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Robots, Meaning, and Self-Determination

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Robots, Meaning, and Self-Determination

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Abstract

We are the first to examine the impact of robotization on work meaningfulness and autonomy, competence, and relatedness, which are key for motivation and human flourishing at work. Using worker-level data from 13 industries in 20 European countries and OLS and instrumental variables estimations, we find that industry-level robotization harms all work quality aspects except competence. We also examine the moderating role of routine and cognitive tasks, skills and education, and age and gender. While we do not find evidence of moderation concerning work meaningfulness in any of our models, noteworthy differences emerge for autonomy. For instance, workers with repetitive and monotonous tasks drive the negative effects of robotization on autonomy, while social tasks and working with computers - a tool that provides worker independence - help workers derive autonomy and competence in industries and jobs that adopt robots. In addition, robotization increases the competence perceptions of men. Our results highlight that by deteriorating the opportunities to derive meaning and self-determination out of work, robotization will impact the present and the future of work above and beyond its consequences for employment and wages.

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

JEL Codes: J01, J30, J32, J81, I30, I31, M50

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1. Introduction

Robots are becoming increasingly more capable than humans in executing a growing range of complex tasks. Smart machines can now perform surgeries, assemble automotive parts, distribute packages, and dispense medicine. They are found on factory floors, in restaurants, and even on the surface of Mars. This rapidly accelerating wave of automation is arguably one of the most powerful forces that will reshape the future of work.

Much of the academic literature and the media have focused on the labor-saving aspects of automation and have painted a pessimistic picture for the number of jobs left for humans after the introduction of robots. For example, a seminal paper by Frey and Osborne (2017) estimated that about 47% of all US occupations could be replaced by machine learning or mobile robotics over the next decades. While the *potential* for automation is not deterministic and does not necessarily imply unemployment (Arntz, Gregory, & Zierahn, 2017), the study and the follow-ups it spurred for other countries generally painted a bleak future for human workers.

The realization that technology affects particular *tasks* rather than whole *occupations* has led to substantial revisions of the Frey and Osborne figures (Arntz et al., 2017; Nedelkoska & Quintini, 2018). For the US and the OECD, the risk of automation is about 9%, ranging from 6% in South Korea to 12% in Austria (Arntz et al., 2016).¹ When firms adopt technology, workers typically adapt their tasks (Dauth, Findeisen, Suedekum, & Woessner, 2021; Spitz-Oener, 2006), which is why whole professions typically do not disappear. Therefore, how robotization affects workers' quality of work and which tasks enhance or reduce their well-being at work are pivotal questions. Examining the consequences of automation in terms of wages and employment thus paints an incomplete picture. This is particularly true because ongoing developments in robot technologies and artificial intelligence may imply that the full consequences of the current automation wave are yet to unravel.

An emerging body of literature has explored how the adoption of automated technologies affects individual-level outcomes, such as job satisfaction, fear of replacement, and mental health, that go beyond wages and employment prospects (see Table 1 for a summary). We substantively contribute to this novel body of research by examining how robotization affects workers' perceptions of meaningfulness and the fulfillment of their basic psychological needs of autonomy, competence, and relatedness. Finally, we explore heterogeneities in these relationships based on the workers' socio-demographic characteristics (i.e., skills, education, age, gender) and the nature of work tasks (i.e., routine, nonroutine cognitive, and nonroutine interactive tasks).

Our outcome variables are about work meaningfulness and the three core psychological needs—autonomy, competence, and relatedness—that form the basis of the self-determination theory (SDT) for several reasons. First, based on self-determination theory, autonomy, competence, and relatedness are critical to workplace motivation and optimal human functioning (Deci & Ryan, 1985).² Because robots interact with workers' competencies by changing the nature of their tasks and workplace relationships, their adoption can directly affect their sense of self-determination. Second, work meaningfulness is instrumental in workers' efforts and has been linked to key organizational outcomes such as absenteeism, retirement intentions, and the

¹ For example, focusing on data based on the actual tasks of workers, two studies estimated that the risk of automation in the US is 9% (Arntz et al. 2016) or 10% (Nedelkoska & Quintini, 2018), and not 47%. In addition, Nedelkoska & Quintini (2018) found that only 14% of jobs in OECD countries are highly automatable in the sense of having an automation probability of over 70%. These estimates, while much lower than those in Frey and Osborne, still imply massive potential job losses (e.g., 66 million workers in the 32 OECD countries) that can cause a much larger disruption in local economies compared to previous automation waves.

² Therefore, we refer to autonomy, competence, and relatedness perceptions as “self-determination variables.”

willingness to take on skills training (Nikolova & Cnossen, 2020; Rosso et al., 2010). Finally, paid work is a crucial part of people's lives and takes a large part of the day. Therefore, understanding whether and how the adoption of new technologies, such as industrial robots, has the potential to make work dull or degrading, or on the contrary, interesting and creative, can provide critical insights for job design and job crafting.

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, Gutierrez, Clarke, Sturla, & Shah, 2015).

However, robotization is not necessarily detrimental 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). Human beings can then have more time and space to focus on creative tasks or those that require interaction and human judgment. Thus, the extent to which robots affect workers' perceptions of work meaningfulness and self-determination remains an empirical question.

To investigate this question, we use worker-level data from 2010 and 2015 from 20 European countries and 13 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 erode work meaningfulness and all aspects of self-determination except competence. When it comes to competence, robotization enhances the competence perceptions of men. Furthermore, the negative consequences of robotization for work meaningfulness are regardless of workers' tasks, skills, and socio-demographic characteristics. In other words, robotization negatively and similarly affects workers despite their tasks and despite their career stage, gender, and skills.

At the same time, we find important heterogeneity when it comes to self-determination outcomes and autonomy in particular. Specifically, working with computers and clients substantially cushions or completely offsets the negative consequences of automation for autonomy. At the same time, monotonous and repetitive tasks and the dependence on the work pace of a machine amplify the already negative effects of automation on autonomy. The negative ramifications of robotization for autonomy are also stronger for the lower-skilled, meanwhile. The groups that are disproportionately affected based on our research also overlap with those that prior studies focusing on wages have identified (e.g., Graetz & Michaels, 2018). We document that low-skilled workers suffer less task autonomy above and beyond the negative wages or employment effects they incur due to automation.

More generally, the value-added of our work is that we document that robotization advantages or disadvantages certain workers or groups in terms of their perceived work quality above and beyond any consequences that it may have for their wages and employment contracts. In addition, we help identify which tasks and arrangements may help workers adapt to technology and take advantage of it.

The effects we document are relatively modest, if meaningful. For example, our elasticity estimates suggest that a 100% increase in robotization (i.e., doubling) corresponds to a 1% decline in work meaningfulness and 0.8% relatedness, and a 2% decline in autonomy. Indeed, rises in robotization were high across many industries (Figure 1 and Table A1). Across all industries in our sample, the average increase in robotization was 64% in the 2005-2009 period and 28% in the 2010-2014 period (Figure 1 and Table A1), or 126% for the 2005-2014 period overall. The industries with the largest increases included metal, construction, food and beverages, electricity, gas, water supply, and mining and quarrying.

There are relatively few robots per worker in some industries, such as education (See Table A1 and Figures 1 and 10). Such industries with low levels of robotization can potentially face large increases in the future. If the adoption of industrial robots continues to accelerate, the negative well-being consequences we document can be substantial. The IFR reports that robot installations in Europe declined in 2019 and 2020, though the prediction is that there will be small growth in robotization in the European region in the near future (IFR, 2021b). Over a longer time period, the increases may be even larger, especially as new technologies related to AI and machine learning proliferate.

This suggests that the consequences of robotization for work meaningfulness and self-determination we find are small but important. Furthermore, our tests on heterogeneity show that these effects may vary substantially across tasks, skills, and demographic characteristics of workers, where we find even positive effects for some groups.

2. Literature Review

The extant literature has mainly focused on robotization's consequences on employment and wages (e.g., Acemoglu & Restrepo, 2020; Borjas & Freeman, 2019; Dauth et al., 2021). For example, Acemoglu and Restrepo (2020) show that robot adoption between 1990 and 2007 corresponds with large declines in employment and wages in US commuting zones. Similarly, Borjas and Freeman (2019) estimate that robotization led to wage and employment declines between 2014 and 2016 in the US. In China, robot adoption is also negative for employment and wages across cities for the 2000-2016 period (Giuntella & Wang, 2019). Nevertheless, recent work using data from other countries has challenged this gloomy view of robots in the labor market.

For example, in the German context, Dauth et al. (2021) show that robots improve the job security of those already on the job, even though they reduce the demand for young workers. Adachi, Kawaguchi, and Saito (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, Lelarge, & Restrepo, 2020; Aghion, Antonin, Bunel, & Jaravel, 2020), with no consequences for wages (Acemoglu et al., 2020). Across 17 advanced economies, robotization has led to increases in wages but declines in the hours worked among the low-skilled (Graetz & Michaels, 2018). Similarly, de Vries et al. (2020) found that robotization decreases the employment share of routine manual jobs.

Despite the burgeoning literature on robotization, economists have paid little attention to its broad job quality ramifications. This is unfortunate because it limits our understanding of workers' perspectives on the issue of how automation affects their job quality beyond wages and employment prospects. Nevertheless, the previous literature has focused on information and communication technologies and how they affect well-being at work and beyond (see Castellacci & Tveito, 2018 for a review).

