of autonomy and creativity [25].

The main variable of interest in table 6 is machine replacement. The estimated coefficient for this variable is as expected negative and significant. This means that workers that report higher fear of replacement from smart machines have on average lower job satisfaction. As noted in section 3, the reason for this is that for workers that are currently employed, the prospect that smart machines could replace some of their current working tasks in the future, or even the whole job, does create uncertainty about future job prospects and personal finance, thus lowering job satisfaction. Table A6 in the appendix reports second stage regressions that also include two additional control variables that measure *fear of job loss*: (job loss worry; unemployed in five years; see definition of these two survey questions in section 6.1 above). The additional control variables are positive and significant in the regressions, and their inclusion in the model does not affect the size and significance of the estimated effect of machine replacement on job satisfaction, indicating that fear of replacement due to automation is important for workers' subjective well-being even after controlling for the more general construct fear of job loss.

How is this relationship moderated by workers' skill level? Table 7 investigates this question by reporting marginal effects of the machine replacement variable for workers that have tertiary education *versus* those that do not have a college degree. The table shows that both groups have a negative and significant marginal effect on job satisfaction, and that such negative effect is stronger for low-skilled workers. Abeliansky and Beulmann [11] also carried out some regressions to study the relationships between automation and mental health for different educational groups (tertiary vs secondary education), but they did not find any significant difference among these groups of workers in Germany. As discussed in section 3, the interpretation of our finding is that low-skilled workers, if replaced, will on average have fewer possibilities to find another occupation in the labor market. This is in line with recent literature that provides evidence that displacement effects of industrial robots on employment and wages are stronger and more significant for low-education workers [20, 22]. On the other hand, automation technologies can have more positive effects on high-skilled workers, increasing the demand for labor, wages and the complexity and interest of their tasks [18]. In short, we posit that workers are at least to some extent aware of the distinct impacts that automation can have for different types of occupations, and this explains why fear of replacement turns out to be a greater concern for low-skilled employees.

It may be argued that the education level dummy variables that we have used in these regressions only reflect formal education acquired through the school and University system, and disregards other skills that workers acquire during the working life through training, apprenticeships and learning by doing. Ideally, if we had information about each worker's occupation, we could construct a proxy measure for skills by using the three-level job complexity schema developed by Hunter et. al. [55], which creates a correspondence between job types and corresponding skill content.. However, our dataset does not have information about workers' occupation type, and we are therefore not able to follow this route. Hence, in the absence of a more specific variable measuring workers' skills, we carry out two additional exercises. First, we use age as an additional proxy of workers' skills and abilities to perform their job. Table 8 reports marginal effects of machine replacement on job satisfaction for workers of different education levels *and* for different age groups. The results confirm the main finding noted above. The marginal effect of anticipated machine replacement on present job satisfaction is negative for all sub-groups, and the size of the effect is higher for low-skilled workers (with the only exception of older workers (>60 years)). This corroborates the main finding of our analysis that machine replacement has a negative effect on job satisfaction, and that this effect is stronger for low-skilled workers.

Second, it may be argued that the education variable does not only measure workers' skills, but it is also a proxy for *employability*, since workers with higher education levels can more easily find a new job. If so, employability, rather than skills, could be the latent variable moderating the effect of fear of replacement on job satisfaction. To address this possibility, we make use of two additional variables measuring employability: (1) Difficult to find a new job ("How difficult or easy do you think it would be for you to find a job that is at least as good as the one you have now?"); (2) Insufficient skills in current job ("How often do you experience insufficient competence to perform your tasks?"). Then we include these two variables as additional controls in our first and second stage regressions, and report the results of these robustness tests in tables A7 to A10 in the online appendix. First stage results (tables A7 and A8) show that the inclusion of the additional controls for employability does not affect the main result about the effect of robot adoption on machine replacement, and that this effect is still stronger for workers with lower education level. Second stage results (tables A9 and A10) are also in line with our baseline estimations: in the extended model specification that controls for employability, the effect of machine replacement on job satisfaction is still negative and significant, and consistently stronger for workers of lower education level (across age groups). In short, these additional exercises show that, even when we control for employability, workers' education level moderates the effect of fear of replacement on job satisfaction, and it may thus be considered as a reasonable proxy measure of latent workers' skills.

< Tables 6, 7 and 8 here >

Robustness tests

Our identification strategy rests on the assumption that the (lagged) introduction of robots in local labor markets in Norway affects current job satisfaction only through its effects on workers' fear of replacement. Although our regressions control for a set of relevant employee-level characteristics and include region- and time fixed effects, it is also useful to carry out some additional robustness exercises to test the potential confounding effects of omitted variables that may in principle affect both fear of replacement and the error term of the outcome equation.

Tables A11 and A12 report estimation results of first and second stage regressions that include some additional region-level control variables in the model. The first two columns add region's GDP and tertiary education level, which may be thought to be general relevant factors that may drive both the introduction of industrial robots and job satisfaction patterns. Though, the estimated coefficients of the instrumental variable robot adoption (table A11) and of the machine replacement variable (table A12) are still significant and stable after the introduction of these two possible confounding factors. Regressions in column 3 add a variable measuring business building broadband infrastructure in each region. The reason for including this variable is that ICT diffusion may be a potentially conflating factor that can disturb the effect of robots adoption on employment [3, 37]. By controlling for broadband internet access in office buildings we address this concern, reasonably assuming that the development of broadband infrastructure is driven by policies and investments that are exogenous to the individual worker. Again, the inclusion of this additional control does not affect the estimated coefficient of the robot variable in table A11, and of the machine replacement variable in table A12. These coefficients still have the same signs and significance levels, and their estimated size is slightly larger than in baseline regressions. Finally, columns 4, 5 and 6 also add three other region-level controls: unemployment benefit recipients (share of population in each region), share of large companies in each region, and population size (log). The unemployment benefit variable controls for the possible confounding effect of different unemployment rates across regions. The share of large companies takes into account the fact that large firms do on average have a higher rate of introduction and use of industrial robots (see tables A1 and A4 in the online appendix), so that employees in regions with a high share of large firms are potentially more exposed to the effects of automation. Finally, the population variable is a standard control for the size and density of the region, which may be related to the extent and intensity of peer effects that affect workers' fear of replacement. However, the inclusion of these additional variables does not affect the main results for the explanatory variables of our interest.

As a further robustness test, table A13 reports the results of a placebo test that adds a lead variable – robust exposure at year *t+1* – to the set of regressors in the first stage equation (including also the three additional region-level control variables noted in the previous paragraph). In these placebo regressions, the future robot adoption variable is not significant, and its inclusion does not affect the sign and size of the estimated coefficient of the instrumental variable (lagged pace of robot adoption). This further rules out the possibility that our results are driven by some omitted variables that are related to both job satisfaction and robot adoption.

