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## Robots, Meaning, and Self-Determination

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DISCUSSION PAPER SERIES

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DECEMBER 2023

## DISCUSSION PAPER SERIES

IZA DP No. 16656

# Robots, Meaning, and Self-Determination

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## ABSTRACT

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### **Robots, Meaning, and Self-Determination\***

This paper is the first to examine the impact of robotization on work meaningfulness and autonomy, competence, and relatedness, which are essential to motivation and well-being at work. Drawing on surveys from workers and industry-specific robotization data across 14 industries in 20 European countries from 2005 to 2021, our analysis reveals a consistent negative impact of robotization on perceived work meaningfulness and autonomy. Using instrumental variables, we find that doubling robotization correlates with a 0.9% decrease in work meaningfulness and a 1% decrease in autonomy. To put this in perspective, aligning the robotization intensity of the top five industry with the leading industry's robotization level in 2020—which would mean a 7.5-fold increase—would lead to a 6.8% reduction in work meaningfulness and a 7.5% reduction in autonomy. The link between robotization, competence, and relatedness is also negative but less robust. We also examine how tasks, skills, and socio-demographic characteristics moderate the relationship. We find that workers with routine tasks drive the negative effects of robotization on autonomy. However, we also discover that engaging in social tasks and utilizing computers as tools for independent work can help workers maintain a sense of autonomy in industries and job roles that adopt robots. Our results highlight that by deteriorating work meaningfulness and self-determination, robotization can impact work life above and beyond its consequences for employment and wages.

**JEL Classification:** J01, J30, J32, J81, I30, I31, M50

**Keywords:** work meaningfulness, self-determination theory, robotization, automation

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## 1. Introduction

Robots are matching or outperforming humans in a growing range of tasks, including welding, packing, painting, filling prescriptions, and assembling intricate automotive parts. With the integration of artificial intelligence (AI), smart machines are now pioneering new frontiers, from performing complex surgeries on Earth, to exploring the harsh, uncharted surface of Mars. This rapid and ongoing wave of automation is arguably one of the most powerful forces that has already reshaped and will continue to reshape work in the future.

This rapid advancement of automation technologies has understandably sparked widespread fears about the future of work (e.g., Dekker et al., 2017; Hinks, 2021), reigniting age-old anxieties concerning the impact of technology on employment (e.g., Mokyr et al., 2015; Spencer, 2023). Recent projections for automation potential in the US (Frey & Osborne, 2017) and Europe (Bonin et al., 2015; Bowles, 2014; Pajarinen & Rouvinen, 2014) have recently rekindled debates and public fears.<sup>1</sup> While subsequent studies temper these estimates by considering task heterogeneity within occupations (Arntz et al., 2016, 2017; Nedelkoska & Quintini, 2018), the underlying fear of unemployment is understandable given the large earnings (e.g., Couch & Placzek, 2010; Huckfeldt, 2022) and psychological costs of unemployment (e.g., Nikolova & Ayhan, 2019; Haisken-DeNew & Kassenboemer, 2009), and the fact that automation's consequences are negative for low-skilled workers and those performing routine tasks. Unsurprisingly, academic research has primarily focused on the repercussions of technology on employment and income.

However, recent developments have fostered a broader understanding of automation's impact. Models of routine-biased technological change suggest that the job losses from automation can be counterbalanced by productivity and reinstatement effects (Acemoglu & Restrepo, 2019; Arntz et al., 2019), potentially leading to a net economic gain (e.g., Gregory et al., 2022). Moreover, when firms adopt new technology, workers typically adapt their tasks (Dauth et al., 2021; Spitz-Oener, 2006), which is why whole professions typically do not disappear. Nevertheless, the replacement of some tasks can lead to a reduction in task variety and autonomy. Therefore, how robotization affects job quality and how various tasks impact worker well-being are critical questions that the current literature on the employment and earnings effects of automation has yet to explore.

In this paper, we advance previous research by providing a more holistic picture of the impact of robotization on workers' lives. Beyond income and job security, workers also value other aspects of their jobs that contribute to their well-being and motivation. For example, workers care about whether their work is meaningful or fulfilling (Hu & Hirsh, 2017; Kesternich et al., 2021), whether they have autonomy or discretion over their tasks, feel competent in executing their tasks, and have positive relationships with their co-workers or clients (Deci & Ryan, 1985; Hackman & Oldham, 1976). These factors, intrinsic to human motivation and basic psychological needs, have profound effects on performance, productivity, and learning outcomes, and are key to optimal human functioning (Ryan & Deci, 2017). Therefore, it is important to examine how automation affects non-monetary aspects of work quality and how workers can cope with the challenges and opportunities that automation brings.

In this paper, we contribute to the literature by examining the impact of one type of automation— industrial robots— on two key aspects of work quality: work meaningfulness and self-determination. Work meaningfulness refers to the extent to which workers perceive their work

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<sup>1</sup> In 2021, only 29% of European respondents believed that artificial intelligence and automation would create more jobs than they would eliminate (European Commission, 2021).

as valuable, significant, or purposeful (Nikolova & Cnossen, 2020; Rosso et al., 2010). Self-determination denotes the extent to which workers experience autonomy, competence, and relatedness (Ryan & Deci, 2017). These aspects are derived from the seminal theory in psychology: self-determination theory (Ryan & Deci, 2017). According to Nikolova and Cnossen (2020), autonomy, competence, and relatedness are key pre-conditions to achieving work meaningfulness. Furthermore, work meaningfulness is instrumental in workers' efforts and has been linked to key organizational outcomes such as absenteeism, retirement intentions, and the willingness to take on skills training (Nikolova & Cnossen, 2020; Rosso et al., 2010).

Industrial robots are capable of interacting with their environment by handling or moving objects and primarily perform routine manual tasks, such as reaching and handling.<sup>2</sup> Adopting industrial robots in the workplace can affect work meaningfulness and self-determination through several channels. For example, it can lead to diminishing human interactions and worsening relationships at work. Automation can also reduce workers' creativity and learning potential and diminish skill utilization and competence development, especially for those performing routine or manual tasks. In addition, industrial robots could reduce workers' autonomy if robots and algorithms determine their tasks and work sequence (Gombolay et al., 2015).

Robotization need not be harmful to work meaningfulness and self-determination. For instance, automation can also reduce “the drudgery of work” by eliminating repetitive tasks and freeing up time for creative pursuits (Spencer, 2018), which can improve job quality and the ability of workers to satisfy their innate psychological needs from work (Deci & Ryan, 2000). For example, by replacing dangerous or dull tasks, robots can improve working conditions, which can increase work meaningfulness and self-determination. Indeed, robots are already taking over tasks related to high-risk military operations, space explorations, bomb detection, and detonation, as well as “dirty” jobs, such as sewer cleanup, milking cows, or conducting autopsies (Marr, 2017). Adoption of such technologies can then free humans to have more time and space to focus on creative tasks, especially those that require human judgment or interaction. Thus, the extent to which robots affect workers' perceptions of work meaningfulness and self-determination remains an empirical question.

To explore how automation technologies impact workers' meaningfulness and self-determination, we use worker-level survey data for 2010, 2015, and 2021 from 20 European countries and 14 industries. We combine these data with industry-level information on changes in robots per 10,000 workers (i.e., robotization) and analyze the data using Ordinary Least Squares (OLS) and Instrumental Variable (IV) techniques.

Our key finding is that robots harm work meaningfulness and autonomy. Specifically, based on the IV coefficient estimates, doubling robotization would entail a 0.9% decline in work meaningfulness and a 1% drop in autonomy. Across all industries in our sample, the average increase in robotization between 2005 and 2020 was 389% (almost a four-fold increase). For some industries, the increase was even more dramatic. In mining and quarrying, for instance, there was a staggering 26-fold increase in robotization over the same period, implying a substantial loss in meaningfulness and autonomy. To further put our estimates in perspective, consider the food and beverages industry, a top 5 industry in robot adoption, and the automotive industry (the sector with the highest level of robot adoption). Should robot adoption in the food and beverages industry increase to match that of the automotive industry (representing a 7.5-fold increase in

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<sup>2</sup> In this paper, we focus on industrial robots, rather than service robots used, for example, in surgery. The reason for the restriction is that industrial robots have seen by far the most adoption, whereas the adoption of service sector robots is still in its infancy during our analysis time period.

robotization), we estimate a 6.8% decrease in work meaningfulness and a 7.5% decrease in autonomy. Based on EUKLEMS data, in 2020, nearly 4.5 million individuals worked in the food and beverages industry and about 3.3 million in the automotive industry across the countries in our study. Therefore, the impact sizes we document may seem small in isolation, but the cumulative and long-term effect could be substantial given the large number of employees affected in such sizable industries and long-term trends in robotization.

Furthermore, we find that the negative consequences of robotization for work meaningfulness are mostly independent of workers' tasks, skills, and socio-demographic characteristics. We do, however, find important heterogeneity related to autonomy. Specifically, working with computers —i.e., being in control of the machine— completely offsets the negative consequences of automation for autonomy. At the same time, the detrimental effects of robotization on autonomy are entirely driven by workers performing repetitive tasks and are more pronounced among individuals with less than tertiary education and low-skilled workers. Our research highlights that the groups disproportionately affected by robotization overlap with those identified in prior studies focusing on wages (e.g., Acemoglu et al., 2023; Graetz & Michaels, 2018). With respect to competence and relatedness, the results are less robust across the specifications, but they also appear to be negative for those engaged in repetitive tasks and positive for those working with computers.

Overall, our study contributes to the scarce literature on the well-being implications of automation technology by examining how robotization affects workers' perceptions of meaningfulness and the fulfillment of their basic psychological needs of autonomy, competence, and relatedness. In addition, we explore heterogeneities in these relationships based on workers' socio-demographic characteristics (i.e., skills, education, age, gender) and the nature of their tasks (i.e., routine, nonroutine cognitive, and nonroutine interactive). More generally, the unique contribution of our study lies in documenting how robotization can benefit or disadvantage various groups of workers in terms of their perceived work quality above and beyond its impact on wages and employment contracts. Importantly, we also highlight which tasks and arrangements could help workers adapt and leverage automation technology more effectively. While future patterns of robotization remain uncertain, our results provide a useful framework and baseline for understanding their effects on job quality and well-being outcomes.

## 2. Literature Review

The extant literature has mainly focused on the impact of robotization on employment and wages without reaching a consensus about the overall effects. The main conclusions depend on multiple factors, including the level of analysis – firm, industry, or worker – and the country context (the US, cross-country, or Europe). Robot-adopting firms, which are typically more productive than their counterparts, tend to expand their employment (Acemoglu et al., 2023; Bessen et al., 2021; Dixon et al., 2021; Koch et al., 2021), and even increase workers' wages (e.g., Bessen et al., 2021). At the same time, their non-robot-adopting competitors experience the opposite effects, reducing employment. These effects may result in an overall decline in employment at the economy level.

At the industry level, the evidence for some countries is negative, and for others not. Across 17 advanced economies, robotization has led to increases in wages overall but declines in the hours worked among the low-skilled (Graetz & Michaels, 2018). Furthermore, Acemoglu and Restrepo (2020) show that robot adoption between 1990 and 2007 led to large declines in employment and wages in US commuting zones. Similarly, Borjas and Freeman (2019) estimate

that robotization entailed wage and employment declines between 2014 and 2016 in the US. In China, robot adoption also negatively affects employment and wages across cities for the 2000-2016 period (Giuntella & Wang, 2019). Adachi et al. (2020) found that robot adoption in Japanese industries and regions increased employment in the 1978-2017 period. The French evidence on robots and employment is also positive (Acemoglu et al., 2020; Aghion et al., 2020), with no consequences for wages (Acemoglu et al., 2020). Using data on 98 EU regions during the 2001-2016 period, Jestl (2022) finds relatively modest effects of robotization on total employment. There are negative effects on local manufacturing industries, which are offset by employment in local services industries (Jestl, 2022). This evidence is in line with the German findings that industrial robots displace manufacturing workers, but this is offset by job creation in the services sector (Dauth et al., 2021).

The evidence on the wages and employment of individual workers is not only mixed but also scarce. The cross-country evidence for 20 European countries suggests that robots increased the wages of both male and female workers (Aksoy et al., 2021). When looking at individual workers in Germany, Dauth et al. (2021) find that robotization is associated with small employment increases and small wage declines, on average. In the Netherlands, robots increase the average hourly wages and decrease the hours worked, with no average consequences for employment (Acemoglu et al., 2023). Nevertheless, blue-collar, low-educated workers, and those performing routine tasks tend to see their wages decline (Acemoglu et al., 2023).

While the literature on robotization is rapidly expanding, economists have paid little attention to its comprehensive impact on job quality and its ensuing consequences from the viewpoint of individual workers (see a discussion in Berg et al., 2023). Investigating how automation influences job quality beyond wages and employment, however, could significantly contribute to our understanding of the broader consequences of robotization on workers' well-being. Factors beyond financial compensation, such as autonomy and a sense of meaning, play a crucial role in defining the comprehensive value of a job (e.g., Clark, 2015; Green, 2006; Nikolova & Cnossen, 2020) and are essential elements for evaluating the broader impact of robotization on the workforce.

The existing body of research on the effects of robotization on health and well-being outcomes, however, is still very limited (see Table 1).<sup>3</sup> Documented outcomes differ based on the period, context, and dependent variables. Some studies suggest that robotization seems to positively affect the health of low-skilled US workers by reducing physically demanding tasks, but does not affect high-skilled workers (Gunadi & Ryui, 2021). Other studies from the US find that while workplace injuries decline (Gihleb et al., 2022), there are decreases in mental health (Gihleb et al., 2022) and increases in substance-abuse-related deaths (Gihlebl et al., 2022; O'Brien et al., 2022) and mortality from suicide, homicide, cancer, and cardiovascular causes in certain age groups (O'Brien et al., 2022). The evidence on the health consequences for Germany is more mixed, with Gihleb et al. (2022) finding no effects on mental health, and Abeliatsky and Beulmann (2021) finding the opposite. Studies link automation to worsened job satisfaction in Norway, driven by low-skilled workers (Schwabe & Castellacci, 2020) and greater work intensity in Europe (Antón et al., 2022).

While the existing literature offers preliminary insights into the varying impact of robotization on worker health and well-being, it also underscores the significant role of automation

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<sup>3</sup> See Castellacci and Tveito (2018) for an overview of the literature on well-being and ICT and Martin and Huret (2022) for a summary of the studies on the effects of digitalization, including robotization and automation risk, on different measures of job quality.



in shaping job quality. First, adopting industrial robots can harm job satisfaction by inducing greater fear of future machine replacement. For example, studying a large sample of workers in Norway for the period 2016-2019, Schwabe & Castellacci (2020) find that introducing industrial robots in local labor markets increases workers' fear of machine replacement, which, in turn, significantly decreases their job satisfaction. Remarkably, 40% of workers in their sample report fear that smart machines will substitute their working tasks in the future, a percentage that is similar to other European countries. The results reported by Schwabe & Castellacci (2020) were predominantly driven by low-skilled workers who, due to their routine-based tasks, are more likely to be exposed to automation.

Similarly, Gorny and Woodard (2020), using data from the US and Europe, show that workers in occupations with higher *automation potential* through computer-controlled equipment are more likely to experience lower job satisfaction. However, they find that it is the monotonicity and low perceived meaning of such jobs that drive low job satisfaction rather than fears of future job replacement. Their results emphasize the crucial role job meaning plays in the relationship between robot adoption and subjective well-being outcomes such as job satisfaction.

Second, a related body of work suggests that the *actual* adoption of industrial robots and *automation risk*—typically associated with expectations of reduced wages and potential future unemployment—can also negatively impact workers' physical and mental health (e.g., Abeliasky & Beulmann, 2021; Lordan & Stringer, 2022; Patel et al., 2018). Specifically, job-loss-related fear and anxiety can lead to job insecurity (Reichert & Tauchmann, 2017), subsequently culminating in poor physical and mental health outcomes (De Witte et al., 2016). Indeed, using data from the General Social Survey in the US, Patel et al. (2018) find that a 10% increase in automation risk at the county level is associated with 2.38, 0.8, and 0.6 percentage points lower general, physical, and mental health, respectively.

Likewise, using data from the German Socio-Economic Panel, Abeliasky & Beulmann (2021) demonstrate that workers in industries that experience a surge in the stock of robots are more likely to report poorer mental health outcomes due to greater job insecurity. Again, the results are primarily driven by routine task jobs, but are also concentrated among men. Nevertheless, using the same German data, Gihleb et al. (2018) found no effects of robotization on psychological burdens, work satisfaction, or life satisfaction.

Finally, Antón et al., (2022) examined the effects of robot adoption on job quality and working conditions, focusing on elements, such as work intensity (e.g., the pace of work, time pressure, etc.), the physical environment, and skill discretion (Antón et al., 2022). Their findings suggest that an increase in the robot stock at the regional level is associated with higher work intensity but has no effect on any other job quality indicator related to the physical environment.