Table 2 summarizes the extant studies in the literature that examine the effect of automation risk and robot adoption on job demands and different well-being outcomes (Abeliansky & Beulmann, 2021; Antón Pérez, Fernández-Macías, & Winter-Ebmer, 2021; Lordan & Stringer, 2022; Gorny & Woodard, 2020; Patel & Wolfe, 2020; Schwabe & Castellacci, 2020). Most of the literature has focused on health outcomes, with only a few papers looking at job satisfaction and job quality.

The main conclusion of this emerging research stream is that automation exposure negatively affects mental and physical health in the United States. The evidence on the health consequences for Germany and Australia is more mixed. Studies link automation to worsened job satisfaction in the US and Europe, including Norway, and greater work intensity in Europe. Most of these effects are concentrated among low-skilled workers in routine jobs.

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. In fact, 40% of workers in their sample report fear that their working tasks will be substituted by smart machines in the future, a number that is similar to other European countries. Schwabe & Castellacci's (2020) results are driven mostly by low-skilled workers, who are more likely to engage in routine-based tasks and hence be exposed to automation.

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

Second, a related strand of the literature suggests that the adoption of industrial robots and automation risk, which come with expectations of reduced wages and higher unemployment in the future, can also negatively impact workers' physical and mental health more generally (e.g., Abeliansky & Beulmann, 2021; Lordan & Stringer, 2022; Patel et al., 2018). Specifically, fear and anxiety of future job losses associated with the introduction of smart machines can lead to job insecurity (Reichert and Tauchmann, 2017). In turn, meta-analytic studies show that higher levels of job insecurity can lead to 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.

Similarly, using data from the German Socio-Economic Panel, Abeliansky & Beulmann (2021) show that workers in industries that experience an increase in the stock of robots are more likely to report poorer mental health outcomes due to greater job insecurity. Once again, the results tend to be driven by routine task jobs but are also concentrated among males. Nevertheless, using

the same German data, Gihleb et al. (2018) found no effects of robotization on psychological burdens, work, or life satisfaction.

Finally, one study has examined the effects of robot adoption on job quality and working conditions, such as work intensity (e.g., the pace of work, time pressure, etc.), the physical environment, and skill and discretion. A recent study by Antón et al. (2020) finds that the 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. This is important because recent models of sustainable happiness suggest that subjective well-being (e.g., job satisfaction) is a *by-product* of engaging in eudaimonic and growth-promoting activities that help satisfy people's basic psychological needs (Ryan & Deci, 2001; Sheldon & Lyubomirsky, 2021). In other words, the variables we study are critical psychological mechanisms that underpin the relationship between robotization and key organizational outcomes such as job satisfaction.

Table 1: Related Literature

Reference	Outcome variable(s)	Automation measure	Level of analysis	Main Data Sources	Econometric technique(s)	Key findings
Health						
Patel et al. (2018)	Health (general, physical, mental)	Automation risk at the occupation level	US county-level	Health Rankings (CHR) 2017, Frey and Osborne's (2017) occupational automation probabilities aggregated at the county level using American Community Survey (ACS) 2015, and Statistics of US businesses 2014	2SLS (instruments = surrounding counties' automation risk, Chinese imports since the 1990's)	Worse likelihood of poor/fair health; frequent physical distress; frequent mental distress
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)	W(Schwabe & Castellacci, 2020)orse mental health; driven by job insecurity fears, especially for routine-task workers and males.
Lordan and Stringer (2022)	Mental health and life satisfaction; physical health; general health	Job automation risk	Individual-level	Australian panel dataset HILDA 2001-2018, Autor and Dorn job automation classification (Routine Task Intensity) index	Individual panel regressions (individual, time, area, occupation, & industry fixed effects)	No effects overall, but in industries at high risk of automation => worse mental health and life sat. but better mental health and life sat. in the services industry; heterogeneity by socio-demographics
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 and life satisfaction
Job satisfaction and job quality						
Schwabe & Castellacci (2020)	Job satisfaction	Fear of machine replacement	Individual-level	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).

Reference	Outcome variable(s)	Automation measure	Level of analysis	Main Data Sources	Econometric technique(s)	Key findings
Gorny & Woodard (2020)	Job satisfaction	Automation risk	Individual-level	General Social Survey (US), European Social Survey, Work Orientations IV dataset of the International Social Survey Programme or ISSP, automation risk from Frey and Osborne (2017), Dengler and Matthes (2015), Arntz et al. (2016), and Manyika et al. (2017)	Ordered probits	Worse job satisfaction; due to monotonicity and low perceived job meaning driving both automatability <i>and</i> low job satisfaction.
Anton et al. (2020)	Job quality aspects (work intensity, physical environment, skills & discretion)	Change in the robot stock per worker at the regional (NUTS-2) level	Regional-level	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 an important aspect of “subjective” job quality and 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 job 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 goal. The motivation 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). Experimental studies from the US and Germany also demonstrate that work meaningfulness lowers reservation wages (Ariely et al., 2008; Kesternich et al., 2021), yet only in the case of high work meaningfulness in the German case (Kesternich et al., 2021). Therefore, work meaningfulness is an important work aspect for many individuals, also demonstrated by recent trends related to the Great Resignation and Quiet Quitting.

Furthermore, feelings of self-determination are based on three different but complementary inputs: competence, autonomy, and relatedness (Deci & Ryan, 1985; Ryan & Deci, 2017). Workers feel competent when their skills match the complexity of the task. When a task is too easy, they feel like anyone could have done it, and when it is too hard, they do not feel they contributed anything personally to the final product. Therefore, feeling competent and that one’s skills are necessary for the workplace is an important aspect of self-determination.

Second, people feel autonomous when they make decisions regarding the execution and planning of the order of tasks. In the job characteristics model, autonomy is about “freedom, independence, and discretion” when it comes to scheduling and carrying out the work (Hackman & Oldham, 1976). It is about own initiatives and decisions rather than top-down instructions in the organization of work.

Finally, according to the self-determination model, people require a sense of belonging: they want to feel appreciated and supported by their co-workers and employers in their efforts for the company. Such high-quality relationships at work are important for fostering work meaningfulness (Bailey, Yeoman, Madden, Thompson, & Kerridge, 2019), especially when it comes to the “giving to others” aspects (Colbert, Bono, & Purvanova, 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 can contribute to creating a sense of work meaningfulness (Nikolova and 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.³ Most of the tasks that industrial robots perform are essentially reaching and handling tasks. Examples of robots fitting this definition include manipulators that weld or paint cars, load and unload workpieces from factory equipment such as CNC (Computer Numerical Control) machine tools and semiconductor fabricators, and move materials and pack boxes. Examples of pieces of industrial equipment that are not robots include most machine tools, an assembly line conveyor belt, and a flexible manufacturing cell (Webb, 2019).

When adopted in the workplace, robots can alter the tasks performed by human labor. Workers’ jobs comprise task bundles (Autor, 2013; Autor, Levy, & Murnane, 2003). “Human” tasks overlapping with the capabilities of a robot are susceptible to automation. As 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, 2019). However, due to their pre-programmed nature, industrial robots have limited capabilities for executing tasks in unpredictable environments, mostly those involving human contact.

Robots still have relatively little capacity to replace cognitive, non-routine, and interpersonal tasks. Webb (2019) 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 Artificial Intelligence (AI) technologies might substitute for 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; Parker & Grote, 2020), increasing 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).

However, if the task replacement is not met with a simultaneous shift towards more meaningful tasks, experiences of meaningfulness might decrease. Robots that directly replace tasks humans used to perform will reduce that person’s sense of meaning. This may also occur if only small 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 tasks 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 perception of self-determination. This depends strongly on how robots are introduced in the workplace. For instance, autonomy might decrease if one’s workflow becomes dependent on the work-pace of the 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

³ In this paper, we focus on industrial robots, rather than service robots used, for example, in surgery, or in other parts of the service sector. The reason for the restriction is that industrial robots have seen by the far the most adoption, whereas the adoption of service sector robots is still in its infancy during our time period.

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 meaningful 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. However, relatedness can decrease if the robot affects the physical environment in such a way that personal connections are disrupted.

Barrett, Oborn, Orlikowski, and Yates (2012) provide a telling case study highlighting how the introduction of a robot may affect workers within the same workplace differently. 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 job 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 opposite experiences. 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 a yet again different 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 hypothesis:

H1: *The consequences of robotization for work meaningfulness and one's sense of self-determination (autonomy, competence, and relatedness) can be positive or negative.*

2.3. The moderating effect of workers' skills and demographics

As the pharmacy case study shows, 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 rely on the tasks people perform and their skills. The impact of robots on meaningfulness and self-determination is not straightforward and may depend on a worker's tasks, skills, and other personal characteristics.⁴

We propose three moderating variables: task-, skill-, and demographic-based moderators. First, technology adoption (robots and ICT) generally leads to tasks being *replaced*, *augmented*, or *created* (Acemoglu & Restrepo, 2016). The extant literature suggests that individuals performing tasks comparable to those performed by technology (i.e., routine and manual tasks) are relatively

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

more at risk of seeing task replacement (Autor et al., 2003; Autor, 2013; Acemoglu & Restrepo, 2019). While these workers may not necessarily be facing unemployment, the fact that robots perform some tasks may have implications for workers' work meaningfulness and self-determination. In addition, workers performing nonroutine cognitive (i.e., analytical and interpersonal) tasks face a relatively lower risk of replacement, and higher chances of augmentation.