Finally, it is relevant to comment further on the role of one of the control variables in the model: union membership. As noted in relation to table 4 (and other first stage results reported in the online appendix), workers that belong to a trade union do on average report lower fear of machine replacement. This may suggest that workers in trade unions feel they are more protected from the impacts of industrial robots. However, this pattern is in contrast with Acemoglu and Restrepo [44], which find a positive association between industrial robot adoption and unionization rates across countries, arguing that this is due to the fact that unionization may raise labor costs. Yet, skill-biased technical change also creates a stronger incentive for deunionization because the outside employment and wage options of skilled workers have improved [56]. To investigate this further, we run additional regressions in which we interact our two main explanatory variables (robot adoption in the first stage, and machine replacement in the second stage) with the union membership variable. The idea is to test directly whether Norwegian workers that belong to a trade union do on average think that they are less likely to be affected by automation. However, the results of these regressions (reported in table A14 in the online appendix) show that the two additional interaction variables are not statistically significant. We think that the role of union membership as a factor moderating the effects of industrial automation is an interesting topic for future research.

7. Conclusions

The swift pace of introduction of industrial robots, AI and smart machines in production activities in recent years represents a new major process of Schumpeterian creative destruction. This process will in the near future lead to dramatic consequences for employment in many sectors and regions, and it will at the same time create new unprecedented opportunities for productivity growth, wealth and well-being. As for other major transformations in the past, this structural change and the related transition and adjustment process will arguably not be smooth and swift: it will unfold over a period of several years, and it will lead to important negative impacts in the short-run before the long-run economic and societal benefits will eventually emerge.

Studying the effects of automation on employment, extant research has so far mostly focused on aggregate impacts that industrial robots and AI have on employment demand and wages for different industries and countries. The present paper has argued that it is important to shift the focus to the micro-level of analysis and study the impacts of automation technologies on individual workers' well-being. Specifically, we have put forward the idea that the relevant impacts that it is important to study are not only pecuniary (i.e. related to workers' employment conditions and wages) but also nonpecuniary (i.e. related to workers' expectations and future job prospects). *Ceteris paribus*, workers that fear that their working tasks might be replaced by a smart machine in the future may have a lower job satisfaction at present than workers who have more secure job prospects and less uncertainty about the future.

We have investigated this idea by considering a large sample of workers in Norway for the period 2016-2019, and studying the extent to which the introduction of industrial robots in local labor markets affect workers' fear of being replaced in the future, and in this way hamper their subjective well-being. Our data and results provide a quite striking picture. 40% of Norwegian workers in our sample think their working tasks might be replaced by a machine, and our analysis shows that this fear of replacement significantly lowers their job satisfaction at present. We also find that this transmission mechanism is even stronger for low-skilled workers, which are those carrying out routine-based tasks, and who are therefore aware to be more exposed to the risks of automation. On the whole, we think that our empirical findings are not only relevant for Norway (the country to which our dataset refers), but they can in principle have more general lessons for other countries too. Automation is by now an important trend that is rapidly diffusing worldwide, and its effect on workers' health and well-being is therefore a topic of high societal relevance. Schwabe (2019) provides related evidence using a different dataset for a larger sample of European countries. The present work calls therefore for further research that may investigate and extend this research topic in a variety of different countries and continents.

A first important policy implication of our results is that the current process of structural change and creative destruction will in the short-run likely lead to stronger fear of replacement and uncertainty about the future for low-skilled workers carrying out routine work in factories, thus possibly leading to further polarization not only in terms of employment and wages, but also in terms of subjective well-being. To mitigate these negative consequences, which are already visible at present, national authorities should actively support training and re-training policies in such a way that workers that are exposed to future replacement may build up new competencies that can increase their ability to work with smart machines, as well as increase their qualifications and the likelihood to find a new job if this will become necessary in the future. If fear of replacement triggers workers to participate in such training is an interesting question for future studies. In other words, by giving better future prospects to more vulnerable workers, training policies will also contribute to enhance their subjective well-being at present.

Our results also suggest a second reflection and possible policy implication. As noted above, 40% of Norwegian workers in our sample think that their working tasks might be replaced by a machine. According to the Eurobarometer survey, the extent of fear of replacement is roughly the same for workers in other European countries [12]. This number is quite high indeed. Is it reasonable that so many workers fear competition from smart machines, and why is it so?

Extant research on automation and employment has not yet reached a consensus on the direction and size of these effects, and it still presents a vivid debate between those that emphasize negative consequences and those that point out positive economic and societal effects. Hence, there is no clear scientific evidence and consensus at present that could provide the basis for individual workers to form rational and well-informed assessments and expectations about their job prospects in the future. It is therefore reasonable to ask whether the generalized fear of competition from smart machines is actually exaggerated and not based on extant research and established knowledge. The concrete risk is that – in the current phase of rapid and disruptive technological change – societal debates in the media on robots, automation and AI may tend to exaggerate risks and depict gloomy future scenarios, while often neglecting possible long-run benefits for the economy and the society, which are indeed even hard to imagine at the moment [1].

Since media debates on this topic are often biased and tend to overemphasize the negative impacts of automation (which are arguably more "catchy" and attractive for the uninformed audience), this may contribute to explain why so many workers report to fear future machine replacement. However, our paper has shown that such subjective individual assessments about the future may indeed hamper job satisfaction at present. This can also lead to anxiety, mental stress and low motivation at work, which may in turn depress creativity, productivity and innovation in the workplace.

In short, we should not disregard the possibility that a biased and uninformed presentation of this topic in the media may indeed have concrete negative consequences on workers' subjective well-being by affecting their beliefs about future job prospects. The policy implications of this are certainly not easy to draw. A major point, though, is to stress the importance of having better informed societal debates in the media, and particularly in State-owned channels, that take a more balanced view of the negative and positive consequences of automation, and that avoid spreading fears and gloomy scenarios that are not based on solid evidence and arguments.

Supporting information

S1 file. Online appendix: Additional information and robustness tests. Containing tables A.1 to A.14.