Our study advances this emerging stream of research by examining the effect of robotization on work meaning and self-determination (i.e., competence, relatedness, and autonomy). This is important because prior research underscores that these dimensions do not merely enrich job experiences, but serve as key drivers of workers' motivation, effort, and performance (e.g., Nikolova & Cnossen, 2020) and are key aspects of the overall value of a job.

Table 1: Related Literature

Reference	Outcomes	Automation measure	Level of analysis	Main Data Sources	Econometric technique(s)	Key findings
<b>Health</b>						
Abeliansky & Beulmann (2021)	Mental health	Robot stock per 1,000 workers at the industry level	Individual-level	German Socio-Economic Panel, International Federation of Robotics (IFR), WIOD trade data, Baumgarten et al. (2013) task content data	Individual Fixed Effects; IV (instrument = robotization in other advanced countries)	Worse mental health; driven by job insecurity fears, especially for routine-task workers and males
Gunadi & Ryu (2021)	Share reporting i) poor health; ii) work disability; iii) quitting a job because of health	Robot stock per 1,000 workers at the metropolitan statistical area (MSA) level	MSA-level in the US	Current Population Survey + IFR data on robots (2006-2017)	2SLS regressions (instrument=robot adoption in select European countries)	Reductions in share reporting poor health, work disability, and job quitting due to health among low-skilled workers; no effects for high-skilled workers;
Gihleb et al. (2022)	Workplace injuries, job intensity, disability, mental health, work and life satisfaction	Robot stock per US worker (for the US); Robot stock per German worker based on the initial occupation (German sample)	City-level (US), Individual-level (Germany)	Occupational Health and Safety Administration (OSHA) Data Initiative; Center for Disease Control and National Center for Health Statistics; American Community Survey (ACS); Behavioral Risk Factor Surveillance System (BRFSS); German Socio-Economic Panel (1994-2016); International Federation of Robotics (IFR)	IV (instrument=robot adoption in other countries, only for the US but not for analyses for Germany)	US: declines in workplace injuries; increase in drug- and alcohol-related deaths and worse mental health; Germany: less physical intensity; less disability; no effects on mental health and work/ life satisfaction
<b>Job satisfaction and job quality</b>						

<b>Reference</b>	<b>Outcomes</b>	<b>Automation measure</b>	<b>Level of analysis</b>	<b>Main Data Sources</b>	<b>Econometric technique(s)</b>	<b>Key findings</b>
Schwabe & Castellacci (2020)	Job satisfaction	Fear of machine replacement, instrumented using the robot stock	Individual	Norway, 2007-2019, Working Life Barometer, International Federation of Robotics (IFR), Eurostat employment data	IV (instrument=lagged change in the robot stock per 1000 workers at the region-industry level)	Worse job satisfaction; driven by low-skilled workers (more exposed due to routine tasks)
Antón, et al. (2022)	Job quality aspects (work intensity, physical environment, skills & discretion)	Change in the robot stock per worker at the regional (NUTS-2) level	Regional	European Working Conditions Surveys (1995-2005), International Federation of Robotics (IFR), European Union Labour Force Survey, European Community Household Panel, EUKLEMS	IV (instrument = change in the robot stocks in other advanced countries)	Worsens work intensity; No effects on any other job quality indicators

### **3. Conceptual Framework**

#### **2.1. Meaningful work and self-determination**

Work meaningfulness is a critical aspect of subjective job quality that matters for motivation and work effort (Cassar & Meier, 2018; Nikolova & Cnossen, 2020). People derive meaning from the intrinsic value of their work when they think they engage in useful, interesting, or fulfilling activities. In this sense, work meaningfulness is a psychological state that depends on the workers' perception of their jobs as valuable and worthwhile (Hackman & Oldham, 1976).

When people feel that their efforts are important for successfully executing a certain task, they tend to strongly identify with that goal. As a result, they are relatively more likely to experience meaning compared with a situation when they do not identify themselves with the objective. The inner drive to experience a sense of meaning at work is so strong that, on average, people are willing to accept a 37% salary cut to engage in more meaningful work—\$32,666 for a meaningful job vs. \$52,498 for a meaningless job (Hu & Hirsh, 2017). Similarly, experimental studies from the US and Germany demonstrate that work meaningfulness lowers reservation wages (Ariely et al., 2008; Kesternich et al., 2021), yet only among those for whom work meaningfulness is very important in the German case (Kesternich et al., 2021).

Simultaneously, feelings of self-determination are based on three separate but complementary psychological needs: competence, autonomy, and relatedness (Deci & Ryan, 1985; Ryan & Deci, 2017). Workers feel competent when their skills match the complexity of the task. In such cases, when employees know that their skills are instrumental to the task at hand, they feel a greater sense of contribution. When a task is too easy, they feel like anyone could have done it, and when it is too hard or complex, they feel less self-efficacy and personal contribution. Therefore, feeling competent in the workplace is an important aspect of self-determination.

Second, people feel a sense of autonomy when they have “freedom, independence, and discretion” to make decisions regarding the planning and execution of their tasks (Hackman & Oldham, 1976). Promoting own initiatives and encouraging decision-making at the individual level, as opposed to traditional top-down directives, can foster an environment where employees feel an enhanced sense of control over their work.

Finally, according to the self-determination theory, people have a deep psychological need for connectedness and belonging: they want to feel appreciated and supported by their co-workers and managers in their efforts at the company. Such high-quality relationships at work are also important for fostering work meaningfulness (Bailey et al., 2019), especially when it comes to the “giving to others” aspects (Colbert et al., 2016). If such appreciation and opportunities to assist others fall short, people can become demotivated and experience feelings of uselessness: they don't matter for the final product. The three self-determination variables are also key factors that empirically underpin having a sense of work meaningfulness (Nikolova & Cnossen, 2020).

#### **2.2. Robots, work meaningfulness, and self-determination**

An industrial robot is a machine able to “manipulate” its environment by grasping or moving objects around it. Most of the tasks that industrial robots perform are reaching and handling tasks. Examples of robots fitting this definition include manipulators that weld or paint cars, move materials and pack boxes, and load and unload workpieces from factory equipment such as Computer Numerical Control (CNC) machine tools and semiconductor fabricators.

Examples of industrial equipment that are not robots include most machine tools, an assembly line conveyor belt, and a flexible manufacturing cell (Webb, 2020).

“Human” tasks overlapping with the capabilities of a robot are susceptible to automation. As industrial robots have a comparative advantage in repetitive activities and working with objects, workers with relatively routine and manual task-intensive occupations are at greater risk of replacing a large share of their tasks (Autor et al., 2003; Webb, 2020). However, due to their pre-programmed nature, industrial robots without artificial intelligence (AI) capabilities have limited ability to execute tasks in unpredictable environments, mostly those involving human contact.

Therefore, industrial robots have relatively little capacity to replace cognitive, non-routine, and interpersonal tasks. Webb (2020) shows that the patent texts for robotic inventions strongly overlap with relatively routine and manual occupations and little with nonroutine cognitive and interpersonal occupations. While AI technologies may substitute these tasks in the future, (industrial) robots are generally inefficient in performing nonroutine cognitive and nonroutine interactive tasks.

Because robots only execute a specific set of tasks, the effect of robots on meaningfulness and self-determination is ambiguous: robots replace relatively mundane tasks, and this may indirectly give rise to focusing on new, interesting, and more complex tasks (Berg, 2019; Berg et al., 2023; Parker & Grote, 2020), increasing the potential of experiencing meaningful work. In this sense, automation could reduce unpleasant, dirty, dull, or dangerous work and free up time to pursue tasks and activities that bring freedom and fulfillment – an idea dating back to Karl Marx (Spencer, 2018; Spencer, 2023).

However, if the task replacement is not met with a simultaneous shift towards more purposeful activities, experiences of meaningfulness might decrease. Robots that directly replace tasks humans perform or limit task variety may reduce that person’s sense of meaning. This may also occur if only minor or unimportant tasks that are no longer directly associated with the final product’s success remain. Such “micro-tasks” bear little meaning in themselves, as they are not connected to a purpose or directly useful in and of themselves (Parker & Grote, 2020). Moreover, given that robots may replace certain activities and make way for others, the impact of robots on work design may strongly differ between workers in the same workplace.

Similarly, robots may also positively or negatively affect one’s sense of self-determination. This strongly depends on how robots are introduced in the workplace. For instance, autonomy might decrease if one’s workflow becomes dependent on the work-pace of a robot. Conversely, if workers can use the robot to their benefit, it might create room for autonomous agency and discretion in developing new tasks. Likewise, one’s feeling of competence may increase if relatively mundane tasks are replaced, clearing the way for more skillful tasks. However, if the robot substitutes for tasks that a worker takes pride in, and no challenging tasks are introduced, the feeling of competence can decrease. Lastly, if robots are seen as partners at work, one’s sense of relatedness might not be compromised. And yet, relatedness can decrease if the robot affects the physical environment in such a way that personal connections are disrupted.

Barrett et al. (2012) provide an insightful case study highlighting how the introduction of a robot may affect workers differently within the same workplace. They show that the introduction of a drug-dispensing robot in a hospital pharmacy led to contrasting experiences for different workers, depending on how the robot altered their work. First, pharmacists indicated that their jobs had improved due to the increased delivery speed of medication, which provided more room for in-depth patient counseling. This made their work more interesting – appealing more strongly

to their sense of competence – and more interactive, increasing their sense of relatedness to their patients.

Second, the assistants to the pharmacist, originally responsible for selecting and delivering the medications to the pharmacist, had the opposite experience. Their responsibilities diminished to the point where they were only required to load medicine onto the robot, which put the medicine in the right place. Their sense of competence decreased, as the original expertise of knowing where to shelve which medicine was no longer necessary. Furthermore, they also experienced a decrease in autonomy, as the robot now guided where to place each item.

The third group, the technicians, had an entirely distinct experience. Before the robot was introduced, they operated similarly to the assistants. However, with the introduction of the robot, their relative position in the organization changed. As the robot often stagnated and the technicians were the only workers authorized to fix the problems (even if the assistants knew how to), this increased their sense of competence and feeling of status within the organization.

These considerations lead to the following testable hypothesis:

**H1:** *The impact of robotization on work meaningfulness and one's sense of self-determination, encompassing autonomy, competence, and relatedness, can manifest either positively or negatively.*

### **2.3. The moderating effect of workers' skills and demographics**

As the pharmacy case study illustrates, robot adoption can significantly impact the experience of meaning and self-determination in the workplace. Some workers experience more competence as they can focus more on tasks that require their specific human capital (such as fixing the machine for the technicians), whereas others experience lower competence because the machine makes their expertise and contributions obsolete. Importantly, these changes can occur even within the same company and seem to depend on the tasks people perform and their skills. Thus, the impact of robots on meaningfulness and self-determination is not straightforward and may be contingent on a worker's tasks, skills, and other personal characteristics.<sup>4</sup>

Therefore, we also explore the effects of several moderating variables: tasks, skill and education levels, and worker demographics. First, technology adoption (robots and ICT) generally leads to tasks being *replaced*, *augmented*, or *created* (Acemoglu & Restrepo, 2019). The extant literature suggests that individuals performing tasks comparable to those performed by technology (i.e., routine and manual tasks) are at relatively higher risk of task replacement (Autor et al., 2003; Autor, 2013; Acemoglu & Restrepo, 2019). While these workers may not face immediate unemployment, the introduction of robots that can perform some of their tasks may have implications for workers' work meaningfulness and self-determination, such as reducing the variety of tasks or the discretion over when to perform tasks. In addition, workers performing nonroutine cognitive (i.e., analytical and interpersonal) tasks face a relatively lower risk of replacement, and higher chances of task augmentation.

Therefore, we hypothesize that the nature of tasks significantly moderates the effect of robots on the workers' perceptions of work meaningfulness and self-determination. Some of these tasks, due to their routine nature, might be more susceptible to replacement (e.g., the assistants placing the medicine in the right place). In contrast, other tasks can be enhanced by technology

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<sup>4</sup> Furthermore, institutional and firm-specific characteristics may also play an important role – but we refrain from discussing those factors here.

(e.g., the pharmacists seeing productivity increases due to faster medicine delivery) or can even lead to the emergence of entirely new tasks (e.g., the technicians working on robot maintenance).

In the pharmacy example, the assistants' tasks are mainly substitutable due to their routine nature: their tasks are now relatively more repetitive and monotonous, affecting their sense of meaningfulness and the fulfillment of their basic psychological needs. Conversely, the pharmacists, with enhanced opportunities for client interaction, can see an increase in the relative importance of social-intensive tasks in their jobs – activities in which humans have a comparative advantage over robots. Finally, the technicians can experience greater meaningfulness and competence at work, as they are now able to operate and service the machine. However, unlike the assistants, their tasks do not depend on the work pace of the machine. Rather, their involvement in troubleshooting, a relatively nonroutine cognitive task, allows them to operate with more autonomy.

Generalizing the findings from the Barrett et al. (2012) case study detailed in section 2.2., we distinguish between two types of task characteristics that we use as moderators in our analysis. First, we observe the *routine intensity* of tasks. To capture routine tasks, we use worker-level information on repetitive tasks. Second, we have information about the nonroutine intensity of tasks, which we split into *non-routine cognitive* and *nonroutine interactive*. For the nonroutine cognitive tasks, we rely on information on whether one has to work with a computer, meaning that they are in charge of operating and working with the technology. We capture the degree of interactivity at work by utilizing information on the respondent's degree of working with clients.

Second, we conjecture that the effect of robots on meaningfulness and self-determination depends on workers' skill levels. High-skilled workers are more likely to benefit from the complementarity between human skills and machines compared with the low-skilled (Autor et al., 2003; Webb, 2020). Robots can act as complements to high-skill workers by automating only portions of routine and manual jobs, thereby increasing the value of the non-routine and cognitive tasks that these workers perform (Autor & Dorn, 2013). Therefore, we also include interactions with workers' skills to see whether these moderate the main effects. We utilize two measures of skills – one based on educational attainment and one based on the occupational category of the respondent.

Third, demographic characteristics could moderate the effects as well. On the one hand, older workers might have more trouble accepting the reality of the machines, but on the other hand, they may be less affected by automation if they have survived past automation waves. For example, Schwabe and Castellacci (2020) show that older workers view technology as a force that does not directly threaten their careers but adds positive value to work and society. This may be because smart machines substitute for young unskilled workers but complement older skilled ones, as predicted by Sachs and Kotlikoff (2012) and empirically demonstrated by Battisti and Gravina (2021), thus possibly increasing the job quality of older workers.

We also explore whether there are gender differences in the relationship between automation and work meaningfulness and self-determination. For instance, Aksoy et al. (2020) also show that the gender pay gap increases with robotization, and medium- and high-skilled males disproportionately benefit from robot exposure. While Aksoy et al.'s (2020) results highlight differences in pay, the fact that robots predominantly increase the productivity of men suggests that the impact on their experience of meaningfulness and self-determination might also be more positive than for women.

As summarized in Table 2, these considerations form the basis of our analysis and lead to our second set of hypotheses:

**H2a:** *Workers' tasks moderate the impact of robotization on work meaningfulness and self-determination: robotization is more likely to negatively affect those performing routine-based tasks, whereas workers with nonroutine-based tasks should be positively affected.*

**H2b:** *The work meaningfulness and self-determination of highly skilled workers and those with higher education are less likely to be negatively affected by robotization than the corresponding outcomes of low-skilled and low-educated workers.*

**H2c:** *The work meaningfulness and self-determination of older workers are less likely to be negatively affected by robotization than those of younger workers.*

**H2d:** *Female workers' work meaningfulness and self-determination are more likely to be negatively affected by robotization compared with those of male workers.*



Table 2: Possible consequences of robots on work meaningfulness and self-determination, with explanations regarding the moderators

<b>Experiences of:</b>	<b>Potential positive consequences of robots</b>	<b>Potential negative effects of robots</b>	<b>Moderators of the consequences of robotization for work meaningfulness, autonomy, competence, and relatedness</b>
Meaningfulness <i>(a sense of doing useful and fulfilling work)</i>	Robots as partners in pursuing a worthy cause, increasing efficiency and the successful completion of tasks	Robots replacing tasks, reducing personal contribution to the end goal  Technology-enabled “micro-tasks” that lack meaning	<b>Task-based moderators</b> Routine intensity of tasks (repetitiveness, monotonicity, and dependency on the work pace of a machine)  Nonroutine-cognitive and -interactive intensity of tasks (working with computers and working with clients)
Autonomy <i>(a sense of discretion in determining the order, speed, and methods of work)</i>	Increased room for job crafting and autonomous agency if human workers control robots  Discretion over the development of new tasks, when old tasks are replaced	Few opportunities for job crafting due to dependence on the workflow of robot  Robot control reduces opportunities for exercising judgment and agency  More opportunities for management to monitor human work	
Competence <i>(a sense of having the right skills to do one’s job, the ability to solve unforeseen problems, and learning new things)</i>	Replacing “dull, dangerous, and dirty” work with cognitively demanding tasks  Creation of new tasks related to operating robots, requiring new complex skills	Increased standardization and fragmentation of tasks, requiring fewer skills  Replacement of tasks makes corresponding human skills obsolete	<b>Skill-based moderators</b> Level of education Occupational skill  <b>Individual-level moderators</b> Age
Relatedness <i>(a sense of feeling helped and supported by your co-workers and supervisors)</i>	Robots as colleagues, capable of high-level social interaction  Replacement of non-social tasks, increasing time for interpersonal contact	Workers may interpret task replacement as being personally replaceable: reducing the feeling of being appreciated  Changes to the physical aspects of work that disrupt social connections	Gender

Note: Authors' adaptation based on Smids et al. (2020) and Parker and Grote (2020).