We, therefore, expect that the tasks moderate the effect of robots on the workers' perceptions of work meaningfulness and self-determination. Some of these tasks might be more susceptible to replacement (e.g., the assistants placing the medicine in the right place). In contrast, other tasks can be augmented by technology (e.g., the pharmacists seeing productivity increases due to faster medicine delivery) or can even lead to new tasks altogether (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 their fulfillment of psychological needs. The pharmacists had more opportunities to interact with clients, increasing the relative importance of social-intensive tasks in their jobs – tasks in which humans have a comparative advantage over robots. Lastly, the technicians were able to increase their meaningfulness at work, as they were able to operate and service the machine. However, they did not depend on the work-pace of the machine (unlike the assistants) but rather were involved with trouble-shooting, a relatively nonroutine cognitive task.

Generalizing the findings from this case study, 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 measure routine tasks, we use questions on one's dependence on the work pace of a machine, repetitiveness of tasks, and monotonicity. Second, we have information about the nonroutine intensity of tasks, which we split into *non-routine cognitive* and *nonroutine interactive*. For the nonroutine cognitive task, we rely on a variable about whether one has to work on a computer, meaning 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, whereas low-skilled workers face more difficulty using robots (Autor et al., 2003; Webb, 2019). Therefore, we also include interactions with skill-related variables to see whether skills potentially moderate the 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 positively 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 (Sachs & Kotlikoff, 2012), 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 strongly negatively affect those performing routine-based tasks (i.e., repetitive or monotonous tasks and those depending on the work-pace of a machine), 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 low-skilled and low-educated workers.*

H2c: *The consequences of robotization for older and younger workers' work meaningfulness and self-determination are ambiguous.*

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

Table 2: Possible consequences of robots on work meaningfulness and self-determination and example moderators of

Experiences of:	Potential positive consequences of robots	Potential negative effects of robots	Moderators of the consequences of robotization for work meaningfulness, autonomy, competence, and relatedness
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	Task-based moderators 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	Skill-based moderators Level of education Occupational skill
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	Individual-level moderators Age Gender

Note: Authors' adaptation based on Smids, Nyholm, and Berkers (2020) and Parker and Grote (2020).

3. Data and variables

There are two main measures of automation exposure used in the literature. First, one can observe the amount of automation technology used in an industry to capture changes in the physical work environment. Second, risk automation at the occupational level can be gauged by the replaceability of tasks in that occupation, regardless of whether the worker is actually exposed to that technology. An example of such a measure is the paper by Frey and Osborne (2017), in which a group of experts estimates the potential risk of automation for each occupation by observing the overlap between the typical tasks in that occupation and the (expected) capabilities of technology.

Our paper adopts the first method of capturing automation exposure. As such, we relate whether an increase in the stock of robots affects one's individual-level experience at work. We further use task-based moderators to account for the type of work people execute, where we select those tasks that are commonly seen as either replaceable or augmented by technology.

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 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, 2021a, p. 30). The robotization data have many missing values in the early years, especially for countries in Central and Eastern Europe. This is why, like other papers in the literature (e.g., (Aksoy, Özcan, & Philipp, 2021); de Vries, Gentile, Miroudot, and Wacker (2020)), we rely on the IFR data starting in 2005. Like other studies, we had to impute the data for 2005 for Bulgaria, Greece, and Lithuania. In principle, the IFR data go back in time to 1995 for some countries. However, they have been consistently available for various countries and industries since 2005.

To calculate robotization per 10,000 workers, we also take data on the number of employed persons per industry and country in 2005 from the EU KLEMS. The EU KLEMS database is also the source of information on the investments in fixed capital stock in computing, communications, computer software, and databases, underpinning our ICT control variable. Information for several Eastern European countries in our analysis sample is missing, 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 and 2015 (Eurofound, 2012; 2017). While the EWCS has been conducted every 5 years since 1991, we only include surveys from 2010 and 2015 in our analysis because we are limited by the robotization measure. The dataset contains worker-level survey answers collected via face-to-face interviews with about 1,000 workers per country. The eligible respondents are those aged 16 and older who work at least one hour per week. Different workers are polled each year, and the dataset is thus not a panel.

The EWCS dataset is very opportune for our purposes for several reasons. First, the surveys ask many 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 2005 (Nikolova & Cnossen, 2020), the two-digit NACE Rev 2 required for merging on the industry level information is only available for 2010 and 2015. We drop individuals from the EWCS with missing information on the industry of employment as they cannot be merged with the rest of the data.

After merging all the information, we drop individuals with more than one job. Our final merged dataset has information on individuals working in 13 industries and 20 countries in 2010 and 2015. We exclude the “all other non-manufacturing” industry and the armed forces’ occupation from the analyses.

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, Bittschi, & Sellner, 2021). The hyperbolic sine transformation is 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.

Specifically, for each industry j in country c and year t :

$$robotization_{j,c,t} = IHS \left[\frac{num.robots_{j,c,t-1}}{10,000 employees_{j,c,2005}} - \frac{num.robots_{j,c,t-5}}{10,000 employees_{j,c,2005}} \right] \quad (1)$$

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. It 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 2005 in the denominator so that the changes in the robot stock are independent of changes in the number of employees.

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 (Olsson, 1979). These variables are based on items and indices in Nikolova and Cnossen (2020) and Nikolova, Nikolaev, and Boudreaux (2022). Table 3 details the concrete steps involved in constructing the variables. We standardize the indices to have a mean of 50 and a standard deviation of 10 for ease of interpretation. Our measure of autonomy deviates from that of Nikolova and Cnossen (2020) and is instead based on combining only three variables (and not five) into the index.⁵ 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.

3.3. Control variables

We source additional control variables at the individual level from the European Working Conditions survey. We create an additional “missing information” indicator for all categorical control variables to avoid omitting from the analyses observations with missing information. 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, and ISCO-08 occupation (excluding the armed services due to the small number of observations).

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. The idea is that we want to ensure that we are capturing the effects of robotization on work meaningfulness and self-determination above and beyond any consequences of digitalization.

4. Empirical Strategy

5.1. OLS

We explore the causal effects of robotization on work meaningfulness and self-determination using ordinary least squares (OLS) and instrumental variables. Our analyses dovetail with and combine strategies explored in the extant literature (Acemoglu & Restrepo, 2020; Adachi et al., 2020; Aksoy et al., 2021; Anelli, Colantone, & Stanig, 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:

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

⁵ According to Parker and Grote (2020), job autonomy has two inter-related aspects – decision-making over the work-process and choice over when and where to work. Nevertheless, our autonomy measure captures only the first of these two aspects, namely the decision-making latitude about the process of work.

In Equation (2), we specify *robotization* the same way as in Equation (1). Furthermore, the control variables Z include age group, gender, working hours, education, and ISCO-08 occupation detailed in Section 3.3 above, ΔI is a measure of digitalization (computed similarly to robotization), π_t denotes time fixed effects (a dummy variable for 2010 or 2015 survey year), μ_c denote country fixed-effects, and $\sum_{i,c,j,t}$ is the stochastic error term. We use robust standard errors clustered at the countryXindustry level. All regressions are weighted using the survey weight. In additional specifications (Table A3), we also report results using weights calculated using 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.

We include time dummies to account for shocks and cyclicalities that affect countries and industries similarly. Specifically, technological adoption is often pro-cyclical (Anzoategui, Comin, Gertler, & Martinez, 2019; Leduc & Liu, 2019, 2021), and economic booms and busts may also affect the work meaningfulness and self-determination of workers. Furthermore, country-specific fixed effects account for different institutional and cultural features across countries, including cultural interpretation of the underlying self-reported work meaningfulness and self-determination variables and labor market regulations.

We also report the elasticities, which are calculated based on Equation (3) in Bellemare and Wichman (2020) to facilitate the interpretation of our IHS-transformed robotization variable. Specifically, the elasticity is calculated as follows:

$$\xi_{yR} = \frac{\widehat{\alpha}_1}{y} \frac{R}{\sqrt{R^2+1}} \quad (3)$$

5.2. 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.⁶

⁶ 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

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 industry’s employment hours performed in occupations that are potentially replaceable by robots from the viewpoint of 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 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). In addition, these instruments do not perform well in first-stage analyses. Nevertheless, for completeness and transparency, we present the results with these instruments (Table A2), though we advise readers to exercise caution with 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 seems 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.

5.3. Exploring Heterogeneities

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 five tasks: i) repetitive tasks, ii) monotonous tasks, iii) dependence on a machine, iv) working with computers, and v) social tasks.

$$Y_{i,c,j,t} = \alpha_0 + \alpha_1 R_{j,c,t} + \beta_\tau \tau_{j,c,j,t} + \gamma_\tau R_{j,c,t} * \tau_{j,c,j,t} + \alpha_2 I_{j,c,t} + Z_{i,c,t} \varphi + \mu_c + \pi_t + \varepsilon_{i,j,c,t} \quad (4)$$

In Equation (4), the coefficient estimates $\hat{\gamma}_\tau$ allow us to see whether robotization differentially affects the work meaningfulness and self-determination of people working in jobs that require performing particular tasks. We estimate Equation (4) based on the IV strategy.