References

1. Mokyr, J., C. Vickers, and N.L. Ziebarth, *The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different?* Journal of Economic Perspectives, 2015. **29**(3): p. 31-50.
2. Frank, M.R., et al., *Toward understanding the impact of artificial intelligence on labor.* Proceedings of the National Academy of Sciences, 2019. **116**(14): p. 6531-6539.
3. Autor, D.H. & D. Dorn, *The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market.* The American Economic Review, 2013. **103**(5): p. 1553-1597.
4. Goos, M., A. Manning, and A. Salomons, *Explaining Job Polarization: Routine-Biased Technological Change and Offshoring.* American Economic Review, 2014. **104**(8): p. 2509-26.
5. Acemoglu, D. & P. Restrepo, *Artificial Intelligence, Automation and Work.* NBER Working Paper (No. w24196), 2018.
6. Kaplan, G. & S. Schulhofer-Wohl, *The Changing (Dis-)Utility of Work.* Journal of Economic Perspectives, 2018. **32**(3): p. 239-58.
7. Erdogan, B., et al., *Whistle While You Work: A Review of the Life Satisfaction Literature.* Journal of management, 2012. **38**(4): p. 1038-1083.
8. Clark, A., A. Oswald, and P. Warr, *Is job satisfaction U-shaped in age?* Journal of occupational and organizational psychology, 1996. **69**(1): p. 57-81.
9. Böckerman, P., P. Ilmakunnas, and E. Johansson, *Job security and employee well-being: Evidence from matched survey and register data.* Labour Economics, 2011. **18**(4): p. 547-554.
10. Oswald, A.J., E. Proto, and D. Sgroi, *Happiness and Productivity.* Journal of Labor Economics, 2015. **33**(4): p. 789-822.
11. Abeliansky, A.L. & M. Beulmann. (2019). *Are they coming for us? Industrial robots and the mental health of workers.* cege Discussion Papers, No. 379. University of Göttingen, Center for European, Governance and Economic Development Research (cege), Göttingen.
12. Schwabe, H., *Automation, Fear of Replacement and the Subjective Well-Being of Workers.* TIK working paper, 2019.
13. Rajan, K. & A. Saffiotti, *Towards a science of integrated AI and Robotics.* Artificial Intelligence: Special Issue on AI and Robotics, 2017. **247**: p. 1-9.
14. Acemoglu, D. & D. Autor, *Skills, tasks and technologies: Implications for employment and earnings*, in *Handbook of labor economics.* 2011, Elsevier. p. 1043-1171.
15. Sachs, J.D. & L.J. Kotlikoff. (2012). *Smart Machines and Long-Term Misery.* NBER Working Paper (No. w18629). National Bureau of Economic Research.
16. Autor, D.H., *Why Are There Still So Many Jobs? The History and Future of Workplace Automation.* Journal of Economic Perspectives, 2015. **29**(3): p. 3-30.
17. Houseman, S.N. (2018). *Understanding the decline of US manufacturing employment.* W.E. Upjohn Institute for Employment Research. Upjohn Institute working paper.
18. McGuinness, S., K. Pouliakas, and P. Redmond, *Skills-Displacing Technological Change and Its Impact on Jobs: Challenging Technological Alarmism?* IZA Discussion Paper No. 12541, 2019.
19. Klenert, D., E. Fernandez-Macias, and J.-I. Anton. (2020). *Do robots really destroy jobs? Evidence from Europe.* Seville: European Commission. Joint Research Centre.
20. Blanas, S., G. Gancia, and S.Y.T. Lee. (2019). *Who is afraid of machines?* Barcelone GSE Working Paper Series.
21. Beaudry, P., D.A. Green, and B.M. Sand, *The great reversal in the demand for skill and cognitive tasks.* Journal of Labor Economics, 2016. **34**(S1): p. S199-S247.

22. Acemoglu, D. & P. Restrepo, *Robots and Jobs: Evidence from US Labor Markets.* Journal of Political Economy, 2020. **128**(6): p. 2188-2244.
23. Acemoglu, D. & P. Restrepo. (2020). *Unpacking Skill Bias: Automation and New Tasks.* National Bureau of Economic Research.
24. Bessen, J., et al. (2020). *Automation: A Guide for Policymakers.* Retrieved from https://www.brookings.edu/wp-content/uploads/2020/01/Bessen-et-al_Full-report.pdf
25. Castellacci, F. & C. Viñas-Bardolet, *Internet use and job satisfaction.* Computers in Human Behavior, 2019. **90**: p. 141-152.
26. Green, F. & Y. Zhu, *Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education.* Oxford economic papers, 2010. **62**(4): p. 740-763.
27. Sousa-Poza, A. & A.A. Sousa-Poza, *Well-being at work: a cross-national analysis of the levels and determinants of job satisfaction.* The journal of socio-economics, 2000. **29**(6): p. 517-538.
28. Salvatori, A., *Labour contract regulations and workers' wellbeing: International longitudinal evidence.* Labour Economics, 2010. **17**(4): p. 667-678.
29. Kahneman, D. & A. Tversky, *Prospect Theory: An Analysis of Decision under Risk.* Econometrica, 1979. **47**(2): p. 263-291.
30. Belfield, C.R. & R.D. Harris, *How well do theories of job matching explain variations in job satisfaction across education levels? Evidence for UK graduates.* Applied economics, 2002. **34**(5): p. 535-548.
31. Aghion, P., et al., *Creative destruction and subjective well-being.* American Economic Review, 2016. **106**(12): p. 3869-97.
32. IFR. (2017). *World Robotics: Industrial Robots*. International Federation of Robotics.
33. IFR. (2018). *World Robotics 2018: Industrial Robots*. Retrieved from International Federation of Robotics: https://ifr.org/
34. Chiacchio, F., G. Petropoulos, and D. Pichler, *The impact of industrial robots on EU employment and wages: A local labour market approach.* Bruegel Working Papers (02), 2018.
35. Graetz, G. & G. Michaels, *Robots at work.* The Review of Economics and Statistics, 2018. **100**(5): p. 753-768.
36. Dauth, W., et al., *Adjusting to Robots: Worker-Level Evidence.* Opportunity and Inclusive Growth Institute Working Paper (13), 2018.
37. Michaels, G., A. Natraj, and J. Van Reenen, *Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years.* Review of Economics and Statistics, 2014. **96**(1): p. 60-77.
38. Falk, M. & F. Biagi, *Relative demand for highly skilled workers and use of different ICT technologies.* Applied Economics, 2017. **49**(9): p. 903-914.
39. Bhuller, M., et al., *Broadband internet: An information superhighway to sex crime?* Review of Economic Studies, 2013. **80**(4): p. 1237-1266.
40. Akerman, A., I. Gaarder, and M. Mogstad, *The skill complementarity of broadband internet.* The Quarterly Journal of Economics, 2015. **130**(4): p. 1781-1824.
41. Angrist, J.D. & J.-S. Pischke, *Mostly harmless econometrics: An empiricist's companion*. Vol. . 2009, Princeton, NJ.: Princeton university press.
42. European Commission. *Digital Single Market.* 2014; Available from: https://europa.eu/european-union/file/1497/.
43. Frank, M.R., et al., *Small cities face greater impact from automation.* Journal of the Royal Society Interface, 2018. **15**(139): p. 20170946.
44. Acemoglu, D. & P. Restrepo, *Demographics and Automation.* NBER Working Paper (No. w24421), 2018.
45. Card, D., et al., *Inequality at work: The effect of peer salaries on job satisfaction.* American Economic Review, 2012. **102**(6): p. 2981-3003.

46. Sajaia, Z., *Maximum likelihood estimation of a bivariate ordered probit model: implementation and Monte Carlo simulations*. The Stata Journal, 2008. **4**(2): p. 1-18.
47. Monfardini, C. & R. Radice, *Testing exogeneity in the bivariate probit model: A Monte Carlo study*. Oxford Bulletin of Economics and Statistics, 2008. **70**(2): p. 271-282.
48. Wooldridge, J.M., *Econometric analysis of cross section and panel data*. 2010: MIT press.
49. Maddala, G.S. & L.-F. Lee, *Recursive models with qualitative endogenous variables*, in *Annals of Economic and Social Measurement, Volume 5, number 4*. 1976, NBER. p. 525-545.
50. Roodman, D., *Fitting fully observed recursive mixed-process models with cmp*. Stata Journal, 2011. **11**(2): p. 159-206.
51. Moulton, B.R., *Random group effects and the precision of regression estimates*. Journal of Econometrics, 1986. **32**(3): p. 385-397.
52. Cameron, C.A. & D.L. Miller, *A practitioner's guide to cluster-robust inference*. Journal of Human Resources, 2015. **50**(2): p. 317-372.
53. Becker, T.E., *Potential Problems in the Statistical Control of Variables in Organizational Research: A Qualitative Analysis With Recommendations*. Organizational Research Methods, 2005. **8**(3): p. 274-289.
54. Spector, P.E. & M.T. Brannick, *Methodological Urban Legends: The Misuse of Statistical Control Variables*. Organizational Research Methods, 2011. **14**(2): p. 287-305.
55. Hunter, J.E., F.L. Schmidt, and M.K. Judiesch, *Individual differences in output variability as a function of job complexity*. Journal of Applied Psychology, 1990. **75**(1): p. 28-42.
56. Acemoglu, D., P. Aghion, and G.L. Violante. *Deunionization, technical change and inequality*. in *Carnegie-Rochester conference series on public policy*. 2001. Elsevier.