### 3. Data and variables

Research regarding the consequences of automation relies on two main measures: i) industry-level measures of industrial robots or ii) automation potential at the occupational level capturing the risk of replaceability of tasks, regardless of whether the worker is actually exposed to that technology. An example of the latter type of measure is the paper by Frey and Osborne (2017), in which experts estimate the potential risk of automation for each occupation by observing the overlap between the typical tasks in that occupation and the (expected) technology capabilities. This index has been subsequently refined by Nedelkoska and Quintini (2018) and Arntz et al. (2016). The main advantage of the first type of data is that it is based on the actual number of robots employed in an industry, rather than the future potential for robotization and automation. The main disadvantage is the high level of aggregation and the inability to measure the quality of robots, just their quantity. The main advantage of the second measure is that it is available at a more granular level – e.g., two- or three-digit occupations, but the main disadvantage is that the data typically do not vary over time, are based on the US occupational dictionaries, and do not measure actual exposure, but automation potentials.

Our paper adopts the first method of capturing automation exposure. As such, we relate the change in the stock of robots per 10,000 workers to individual-level experiences of job quality at work. We further use task-based moderators to account for the type of work people execute.

We combine information from several sources to conduct our empirical analyses and test our main propositions. First, we rely on data on the number of operational multipurpose industrial robots from the International Federation of Robotics (IFR) for each industry in each country and year. The IFR calculates robot stocks assuming a service life of 12 years, implying that the robot is out of operation after that. The IFR defines an industrial robot as an “automatically controlled, reprogrammable, multipurpose manipulator that is programmable in at least three axes, and either fixed in place or mobile and intended for and typically used in industrial automation applications” (IFR, 2021, p. 30).

We use the IFR data after 2005 because the data source has many missing values before 2005 - Except for Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the UK, the IFR data only provide country totals until 2004, which other papers have circumvented by performing imputations. Furthermore, the share of the robot stock that is not classified to any particular industry also declined after 2005, making 2005 a good starting year for using IFR data (Jurkat et al., 2022). Like other studies, we had to impute the data for 2005 for Bulgaria, Greece, and Lithuania.

The denominator of the robotization variable is calculated based on the number of employed persons per industry and country in 2000 from the EUKLEMS -INTANProd data. We use the national accounts file with information on the number of workers per industry. The EUKLEMS database is also the source of information on the fixed capital stock in computing, communications, computer software, and databases, underpinning our ICT control variable. We use the capital accounts data file for the ICT information. Information for several Eastern European countries in our analysis sample is missing for the ICT variable, which is why we imputed this information based on the non-missing information from neighboring countries.

Finally, we use worker-level data from the European Working Conditions Surveys for 2010, 2015, and 2021 (Eurofound, 2022; 2023a; 2023b). The EWCS dataset contains worker-level survey answers collected via face-to-face interviews with about 1,000 workers per country in 2010 and

2015. In 2021, because of the COVID-19 pandemic, the survey was conducted via the telephone, and sample sizes per country were about 1,800, ranging from 1,000 to 4,000. To account for the question format and sampling methodology differences in the 2021 wave compared with the previous waves, we add year dummies to our regression analyses. Different workers are polled each year, and the dataset represents pooled cross-sections rather than a panel.

The EWCS dataset is very opportune for our research for several reasons. First, the surveys ask detailed questions about workers’ socio-demographics and work characteristics. Importantly, the EWCS has the variables we need to construct indices of work meaningfulness, competence, autonomy, and relatedness based on the methodology in Nikolova & Cnossen (2020) and Nikolova et al. (2022). Second, the survey elicits information about the industry of employment (NACE Rev 2, two-digit), which allows us to merge the information from the IFR and EUKLEMS with the EWCS. While the EWCS also has information on work meaningfulness and self-determination in 200, the two-digit NACE Rev 2 required for merging on the industry level information is only available starting in 2010. We drop individuals from the EWCS with missing information on the industry of employment as their information cannot be merged with the rest of the data.

After merging all the information, we drop individuals with more than one job and those in the armed forces occupation. Our final merged dataset has information on individuals working in 14 industries and 20 countries in 2010, 2015, and 2021. Like most other papers using the IFR data, we exclude the “all other non-manufacturing” industry, which mostly represents services. Table 3 details the construction of the key variables used in the analyses.

### 3.1. Key Independent Variable: Robotization

Our key regressor is the change in the number of robots per 10,000 workers in each industry, country, and year. Following Aksoy et al. (2021), we transformed the robotization measure using the inverse hyperbolic sine transformation (IHS). This transformation deals with the issue that the distribution of the change in robots is highly skewed. Taking the logarithm is less desirable than the IHS because the log transformation does not deal with negative numbers and zeros. Other authors in the literature have addressed the skewed distribution of the robotization variable by taking the percentile rankings of the industries (de Vries et al., 2020; Graetz & Michaels, 2018). Nevertheless, this solution is problematic because it over-emphasizes small differences between the values at the top of the distribution and under-emphasizes large differences between changes in the robotization at the bottom of the distribution (Bekhtiar et al., 2021). The IHS transformation is, therefore, preferable because it is similar to a logarithm but preserves zero and negative observations (Bellemare & Wichman, 2020). To ease the interpretation of the magnitudes of the estimated coefficient estimates, we calculate and report elasticities, where possible.

Specifically, for each industry  $j$  in country  $c$  and year  $t$ , the robotization measure is defined as:

$$robotization_{j,c,t} = IHS \left[ \frac{num.robots_{j,c,t-1}}{10,000 employees_{j,c,2000}} - \frac{num.robots_{j,c,t-5}}{10,000 employees_{j,c,2000}} \right] \quad (1)$$

We define robotization as a change because we are interested in technological change in terms of a “shock.” We use a four-year gap to calculate the change between  $t-1$  and  $t-5$  because of the 5-year gap between the EWCS survey waves. Robotization is also lagged one year to mitigate

reverse causality issues and to minimize inconsistencies in terms of when the EWCS data were collected and the reference period for the robotization stocks. We use the number of workers in 2000 in the denominator so that the changes in the robot stock are independent of changes in the number of employees. The year 2000 was selected because it predates the explosive growth in adopting robots in many countries in the sample.

### 3.2. Dependent Variables

We rely on four dependent variables, all standardized composite indices with a mean of 50 and a standard deviation of 10. These variables are based on items and indices in Nikolova and Cnossen (2020) and Nikolova et al. (2022). Table 3 details the concrete steps involved in constructing the variables. Our measure of autonomy deviates from that of Nikolova and Cnossen (2020) as it is based on combining only three variables (and not five) into the index. Specifically, we rely on a measure of task autonomy based on the following variables: (1) ability to choose or change the order of tasks, (2) ability to select or change methods of work, and (3) ability to choose or change speed or rate of work. According to Parker and Grote (2020), job autonomy has two interrelated aspects: i) decision-making over the work process and ii) choice over when and where to work. Nevertheless, our autonomy measure captures only the first of these two aspects: the decision-making latitude about the work process. The construction of the variables is detailed in Table 3.

### 3.3. Control variables

We source other control variables at the individual level from the EWCS files. We create an additional “missing information” indicator for all categorical control variables to avoid omitting observations with missing information from the analyses. This additional “missing information” category has no informational value but only helps us preserve the number of observations.

The control variables include age group, gender, working hours, education level, private or public sector of employment, number of years with the firm (tenure), and ISCO-08 occupation (excluding the armed services due to the small number of observations), and company size.

Finally, we include the inverse hyperbolic sine transformation of changes in ICT capital (per 10,000 workers) as an additional control variable. The construction of this variable is identical to that of the robotization variable. We want to ensure that we capture the effects of robotization on work meaningfulness and self-determination above and beyond any consequences of digitalization.

## 4. Empirical Strategy

### 4.1. OLS

We explore the causal effects of robotization on work meaningfulness and self-determination using ordinary least squares (OLS) and instrumental variables techniques. Our analyses dovetail with and combine strategies explored in the extant literature (e.g., Aksoy et al., 2021; Anelli et al., 2021; Dauth et al., 2021; de Vries et al., 2020; Graetz & Michaels, 2018).

In our OLS estimations, the work meaningfulness or self-determination outcome  $Y$  of individual  $i$ , living in country  $c$  and working in industry  $j$  in survey year  $t$  is:

$$Y_{i,c,t} = \alpha_0 + \alpha_1 R_{j,c,t} + \alpha_2 I_{j,c,t} + Z_{i,c,t} \varphi + \mu_c + \pi_t + \varepsilon_{i,j,c,t} \quad (2)$$

Where  $R$  denotes *robotization* as detailed in Equation (1). Furthermore, the control variables  $Z$  include age group, gender, working hours, education, sector of employment (public or private), number of years with the firm, and ISCO-08 occupation detailed in Section 3.3 above,  $I$  is a measure of digitalization (constructed similarly to robotization),  $\pi_t$  denotes time fixed effects (a dummy variable for the 2010, 2015, or 2021 survey wave),  $\mu_c$  denotes country fixed-effects, and  $\varepsilon_{i,j,c,t}$  is the stochastic error term. We use robust standard errors clustered at the countryXindustry level. In additional specifications (Table A3), we also report results using weights calculated with the within-country industry employment shares of hours (Aksoy et al., 2021; Graetz & Michaels, 2018) that provide more importance to industries with larger employment shares. Furthermore, we check whether the results are based on the differential number of worker-level observations available in the EWCS. To this end, we weigh all regressions using the inverse of the number of observations in each analysis sample in each year (Table A3).

We include time dummies (i.e., EWCS survey wave) to, at least in part, account for shocks and cyclicalities that affect countries and industries similarly in the year of the survey. Specifically, technological adoption is often pro-cyclical (Anzoategui et al., 2019; Leduc & Liu, 2019, 2021), and economic booms and busts may also affect workers' work meaningfulness and self-determination. Of course, we cannot perfectly capture all cyclical effects given the frequency of our data, but the inclusion of the time dummies should account for some of these influences, as well as differences in the survey mode. Furthermore, country-specific fixed effects account for different institutional and cultural features across countries, including cultural interpretation of the underlying self-reported work quality, as well as slow-changing institutions and labor market regulations.

We also report the elasticities, as suggested by Bellemare and Wichman (2020) to facilitate the interpretation of our IHS-transformed robotization variable.

## 4.2. Instrumental Variables

The two main challenges of estimating causal effects with Equation (2) are omitted variables bias and sorting of workers into industries. First, there may be omitted industry-specific shocks that are correlated with both the pace of adopting automation and also affect the way that individuals perceive their work meaningfulness and can derive autonomy, competence, and relatedness from their jobs. Second, workers with particular unobservable traits may be more likely to choose jobs that are more or less likely to be automated.

We mitigate these issues by relying on instrumental variables techniques. Like Anelli et al. (2021), our main instrument is based on the industry adoption of robotization in all other countries in the sample except the respondent's, which is similar to the instrument used in Acemoglu and Restrepo (2020). The logic of this instrument is that we are trying to capture the industry-specific trends in innovation and technological progress that are common across all countries. The instrument deals well with the first source of endogeneity outlined above but not with self-selection. We include relevant control variables to mitigate selection issues and offer several sensitivity checks.

This instrument relies on the untestable assumption the industry level of robotization in other countries is independent of the respondents' work meaningfulness and self-determination. The instrument would be invalid if it correlates with unobserved shocks that are common across all countries and industries and cause all industries to undertake robotization.<sup>5</sup>

The cross-country literature on automation has mostly relied on two instruments proposed by Graetz and Michaels (2018), i.e., the so-called “replaceable hours” and “robot arms” instruments (see, for example, Aksoy et al., 2021 and de Vries et al., 2020). The first instrument captures the share of the industry's employment hours performed in occupations that are potentially replaceable by robots from the viewpoint of the task descriptions of occupations in the 1980s in the US. The second instrument captures the extent to which US industries in 1980 contained occupations with reaching and handling tasks relative to other physical tasks.

These instruments have several limitations, as discussed in, for example, de Vries et al. (2020). The variables are based on the US's industrial structure and may capture trends and developments across industries that correlate with other changes over time (e.g., digitalization or globalization). More fundamentally, these instruments have recently come under attack because they violate the monotonicity assumption. Specifically, the first-stage results show implausible correlations when we split the data into the manufacturing and non-manufacturing sectors, a problem described in Bekhtiar et al. (2021). Nevertheless, for completeness and transparency, we present the results with these instruments (Table A2), though we advise readers to exercise caution when interpreting these results.

While the instrument of the industry-level adoption of automation in all other countries except the respondent's is not a silver bullet, its performance in the first-stage regressions and associated diagnostic tests seem reasonable. The IV results are also qualitatively in line with the OLS results, though the magnitudes of the coefficient estimates are higher with the IV than with the OLS results, which is plausible.

Our goal is not to argue about the superiority of one set of instruments over another or claim that we resolve all endogeneity concerns. Rather, it is to provide plausibly causal estimates and compare and contrast the performance of OLS vs. the 2SLS, while also providing additional robustness checks.

### 4.3. Exploring heterogeneity

We empirically test whether workers performing different tasks differentially experience self-determination and work meaningfulness by interacting the tasks with robotization, following from H2a-H2d. We focus on three tasks: i) repetitive tasks ii) working with computers, and iii) social tasks.<sup>6</sup>

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<sup>5</sup> Moreover, workers sort into industries and jobs offering different opportunities for meaningfulness and self-determination because they have particular unobserved traits, such as motivation or particular preferences for work meaningfulness and job quality. The IV strategy is unable to deal with this problem. We include individual-level controls to mitigate this issue.

<sup>6</sup> In a working paper version of this manuscript, which only relied on the 2010 and 2015 EWCS waves, we also reported heterogeneity by dependence on the work pace of a machine and performing monotonous tasks. Unfortunately, these heterogeneity analyses are not possible with the 2021 EWCS as these questions were not asked then.

$$Y_{i,c,j,t} = \alpha_0 + \alpha_1 R_{j,c,t} + \beta_\tau \tau_{j,c,j,t} + \gamma_\tau R_{j,c,t} * \tau_{j,c,j,t} + \alpha_2 I_{j,c,t} + Z_{i,c,t} \varphi + \mu_c + \pi_t + \varepsilon_{i,j,c,t} \quad (3)$$

In Equation (3), the coefficient estimates  $\hat{\gamma}_\tau$  allow us to explore whether robotization differentially affects the work meaningfulness and self-determination of people working in jobs requiring different tasks. We estimate Equation (3) based on the IV strategy using the 2SLS estimator.

Furthermore, we explore whether workers in different parts of the skills distribution and of different ages and genders differentially experience meaningfulness and self-determination. Specifically, we anticipate that automation may lead to de-skilling and therefore worsen the work meaningfulness and self-determination experiences of low-skilled workers while providing high-skilled workers with the opportunity to shift to new and creative tasks. In this instance,  $\tau_{j,c,j,t}$  indicates skill levels (high, medium, and low).

We operationalize skills by education (i.e., primary, secondary, and tertiary) and by grouping 1-digit ISCO occupations into high-, medium-, and low-skilled based on the ILO definitions. Specifically, we classify managers, professionals, technicians and associate professionals as high-skilled; clerical support workers, service and sales workers, skilled agricultural, forestry, and fishery workers as “medium-skilled” workers; and craft and related trades workers, plant and machine operators, and assemblers, and elementary occupations as “low-skilled.” The analyses by age and gender are analogous to those with tasks and skill levels.

## 5. Results

### 5.1. Descriptive Statistics

Figure 1 depicts the average number of robots per 10,000 workers for the years: 2005, 2009, 2010, 2014, 2016, and 2020. Given our empirical setup, our measures of robotization refer to changes between 2005-2009 (for EWCS observations in survey wave 2010), 2010-2014 (for EWCS observations in survey wave 2015), and 2016-2020 (for EWCS observations in survey wave 2021). Industrial robots are most prevalent in the automotive industry (e.g., 623 robots per 10,000 workers in 2020) and least widespread in the electricity, gas, water supply, construction, and education/research industries.