Furthermore, we explore whether workers in different parts of the skills distribution and of different ages and gender differentially experience meaningfulness and self-determination. Specifically, we anticipate that automation may lead to de-skilling and therefore worsen the work

meaningfulness and job quality. The IV strategy is unable to deal with this problem. We include individual-level controls to mitigate this issue.

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 levels (i.e., primary, secondary, and tertiary) and by grouping 1-digit ISCO occupations. 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.

6. Results

6.1. Descriptive Statistics

Figure 1 depicts the average number of robots per 10,000 workers for the four years we used in our analysis sample: 2005, 2009, 2010, and 2014. Given our empirical setup, our measures of robotization refer to changes between 2005-2009 (for EWCS observations in survey wave 2010) and 2010-2014 (for EWCS observations in survey wave 2015). Industrial robots are most prevalent in the automotive industry (e.g., 367 robots per 10,000 workers in 2014) and least widespread in the electricity, gas, water supply, construction, and education/research industries. During the 2005-2009 period, several industries saw substantial increases in robot adoption, with the biggest increases in the automotive, plastic and chemicals, metal, and food and beverages industries (see also Table A1). Some industries saw small declines in robotization over the 2005-2009 period, namely the agriculture, textile, all other manufacturing, and electronics industries. In the 2010-2014 period, the biggest increases in robotization were in the construction, mining and quarrying industries. Several industries, including plastics and chemicals, electrical, education/research, textiles, wood and paper, saw small declines in robotization.

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 dependent variables change little over the analysis period and tend to be rather stable both within industries and over time. This is potentially important when trying to identify whether changes in robotization influence work meaningfulness and self-determination.

Table 4 details the summary statistics for our two analysis samples for survey waves 2010 and 2015. The first analysis sample relates to specifications, whereby the dependent variable relates to work meaningfulness, autonomy, and competence. Because those who work alone did not answer the relatedness questions, the analysis sample for relatedness is smaller than for the other dependent variables. The sample compositions tend to be relatively stable in terms of most socio-demographic characteristics.

6.2. Main Results based on OLS and IV Estimations

Table 5 details our main results on the relationship between robotization, work meaningfulness, and self-determination, based on estimating Equation (2) above. Panel A reports OLS estimates. Panels B and C feature the first- and second-stage IV estimations, respectively.

Our OLS results suggest that robotization is negatively associated with work meaningfulness, autonomy, competence, and relatedness. The IV estimates also corroborate this conclusion. Using the instrument of the industry-level automation shock in all other countries except the respondent's, the coefficient estimates from the first-stage regressions (Panel C) show that our instrument is good at predicting robotization. The F -statistic of about 100 is relatively large, suggesting that our instrument is strong.

The second-stage results (Panel B) further confirm the negative relationship between robotization, work meaningfulness, and its determinants. The coefficient estimates in Panel B are larger than the OLS ones, suggesting that the OLS estimates are plagued by endogeneity that leads to underestimating the impact of robotization on these worker well-being aspects (Aksoy et al., 2021).

The elasticity estimates suggest that the effect sizes we identify are relatively small. For example, a 10% increase in robotization corresponds to a 0.1% decline in work meaningfulness and relatedness, a 0.2% decline in autonomy, and a 0.04% fall in competence. However, the latter effect is not statistically significant. Admittedly, these effect sizes are relatively small, though we argue that they are important. Across all industries in our sample, the average increase in robotization was 64% in the 2005-2009 period and 28% in the 2010-2014 period (Figure 1 and Table A1), suggesting the implications of changes in work meaningfulness and self-determination are indeed meaningful. Therefore, the main conclusion from Table 5 is that robotization hurts work meaningfulness and self-determination, and the consequences are small but meaningful, given that automation processes in many industries are yet to unfold. 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. The negative channels we describe seem to dominate the overall patterns, though, as we show in Section 6.4., the results are stronger or weaker (or even positive) for some groups.

6.3. Robustness Checks

We offer a battery of sensitivity checks. First, using specification curve analyses (Simonsohn, Simmons, & Nelson, 2015, 2020), we check whether our results are robust to using different sub-samples 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 curves 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 have 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 blocks of control variables and exclude one country at a time from the regression results. Figures 6-9 detail that the results in Table 5 are remarkably 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). As we explain in Section 5.2. above, these instruments are less desirable than the instrument we utilize in the main specifications. Nevertheless, for completeness, we also offer these results in Table A2. The results remain in line with the OLS and main IV results in Table 5.

In Table A3, we investigate whether the results are robust to including different weights. Unlike in the main specifications, where we include the survey weights, in Table A3, we use the country-specific industry employment shares as Graetz and Michaels (2018) and Aksoy et al. (2021). This weight puts more importance on larger industries. Nevertheless, the results are still very much in line with our main results in Table 5.

Furthermore, Table A3 offers a robustness check whereby we include countryXyear fixed effects, which control for shocks and omitted factors that differentially affect countries across time (e.g., globalization shocks, or country-specific natural disasters). The results are largely in line with the main estimates we provide in Table 5.

Finally, Table A4 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 into industries. 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.

6.3. 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 based on the respondent's task content, skills, or demographics. This suggests that workers experience a detrimental effect of robotization on their work meaningfulness regardless of their tasks, skills, age, and gender. This suggests that people do not derive meaning directly from the content of their tasks, but from the individual goals they pursue by doing these tasks. In many cases, technology may not change the perception of a task as being useful or fulfilling. Rather, technology might change how people think about their contributions to the goal on a higher level than their task content.

Furthermore, we find that all our measures of routine intensity (working in routine jobs, performing monotonous tasks, and being dependent on the work pace of a machine) worsen the already adverse impact of robotization on autonomy (Model (2) in Panels A, B, and C in 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 monotonous tasks adversely impact robotization on competence, even though there is no main effect of robotization on competence. In other words, the effects of robotization on competence are only negative for those with monotonous tasks. Still, we find no such pattern for those dependent on a machine's work pace or executing routine tasks. 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. We find one exception in Panel B: carrying out repetitive tasks diminishes robotizations' harmful influence on relatedness. While this is a surprising finding, a potential explanation can be that workers with repetitive tasks who may be working in a robot-intensive factory learn to humanize the robots. In one example of an Amazon factory, the workers gave their robot colleagues human names (Wingfield, 2017). Alternatively, robotization frees up time for workers with routine tasks to socialize with their colleagues.

Conversely, nonroutine tasks positively moderate the relationship between robotization and autonomy. Those working with computers (Panel D of Table 6) –which we interpret as being in control of the workflow of technology by operating it— experience more autonomy than those who do not. Nevertheless, the effect is merely cushioning the negative impact of robots and does not cancel it out. On the other hand, working with clients (Panel E of Table 6) in robot-intensive industries fully mitigates the detrimental impact of robots on autonomy. 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. We also find that working with computers offsets the negative effect of robots on competence, but we find no such moderator for nonroutine interactive tasks. We do not find any moderating effect of nonroutine tasks on relatedness.

As Section 5.3 details, 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). Primary education and low-skilled workers are the reference group in these estimations (Table 7). 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 work meaningfulness, 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. While age does not seem to significantly affect the relationship between robots and work meaningfulness and self-determination, gender does. More specifically,

robotization increases the competence perception of men. This is an interesting finding and suggests that automation increases the self-efficacy beliefs of men.

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. Discussion and Conclusion

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 fundamentally change the nature of work.

Previous 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; Patel et al., 2018; 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. The consequences for competence are not statistically significant, meanwhile. Specifically, we find that a doubling robotization corresponds to a 1% decrease in the experience of meaningfulness, 1.5% in autonomy, and 0.8% in relatedness. These may seem like small effect sizes, but they are significant for several reasons.

First, 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. Many industries show growth rates of over 50% during the period we study. As such, workers' working conditions and perceived job quality will likely change in the future. That may suggest that as an ongoing process, automation's consequences for work meaning and autonomy are yet to arise.

While past automation waves have affected individuals performing routine cognitive tasks, the technologies of the future – such as AI – may affect different types of workers, namely high-skilled ones (Brynjolfsson, Mitchell, & Rock, 2018; Webb, 2019). While all occupations have *some* tasks that can be replaced by machine learning, the authors find few (if any) occupations in which *all* tasks are replaceable by machine learning. For example, among the occupations with the lowest suitability for machine learning are massage therapists, animal scientists, and archeologists. In contrast, the occupations with the highest levels of replaceability are concierges, mechanical drafters, and morticians (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.

Therefore, while robots are yet to penetrate most industries, our results provide a glimpse of some of the challenges associated with the upcoming waves of technological change related to mass robot adoption, machine learning, and AI.

Second, our analysis sample only includes employed people who have thus not lost their job due to robotization. It implies that those individuals may have largely adjusted to their new circumstances. If that is the case, our estimates reflect only the tip of the iceberg: there may be many people that cannot cope with changing circumstances, and, as a result, may have opted for a different occupation, a different industry, or have become unemployed. 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 A4). 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.