Tables and figures

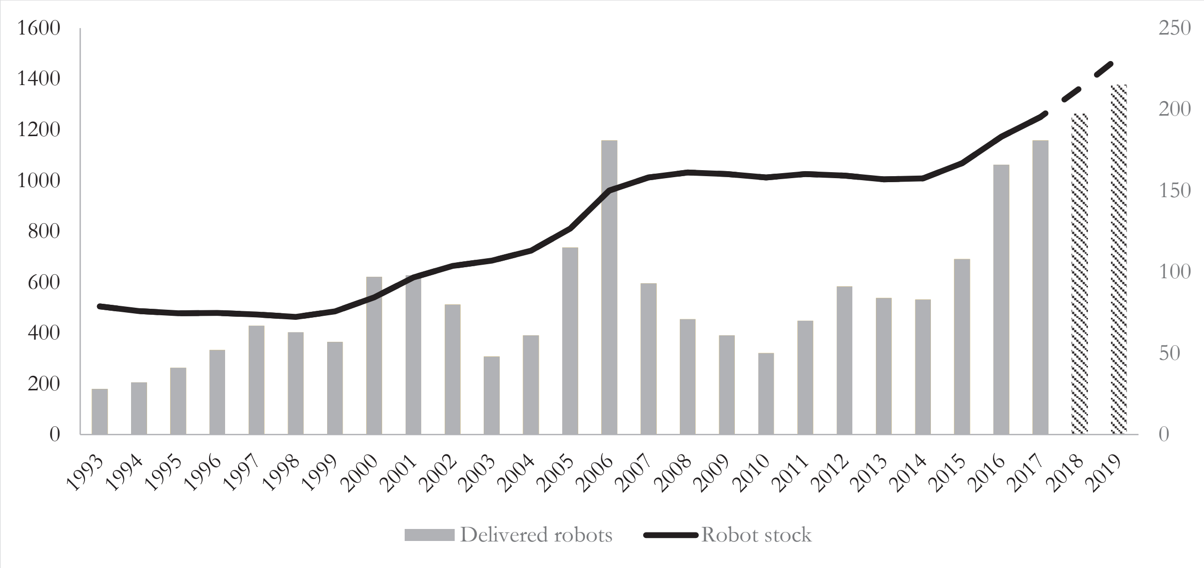
Table 1: Variables.

Variable	Definition
	Individual level variables
Job satisfaction	Respondents indicate their job satisfaction ranging from 1 "Very dissatisfied"; 2 "Pretty dissatisfied"; 3 "Neither satisfied nor dissatisfied"; 4 "Pretty satisfied"; 5 "Very satisfied".
Machine replacement	Respondents indicate whether they believe that a machine can perform some of their job tasks.
Union membership	Dummy indicating whether the respondent is unionized.
Age	Age of respondent.
Women	Dummy indicating the gender of the respondent.
University degree	Dummy indicating whether the respondent has a university degree.
Working in industry	Dummy indicating whether the respondent is an industry worker.
	Regional level variables
ΔRobot exposure	Regional long-term robot adoption per thousand workers. More detailed definition in main text.
Unemployment benefit recipients	Share of regional population that are registered recipients of unemployment benefits.
Business building broadband infrastructure availability	Fixed broadband penetration per 100 inhabitants.
Population	Log of regional population.
GDP per capita	Log of regional GDP per capita.
Tertiary education	Regional share of population (aged 25-64) with tertiary education.
Share of big industrial companies	Big industrial companies as share of total firm population by region.

Table 2: Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Job satisfaction	10,051	3.99	0.84	1.00	5.00
Machine replacement	10,051	0.40	0.49	0.00	1.00
Union membership	10,051	0.69	0.46	0.00	1.00
Age	10,051	46.44	11.67	19.00	68.00
Income scale	10,051	4.81	1.81	1.00	9.00
Women	10,051	0.52	0.50	0.00	1.00
University degree	10,051	0.56	0.50	0.00	1.00
Working in industry	10,051	0.08	0.26	0.00	1.00
Robot exposure	10,051	0.06	0.03	0.00	0.20
Log(GDP per capita)	10,051	12.89	0.53	12.14	13.69
Tertiary education (share of population)	10,051	43.81	6.68	35.5	54.3
Business building broadband infrastructure availability	10,051	0.74	0.14	0.56	0.97
Log(population)	10,051	14.09	0.20	13.74	14.33
Unemployment benefit recipients (share of population)	10,051	4.34	0.45	3.41	5.12
Share of big industrial companies	10,051	10.72	1.20	8.05	12.61

Figure 1: Robot deliveries and operational stock for Norway between 1993 and 2019.



The data for 2018 and 2019 are estimated (see data section).

Table 3: Adoption of robots (operational stock) in Norwegian regions and industries.

Region	Sector	2008	2017
Oslo & Akershus	Agriculture, forestry and fishing	0	1
	Industry	113	140
	Construction	0	0
	Services	3	13
Eastern Norway	Agriculture, forestry and fishing	3	4
	Industry	296	294
	Construction	0	1
	Services	3	11
Southern & Western Norway	Agriculture, forestry and fishing	3	4
	Industry	444	521
	Construction	0	1
	Services	3	14
Mid- and Northern Norway	Agriculture, forestry and fishing	3	5
	Industry	141	173
	Construction	0	0
	Services	3	13

Table 4: First stage results. Dependent variable: machine replacement.

	(1)	(2)	(3)	(4)
Robot adoption	0.711***	0.853***	1.845***	2.250***
	(0.171)	(0.180)	(0.439)	(0.474)
Age		-0.004***		-0.011***
		(0.000)		(0.001)
Union membership		-0.056***		-0.149***
		(0.011)		(0.028)
Income scale = 2		-0.093***		-0.268***
		(0.033)		(0.094)
Income scale = 3		-0.006		-0.019
		(0.028)		(0.073)
Income scale = 4		0.024		0.063
		(0.025)		(0.067)
Income scale = 5		0.027		0.072
		(0.026)		(0.068)
Income scale = 6		0.043		0.112
		(0.028)		(0.073)
Income scale = 7		0.078***		0.206***
		(0.030)		(0.079)
Income scale = 8		0.039		0.100
		(0.031)		(0.082)
Income scale = 9		0.069**		0.182**
		(0.035)		(0.092)
University degree		0.037***		0.098***
		(0.011)		(0.029)
Woman		-0.011		-0.030
		(0.011)		(0.029)
Industry employment		-0.044**		-0.119**
		(0.020)		(0.053)
<u>Controls</u>				
Regional dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
F-stat	17.39	22.38		
N	10,051	10,051	10,051	10,051

Robust standard errors in parentheses. Columns 1 and 2 present OLS estimates. Columns 3 and 4 show probit estimates. * p<0.10, ** p<0.05, ***p<0.01

Table 5: First stage results by workers' skill level.