During the 2005-2020 period, the average increase in robotization across all industries was 389%, with the mining and quarrying industry realizing a change of 2,601%, followed by growth of 689% in the industrial machinery sector, and 475% in the electricity, gas, and water supply. These were all industries that started with relatively low levels of robots in 2005, which explains these high increases (See Table A1).

Figures 2-5 detail the development of work meaningfulness and self-determination variables over the analysis period. The key takeaway from these figures is that the changes in the dependent variables tend to be rather stable both within industries and over time.

Table 4 provides summary statistics for the analysis samples for each dependent variable. Because those who work alone did not answer the relatedness questions, the analysis sample for relatedness is smaller than for the other dependent variables. In addition, the competence questions were not asked in the 2021 survey. Table A9 also details the sample composition for the work meaningfulness sample across the 2010, 2015, and 2021 survey waves. The 2021 sample

contains a much larger share of individuals with tertiary education (0.54 in 2021 compared with roughly 0.3 in 2010 and 2015), which is because these respondents were easier to reach during the pandemic (Ipsos NV, 2022).

## 5.2. Main Results based on OLS and IV Estimations

Table 5 details our main results regarding the relationship between robotization, work meaningfulness, and self-determination. Panel A reports OLS estimates. Panels B and C feature the IV estimates.

Our OLS results suggest that robotization is negatively associated with work meaningfulness, autonomy, competence, and relatedness, with the latter association being statistically insignificant. The IV estimates also corroborate this conclusion. The second-stage results (Panel B) further confirm the negative relationship between robotization, work meaningfulness, and self-determination. The coefficient estimates in Panel B are larger than the OLS ones, suggesting that the OLS estimates are likely affected by endogeneity that leads to underestimating the impact of robotization on the well-being outcomes we study. The coefficient estimates from the first-stage regressions (Panel C) show that our instrument is good at predicting robotization. The  $F$ -statistic ranges from 79 to 262, which is relatively large, suggesting that our instrument is strong.

At first sight, the elasticity estimates appear rather small. For example, doubling robotization corresponds to a 0.9% decline in work meaningfulness, a 1% decline in autonomy, a 0.6% decline in competence, and a 0.3% decline in relatedness. However, to put them in perspective, we illustrate their significance by using the robotization levels of two industries – the food and beverages (74 robots per 10,000 workers) and the automotive industry (629 robots per 10,000 workers) in 2020. Should robot adoption in the food and beverage industry increase to match that of the automotive industry (representing a 7.5-fold increase in robotization), we estimate a 6.8% ( $750 \times 0.009$ ) decrease in work meaningfulness and 7.5% ( $750 \times 0.010$ ) decrease in autonomy, as well as a 4.5% ( $750 \times 0.006$ ) drop in competence (based on the elasticities reported below our IV estimations in Table 5, Panel B). Our calculations are based on a move from a top 5 to a top 1 industry regarding robot adoption levels in 2020 (see Table A1). Based on the EUKLEMS data, in 2020, nearly 4.5 million individuals worked in the food and beverages industry and about 3.3 million in the automotive industry across the countries in our study. Therefore, the impact sizes we document may seem small in isolation, but given the large number of employees affected in such sizable industries, the overall effect could be substantial.

Moreover, if we extrapolate these calculations to less automated industries such as agriculture, the effect sizes become even more pronounced. An increase from the robot adoption levels in agriculture in 2020 (roughly 6 robots per 10,000 workers) to the levels in Plastic, chemical products, and glass (93 robots per 10,000 workers) (a 14.5-fold increase) could result in a 13% drop in work meaningfulness and a 14.5% drop in autonomy. We note that this is a shift from the top 10 industry to the top 4 industry in terms of robot adoption in 2020.

The substantial surge in robot adoption within various industries during our study period, especially among those industries with previously low levels of robot adoption, could significantly impact work meaningfulness and autonomy. The average percentage change in the industries we studied across the 2005-2020 time period was 389%. This change suggests that the average loss of meaningfulness and autonomy for a typical worker in our sample would be around 3.5% ( $0.009 \times 389$ ) and 4% ( $0.010 \times 389$ ), respectively.



Therefore, the main conclusion from Table 5 is that robotization hurts work meaningfulness and self-determination, and the consequences may appear modest but are economically significant. Therefore, we show support for Hypothesis 1 in the sense that we find a negative and statistically significant relationship between robotization and our outcome variables.

### 5.3. Robustness Checks

We offer a battery of sensitivity checks. First, using specification curve analyses (Simonsohn et al., 2020), we investigate whether our results are robust to using different subsamples and modifications of Equation (2). The main logic of the specification curve analyses is to re-estimate Equation (2) with alternative control variables (e.g., including and excluding the ICT control, including and excluding demographic variables, education, and job controls), estimating the equation using OLS or an IV, and excluding one country at a time from the analysis sample. We provide such specification charts for all four dependent variables. We then graphically present the distribution of the estimates and their confidence intervals in Figures 6-9.

All estimates we detail in those figures include country and year fixed effects but differ based on the estimator and the included covariates and countries. Specifically, we present the first set of estimates based on OLS estimations – first only including the ICT control in addition to the country and year fixed effects. We then sequentially include education variables, demographic variables, job characteristics, or only education and demographic variables, and finally, all possible controls. We then show different variations of the IV specifications. The baseline IV estimates from Table 5, Panel B, are highlighted in blue. We sequentially include different sets of control variables and exclude one country at a time from the regression models. Figures 6-9 detail that the results in Table 5 are consistent across different specifications and modifications of Equation (2).

This set of sensitivity checks indicates that our findings are robust to including or excluding control variables and countries from the analysis samples. The results we present are not a data artifact based on a particular country being included or excluded, the sample, or the choice of the control variables.

In addition, we have checked whether the results are robust to using the replaceable hours and robotic arms instruments from Graetz and Michaels (2018), which we offer for completeness in Table A2. As we explain in Section 4.2. above, these instruments are less desirable than the instrument we utilize in the main specifications. The results remain in line with the OLS and main IV results in Table 5.

Table A3 investigates whether the results are robust to different weighting schemes. In Panel A of Table A3, we use the country-specific industry employment shares as Graetz and Michaels (2018) and Aksoy et al. (2021), which puts more importance on larger industries. Furthermore, in Panel B of Table A3, we check whether the results are driven by countries with a larger number of observations by weighting all regressions using the inverse of the number of observations in each country and year as a weight. The results support our conclusions from our estimations in Table 5.

Furthermore, Table A4 offers a robustness check where we include countryXyear fixed effects, which control for shocks and omitted factors that differentially affect countries across time (e.g., globalization shocks, country-specific natural disasters, or technological breakthroughs in particular countries). In Panel B, we also add an offshorability control, which is at the industry

level and sourced from Graetz and Michaels (2018). The results largely align with our main findings, though the evidence for competence and relatedness is less robust, which is why we put less emphasis on it in the paper.

Finally, Table A5 checks whether our results differ based on workers' job tenure (number of years in the company). Specifically, our results may be driven by the self-selection of workers into industries that have become automated, or particular workers may be self-selecting into staying in given industries. In addition, our sample only includes employed people who have thus not lost their jobs due to robotization. This implies that those individuals may have largely adjusted to their new circumstances. While testing the adaptation explanation requires panel data on the same workers over time, our results suggest that our findings do not differ among people who just started the job compared to those with longer tenure (Table A5). This suggests that adaptation may not be the main driver of our findings, as workers who have been in the company for a long time do not experience automation differently than the newcomers. There are no differences between employees who have been at the company for 0-2 years and those who have worked for their employer longer, which suggests that these considerations are unlikely to be the main drivers behind our findings.

## 6. Heterogeneity

We next turn to the tests of Hypotheses H2a-H2d. The results of our heterogeneity analyses based on the type of tasks, skills, and socio-demographic characteristics are presented in Tables 6 and 7, respectively.

Tables 6-7 demonstrate that robotization's effect on work meaningfulness does not differ much based on the respondent's task content, skills, or demographics. This suggests that the negative effect of robotization on work meaningfulness is independent of workers' tasks, skills, age, and gender. These findings could imply that people do not derive meaning directly from the content of their tasks, but from the individual goals they pursue by doing these tasks that imbue their work with meaning

Furthermore, we find that having a routine role exacerbates the already negative impact of robotization on autonomy (Model (2) in Panel A of Table 6). This may be because robotization furnishes fewer opportunities for job crafting, and in the presence of routine tasks, leaves even fewer tasks requiring judgment and agency in the work process. We also find that repetitive tasks fully explain the drop in competence and relatedness due to robotization. This is in line with the insights from the Barrett et al. (2012) pharmacy case study, as well as the broader literature documenting the negative impacts of technology on workers executing routine tasks. Alternatively, robotization frees up time for workers with routine tasks to socialize with their colleagues.

Conversely, those working with computers (Panel B of Table 6)—which we interpret as being in control of the workflow of technology by operating it— can completely offset the negative impact of robotization on autonomy, competence, and relatedness (but not work meaningfulness). On the other hand, working with clients (Panel C of Table 6) in robot-intensive industries may offset part of the negative effects of robotization on autonomy, though the results are marginally statistically significant. These findings suggest that some of the strain robots exert on autonomy in the workplace is alleviated by working with computers and performing social tasks, such as working with customers.

When exploring skills' moderating effect on the relationship between robotization and work meaningfulness and self-determination, we perform two separate regressions - based on the educational level (primary, secondary, and tertiary) and skill level (low-, medium-, and high-skilled). Higher education seems to cushion the negative effects of robotization on autonomy. This finding is unsurprising: those with higher education can enjoy more autonomy due to robots' introduction in the workplace, as they can outsource some tasks, giving them the freedom to focus on developing new ones. Beyond that, robotization negatively and similarly impacts respondents' work meaningfulness, competence, and relatedness regardless of their education level.

The results based on skill levels (Panel B of Table 7) provide similar insights – medium-skilled workers see somewhat smaller negative consequences of robotization when it comes to autonomy, while workers' skills do not attenuate the effect of robots on competence, and relatedness.

Finally, Panels C and D of Table 7 detail the results of our heterogeneity analysis based on age group and gender, respectively. Age does not significantly affect the relationship between robots and work meaningfulness and self-determination. More specifically, robotization increases the competence perception of men, likely because robotization increases the productivity of men (Aksoy et al. 2021). Men may perceive their competencies more highly than women because they have more exposure or access to robots, or because they have more confidence or self-efficacy in using them. Alternatively, women may perceive their competencies less highly than men because they face more barriers or challenges in using robots or because they have more negative or fearful attitudes towards them. Understanding these gender differences may help to design more inclusive and equitable policies and practices for robotization. These patterns should be explored in future research.

Gender, however, does not moderate robots' impact on work meaningfulness, autonomy, and relatedness. Furthermore, the finding that robotization equally erodes the work meaningfulness and self-determination of workers of all ages is interesting, suggesting that employers need to pay attention to workers of all ages and help them adapt to new technologies.

## **7. Potential Mechanisms and Alternative Explanations**

At the outset, we acknowledge that our ability to definitively pinpoint the mechanisms behind our finding is limited, not least because our dataset presents pooled cross-sections rather than a panel of individual workers. Nevertheless, we explore several aspects of the data, which provide more detail and help explore the channels.

One possibility is that our results merely reflect job loss and restructuring more generally rather than automation per se. We lack information on workers' job spells and previous unemployment experiences, but we have data on workers' job security fears, elicited using the survey item, "I might lose my job in the next 6 months." This allows us to understand whether what we are capturing is fear of the labor-saving aspects of robotization or whether we are measuring the job quality consequences of automation. We recoded the original responses, which ranged from strongly agree to strongly disagree on a 5-point scale into 1 = "Agree" and 0 = "Neutral and disagree." The results, reported in Table A6, suggest that individuals experiencing job insecurity are more likely to experience their jobs as less meaningful and bringing less autonomy, competence, and relatedness. Nevertheless, robotization does not seem to be amplifying these effects. Therefore, it is unlikely that all of our results are driven by job insecurity and fear of job loss.

It may still be possible that our results are driven by structural changes affecting different occupations and industries. In Table A4, we demonstrated that the results survive the inclusion of offshorability control and country and year fixed effects. Nevertheless, it is possible that other structural changes simultaneously coincide with robot adoption. To check whether this is the case, we conduct analyses adding occupation $\times$ year interactions and also education $\times$ year, which capture shocks that affect whole occupations in particular years, such as, for example, the COVID-19 pandemic, which had differential impacts on workers in different occupations and skills levels. Furthermore, a study by Dixon et al. (2021) finds that robotization leads to a decline in the employment of managers and supervisors employed in a firm, because robots reduce the quality variance, leading to less need for managerial control. If such trends are indeed occupation-specific, we could capture them, at least in part, through the use of occupation-by-year or education-by-year fixed effects. The results, reported in Table A7, show that such trends do not seem to influence our results.

Furthermore, we explore whether the results differ across the survey waves, which could shed light on issues related to the temporal distribution of the impacts (Table A8). Importantly, the results seem to be largely consistent across the different survey waves, except autonomy. Specifically, workers in the 2021 EWCS survey seem to have experienced positive and not negative effects of automation, likely because they have adapted to the previous automation shocks and have learned to benefit from the technology. Alternatively, this finding may be driven by the fact that the 2021 EWCS survey over-sampled highly educated individuals who benefited from more autonomy during the COVID-19 pandemic (Table A9). Whether future technological developments will change these trends or yield similar results and how they will interact with other trends related to the world of work is still an open question that future research should address.

Overall, the results presented so far seem to suggest that the effects we document do not simply reflect structural changes in the economy and fear of imminent job loss, but rather the consequences of technological change related to robotization. Taken together with the evidence in Section 6., our findings imply that workers performing routine tasks, who are also most affected by industrial robots, are the losers of this process. In contrast, workers who can benefit from the new technologies and have the right skills and occupational background are the winners.

## 8. Discussion and Conclusion

This paper studies the implications of robotization for workers' work meaningfulness, autonomy, competence, and relatedness. Our analysis relies on worker-level data from the 2010, 2015, and 2021 European Working Conditions Surveys and data on robotization for 14 industries in 20 countries and OLS and 2SLS estimations. We discover that robotization negatively affects work meaningfulness and autonomy. The results related to competence and relatedness are also negative but less robust. The effect sizes we document imply that doubling robotization reduces work meaningfulness by 0.9% and autonomy by 1%.

To provide context for our findings, we compared the robotization levels of the food and beverages industry (one of the top five industries in terms of robot adoption) and the automotive industry (the leading industry in robot adoption). If the food and beverage industry were to match the level of robot adoption seen in the automotive industry, representing a 7.5-fold increase in robotization, our estimates would imply a decrease of 6.8% in the meaningfulness of work and a 7.5% decrease in autonomy, which is economically important.

Future robotization and technology adoption patterns are uncertain. Some industries, such as agriculture or textiles, have relatively low levels of industrial robot penetration that may increase in the future (See Table A1 and Figure 1). Large increases in the stock of robots per worker are not uncommon across the industries we study, as illustrated in Table A1 and Figure 1. Such industries with low levels of robotization might see large increases in the future because robots are resource and energy-efficient and becoming increasingly enhanced with AI capabilities (IFR, 2023). This is in line with the large increases in robotization seen in the past (a fourfold increase in industrial robots in the US and Western Europe between 1993 and 2007) and what experts predict for the future – a twofold to a fourfold in the next decade (Acemoglu & Restrepo, 2020).

While past automation waves have affected individuals performing routine cognitive tasks, future technologies – such as AI – will affect different types of workers, namely high-skilled ones (Brynjolfsson et al., 2018; Webb, 2020). While all occupations have *some* tasks that can be replaced by machine learning, there are few (if any) occupations in which *all* tasks are replaceable by machine learning (Brynjolfsson et al., 2018). This suggests that the nature of many people's jobs will change in the near future, which has implications for job quality and perceived well-being at work.

Whether our results hold for future automation waves and technological advances remains to be seen. Yet, they provide a useful benchmark against which we could conceptualize the consequences of these currently emerging and future technologies. If technologies are adopted in a democratic and deliberative way, together with all stakeholders including workers, their consequences for future job quality need not be bleak or deterministic. Firms, supported by representative institutions, such as works councils, trade unions, and work committees, can help deliberate strategies for modifying and creating job designs and tasks for workers. Such job designs can ensure that humans and machines cooperate rather than compete for tasks and that the machines help improve workers' well-being.