Third, as Figures 2-5 indicate, work meaningfulness, autonomy, competence, and relatedness levels are fairly similar across the industries and are stable over time. In other words, these measures have little over-time and between-industry variation. Therefore, the fact that we find a significant effect of robotization on these outcomes is meaningful in and of itself.

Finally, as with any regression-based analysis, we show the *average* consequences of robotization for work meaningfulness and self-determination. Many people may experience strong negative effects, whereas there may also be workers experiencing the exact opposite. The fact that we are showing that the average effect is only marginally negative partially overlooks the fact that some workers experience large drops in meaning or self-determination following exposure to robots in the workplace. This is especially relevant given that robots are not adopted at a rate where everyone in an industry will be directly exposed to the technology.

Nevertheless, our results provide some glimpse into what future automation waves could bring in terms of work meaningfulness and self-determination. Specifically, unless firms implement proper job designs, the intensified cooperation and co-working between humans and technology will likely worsen work meaningfulness and self-determination (i.e., autonomy, competence, and relatedness). Of course, our results are not deterministic, and the outcomes can very much depend on how technology is adopted and whether and how tasks and job designs are modified. It may be possible that humans adapt their ways of looking at their work and find ways to look for and discover meaning in their jobs.

We acknowledge several limitations to our study that future data collection efforts can help address. Our paper only focuses on European countries and the subset of industries common in the IFR, EU KLEMS, and EWCS. In this sense, we cannot say much about developing countries or other countries not included in our sample, limiting our geographic generalizability. Moreover, our study faces temporal limitations as our analysis period focuses on 2010-2015. Furthermore, we lack data on service robots. Our information on industrial robots is likewise limited, and we lack details on the characteristics of the robots, including their quality. We also do not have 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.

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. 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. More specifically, it would be interesting to understand how robotization can be implemented to satisfy workers' key psychological needs.

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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 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.

Key independent variable

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.

Control variables

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 for 8 industries for Estonia, Lithuania, Latvia, and Hungary are imputed based on the average values for the Czech Republic and Slovakia. Missing values for Bulgaria are done based on the imputations based on the averages for all other transition countries; missing values for Poland, Portugal, and Romania are based on imputations using 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); male (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 and by year 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 education or less (no education, early childhood education and primary education); 2= secondary (lower secondary education and upper secondary education); 3=tertiary (post-secondary non-tertiary education, 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.

Table 4: Summary statistics

	2010				2015			
	Work meaningfulness, autonomy, competence sample, N=8,364		Relatedness sample, N=6,715		Work meaningfulness, autonomy, competence sample, N=7,842		Relatedness sample, N=6,326	
	Mea n	St. Dev.	Mea n	St. Dev.	Mea n	St. Dev.	Mea n	St. Dev.
Robotization	0.710	1.666	0.767	1.734	0.859	1.762	0.947	1.840
ICT adoption	1.650	2.722	1.690	2.713	1.236	2.693	1.236	2.740
Age group								
15-35	0.265	0.442	0.285	0.451	0.242	0.428	0.260	0.439
36-45	0.285	0.451	0.285	0.451	0.265	0.442	0.269	0.443
45-60	0.388	0.487	0.387	0.487	0.411	0.492	0.410	0.492
Over 60	0.058	0.233	0.039	0.194	0.079	0.269	0.058	0.233
Missing information	0.004	0.066	0.004	0.066	0.003	0.055	0.003	0.052
Gender								
Female	0.405	0.491	0.427	0.495	0.397	0.489	0.423	0.494
Male	0.595	0.491	0.573	0.495	0.603	0.489	0.577	0.494
Missing information					0.000	0.016	0.000	0.018
Working hours quartile								
1st	0.461	0.498	0.493	0.500	0.405	0.491	0.425	0.494
2nd	0.181	0.385	0.207	0.405	0.213	0.409	0.235	0.424
3rd	0.135	0.342	0.141	0.349	0.146	0.353	0.158	0.365
4th	0.197	0.398	0.148	0.355	0.207	0.406	0.166	0.372
Missing information	0.026	0.158	0.010	0.102	0.029	0.167	0.016	0.124
Education								
Primary	0.064	0.244	0.049	0.216	0.050	0.217	0.036	0.187
Secondary	0.640	0.480	0.634	0.482	0.637	0.481	0.625	0.484
Tertiary	0.294	0.456	0.315	0.465	0.309	0.462	0.334	0.472
Missing information	0.002	0.044	0.002	0.044	0.004	0.064	0.004	0.064
Occupation								
Managers	0.074	0.261	0.049	0.216	0.065	0.246	0.046	0.210
Professionals	0.180	0.384	0.204	0.403	0.192	0.394	0.221	0.415
Technicians and associate professionals	0.105	0.307	0.117	0.322	0.075	0.263	0.081	0.273
Clerical support workers	0.059	0.236	0.069	0.253	0.059	0.236	0.067	0.250
Service and sales workers	0.039	0.194	0.043	0.202	0.041	0.198	0.046	0.210

Skilled agricultural, forestry, and fisheries workers	0.066	0.249	0.019	0.137	0.062	0.242	0.020	0.141
Craft and related trades workers	0.254	0.435	0.251	0.433	0.277	0.447	0.259	0.438
Plant and machine operators and assemblers	0.121	0.326	0.143	0.350	0.132	0.338	0.153	0.360
Elementary occupations	0.098	0.297	0.102	0.303	0.093	0.290	0.099	0.299
Unknown occupation	0.004	0.064	0.003	0.058	0.006	0.076	0.006	0.079
Company size								
Less than 250 workers	0.858	0.349	0.835	0.372	0.849	0.358	0.820	0.384
250 workers and more	0.115	0.319	0.138	0.345	0.134	0.341	0.163	0.369
Missing information	0.027	0.161	0.028	0.164	0.016	0.127	0.017	0.130

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

Notes: The table denotes the summary statistics for the key variables used in the regression analyses. Variable definitions are available in Table 3. We report the summary statistics for the two analysis samples we use: the full analysis samples using the dependent variables work meaningfulness, autonomy, and competence, and the smaller analysis sample using the dependent variable relatedness. The underlying questions for the relatedness index were not asked to individuals working alone, which limits the number of observations.

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

	(1)	(2)	(3)	(4)
Panel A: Ordinary Least Squares				
	Work meaningfulness	Autonomy	Competence	Relatedness
Robotization	-0.234*** (0.062)	-0.300*** (0.065)	-0.108 (0.068)	-0.183*** (0.066)
Elasticity	-0.005	-0.006	-0.002	-0.004
R ²	0.070	0.171	0.175	0.075
Panel B: IV Peer Robot Adoption Second Stage				
	Work meaningfulness	Autonomy	Competence	Relatedness
Robotization	-0.505*** (0.128)	-0.765*** (0.133)	-0.206 (0.127)	-0.409*** (0.127)
Elasticity	-0.010	-0.015	-0.004	-0.008
R ²	0.068	0.167	0.176	0.074
Panel C: IV Peer Robot Adoption First Stage				
	Robotization	Robotization	Robotization	Robotization
Peer robot adoption	0.625*** (0.061)	0.625*** (0.061)	0.625*** (0.061)	0.624*** (0.061)
1st stage F-stat	106.6	106.6	106.6	103.2
Number of observations	16,206	16,206	16,206	13,041

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, 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 in Panel B is based on the industry adoption of automation in all other countries in the sample (except that particular country). The elasticity estimate is calculated following Bellemare and Wichman (2020). The interpretation of the elasticity estimate in Model (2), Panel (B), for example, is: a 10% increase in robotization corresponds to a 0.15% decrease in autonomy. All regressions are weighted using the survey weight. The analysis sample is based on 20 European countries and 13 industries. See Table 3 for variable definitions. The instrumental variable is based on the industry adoption of automation in all other countries in the sample (except that particular country).

*** 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)	(2)	(3)	(4)
	Work meaningfulness	Autonomy	Competence	Relatedness
Panel A: The moderating effect of individual-level repetitive tasks, IV regressions second stage				
Robotization	-0.539*** (0.173)	-0.568*** (0.147)	-0.159 (0.161)	-0.670*** (0.157)
Repetitive tasks	-0.717** (0.304)	-0.178 (0.259)	0.697*** (0.231)	-1.211*** (0.289)
RobotizationXRepetitive tasks	0.154 (0.253)	-0.446** (0.187)	-0.151 (0.209)	0.594*** (0.213)
R ²	0.069	0.168	0.176	0.074
1st stage F-stat	50.91	50.91	50.91	49.30
Number of observations	15,917	15,917	15,917	12,839
Panel B: The moderating effect of individual-level monotonous tasks, IV regressions second stage				
Robotization	-0.352** (0.150)	-0.388*** (0.149)	-0.027 (0.164)	-0.358** (0.152)
Monotonous tasks	-2.010*** (0.269)	-0.810*** (0.273)	0.070 (0.274)	-1.396*** (0.264)
RobotizationXMonotonous tasks	-0.216 (0.222)	-0.718*** (0.203)	-0.376* (0.199)	-0.045 (0.229)
R ²	0.080	0.173	0.176	0.079
1st stage F-stat	53.24	53.24	53.24	50.98
Number of observations	16,113	16,113	16,113	12,974
Panel C: The moderating effect of dependence on a machine, IV regressions second stage				
Robotization	-0.381*** (0.141)	-0.288** (0.127)	-0.184 (0.155)	-0.426*** (0.151)
Dependence on the work pace of a machine	-1.935*** (0.391)	-2.365*** (0.366)	0.340 (0.327)	-0.655* (0.391)
RobotizationX Dependence on the work pace of a machine	0.011 (0.238)	-0.714*** (0.225)	-0.065 (0.209)	0.085 (0.241)
R ²	0.075	0.186	0.175	0.075
1st stage F-stat	53.60	53.60	53.60	49.89
Number of observations	15,882	15,882	15,882	12,860
Panel D: The moderating effect of working with computers, IV regressions second stage				
Robotization	-0.607***	-1.265***	-0.624***	-0.560***