	(1) No university education	(2) University education
Robot adoption	1.040***	0.749**
	(0.218)	(0.337)
Age	-0.004***	-0.004***
	(0.001)	(0.001)
Union membership	-0.024	-0.085***
	(0.015)	(0.015)
Income scale = 2	-0.111**	-0.048
	(0.044)	(0.061)
Income scale = 3	0.005	-0.024
	(0.039)	(0.040)
Income scale = 4	0.037	0.031
	(0.038)	(0.035)
Income scale = 5	0.092**	0.010
	(0.040)	(0.035)
Income scale = 6	0.024	0.067*
	(0.043)	(0.037)
Income scale = 7	0.099**	0.080**
	(0.047)	(0.040)
Income scale = 8	0.061	0.032
	(0.048)	(0.041)
Income scale = 9	0.072	0.068
	(0.058)	(0.045)
Woman	0.052***	-0.058***
	(0.017)	(0.014)
Industry employment	-0.057**	-0.005
	(0.024)	(0.034)
<u>Controls</u>		
Regional dummies	✓	✓
Year dummies	✓	✓
N	4,434	5,617

Robust standard errors in parentheses. Columns 1 and 2 present OLS estimates. * p<0.10, ** p<0.05, *** p<0.01

Table 6: Second stage results. Dependent variable: job satisfaction.

	(1)	(2)	(3)	(4)
Machine replacement	-1.093***	-0.760**	-1.268***	-0.999***
	(0.115)	(0.378)	(0.489)	(0.168)
Age		0.007***		0.008***
		(0.002)		(0.002)
Union membership		-0.041		-0.057**
		(0.027)		(0.026)
Income scale = 2		-0.135*		-0.137*
		(0.076)		(0.079)
Income scale = 3		0.009		0.016
		(0.051)		(0.060)
Income scale = 4		0.093**		0.120**
		(0.047)		(0.055)
Income scale = 5		0.144***		0.187***
		(0.048)		(0.056)
Income scale = 6		0.195***		0.246***
		(0.052)		(0.060)
Income scale = 7		0.214***		0.285***
		(0.062)		(0.067)
Income scale = 8		0.203***		0.274***
		(0.058)		(0.069)
Income scale = 9		0.322***		0.434***
		(0.069)		(0.078)
University degree		0.035		0.034
		(0.025)		(0.026)
Woman		0.092***		0.129***
		(0.020)		(0.025)
Industry employment		-0.169***		-0.213***
		(0.035)		(0.041)
<u>Controls</u>				
Regional dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
N	10,051	10,051	10,051	10,051

Robust standard errors in parentheses. Columns 1 and 2 present 2SLS linear estimates. Columns 3 and 4 show bivariate recursive probit estimates. * p<0.10, ** p<0.05, ***p<0.01

Table 7: Second stage results by workers' skill level (marginal effects of machine replacement for workers of different education levels).

	Below university education	University education
Machine replacement	-0.538***	-0.455***
	(0.078)	(0.084)
<u>Controls</u>		
Individual controls	✓	✓
Regional dummies	✓	✓
Year dummies	✓	✓
N	10,051	10,051

Robust standard errors in parentheses. Columns 1 and 2 present results from bivariate recursive probit estimates. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 8: Second stage results by workers' skill level and age (marginal effects of machine replacement for workers of different education levels and different age groups).

	Below university education	University education
At age 20	-0.352***	-0.128*
	(0.095)	(0.067)
At age 30	-0.349***	-0.194***
	(0.068)	(0.046)
At age 40	-0.346***	-0.260***
	(0.044)	(0.031)
At age 50	-0.342***	-0.326***
	(0.035)	(0.033)
At age 60	-0.339***	-0.392***
	(0.048)	(0.050)
Controls		
Individual controls	✓	✓
Regional dummies	✓	✓
Year dummies	✓	✓
N	10,051	10,051

Robust standard errors in parentheses. Columns 1 and 2 present results from bivariate recursive probit estimates. * p<0.10, ** p<0.05, ***p<0.01

Supporting information file

Automation, workers' skills and job satisfaction

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Online appendix:
Additional information and robustness tests

Table A1: Firm adoption of industrial and service robots in Norwegian firms.

Use industrial robots	
All enterprises	3 %
SME	3 %
Large	16 %
Use service robots	
All enterprises	1 %
SME	1 %
Large	10 %
Use industrial or service robots	
All enterprises	4 %
SME	3 %
Large	23 %

All enterprises, without financial sector: 10 persons employed or more. SMEs, without financial sector: 10-249 persons employed. Large enterprises, without financial: 250 persons employed or more. Data source: Eurostat, ICT (Information and Communication Technologies) usage and e-commerce in enterprises 2018.

Table A2: Purpose of use for industrial robots (operational stock).

	1999	2017
000 - All Applications	100 %	100 %
110 - Handling operations/Machine Tending	36%	59%
160 - Welding and soldering	27%	12%
170 - Dispensing	6%	1%
190 - Processing	19 %	3%
200 - Assembling and disassembling	4%	2%
900 - Other	3%	5%

Data source: The International Federation of Robotics (IFR).

Table A3: Purpose of use for service robots (operational stock).

	All enterprises	SME	Large
Surveillance, security or inspection tasks	22 %	23 %	20 %
Transportation of people or goods	17 %	16 %	24 %
Cleaning or waste disposal tasks	19 %	20 %	18 %
Warehouse management systems	22 %	19 %	39 %
Assembly works	12 %	14 %	4 %
Robotic store clerk tasks	20 %	17 %	31 %
Construction works or damage repair tasks	14 %	17 %	2 %
Any of the listed purposes	84 %	82 %	93 %

Data source: Eurostat, ICT (Information and Communication Technologies) usage and e-commerce in enterprises 2016.

Table A4: The use, source and employment of Big Data analysis in Norwegian Firms.

	Share of firms Analyzing Big Data	Big Data source Smart devices/ sensors	Geo-data of portable devices	Social Media	Other sources	Analysts Internal	External
All enterprises	15 %	33 %	33 %	62 %	28 %	59 %	36 %
SMEs	15 %	32 %	33 %	63 %	27 %	57 %	36 %
Large	39 %	55 %	43 %	43 %	52 %	82 %	42 %

Percentage of all enterprises, without financial sector (10 persons employed or more). Data source: Eurostat, ICT (Information and Communication Technologies) usage and e-commerce in enterprises 2016.

Table A5: First stage results, controlling for fear of job loss. Dependent variable: machine replacement.