Against this backdrop, it is important to move beyond the explorations of wage and employment consequences of technology and study the implications for workers' job characteristics and well-being. An emerging body of literature has instead focused on these understudied aspects, such as job quality and health, producing mixed results, which depend on the context. These emerging studies suggest that adopting industrial robots can hurt workers' job satisfaction and mental health by inducing greater fear of future machine replacement and promoting job insecurity (e.g., Schwabe & Castellacci, 2020; Abeliansky & Beulmann, 2021). The fear and anxiety of future job losses associated with the introduction of smart machines can be particularly pronounced for low-skilled occupations where workers are more likely to perform repetitive tasks and be exposed to automation.

Our paper provides novel and complementary evidence that robotization erodes workers' well-being regarding work meaningfulness and self-determination related to autonomy and relatedness. Studying the causes and consequences of automation for work meaningfulness and self-determination is instrumental in designing policies to enhance well-being at work. Understanding how automation shapes meaningful work perceptions is key to ensuring worker productivity and health and minimizing turnover amidst the ongoing processes of globalization and automation that can fundamentally change the nature of work.

We acknowledge several limitations to our study that future data collection efforts and extensions can help address. Our paper only focuses on European countries and the subset of industries common in the IFR, EUKLEMS, and EWCS. In this sense, it is unclear whether our

findings can be extrapolated to developing countries or countries outside our sample, limiting our geographic generalizability. Moreover, our study faces temporal limitations as our analysis stops in 2021. Furthermore, we lack data on service robots. Our information on industrial robots is likewise imperfect, and we lack details on the characteristics of the robots, including their quality. We also do not have matching industry- or occupation-level information on Artificial Intelligence, the more contemporary form of automation. Despite these challenges, the findings of our paper provide important insights that can be used as the basis for public policy and job design or understanding future technological innovations.

In this sense, our results open up several fruitful avenues for future research. For example, combining employer and employee-level data can help shed light on how firm-level technology adoption and management practices influence workers' work meaningfulness and self-determination outcomes. Our data only provide information on robot exposure at the industry level, but we do not know whether workers in the survey work with robots. Such information can be indispensable to better comprehend the underlying mechanisms behind our findings and provide analyses for particular industries and occupations for which our data are underpowered.

In addition, understanding the technology adoption process and whether or not it is being done in consultation with workers can help shed light on the mechanisms through which workers adapt to new technologies in the workplace. "Democratizing" technology adoption and involving workers in the design and implementation of the process could enhance workers' sense of agency and well-being (Spencer, 2023). In this sense, understanding the role of employee representation structures, such as works councils, trade unions, or other representative committees (Belloc et al., 2021), in technology adoption could be crucial to understanding how robotization can be implemented to satisfy workers' key psychological needs.

Finally, labor market institutions, working arrangements, and the institutional environment significantly differ across countries. While we have accounted for these differences using country-fixed effects, an interesting avenue for future research would be to unpack how the new technologies affect workers' work meaningfulness and self-determination in light of employment protection, technology regulations, and regimes, or institutional characteristics, such as the varieties of capitalism (Hall & Soskice, 2021), which have implications for the organization of labor and inequality.

## Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Grammarly and ChatGPT to edit and improve the clarity of parts of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Table 3: Constructions and variable definitions of main variables

Variable	Explanation and coding
<i>Dependent variables</i>	
Meaningful work index	Index based on extracting the first component of a polychoric principal component analysis (PCA) using the following variables: (1) “your job gives you the feeling of work well done” and (2) “you have the feeling of doing useful work.” The response scale is: 1=Never, 2=Rarely, 3=Sometimes, 4=Most of the time, 5=Always. The index is standardized to have a mean of 50 and a standard deviation of 10. The index is created based on Nikolova and Cnossen (2020). Cronbach’s alpha = 0.74. The first principal component has an eigenvalue of 1.69 and explains 85% of the total variance.
Autonomy index	Index based on extracting the first component of a polychoric principal component analysis (PCA) of the following variables: (1) able to choose or change the order of tasks, (2) able to choose or change methods of work, and (3) able to choose or change speed or rate of work. Variables (1)-(3) are originally measured on a scale 0=No, 1=Yes. The index is standardized to have a mean of 50 and a standard deviation of 10. The index is created based on Nikolova, Nikolaev, and Boudreaux (2021). Cronbach’s alpha = 0.79. The first principal component has an eigenvalue of 2.57 and explains 86% of the total variance.
Competence index	Index based on extracting the first component of a polychoric principal component analysis (PCA) of the following variables: (1) respondent has appropriate skills to cope with current or more demanding duties, (2) main paid job involves” solving unforeseen problems on your own,” (3) main paid job involves” learning new things.” Variable (1) is measured as 0 = No. 1 = Yes. Variables (2)-(3) are measured on a scale, whereby 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Most of the time, 5 = Always. The index is standardized to have a mean of 50 and a standard deviation of 10. The index is created based on Nikolova and Cnossen (2020). Cronbach’s alpha = 0.42. The first principal component has an eigenvalue of 1.75 and explains 58% of the total variance.
Relatedness index	Index based on extracting the first component of a polychoric principal component analysis (PCA) using the variables: (1)” your colleagues help and support you,” (2)” your manager helps and supports you.” Both variables are measured on a scale, whereby 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Most of the time, 5 = Always. The index is standardized to have a mean of 50 and a standard deviation of 10. The index is created based on Nikolova and Cnossen (2020). Cronbach’s alpha = 0.7. The first principal component has an eigenvalue of 1.65 and explains 83% of the total variance.
<i>Key independent variable</i>	

Robotization	The inverse hyperbolic sine transformation of the change in robot stocks between year t-1 and year t-5 in each industry and country, normalized by the number of workers (in 10,000s) in 2005 in that industry and country.
<i>Control variables</i>	
ICT	The inverse hyperbolic sine transformation of the change in ICT capital stocks (in computing, communications, computer software, and databases) between year t-1 and year t-5 in each industry and country, normalized by the number of workers (in 10,000s) in 2005 in that industry and country. Missing values were imputed based on data for the neighboring countries.
Other control variables	Age (in years) split into age groups (1 = 15-35; 2=36 - 45; 3 =45 - 60; 4 - over 60; 5 = missing); biological sex dummy (1 = female; 2 = male; 3= missing information); household size (number of people in household); weekly working hours transformed into a categorical variable denoting the within-country hours quartile to which the respondent belongs. 1=lowest quartile, 2=second lowest quartile, 3=third quartile, 4=fourth quartile, 5=missing information; education ( 1=primary = early childhood education, primary education; 2= secondary =lower secondary education, upper secondary education, and post-secondary non-tertiary education; 3=tertiary (short-cycle tertiary education, bachelor or equivalent, master or equivalent, and doctorate or equivalent; 4=missing information); company size indicator (1=less than 250 employees, 2=more than 250 employees, 3=missing information); occupation dummies (ISCO 08 one-digit categories, including a missing category); year dummies; country dummies.

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Table 4: Summary statistics

	Work meaningfulness sample, N=26,083		Autonomy sample, N=26,039		Competence sample, N=16,578		Relatedness sample, N=21,651	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Robotization	1.041	1.808	1.034	1.815	0.767	1.726	1.119	1.869
ICT adoption	1.835	2.350	1.818	2.349	1.725	2.136	1.912	2.386
Age group								
15-35	0.268	0.443	0.268	0.443	0.253	0.435	0.284	0.451
36-45	0.275	0.447	0.276	0.447	0.275	0.447	0.278	0.448
45-60	0.387	0.487	0.386	0.487	0.399	0.490	0.383	0.486
Over 60	0.067	0.250	0.067	0.251	0.068	0.252	0.052	0.222
Missing information	0.003	0.056	0.003	0.059	0.004	0.063	0.003	0.052
Biological sex								
Female	0.406	0.491	0.408	0.491	0.402	0.490	0.428	0.495
Male	0.593	0.491	0.591	0.492	0.598	0.490	0.571	0.495
Missing information	0.001	0.033	0.001	0.032	0.000	0.011	0.001	0.033
Working hours quartile								
1st	0.432	0.495	0.432	0.495	0.435	0.496	0.457	0.498
2nd	0.188	0.391	0.187	0.390	0.195	0.396	0.206	0.404
3rd	0.139	0.346	0.138	0.345	0.139	0.346	0.148	0.355
4th	0.210	0.407	0.213	0.409	0.203	0.402	0.169	0.375
Missing information	0.031	0.173	0.030	0.171	0.028	0.165	0.020	0.139
Education								
Primary	0.043	0.202	0.043	0.204	0.057	0.232	0.033	0.177
Secondary	0.567	0.495	0.569	0.495	0.641	0.480	0.555	0.497
Tertiary	0.386	0.487	0.383	0.486	0.299	0.458	0.408	0.492
Missing information	0.004	0.061	0.004	0.062	0.003	0.055	0.004	0.061
Occupation								
Managers	0.086	0.280	0.086	0.280	0.069	0.253	0.067	0.250
Professionals	0.238	0.426	0.424	0.000	0.185	0.388	0.265	0.441
Technicians and associate professionals	0.102	0.303	0.303	0.000	0.090	0.286	0.113	0.316
Clerical support workers	0.061	0.240	0.061	0.239	0.059	0.235	0.069	0.253
Service and sales workers	0.039	0.193	0.038	0.192	0.041	0.197	0.042	0.200
Skilled agricultural, forestry, and fisheries workers	0.050	0.219	0.052	0.221	0.065	0.246	0.016	0.125
Craft and related trades workers	0.236	0.424	0.236	0.425	0.264	0.441	0.222	0.416

Plant and machine operators, and assemblers	0.107	0.309	0.108	0.310	0.126	0.332	0.122	0.327
Elementary occupations	0.078	0.268	0.079	0.270	0.097	0.296	0.274	0.000
Unknown occupation	0.003	0.056	0.003	0.056	0.005	0.069	0.003	0.055
Company size								
Less than 250 workers	0.831	0.375	0.834	0.372	0.854	0.353	0.807	0.394
250 workers and more	0.145	0.352	0.142	0.349	0.124	0.329	0.167	0.373
Missing information	0.024	0.153	0.024	0.154	0.023	0.149	0.026	0.159
Tenure								
Less than 1 year	0.106	0.308	0.107	0.309	0.131	0.337	0.112	0.315
1-5 years	0.264	0.441	0.267	0.443	0.256	0.436	0.279	0.449
More than 5 years	0.577	0.494	0.575	0.494	0.595	0.491	0.560	0.496
Missing information	0.052	0.223	0.050	0.219	0.019	0.135	0.049	0.215
Employee type								
Private employee	0.750	0.433	0.753	0.431	0.766	0.423	0.715	0.451
Public employee	0.241	0.428	0.239	0.426	0.228	0.420	0.277	0.447
Missing information	0.009	0.093	0.008	0.090	0.005	0.072	0.008	0.090

Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The table denotes the summary statistics for the key variables used in the regression analyses. Variable definitions are available in Table 3. Data on competence is available only for 2010 and 2015. Relatedness questions are not asked of those who work alone.

Table 5: The effect of robotization on work meaningfulness, autonomy, competence, and relatedness

	(1)	(2)	(3)	(4)
<b>Panel A: Ordinary Least Squares</b>				
	Work meaningfulness	Autonomy	Competence	Relatedness
Robotization	-0.259*** (0.043)	-0.168*** (0.052)	-0.120** (0.059)	-0.044 (0.057)
Elasticity	-0.005	-0.003	-0.002	-0.001
R <sup>2</sup>	0.054	0.139	0.188	0.046
<b>Panel B: IV Peer Robot Adoption Second Stage</b>				
	Work meaningfulness	Autonomy	Competence	Relatedness
Robotization	-0.459*** (0.086)	-0.501*** (0.082)	-0.325** (0.129)	-0.168** (0.081)
Elasticity	-0.009	-0.010	-0.006	-0.003
R <sup>2</sup>	0.053	0.136	0.187	0.045
<b>Panel C: IV Peer Robot Adoption First Stage</b>				
	Robotization	Robotization	Robotization	Robotization
Peer robot adoption	0.680*** (0.042)	0.677*** (0.043)	0.577*** (0.065)	0.677*** (0.043)
1st stage F-stat	261.9	250.3	79.4	243.0
Number of observations	26,083	26,039	16,578	21,651

Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The table reports results from OLS (Panel A) and IV (Panel B) regressions of work meaningfulness, autonomy, competence, and relatedness on robotization. The first stage results are reported in Panel C. Robotization is measured as the inverse hyperbolic sine transformation in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, number of years with the company, public/private sector, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the countryXindustry level. All dependent variables are measured on a scale of 0 to 100 and standardized to have a mean of 50 and a standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variable is based on the industry adoption of robots in all other countries in the sample (except that particular country). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1



Table 6: The moderating effects of tasks for the relationship between robotization and work, meaningfulness, autonomy, competence, and relatedness

	(1) Work meaningfulness	(2) Autonomy	(3) Competence	(4) Relatedness
<b>Panel A: The moderating effect of individual-level repetitive tasks, IV regressions second stage</b>				
Robotization	-0.389*** (0.138)	-0.116 (0.118)	0.050 (0.186)	-0.005 (0.103)
Repetitive tasks	-0.722*** (0.219)	0.089 (0.234)	0.111 (0.230)	-0.639*** (0.224)
RobotizationXRepetitive tasks	-0.091 (0.153)	-0.734*** (0.140)	-0.527*** (0.184)	-0.251** (0.118)
R <sup>2</sup>	0.059	0.145	0.187	0.047
1st stage F-stat	89.99	85.92	37.98	119.3
Number of observations	21,240	21,232	16,533	21,595
<b>Panel B: The moderating effect of working with computers, IV regressions second stage</b>				
Robotization	-0.459*** (0.126)	-1.299*** (0.144)	-0.969*** (0.178)	-0.412*** (0.114)
Working with computers	1.122*** (0.152)	2.838*** (0.190)	2.655*** (0.188)	0.398** (0.160)
RobotizationXWorking with computers	0.092 (0.123)	1.505*** (0.137)	1.683*** (0.201)	0.421*** (0.111)
R <sup>2</sup>	0.056	0.157	0.205	0.046
1st stage F-stat	108.5	109.2	39.24	105.6
Number of observations	25,998	25,957	16,512	21,593
<b>Panel C: The moderating effect of social tasks, IV regressions second stage</b>				
Robotization	-0.256** (0.116)	-0.462*** (0.115)	-0.085 (0.162)	-0.193* (0.106)
Working with clients	1.466*** (0.219)	2.777*** (0.261)	2.957*** (0.244)	0.320 (0.210)
RobotizationXWorking with clients	-0.310** (0.128)	0.236* (0.134)	-0.204 (0.181)	0.108 (0.130)
R <sup>2</sup>	0.055	0.157	0.203	0.046
1st stage F-stat	124.6	118.7	37.86	118.1
Number of observations	26,020	25,976	16,527	21,605

Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The table reports results from IV regressions of work meaningfulness, autonomy, competence, and relatedness on robotization, by whether the respondent performs repetitive hand or arm movements (Panel A), by whether the respondent works with a computer (Panel B), and by whether the respondent performs social tasks (dealing directly with people who are not employees at the respondent's workplace, such as customers, passengers, pupils, patients, etc.) (Panel C). Robotization is measured as the inverse hyperbolic sine transformation in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, the number of years with the company, public/private sector, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the countryXindustry level. All dependent variables are measured on a scale of 0 to 100 and standardized to have a mean of 50 and a standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variable is based on the industry adoption of robots in all other countries in the sample (except that particular country). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 7: The moderating effects of skills for the relationship between robotization and work, meaningfulness, autonomy, competence, and relatedness

	(1)	(2)	(3)	(4)
	Work meaningfulness	Autonomy	Competence	Relatedness
<b>Panel A: The moderating effect of skill levels (education), IV regressions second stage</b>				
Robotization	-0.395*** (0.106)	-0.653*** (0.102)	-0.359** (0.148)	-0.242** (0.102)
Tertiary education	-0.059 (0.271)	1.267*** (0.239)	2.347*** (0.300)	0.042 (0.283)
RobotizationXTertiary Education	-0.299* (0.155)	0.498*** (0.114)	-0.004 (0.243)	0.182 (0.140)
R <sup>2</sup>	0.050	0.133	0.184	0.045
1st stage F-stat	120.7	119.7	31.91	120.8
Number of observations	25,984	25,940	16,528	21,570
<b>Panel B: The moderating effect of skill levels (based on ILO classification), IV regressions second stage</b>				
Robotization	-0.418*** (0.140)	-0.903*** (0.130)	-0.333* (0.197)	-0.186 (0.119)
Medium Skilled	1.684*** (0.379)	4.437*** (0.277)	5.097*** (0.430)	0.988*** (0.325)
High Skilled	1.262*** (0.346)	3.858*** (0.455)	1.300*** (0.401)	0.834** (0.413)
RobotizationXMedium Skilled	-0.177 (0.189)	0.749*** (0.146)	-0.030 (0.303)	0.046 (0.151)