	(0.180)	(0.195)	(0.175)	(0.181)
Working with computers	0.428	2.638***	3.607***	0.776**
	(0.322)	(0.396)	(0.352)	(0.384)
RobotizationXWorking with computers	0.161	0.900***	0.679***	0.275
	(0.232)	(0.223)	(0.218)	(0.222)
R ²	0.069	0.181	0.202	0.075
1st stage F-stat	53.47	53.47	53.47	50.60
Number of observations	16,173	16,173	16,173	13,019

Panel E: The moderating effect of individual-level social tasks, IV regressions second stage

Robotization	-0.385**	-0.995***	0.003	-0.432***
	(0.173)	(0.174)	(0.165)	(0.165)
Working with clients	1.425***	2.672***	2.886***	0.638**
	(0.316)	(0.336)	(0.276)	(0.283)
RobotizationXWorking with clients	-0.095	1.074***	-0.093	0.199
	(0.240)	(0.211)	(0.187)	(0.213)
R ²	0.073	0.192	0.191	0.076
1st stage F-stat	52.43	52.43	52.43	50.13
Number of observations	16,158	16,158	16,158	13,008

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

Notes: The table reports results from IV regressions of work meaningfulness, autonomy, competence, and relatedness on robotization, by whether the respondent performs repetitive tasks lasting under 10 minutes (Panel A), by whether the respondent performs monotonous tasks (Panel B), by whether the respondent's work pace is dependent on the automatic speed of a machine or movement of a product (Panel C), by whether the respondent works with a computer at least 25% of the time (Panel D), 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.) at least 25% of the time (Panel E). 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 automation in all other countries in the sample (except that particular country). All regressions are weighted using the survey weight. The analysis sample is based on 20 European countries and 13 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
Panel A: The moderating effect of skill levels (education), IV regressions second stage				
Robotization	-1.041** (0.513)	-1.224*** (0.437)	0.324 (0.448)	-0.917** (0.456)
Secondary Education	0.673 (0.632)	0.930* (0.522)	2.348*** (0.575)	-0.191 (0.693)
Tertiary Education	0.998 (0.739)	2.739*** (0.649)	4.463*** (0.601)	0.170 (0.786)
RobotizationXSecondary Education	0.592 (0.512)	0.382 (0.431)	-0.627 (0.465)	0.608 (0.474)
RobotizationXTertiary Education	0.452 (0.606)	0.797* (0.462)	-0.297 (0.464)	0.256 (0.526)
R ²	0.068	0.167	0.176	0.074
1st stage F-stat	31.34	31.34	31.34	30.79
Number of observations	16,158	16,158	16,158	13,002
Panel B: The moderating effect of skill levels (based on ILO classification), IV regressions second stage				
Robotization	-0.516*** (0.197)	-1.036*** (0.194)	-0.189 (0.195)	-0.243 (0.162)
Medium Skilled	2.216*** (0.463)	4.704*** (0.383)	4.902*** (0.417)	1.410*** (0.447)
High Skilled	1.517*** (0.397)	4.248*** (0.580)	1.443*** (0.478)	0.634 (0.511)
RobotizationXMedium Skilled	0.024 (0.308)	0.399* (0.241)	0.034 (0.292)	-0.226 (0.264)
RobotizationXHigh Skilled	-0.330 (0.301)	0.251 (0.330)	0.076 (0.308)	-0.438 (0.293)
R ²	0.058	0.149	0.155	0.069
1st stage F-stat	34.97	34.97	34.97	30.49
Number of observations	16,127	16,127	16,127	12,978
Panel C: The moderating effect of age, IV regressions second stage				
Robotization	-0.647 (0.412)	-0.567 (0.405)	-0.296 (0.376)	-0.611 (0.444)
Age	0.066*** (0.010)	0.043*** (0.011)	-0.047*** (0.012)	-0.043*** (0.013)
RobotizationXAge	0.003 (0.009)	-0.005 (0.009)	0.002 (0.009)	0.005 (0.010)
R ²	0.068	0.166	0.175	0.073

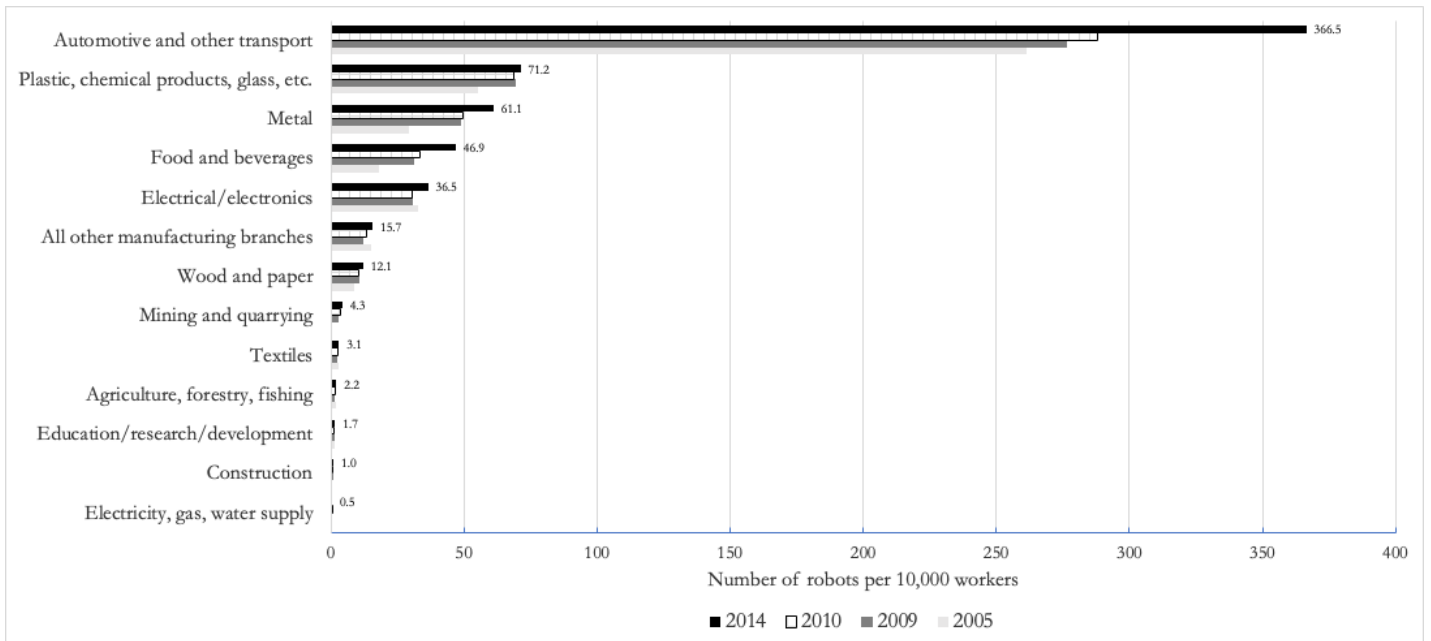
1st stage F-stat	46.97	46.97	46.97	46.00
Number of observations	16,145	16,145	16,145	12,995
Panel D: The moderating effect of gender, IV regressions second stage				
Robotization	-0.458** (0.202)	-0.869*** (0.212)	-0.504** (0.197)	-0.305 (0.217)
Male	0.045 (0.287)	1.030*** (0.310)	1.019*** (0.269)	0.177 (0.306)
RobotizationXMale	-0.067 (0.223)	0.151 (0.227)	0.430** (0.185)	-0.154 (0.226)
R ²	0.068	0.167	0.175	0.074
1st stage F-stat	50.19	50.19	50.19	45.09
Number of observations	16,204	16,204	16,204	13,039

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

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, 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 automation in all other countries in the sample (except that particular country). All regressions are weighted using the survey weight. The analysis sample is based on 20 European countries and 13 industries. See Table 3 for variable definitions.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