	(1) OLS	(2) OLS	(3) Probit	(4) Probit
Robot adoption	0.819***	0.782***	2.168***	2.068***
	(0.182)	(0.187)	(0.479)	(0.494)
Job loss worry	0.074***		0.198***	
	(0.010)		(0.027)	
Unemployed in 5 years		0.154***		0.402***
		(0.039)		(0.101)
Age	-0.004***	-0.004***	-0.010***	-0.011***
	(0.000)	(0.000)	(0.001)	(0.001)
Union membership	-0.057***	-0.058***	-0.151***	-0.154***
	(0.011)	(0.011)	(0.029)	(0.030)
Income scale = 2	-0.095***	-0.104***	-0.272***	-0.296***
	(0.034)	(0.036)	(0.096)	(0.102)
Income scale = 3	-0.002	-0.010	-0.007	-0.029
	(0.028)	(0.030)	(0.075)	(0.079)
Income scale = 4	0.026	0.019	0.069	0.049
	(0.026)	(0.028)	(0.068)	(0.072)
Income scale = 5	0.031	0.026	0.084	0.067
	(0.026)	(0.028)	(0.070)	(0.074)
Income scale = 6	0.045	0.036	0.119	0.092
	(0.028)	(0.030)	(0.075)	(0.079)
Income scale = 7	0.081***	0.082**	0.215***	0.212**
	(0.031)	(0.033)	(0.081)	(0.085)
Income scale = 8	0.041	0.035	0.107	0.091
	(0.032)	(0.033)	(0.084)	(0.088)
Income scale = 9	0.068*	0.065*	0.179*	0.168*
	(0.035)	(0.037)	(0.093)	(0.097)
University degree	0.046***	0.040***	0.124***	0.107***
	(0.011)	(0.012)	(0.030)	(0.031)
Woman	-0.008	-0.010	-0.019	-0.026
	(0.011)	(0.011)	(0.029)	(0.030)
Industry employment	-0.044**	-0.052**	-0.120**	-0.140**
	(0.020)	(0.021)	(0.054)	(0.056)
Controls				
Regional dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
N	9,829	9,184	9,829	9,184

Robust standard errors in parentheses. Columns 1 and 2 present OLS estimates. Columns 3 and 4 show probit estimates.
* p<0.10, ** p<0.05, *** p<0.01

Table A6: Second stage results, controlling for fear of job loss. Dependent variable: Job satisfaction.

	(1) 2SLS	(2) IVOPROBIT	(3) 2SLS	(4) IVOPROBIT
Machine replacement	-0.567	-1.050***	-0.775*	-1.048***
	(0.375)	(0.137)	(0.428)	(0.142)
Job loss worry	-0.299***	-0.340***		
	(0.034)	(0.034)		
Unemployed in 5 years			-0.365***	-0.355***
			(0.111)	(0.102)
Age	0.006***	0.006***	0.006***	0.008***
	(0.002)	(0.001)	(0.002)	(0.001)
Union membership	-0.037	-0.068***	-0.039	-0.058**
	(0.027)	(0.025)	(0.031)	(0.026)
Income scale = 2	-0.089	0.000	-0.146*	-0.156*
	(0.076)	(.)	(0.086)	(0.087)
Income scale = 3	0.023	-0.117	0.008	0.012
	(0.050)	(0.081)	(0.055)	(0.065)
Income scale = 4	0.085*	0.032	0.105**	0.132**
	(0.047)	(0.062)	(0.050)	(0.059)
Income scale = 5	0.130***	0.115**	0.140***	0.178***
	(0.048)	(0.057)	(0.051)	(0.060)
Income scale = 6	0.181***	0.176***	0.176***	0.219***
	(0.052)	(0.058)	(0.056)	(0.065)
Income scale = 7	0.196***	0.240***	0.210***	0.280***
	(0.062)	(0.062)	(0.068)	(0.071)
Income scale = 8	0.193***	0.288***	0.202***	0.269***
	(0.057)	(0.068)	(0.062)	(0.073)
Income scale = 9	0.330***	0.273***	0.333***	0.443***
	(0.066)	(0.070)	(0.072)	(0.082)
University degree	-0.002	0.002	0.028	0.027
	(0.027)	(0.027)	(0.028)	(0.027)
Woman	0.080***	0.114***	0.081***	0.114***
	(0.019)	(0.025)	(0.021)	(0.026)
Industry employment	-0.143***	-0.186***	-0.192***	-0.237***
	(0.034)	(0.041)	(0.038)	(0.043)
<u>Controls</u>				
Regional dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
N	9,829	9,829	9,184	9,184

Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A7: First stage results, controlling for "employability". Dependent variable: machine replacement.

	(2) OLS	(3) OLS	(5) PROBIT	(6) PROBIT
Robot adoption	0.825***	0.910***	2.174***	2.408***
	(0.185)	(0.181)	(0.486)	(0.478)
Difficult to find new job	0.031***		0.085***	
	(0.010)		(0.028)	
Insufficient skills in current job		0.050***		0.131***
		(0.011)		(0.028)
Age	-0.004***	-0.004***	-0.011***	-0.010***
	(0.000)	(0.000)	(0.001)	(0.001)
Union membership	-0.060***	-0.058***	-0.160***	-0.155***
	(0.011)	(0.011)	(0.029)	(0.029)
Income scale = 2	-0.098***	-0.094***	-0.279***	-0.269***
	(0.035)	(0.034)	(0.098)	(0.096)
Income scale = 3	-0.011	-0.015	-0.031	-0.042
	(0.029)	(0.028)	(0.076)	(0.075)
Income scale = 4	0.017	0.018	0.045	0.046
	(0.027)	(0.026)	(0.070)	(0.068)
Income scale = 5	0.021	0.020	0.057	0.053
	(0.027)	(0.026)	(0.071)	(0.069)
Income scale = 6	0.035	0.037	0.093	0.098
	(0.029)	(0.028)	(0.076)	(0.074)
Income scale = 7	0.078**	0.071**	0.204**	0.188**
	(0.032)	(0.031)	(0.082)	(0.080)
Income scale = 8	0.034	0.029	0.089	0.073
	(0.032)	(0.032)	(0.085)	(0.083)
Income scale = 9	0.069*	0.061*	0.181*	0.159*
	(0.037)	(0.036)	(0.095)	(0.093)
University degree	0.041***	0.034***	0.109***	0.091***
	(0.011)	(0.011)	(0.030)	(0.030)
Woman	-0.012	-0.012	-0.030	-0.030
	(0.011)	(0.011)	(0.030)	(0.029)
Industry employment	-0.047**	-0.050**	-0.126**	-0.134**
	(0.020)	(0.020)	(0.055)	(0.054)
Controls				
Regional dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
F-stat	19.89	25.26		
N	9,451	9,890	9,451	9,890

Robust standard errors in parentheses. * p<0.10, ** p<0.05, ***p<0.01

Table A8: First stage results, controlling for "employability". Regressions by education level. Dependent variable: machine replacement.