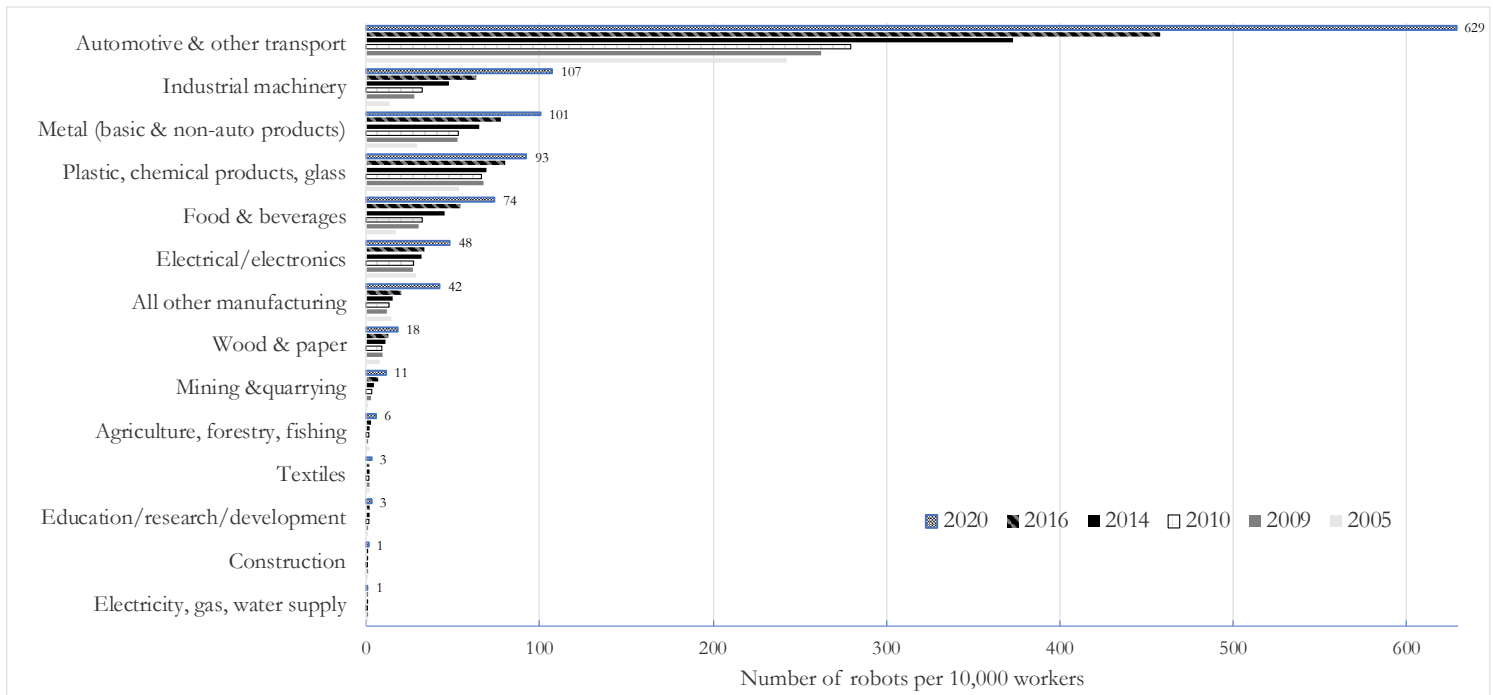
RobotizationXHigh Skilled	-0.332*	0.194	0.032	-0.137
	(0.198)	(0.240)	(0.285)	(0.211)
R <sup>2</sup>	0.041	0.117	0.162	0.041
1st stage F-stat	72.57	70.84	28.62	68.80
Number of observations	26,001	25,958	16,498	21,586
<b>Panel C: The moderating effect of age, IV regressions second stage</b>				
Robotization	-0.507***	-0.450***	-0.388***	-0.138
	(0.091)	(0.088)	(0.138)	(0.089)
Aged 50 and older	1.383***	0.573***	-0.961***	-0.778***
	(0.184)	(0.204)	(0.240)	(0.181)
RobotizationX Aged 50 and older	0.089	-0.227*	0.037	-0.107
	(0.113)	(0.122)	(0.185)	(0.122)
R <sup>2</sup>	0.050	0.134	0.184	0.045
1st stage F-stat	134.3	130	42.04	127.2
Number of observations	26,001	25,949	16,512	21,593
<b>Panel D: The moderating effect of gender, IV regressions second stage</b>				
Robotization	-0.427***	-0.569***	-0.753***	-0.115
	(0.127)	(0.127)	(0.199)	(0.129)
Male	-0.030	0.944***	0.864***	0.290
	(0.248)	(0.232)	(0.251)	(0.268)
RobotizationXMale	-0.103	0.098	0.570***	-0.097
	(0.130)	(0.123)	(0.185)	(0.142)
R <sup>2</sup>	0.051	0.134	0.184	0.045
1st stage F-stat	135.5	123.9	41.34	125.7
Number of observations	26,055	26,013	16,576	21,627

Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The table reports results from IV regressions of work meaningfulness, autonomy, competence, and relatedness on robotization, by the respondent's education level (Panel A), skill level (Panel B), the respondents' age (Panel C), and by the respondent's gender (Panel D). Robotization is measured as the inverse hyperbolic sine transformation in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, number of years with the company, private/public sector, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the countryXindustry level. All dependent variables are measured on a scale of 0 to 100 and standardized to have a mean of 50 and a standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variable is based on the industry adoption of robots in all other countries in the sample (except that particular country). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

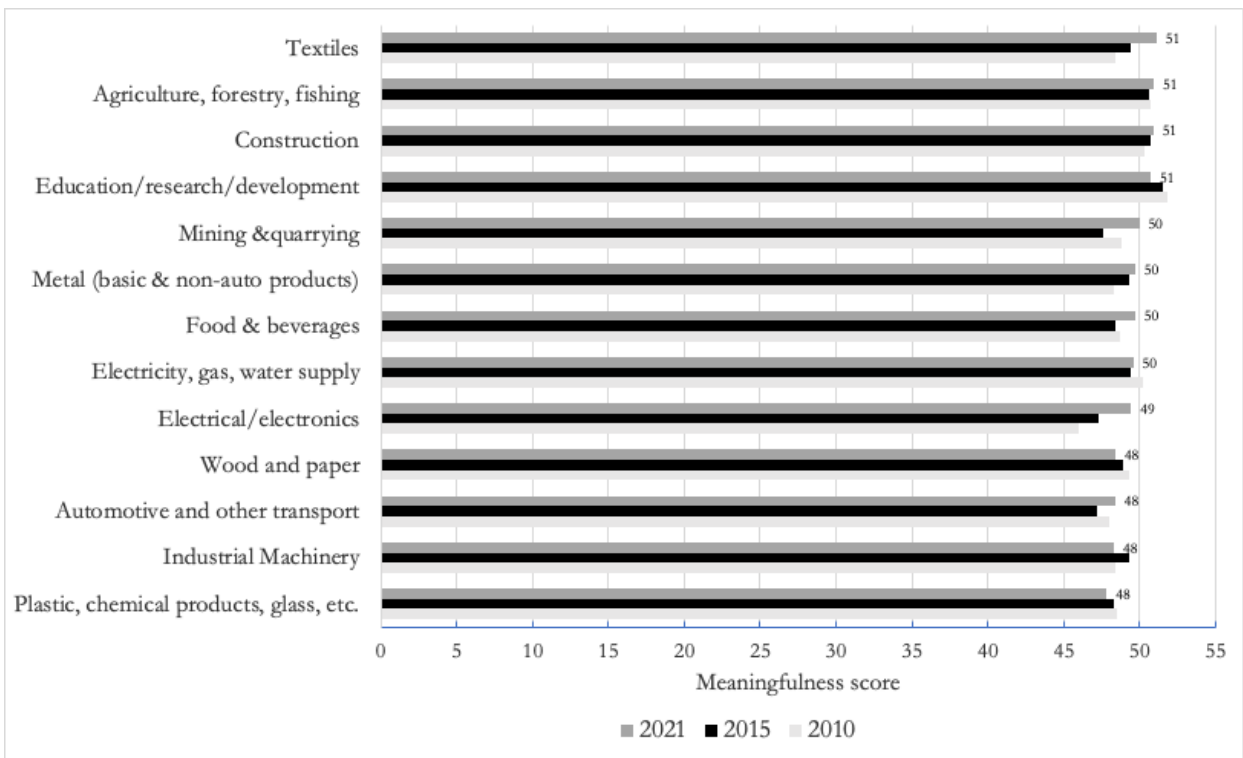
Figure 1: Industrial robots per 10,000 workers by industry and year, 2005-2020



Source: Authors' calculations based on IFR and EUKLEMS

Notes: The figure shows the average robot density (robot stock per 10,000 workers) by industry for 2005, 2009, 2010, 2014, 2016, and 2020. The values for 2020 are shown next to each bar. The industries Construction, Education/research/development, and Electricity, gas, and water supply have very small non-zero values.

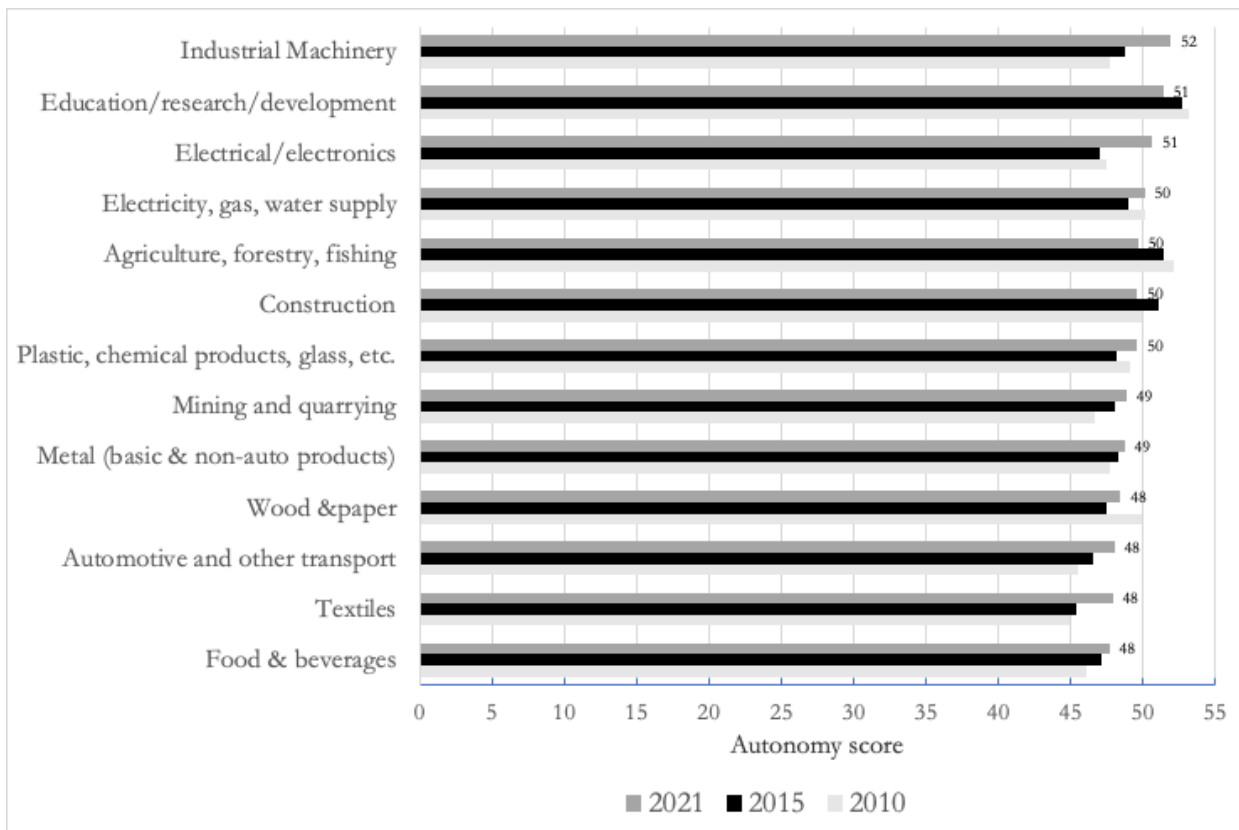
Figure 2: Work meaningfulness, by industry and year



Source: Authors' calculations based on the European Working Conditions Surveys (2010, 2015, 2021)

Notes: The figure shows the average work meaningfulness by industry for 2010, 2015, and 2021. Work meaningfulness is standardized to have a mean of 50 and a standard deviation of 10.

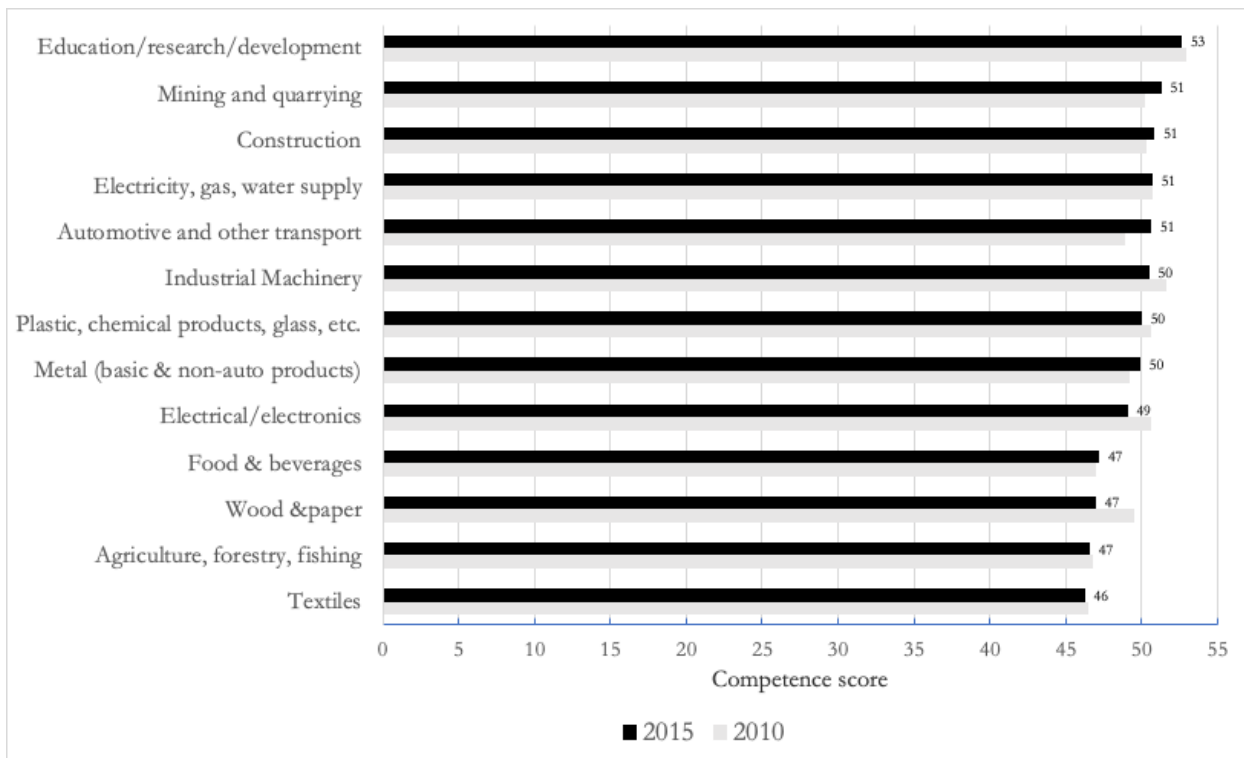
Figure 3: *Autonomy, by industry and year*



Source: Authors' calculations based on the European Working Conditions Surveys (2010, 2015, 2021)

Notes: The figure shows the average autonomy levels by industry for the years 2010, 2015, and 2021. Autonomy is standardized to have a mean of 50 and a standard deviation of 10.