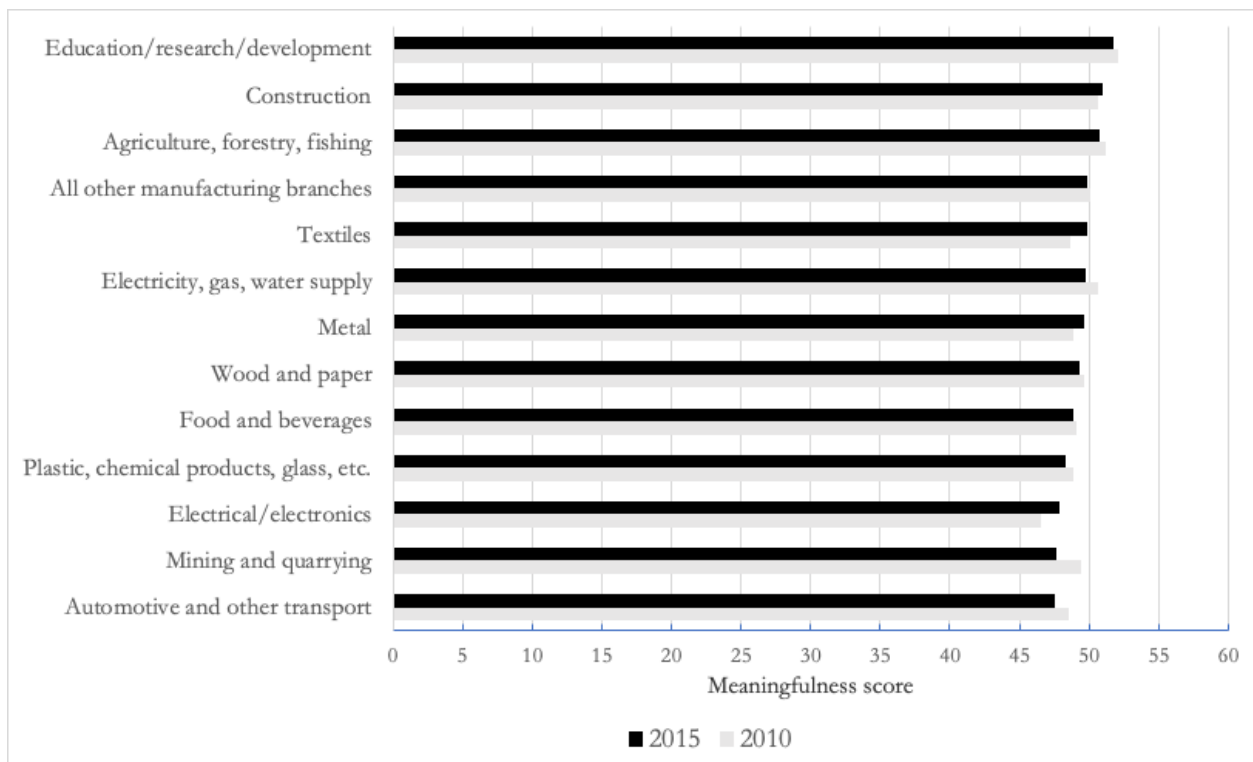
Figure 1: Industrial robots per 10,000 workers by industry and year, 2009-2014



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, and 2014. The values for 2014 are shown next to each bar. The industries Construction, Education/research/development, and Electricity, gas, and water supply have very small non-zero values.

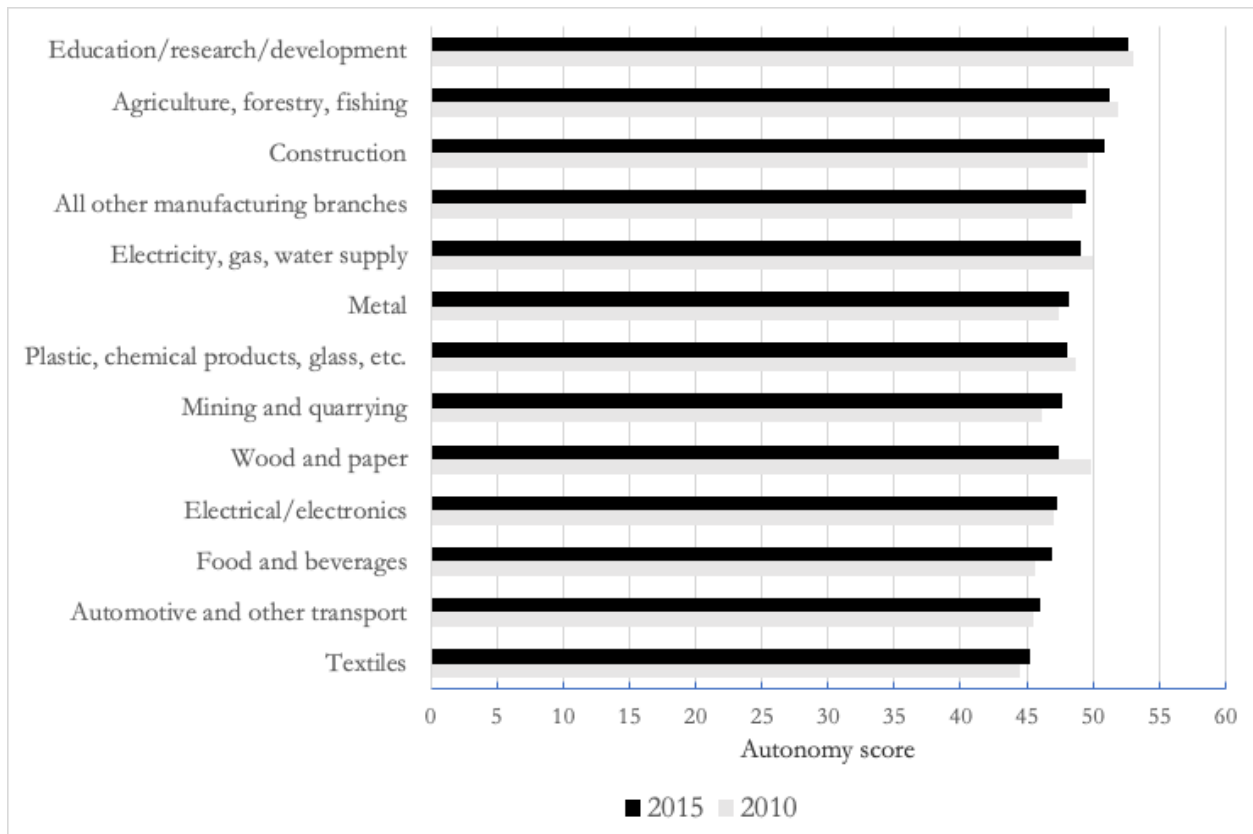
Figure 2: Work meaningfulness, by industry and year



Source: Authors' calculations based on IFR and EUKLEMS

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

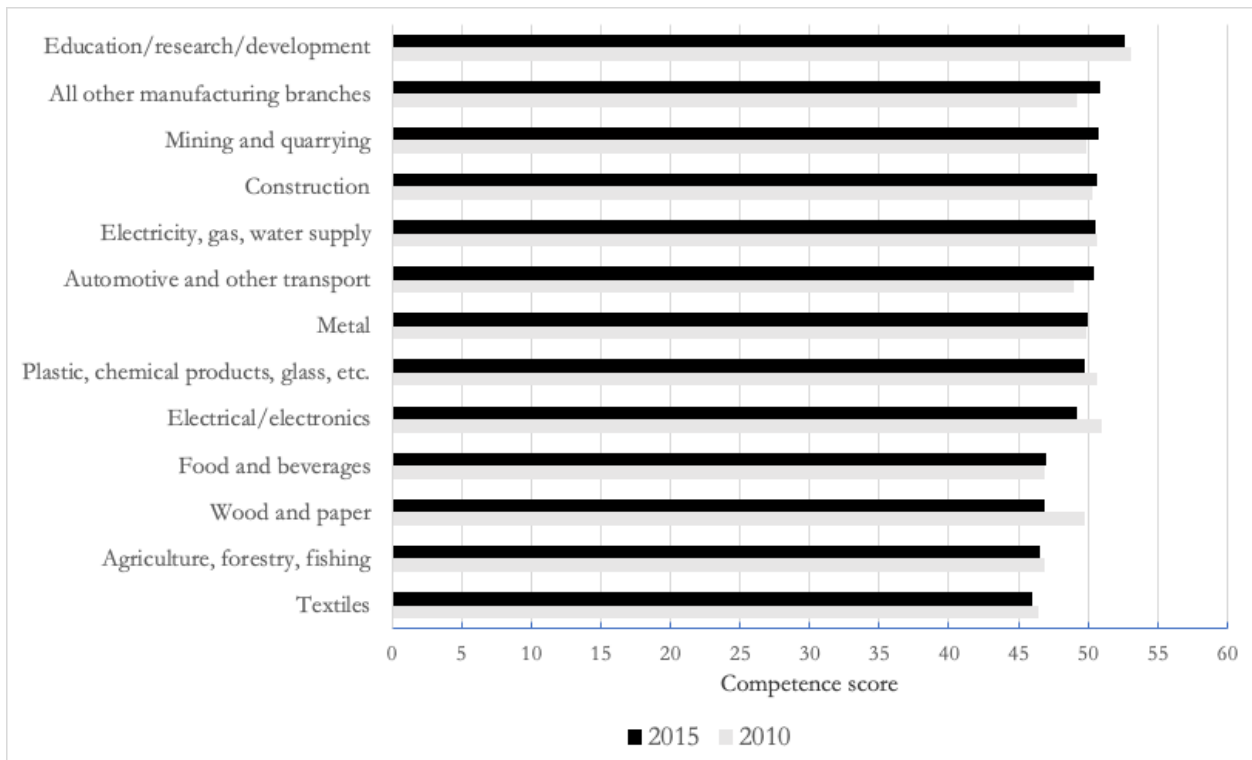
Figure 3: *Autonomy, by industry and year*