	(1) No university education	(2) University education	(3) No university education	(4) University education
Robot adoption	1.032***	0.623*	1.097***	0.811**
	(0.225)	(0.343)	(0.218)	(0.338)
Difficult to find new job	0.042***	0.017		
	(0.016)	(0.014)		
Insufficient skills in current job			0.042***	0.058***
			(0.016)	(0.014)
Age	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Union membership	-0.027*	-0.089***	-0.025*	-0.087***
	(0.016)	(0.016)	(0.015)	(0.016)
Income scale = 2	-0.122***	-0.032	-0.120***	-0.035
	(0.046)	(0.064)	(0.045)	(0.061)
Income scale = 3	0.001	-0.028	-0.008	-0.030
	(0.041)	(0.042)	(0.041)	(0.041)
Income scale = 4	0.028	0.024	0.029	0.026
	(0.040)	(0.036)	(0.039)	(0.035)
Income scale = 5	0.085**	0.002	0.083**	0.005
	(0.042)	(0.036)	(0.041)	(0.035)
Income scale = 6	0.020	0.054	0.013	0.066*
	(0.045)	(0.039)	(0.044)	(0.037)
Income scale = 7	0.108**	0.071*	0.091*	0.075*
	(0.049)	(0.042)	(0.048)	(0.040)
Income scale = 8	0.071	0.016	0.048	0.024
	(0.050)	(0.043)	(0.049)	(0.042)
Income scale = 9	0.065	0.065	0.061	0.060
	(0.062)	(0.046)	(0.059)	(0.045)
Woman	0.049***	-0.055***	0.059***	-0.063***
	(0.017)	(0.015)	(0.017)	(0.014)
Industry employment	-0.066***	-0.001	-0.065***	-0.005
	(0.025)	(0.035)	(0.025)	(0.034)
Controls				
Regional dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
N	4,036	5,285	4,117	5,334

Robust standard errors in parentheses. The table present results from OLS estimations. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A9: Second stage results, controlling for "employability". Dependent variable: job satisfaction.

	(1) IVOPROBIT	(2) IVOPROBIT	(3) 2SLS	(4) 2SLS
Machine replacement	-0.981***	-1.108***	-0.676*	-0.767**
	(0.204)	(0.122)	(0.395)	(0.357)
Difficult to find new job	-0.001		-0.006	
	(0.025)		(0.023)	
Insufficient skill in current job		-0.154***		-0.131***
		(0.027)		(0.026)
Age	0.008***	0.007***	0.007***	0.006***
	(0.002)	(0.001)	(0.002)	(0.002)
Union membership	-0.049*	-0.051**	-0.030	-0.031
	(0.028)	(0.025)	(0.030)	(0.027)
Income scale = 2	-0.058	-0.134*	-0.057	-0.120
	(0.083)	(0.078)	(0.079)	(0.075)
Income scale = 3	0.045	0.013	0.031	0.009
	(0.063)	(0.061)	(0.053)	(0.052)
Income scale = 4	0.137**	0.126**	0.105**	0.099**
	(0.057)	(0.055)	(0.048)	(0.047)
Income scale = 5	0.212***	0.190***	0.162***	0.149***
	(0.058)	(0.056)	(0.049)	(0.048)
Income scale = 6	0.268***	0.251***	0.211***	0.201***
	(0.062)	(0.061)	(0.053)	(0.052)
Income scale = 7	0.300***	0.297***	0.218***	0.222***
	(0.069)	(0.067)	(0.064)	(0.061)
Income scale = 8	0.280***	0.279***	0.206***	0.209***
	(0.071)	(0.069)	(0.060)	(0.058)
Income scale = 9	0.481***	0.446***	0.353***	0.334***
	(0.080)	(0.079)	(0.070)	(0.067)
University degree	0.035	0.041	0.034	0.038
	(0.028)	(0.026)	(0.027)	(0.024)
Woman	0.118***	0.127***	0.083***	0.094***
	(0.026)	(0.025)	(0.020)	(0.020)
Industry employment	-0.209***	-0.204***	-0.166***	-0.165***
	(0.042)	(0.041)	(0.036)	(0.035)
<u>Controls</u>				
Regional dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
N	9,451	9,890	9,451	9,890

Robust standard errors in parentheses. * p<0.10, ** p<0.05, ***p<0.01

Table A10: Marginal effects of machine replacement on job satisfaction for workers of different education levels and of different ages.

	Controlling for: Difficult to find new job		Controlling for: Insufficient skill in current job	
	Below university education	University education	Below university education	University education
At age 20	-0.384***	-0.112	-0.327***	-0.084
	(0.116)	(0.081)	(0.115)	(0.080)
At age 30	-0.372***	-0.175***	-0.330***	-0.153***
	(0.075)	(0.050)	(0.074)	(0.049)
At age 40	-0.360***	-0.237***	-0.332***	-0.221***
	(0.046)	(0.033)	(0.046)	(0.033)
At age 50	-0.348***	-0.300***	-0.335***	-0.289***
	(0.054)	(0.051)	(0.053)	(0.050)
At age 55	-0.342***	-0.331***	-0.336***	-0.324***
	(0.070)	(0.066)	(0.068)	(0.065)
Controls				
Individual controls	✓	✓	✓	✓
Regional dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
N	7,050	7,050	7,238	7,238

Robust standard errors in parentheses. The table present results from bivariate recursive probit estimations. Note that sample is restricted to workers aged 55 years or less to avoid that respondents close to retirement may bias estimations regarding difficulties of finding new jobs. * p<0.10, ** p<0.05, *** p<0.01

Table A11: First stage results. Robustness tests.

	(1) Machine replacement	(2) Machine replacement	(3) Machine replacement	(4) Machine replacement	(5) Machine replacement	(6) Machine replacement
Robot exposure	0.830***	0.831***	0.858***	0.860***	0.864***	0.862***
	(0.182)	(0.182)	(0.182)	(0.182)	(0.182)	(0.182)
Age	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Union membership	-0.056***	-0.056***	-0.056***	-0.056***	-0.056***	-0.056***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Income scale = 2	-0.094***	-0.094***	-0.094***	-0.094***	-0.095***	-0.095***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Income scale = 3	-0.007	-0.007	-0.008	-0.007	-0.007	-0.007
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Income scale = 4	0.023	0.023	0.023	0.023	0.023	0.023
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Income scale = 5	0.027	0.027	0.027	0.027	0.027	0.027
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Income scale = 6	0.042	0.042	0.042	0.042	0.042	0.042
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Income scale = 7	0.078**	0.078***	0.078**	0.078**	0.078**	0.078**
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Income scale = 8	0.038	0.038	0.038	0.038	0.038	0.038
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Income scale = 9	0.069*	0.069*	0.070**	0.070**	0.070**	0.070**
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
University degree	0.037***	0.037***	0.037***	0.037***	0.036***	0.036***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Woman	-0.011	-0.011	-0.011	-0.011	-0.011	-0.011
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Industry employment	-0.044**	-0.044**	-0.044**	-0.044**	-0.044**	-0.044**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
GDP	-0.304	-0.279	-0.252	-0.357	-0.688	-0.752
	(0.282)	(0.305)	(0.305)	(0.512)	(0.551)	(0.603)
% pop. with tertiary educ.		0.004	0.007	0.006	-0.014	-0.015
		(0.017)	(0.017)	(0.018)	(0.022)	(0.023)
Broadband availability in business properties			-0.397***	-0.405***	-0.259	-0.329
			(0.149)	(0.153)	(0.179)	(0.325)
Unemployment benefit recipients				-0.017	-0.094	-0.115
				(0.066)	(0.081)	(0.114)
% large industrial firms					-0.049	-0.053
					(0.030)	(0.035)
Log(population) in region						-0.768
F-stat	20.86	20.91	22.28	22.35	22.57	22.48
N	10,051	10,051	10,051	10,051	10,051	10,051

Robust standard errors in parentheses. The table present results from OLS estimations. * p<0.10, ** p<0.05, *** p<0.01

Table A12: Second stage results. Robustness tests.