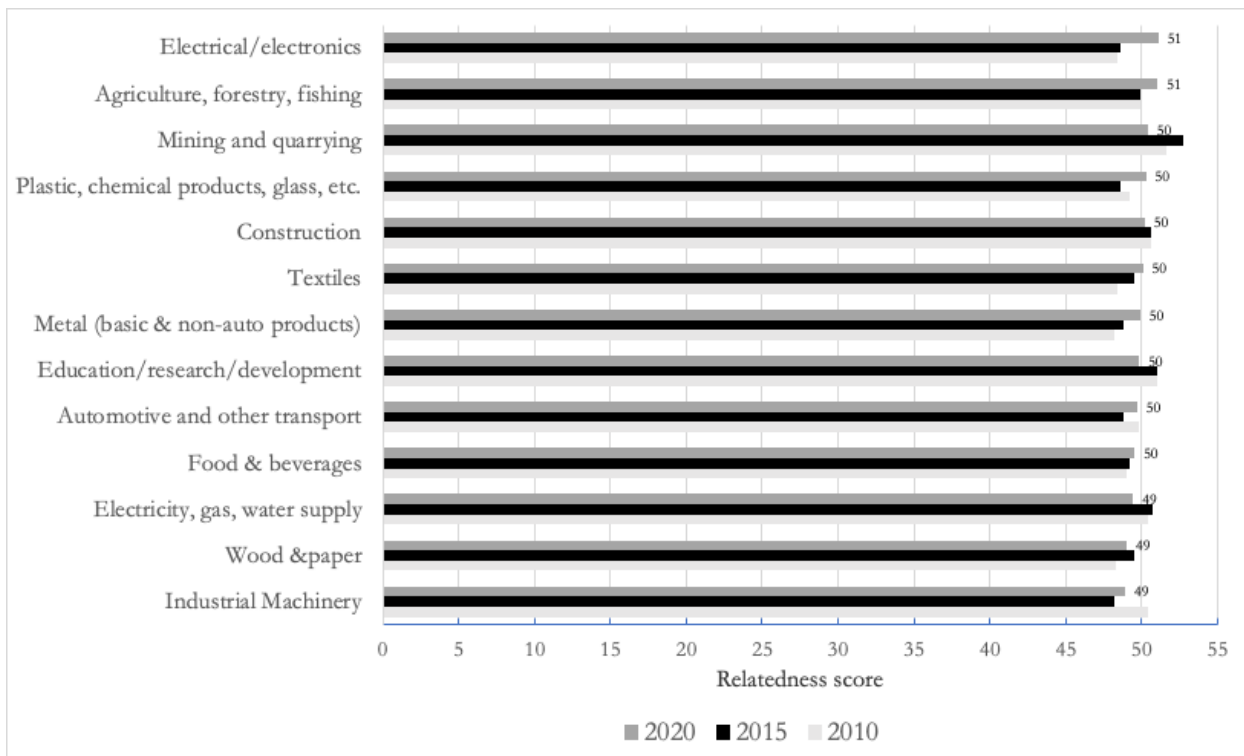
Figure 4: Competence, by industry and year



Source: Authors' calculations based on the European Working Conditions Surveys (2010, 2015, 2021)

Notes: The figure shows the average competence levels by industry for the years 2010 and 2015. Competence is standardized to have a mean of 50 and a standard deviation of 10. There is no information about the underlying variables comprising the competence index in the 2021 EWCS survey

Figure 5: Relatedness, by industry and year

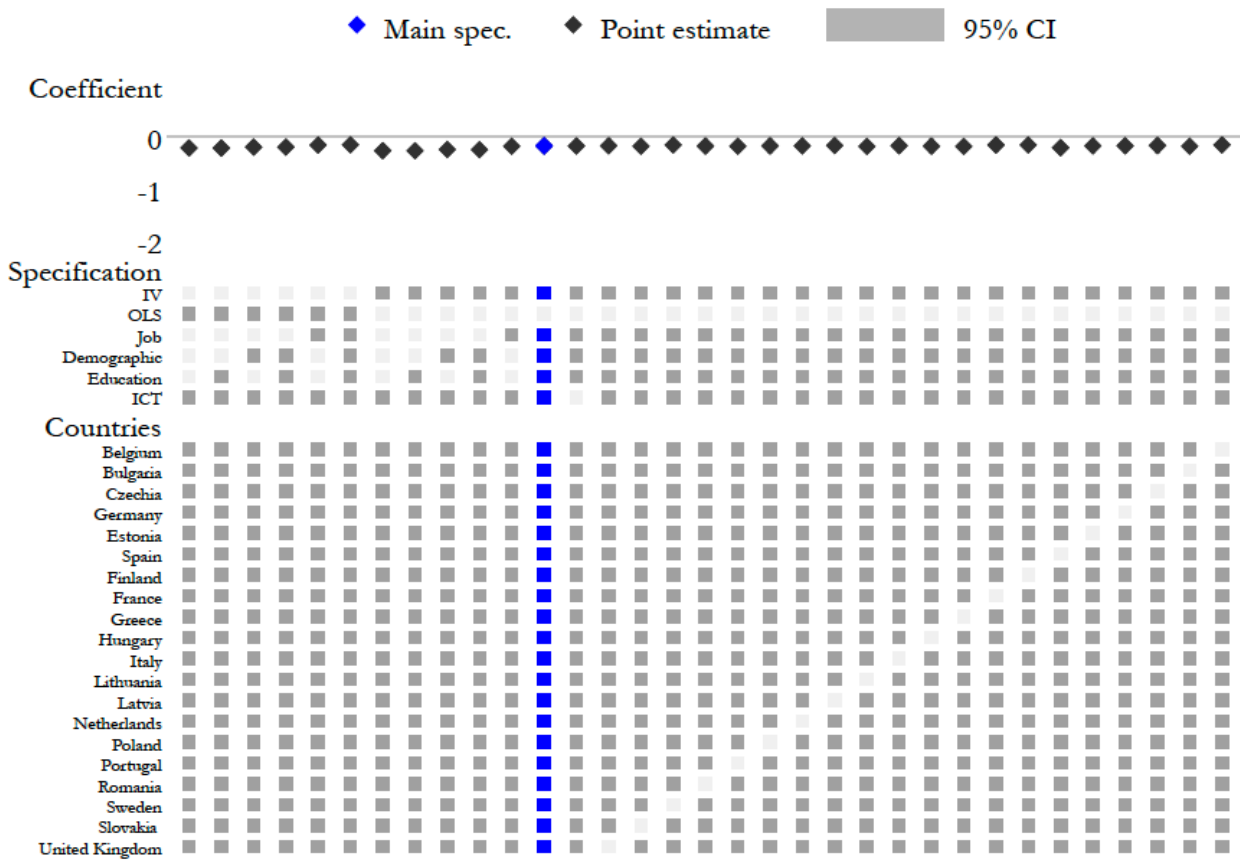


Source: Authors' calculations based on the European Working Conditions Surveys (2010, 2015, 2021)

Notes: The figure shows the average relatedness levels by industry for the years 2010, 2015, and 2021. Relatedness is standardized to have a mean of 50 and a standard deviation of 10.



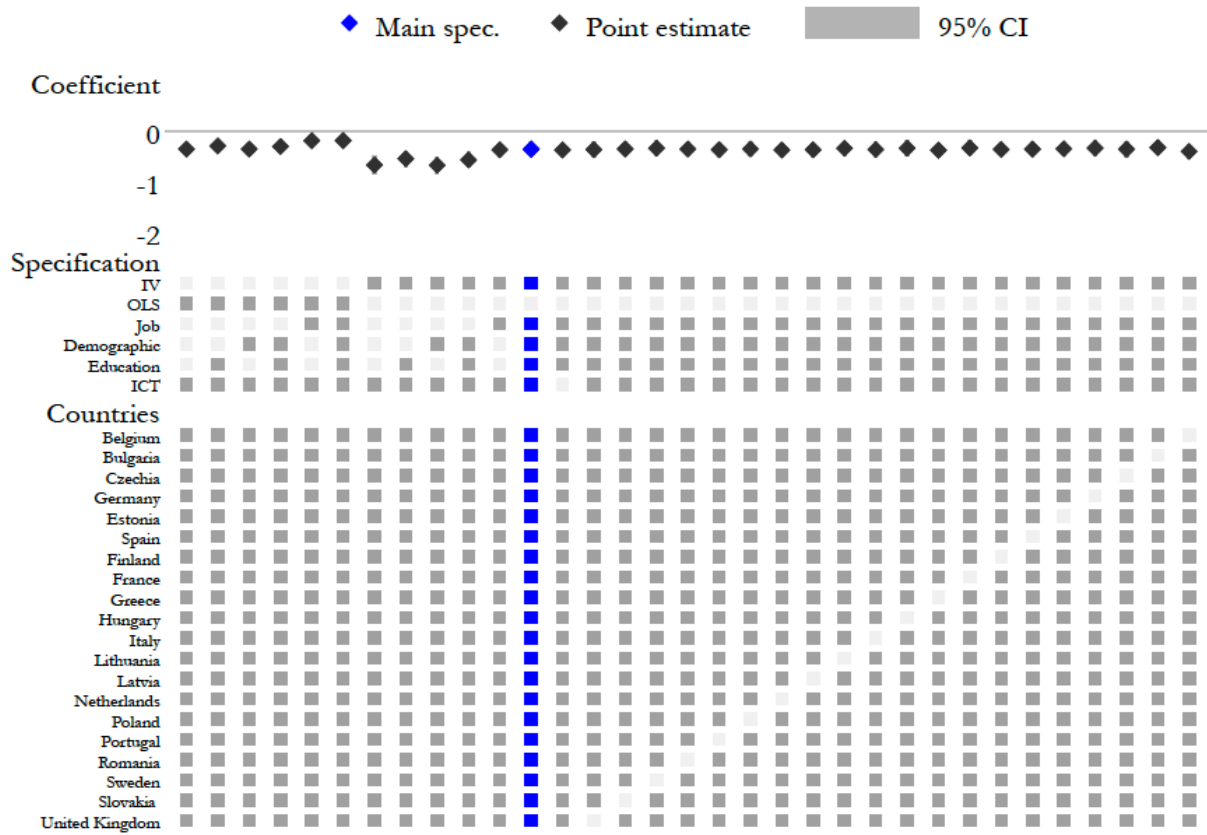
Figure 6: Specification curve analysis, work meaningfulness



Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The figure shows the specification curve analysis for work meaningfulness as the dependent variable and different estimations of Equation (2). The main specification is the one from Table 5, Panel B, Model (1). Work meaningfulness is standardized to have a mean of 50 and a standard deviation of 10.

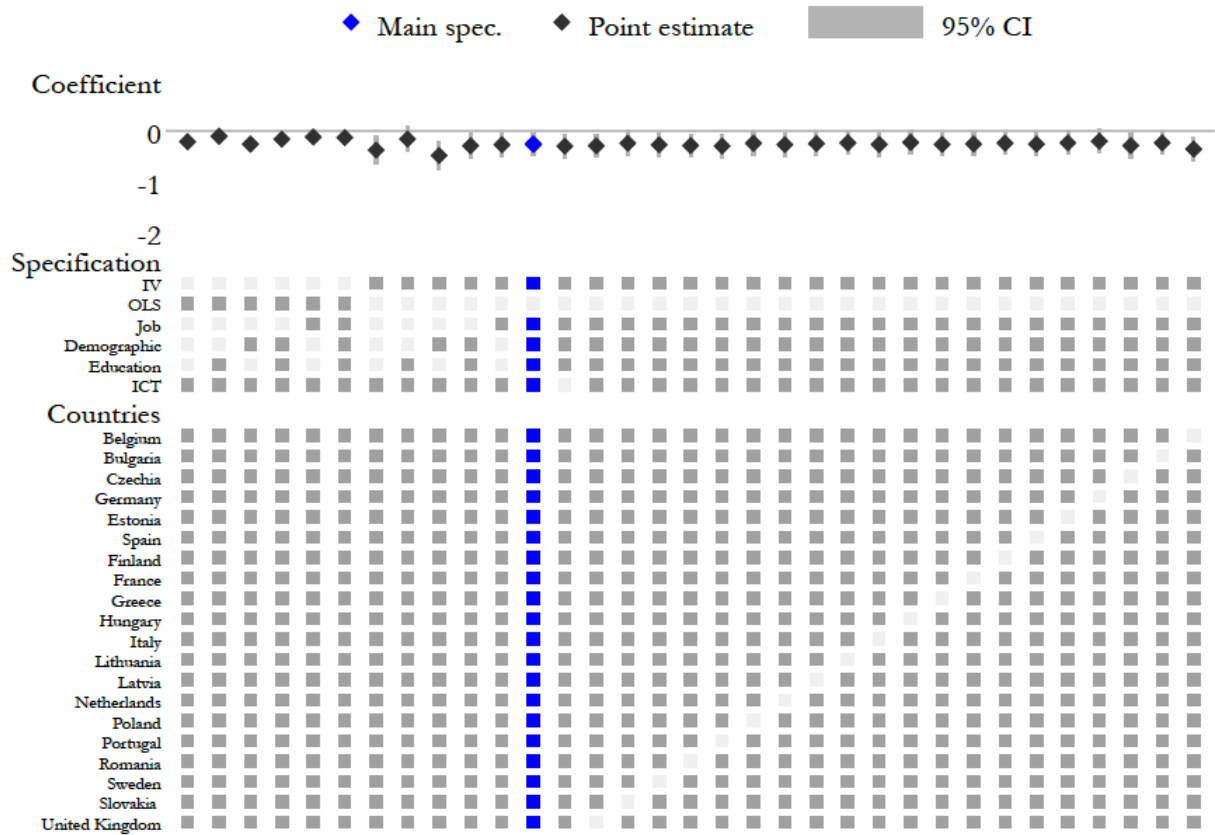
Figure 7: Specification curve analysis, autonomy



Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The figure shows the specification curve analysis for autonomy as the dependent variable and different estimations of Equation (2). The main specification is the one from Table 5, Panel B, Model (2). Autonomy is standardized to have a mean of 50 and a standard deviation of 10.

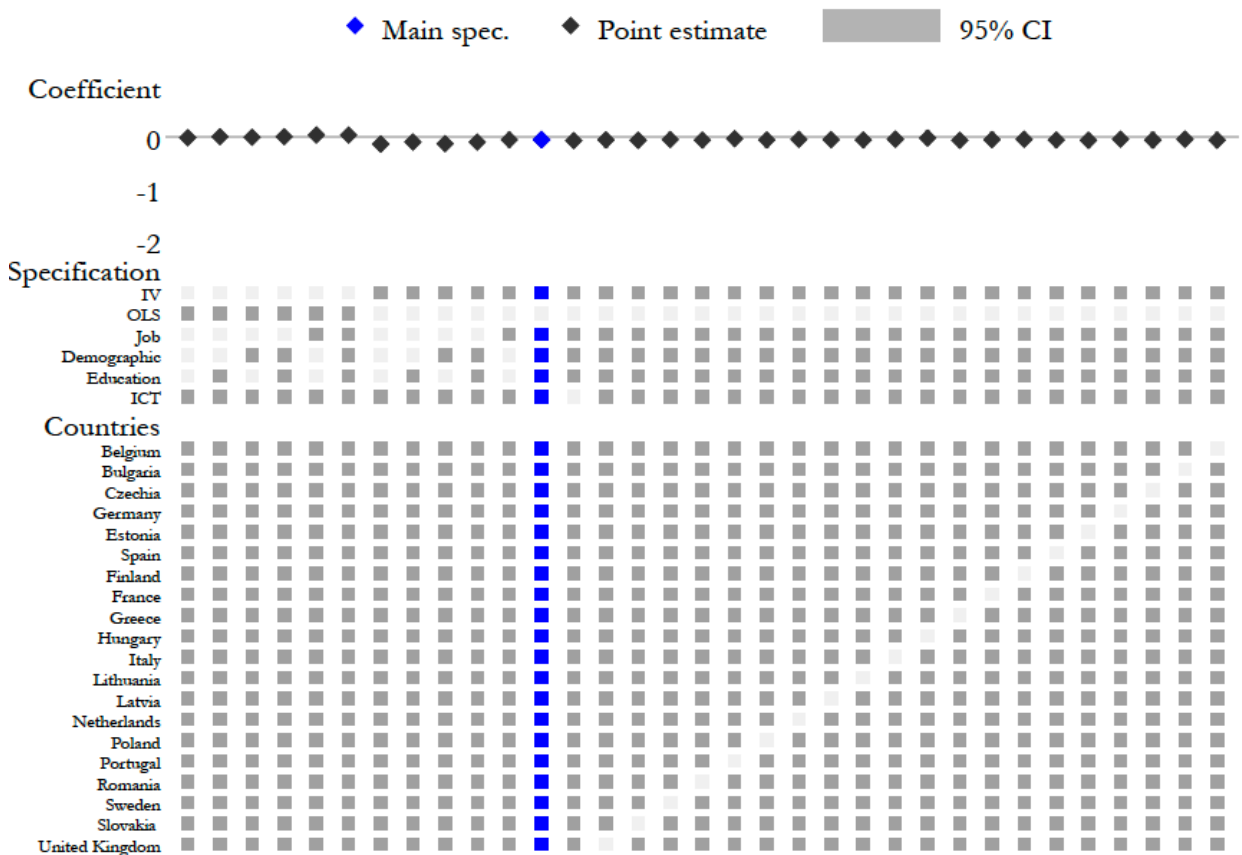
Figure 8: Specification curve analysis, competence



Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The figure shows the specification curve analysis for competence as the dependent variable and different estimations of Equation (2). The main specification is the one from Table 5, Panel B, Model (3). Competence is standardized to have a mean of 50 and a standard deviation of 10.

Figure 8: Specification curve analysis, relatedness



Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The figure shows the specification curve analysis for relatedness as the dependent variable and different estimations of Equation (2). The main specification is the one from Table 5, Panel B, Model (4). Relatedness is standardized to have a mean of 50 and a standard deviation of 10.

## APPENDIX

Table A1: Industrial robots per 10,000 workers by industry and year and percentage changes between 2005-2009, 2010-2014, 2016-2020, and 2005-2020

	2005	2009	2010	2014	2016	2020	Pct. Change 2005- 2009	Pct. Change 2010-2014	Pct. Change 2016-2020	Pct. change 2005- 2020
Textiles	2.246	1.908	1.820	2.245	2.248	2.878	-15.049	23.352	28.025	28.139
Electrical/electronics	28.357	26.863	26.962	32.191	33.815	48.383	-5.269	19.394	43.081	70.621
Plastic, chemical products, glass	53.303	67.359	66.480	69.180	79.864	92.605	26.370	4.061	15.953	73.733
Education/research/development	1.512	1.471	1.421	1.745	1.918	2.856	-2.712	22.801	48.905	88.889
Wood & paper	7.960	9.668	9.443	11.154	12.775	18.214	21.457	18.119	42.575	128.819
Automotive & other transport	242.562	262.191	279.655	372.604	457.623	628.740	8.092	33.237	37.393	159.208
Construction	0.444	0.794	0.922	1.116	1.212	1.213	78.829	21.041	0.083	173.198
Agriculture, forestry, fishing	1.983	1.534	1.572	2.207	2.882	5.612	-22.642	40.394	94.726	183.006
All other manufacturing	14.258	11.850	12.828	15.095	20.252	42.413	-16.889	17.672	109.426	197.468
Metal (basic & non-auto products)	29.304	53.107	52.824	65.342	77.257	100.583	81.228	23.698	30.193	243.240
Food & beverages	17.226	29.939	32.524	45.597	54.129	74.094	73.801	40.195	36.884	330.129
Electricity, gas, and water supply	0.156	0.302	0.303	0.509	0.665	0.897	93.590	67.987	34.887	475.000
Industrial machinery	13.618	27.928	32.033	47.782	63.899	107.493	105.082	49.165	68.223	689.345
Mining & quarrying	0.423	2.702	3.233	4.205	6.540	11.423	538.771	30.065	74.664	2600.473

Source: Authors' calculations based on IFR and EUKLEMS

Notes: The table shows the average robot density (robot stock per 10,000 workers) by industry for the years 2005, 2009, 2010, 2014, 2016, and 2020 which are also presented in Figure 1. In addition, this table shows the percentage change in the robot density between 2005-2009, 2010-2014, and 2016-2020 in the last two columns. The industries Construction, Education/research/development, and Electricity, gas, and water supply have very small non-zero values for the robot density variable.

Table A2: The effect of robotization on work meaningfulness, autonomy, competence, and relatedness, robustness checks with different instrumental variables

	(1)	(2)	(3)	(4)
	Robotization	Robotization	Robotization	Robotization
<b>Panel A: IV Replaceable hours and robotic arms first stage</b>				
Robotic arms	-4.667** (1.975)	-4.492** (1.996)	-5.803*** (2.225)	-4.934** (2.063)
Replaceable hours	8.287*** (0.824)	8.161*** (0.832)	7.198*** (1.087)	8.493*** (0.857)
1st stage F-stat	99.96	96.02	30.02	97.55
Hansen's J statistics (overidentification test)	2.965	9.606	6.650	10.63
Overidentification test p-value	0.0851	0.00194	0.00992	0.00111
<b>Panel B: IV Replaceable hours and robotic arms second stage</b>				
	Work meaningfulness	Autonomy	Competence	Relatedness
Robotization	-0.808*** (0.109)	-0.745*** (0.103)	-0.404*** (0.143)	-0.343*** (0.097)
R <sup>2</sup>	0.046	0.130	0.186	0.043
Elasticity	-0.016	-0.015	-0.008	-0.007
Number of observations	26,083	26,039	16,578	21,651

Source: Authors' calculations based on IFR, EUKLEMS, Graetz and Michaels (2018), and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The table reports results from IV regressions of work meaningfulness, autonomy, competence, and relatedness on robotization. Robotization is measured as the inverse hyperbolic sine transformation in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, number of years with the company, public/private sector, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the countryXindustry level. All dependent variables are measured on a scale of 0 to 100 and standardized to have a mean of 50 and a standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variables are measures of i) the share of hours in an industry that is replaceable by robots in 1980 in US industries and ii) the degree to which industries in 1980 in the US had occupations that required reaching and handling tasks, based on Graetz and Michaels (2018). The elasticity estimate is calculated following Bellemare and Wichman (2020). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A3: The effect of robotization on work meaningfulness, autonomy, competence, and relatedness, robustness checks using weights

	(1)	(2)	(3)	(4)
	Work meaningfulness	Autonomy	Competence	Relatedness
<b>Panel A: Industry employment shares as weights</b>				
Robotization	-0.558*** (0.088)	-0.546*** (0.097)	-0.265* (0.149)	-0.229*** (0.087)
Elasticity	-0.011	-0.011	-0.005	-0.005
R <sup>2</sup>	0.048	0.126	0.199	0.048
1st stage F-stat	250.6	243	92.17	248.6
Number of observations	25,100	25,059	16,043	20,777
<b>Panel B: Inverse number of observations per country as weights</b>				
Robotization	-0.475*** (0.099)	-0.614*** (0.101)	-0.303** (0.133)	-0.184** (0.093)
Elasticity	-0.009	-0.012	-0.006	-0.004
R <sup>2</sup>	0.058	0.148	0.194	0.050
1st stage F-stat	218.3	205.2	96.71	203.6
Number of observations	26,083	26,039	16,578	21,651

Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The table reports results from OLS (Panel A) and IV (Panel B) regressions of work meaningfulness, autonomy, competence, and relatedness on robotization. The main difference with Table 3 is that observations in the estimations in this table are weighted using the country-specific industry employment shares (as of 2000) in Panel A and the inverse of the number of observations per year per country in Panel B. Not all industries and countries have complete information about the weights. Robotization is measured as the inverse hyperbolic sine transformation in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, the number of years with the company, public/private sector, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the countryXindustry level. All dependent variables are measured on a scale of 0 to 100 and standardized to have a mean of 50 and a standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variable is based on the industry adoption of robots in all other countries in the sample (except that particular country). The elasticity estimate is calculated following Bellemare and Wichman (2020). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1



Table A4: The effect of robotization on work meaningfulness, autonomy, competence, and relatedness, robustness checks with country-by-year fixed effects, and offshorability control

	(1)	(2)	(3)	(4)
	Work meaningfulness	Autonomy	Competence	Relatedness
<b>Panel A: With countryXyear Fixed Effects</b>				
Robotization	-0.475*** (0.079)	-0.491*** (0.079)	-0.298** (0.123)	-0.119 (0.074)
Elasticity	-0.009	-0.010	-0.006	-0.002
R <sup>2</sup>	0.066	0.143	0.194	0.070
1st stage F-stat	265.8	253.7	79.83	245.5
Number of observations	26,083	26,039	16,578	21,651
<b>Panel B: With an offshorability control</b>				
Robotization	-0.313*** (0.093)	-0.350*** (0.088)	-0.206 (0.130)	-0.053 (0.090)
Elasticity	-0.006	-0.007	-0.004	-0.001
R <sup>2</sup>	0.073	0.170	0.183	0.079
1st stage F-stat	224.0	214.3	75.93	209.4
Number of observations	26,083	26,039	16,578	21,651

Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The table reports results from IV regressions. The dependent variables are work meaningfulness, autonomy, competence, and relatedness. The main difference with Table 5 is that this table includes countryXyear fixed effects in Panel A, in addition to all the controls and fixed effects included in Table 5. Panel B includes an additional control for offshorability, at the industry level, provided by Graetz and Michaels (2018). Robotization is measured as the inverse hyperbolic sine transformation in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, the number of years with the company, public/private sector, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the countryXindustry level. All dependent variables are measured on a scale of 0 to 100 and standardized to have a mean of 50 and a standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variable is based on the industry adoption of robots in all other countries in the sample (except that particular country). The elasticity estimate is calculated following Bellemare and Wichman (2020). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A5: The effect of robotization on work meaningfulness, autonomy, competence, and relatedness, by job tenure

	Work meaningfulness	Autonomy	Competence	Relatedness
Robotization	-0.497*** (0.085)	-0.506*** (0.081)	-0.349*** (0.132)	-0.199** (0.083)
On the Job 1 Year of Less	-0.539 (0.367)	-1.154*** (0.286)	0.183 (0.298)	-0.095 (0.358)
RobotizationX On the Job 1 Year of Less	0.015 (0.257)	0.067 (0.192)	-0.160 (0.255)	0.177 (0.233)
R <sup>2</sup>	0.051	0.135	0.185	0.045
1st stage F-stat	97.07	90.31	42.25	94.40
Number of observations	26,083	26,039	16,578	21,651

Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The table reports results from IV regressions of work meaningfulness, autonomy, competence, and relatedness on robotization, by the number of years the respondent has worked for that company. Robotization is measured as the inverse hyperbolic sine transformation in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the countryXindustry level. All dependent variables are measured on a scale of 0 to 100 and standardized to have a mean of 50 and a standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variable is based on the industry adoption of robots in all other countries in the sample (except that particular country). The elasticity estimate is calculated following Bellemare and Wichman (2020). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A6: The effect of robotization on work meaningfulness, autonomy, competence, and relatedness, by job insecurity

	Work meaningfulness	Autonomy	Competence	Relatedness
Robotization	-0.475*** (0.076)	-0.462*** (0.084)	-0.414*** (0.131)	-0.151* (0.084)
Job insecurity	-2.636*** (0.292)	-1.664*** (0.266)	-0.184 (0.304)	-2.011*** (0.256)
RobotizationX Job insecurity	-0.026 (0.196)	-0.139 (0.173)	0.210 (0.255)	-0.138 (0.173)
R <sup>2</sup>	0.060	0.142	0.186	0.051
1st stage F-stat	117	123.4	36.35	103
Number of observations	24,205	24,170	14,938	20,501

Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The table reports results from IV regressions of work meaningfulness, autonomy, competence, and relatedness on robotization, by whether the respondent agrees with the statement "I might lose my job in the next 6 months." Robotization is measured as the inverse hyperbolic sine transformation in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the countryXindustry level. All dependent variables are measured on a scale of 0 to 100 and standardized to have a mean of 50 and a standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variable is based on the industry adoption of robots in all other countries in the sample (except that particular country). The elasticity estimate is calculated following Bellemare and Wichman (2020). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.

Table A7: The effect of robotization on work meaningfulness, autonomy, competence, and relatedness, robustness checks with occupation by year and education by year fixed effects

	(1)	(2)	(3)	(4)
	Work meaningfulness	Autonomy	Competence	Relatedness
<b>Panel A: With occupationXyear Fixed Effects</b>				
Robotization	-0.444*** (0.082)	-0.493*** (0.081)	-0.342*** (0.127)	-0.168** (0.079)
Elasticity	-0.00877	-0.00983	-0.00674	-0.00334
R <sup>2</sup>	0.058	0.140	0.191	0.047
1st stage F-stat	261.9	249.9	78.10	243.4
Number of observations	26,083	26,039	16,578	21,651
<b>Panel B: With educationXyear Fixed Effects</b>				
Robotization	-0.447*** (0.085)	-0.518*** (0.149)	-0.346*** (0.050)	-0.164 (0.103)
Elasticity	-0.009	-0.010	-0.007	-0.003
R <sup>2</sup>	0.056	0.138	0.191	0.046
1st stage F-stat	144.3	143.3	3474	139.3
Number of observations	25,984	25,940	16,528	21,570

Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The table reports results from IV regressions. The dependent variables are work meaningfulness, autonomy, competence, and relatedness. The main difference with Table 5 is that this table includes occupationXyear fixed effects in Panel A and educationXyear fixed effects in addition to all the controls and fixed effects included in Table 5. Robotization is measured as the inverse hyperbolic sine transformation in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, the number of years with the company, public/private sector, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the countryXindustry level. All dependent variables are measured on a scale of 0 to 100 and standardized to have a mean of 50 and a standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variable is based on the industry adoption of robots in all other countries in the sample (except that particular country). The elasticity estimate is calculated following Bellemare and Wichman (2020). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A8: The effect of robotization on work meaningfulness, autonomy, competence, and relatedness, by survey year

	Work meaningfulness	Autonomy	Competence	Relatedness
Robotization	-0.485*** (0.165)	-0.907*** (0.177)	-0.342** (0.150)	-0.300* (0.153)
Year 2015	0.066 (0.260)	0.399 (0.288)	-0.166 (0.322)	0.071 (0.279)
Year 2021	0.308 (0.383)	-1.563*** (0.271)		-0.808* (0.461)
RobotizationXYear 2015	-0.230 (0.234)	-0.133 (0.277)	-0.099 (0.231)	-0.237 (0.223)
RobotizationX Year 2021	0.105 (0.209)	0.807*** (0.202)		0.329 (0.212)
R <sup>2</sup>	0.049	0.132	0.189	0.045
1st stage F-stat	10.85	10.51	16.39	9.720
Number of observations	26,083	26,039	16,578	21,651

Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

Notes: The table reports results from IV regressions of work meaningfulness, autonomy, competence, and relatedness on robotization, by survey year. Robotization is measured as the inverse hyperbolic sine transformation in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the countryXindustry level. All dependent variables are measured on a scale of 0 to 100 and standardized to have a mean of 50 and a standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variable is based on the industry adoption of robots in all other countries in the sample (except that particular country). The elasticity estimate is calculated following Bellemare and Wichman (2020). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A9: Summary statistics, work meaningfulness sample, N=26,083

	2010, N=8,650		2015, N=8,063		2021, N=9,370
	Mean	St. Dev.	Mean	St. Dev.	Mean
Robotization	0.692	1.673	0.849	1.775	1.528
ICT adoption	1.912	1.991	1.529	2.270	2.028
Age group					
15-35	0.264	0.441	0.241	0.428	0.293
36-45	0.286	0.452	0.265	0.442	0.275
45-60	0.389	0.487	0.411	0.492	0.364
Over 60	0.057	0.232	0.079	0.270	0.066
Missing information	0.005	0.067	0.003	0.054	0.002
Biological sex					
Female	0.407	0.491	0.398	0.489	0.413
Male	0.593	0.491	0.602	0.489	0.584
Missing information			0.000	0.016	0.003
Working hours quartile					
1st	0.463	0.499	0.407	0.491	0.424
2nd	0.180	0.384	0.213	0.409	0.175
3rd	0.134	0.341	0.144	0.351	0.139
4th	0.196	0.397	0.206	0.405	0.226
Missing information	0.027	0.162	0.030	0.171	0.035
Education					
Primary	0.063	0.244	0.050	0.219	0.017
Secondary	0.642	0.479	0.638	0.480	0.437
Tertiary	0.292	0.455	0.307	0.461	0.541
Missing information	0.002	0.046	0.004	0.066	0.005
Occupation					
Managers	0.062	0.240	0.053	0.223	0.116
Professionals	0.200	0.400	0.208	0.406	0.332
Technicians and associate professionals	0.090	0.286	0.079	0.269	0.125
Clerical support workers	0.058	0.234	0.058	0.234	0.067
Service and sales workers	0.047	0.212	0.051	0.220	0.035
Skilled agricultural, forestry, and fisheries workers	0.071	0.258	0.068	0.252	0.025
Craft and related trades workers	0.262	0.440	0.284	0.451	0.184
Plant and machine operators, and assemblers	0.109	0.312	0.109	0.312	0.071
Elementary occupations	0.096	0.295	0.090	0.286	0.045
Unknown occupation	0.004	0.064	0.000	0.019	
Company size					
Less than 250 workers	0.856	0.351	0.850	0.357	0.791
250 workers and more	0.115	0.319	0.133	0.340	0.184
Missing information	0.029	0.167	0.017	0.130	0.026

Tenure					
Less than 1 year	0.127	0.333	0.137	0.344	0.060
1-5 years	0.270	0.444	0.238	0.426	0.281
More than 5 years	0.587	0.492	0.603	0.489	0.546
Missing information	0.016	0.126	0.021	0.145	0.112
Employee type					
Private employee	0.756	0.430	0.775	0.418	0.723
Public employee	0.239	0.426	0.220	0.414	0.262
Missing information	0.005	0.073	0.005	0.072	0.015

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Source: Authors' calculations based on the working Conditions Surveys (2010, 2015, 2021)

Notes: The table denotes the summary statistics for the key socio-economic characteristics of the respondents across the three waves. Variable definitions are available in Table 1. Data on competence is available only for 2010 and 2015. Relatedness questions are not asked of those who work alone.