	(1) Job satisfaction	(2) Job satisfaction	3) Job satisfaction	(4) Job satisfaction	(5) Job satisfaction	(6) Job satisfaction
Machine replacement	-0.994***	-0.992***	-1.000***	-1.006***	-1.003***	-1.016***
	(0.174)	(0.175)	(0.169)	(0.166)	(0.167)	(0.159)
Age	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Union membership	-0.057**	-0.057**	-0.057**	-0.057**	-0.057**	-0.058**
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.025)
Income scale = 2	-0.136*	-0.135*	-0.136*	-0.135*	-0.135*	-0.134*
	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)
Income scale = 3	0.017	0.017	0.017	0.018	0.018	0.018
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Income scale = 4	0.121**	0.120**	0.121**	0.121**	0.121**	0.122**
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Income scale = 5	0.188***	0.188***	0.188***	0.188***	0.188***	0.188***
	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)
Income scale = 6	0.247***	0.247***	0.247***	0.248***	0.248***	0.249***
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Income scale = 7	0.286***	0.286***	0.286***	0.287***	0.286***	0.287***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
Income scale = 8	0.275***	0.275***	0.275***	0.275***	0.275***	0.276***
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)
Income scale = 9	0.435***	0.435***	0.435***	0.435***	0.435***	0.434***
	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)
University degree	0.034	0.034	0.034	0.034	0.034	0.036
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Woman	0.129***	0.129***	0.129***	0.129***	0.129***	0.128***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Industry employment	-0.212***	-0.212***	-0.212***	-0.211***	-0.211***	-0.211***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
GDP	0.635	0.787	0.773	1.737	1.540	2.683**
	(0.601)	(0.628)	(0.628)	(1.156)	(1.051)	(1.156)
% pop. with tertiary educ.		0.022	0.019	0.034	0.021	0.045
		(0.038)	(0.038)	(0.041)	(0.046)	(0.049)
Broadband availability in business properties			0.277	0.348	0.439	0.851**
			(0.349)	(0.358)	(0.409)	(0.433)
Unemployment benefit recipients				0.157	0.111	0.331**
				(0.150)	(0.164)	(0.157)
% large industrial firms					-0.030	0.028
					(0.067)	(0.066)
Log(population) in region						3.892***
						(1.278)
N	10,051	10,051	10,051	10,051	10,051	10,051

Robust standard errors in parentheses. The table present results from bivariate recursive probit estimations. * p<0.10, ** p<0.05, *** p<0.01

Table A13: Placebo tests (first stage).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot exposure	0.814***	0.767***	0.769***	0.826***	0.829***	0.830***	0.830***
	(0.256)	(0.259)	(0.259)	(0.260)	(0.260)	(0.260)	(0.260)
Robot exposure in *t+1*	0.011	0.018	0.017	0.009	0.009	0.008	0.009
	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
Age	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Union membership	-0.056***	-0.056***	-0.056***	-0.056***	-0.056***	-0.056***	-0.056***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Income scale = 2	-0.093***	-0.093***	-0.093***	-0.094***	-0.094***	-0.094***	-0.094***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Income scale = 3	-0.006	-0.006	-0.006	-0.007	-0.007	-0.007	-0.007
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Income scale = 4	0.024	0.024	0.024	0.023	0.023	0.023	0.023
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Income scale = 5	0.027	0.027	0.027	0.027	0.027	0.027	0.027
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Income scale = 6	0.042	0.042	0.042	0.042	0.041	0.041	0.041
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Income scale = 7	0.078**	0.077**	0.077**	0.078**	0.078**	0.078**	0.077**
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Income scale = 8	0.038	0.037	0.037	0.038	0.037	0.037	0.037
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Income scale = 9	0.068*	0.067*	0.067*	0.069*	0.069*	0.069*	0.069*
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
University degree	0.037***	0.037***	0.037***	0.037***	0.037***	0.037***	0.037***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Woman	-0.011	-0.011	-0.011	-0.011	-0.011	-0.011	-0.011
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Industry employment	-0.047**	-0.048**	-0.048**	-0.047*	-0.047**	-0.047**	-0.047**
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
GDP		-0.315	-0.290	-0.258	-0.361	-0.414	0.137
		(0.284)	(0.306)	(0.307)	(0.512)	(0.674)	(1.035)
% pop. with tertiary education			0.004	0.007	0.006	0.005	0.010
			(0.017)	(0.017)	(0.018)	(0.021)	(0.022)
Broadband availability in business properties				-0.395***	-0.404***	-0.404***	-0.067
				(0.150)	(0.153)	(0.153)	(0.499)
Unemployment benefit recipients					-0.017	-0.025	0.091
					(0.066)	(0.091)	(0.188)
% large industrial firms						-0.284	1.921
						(2.320)	(3.886)
Log(population) in region							3.072
N		10,051	10,051	10,051	10,051	10,051	10,051

Robust standard errors in parentheses. The table present results from OLS estimations. * p<0.10, ** p<0.05, *** p<0.01

Table A14: First and second stage results. Adding interaction variables between union membership, robot adoption and machine replacement.

	(1)	(2)	(3)	(4)
	OLS 1st stage	Probit 1st stage	2SLS 2nd stage	IVOPROBIT 2nd stage
Robot adoption	0.841***	2.160***		
	(0.279)	(0.725)		
Robot adoption X Union	0.019	0.141		
	(0.325)	(0.846)		
Machine replacement			-0.674	-0.393***
			(0.536)	(0.113)
Machine replacement X Union			-0.128	-0.576
			(0.514)	(0.422)
Age	-0.004***	-0.011***	0.007***	0.009***
	(0.000)	(0.001)	(0.002)	(0.002)
Union membership	-0.057***	-0.157***	0.013	0.197
	(0.022)	(0.058)	(0.219)	(0.167)
Income scale = 2	-0.093***	-0.268***	-0.133*	-0.111
	(0.033)	(0.094)	(0.076)	(0.081)
Income scale = 3	-0.006	-0.019	0.010	0.023
	(0.028)	(0.073)	(0.051)	(0.061)
Income scale = 4	0.024	0.063	0.093**	0.119**
	(0.025)	(0.067)	(0.047)	(0.055)
Income scale = 5	0.027	0.072	0.143***	0.182***
	(0.026)	(0.068)	(0.048)	(0.057)
Income scale = 6	0.043	0.112	0.194***	0.237***
	(0.028)	(0.073)	(0.052)	(0.061)
Income scale = 7	0.078***	0.205***	0.213***	0.272***
	(0.030)	(0.079)	(0.062)	(0.067)
Income scale = 8	0.039	0.100	0.200***	0.257***
	(0.031)	(0.082)	(0.060)	(0.070)
Income scale = 9	0.069**	0.181**	0.319***	0.414***
	(0.035)	(0.092)	(0.070)	(0.079)
University degree	0.037***	0.098***	0.034	0.020
	(0.011)	(0.029)	(0.026)	(0.026)
Woman	-0.011	-0.030	0.090***	0.126***
	(0.011)	(0.029)	(0.021)	(0.030)
Industry employment	-0.044**	-0.118**	-0.169***	-0.213***
	(0.020)	(0.054)	(0.035)	(0.042)
Controls				
Regional dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
N	10,051	10,051	10,051	10,051

Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01