Source: Authors' calculations based on IFR and EUKLEMS

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

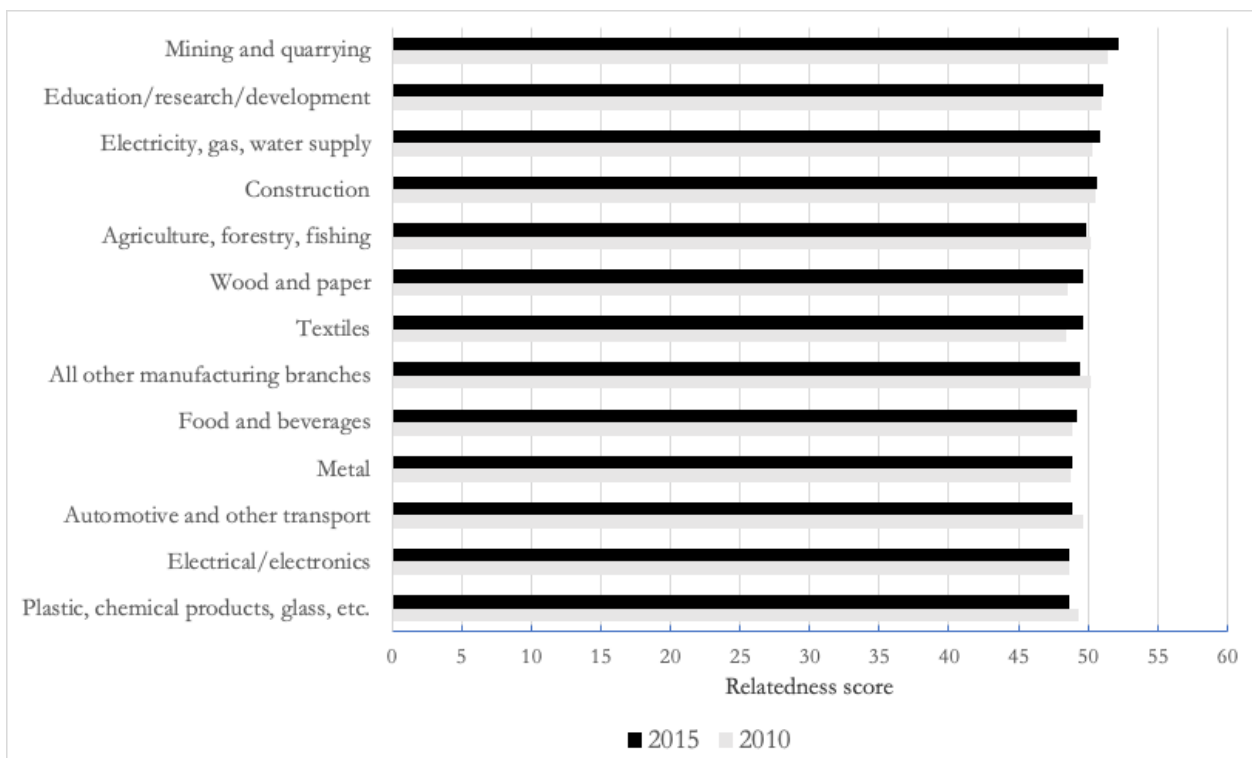
Figure 4: Competence, by industry and year



Source: Authors' calculations based on IFR and EUKLEMS

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.

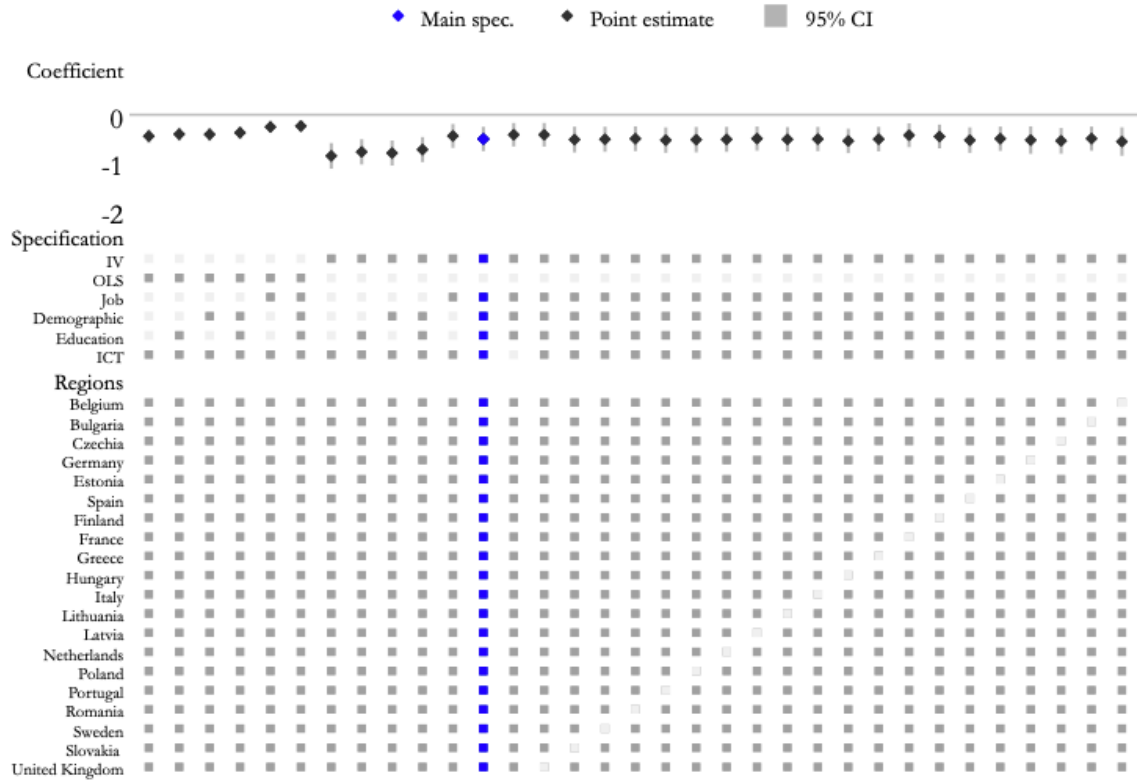
Figure 5: Relatedness, by industry and year



Source: Authors' calculations based on IFR and EUKLEMS

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

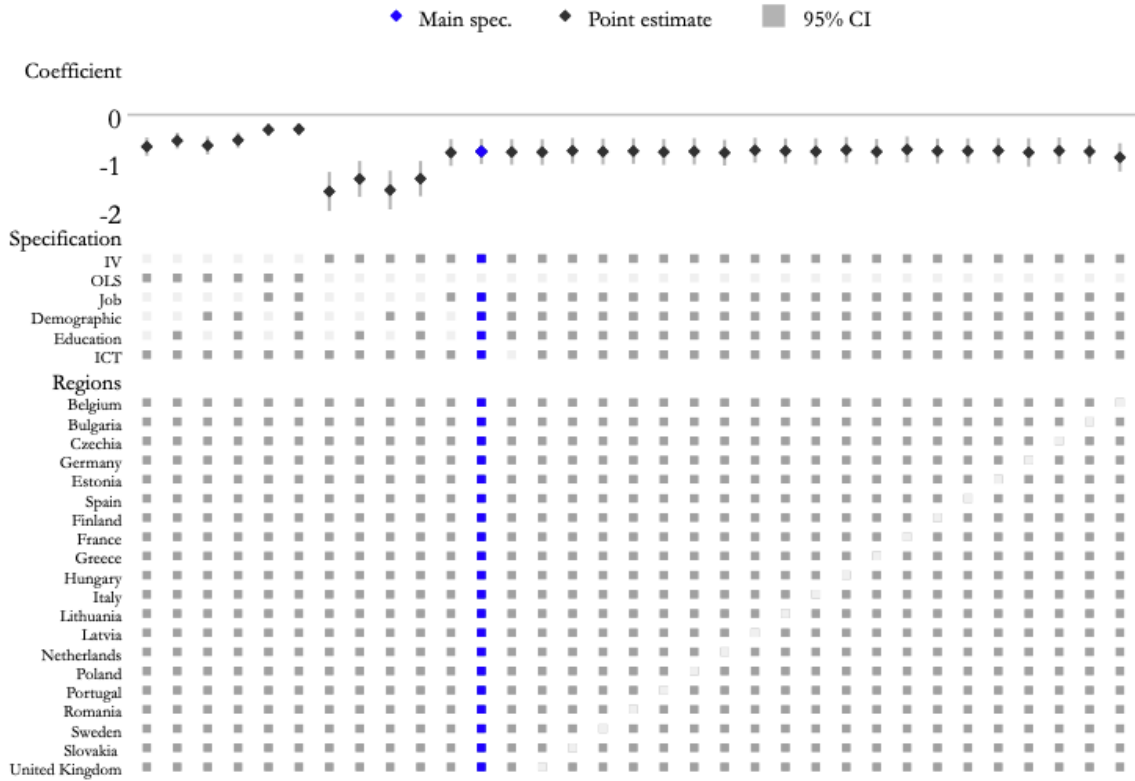
Figure 6: Specification curve analysis, work meaningfulness



Source: Authors' calculations based on IFR and EUKLEMS

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.

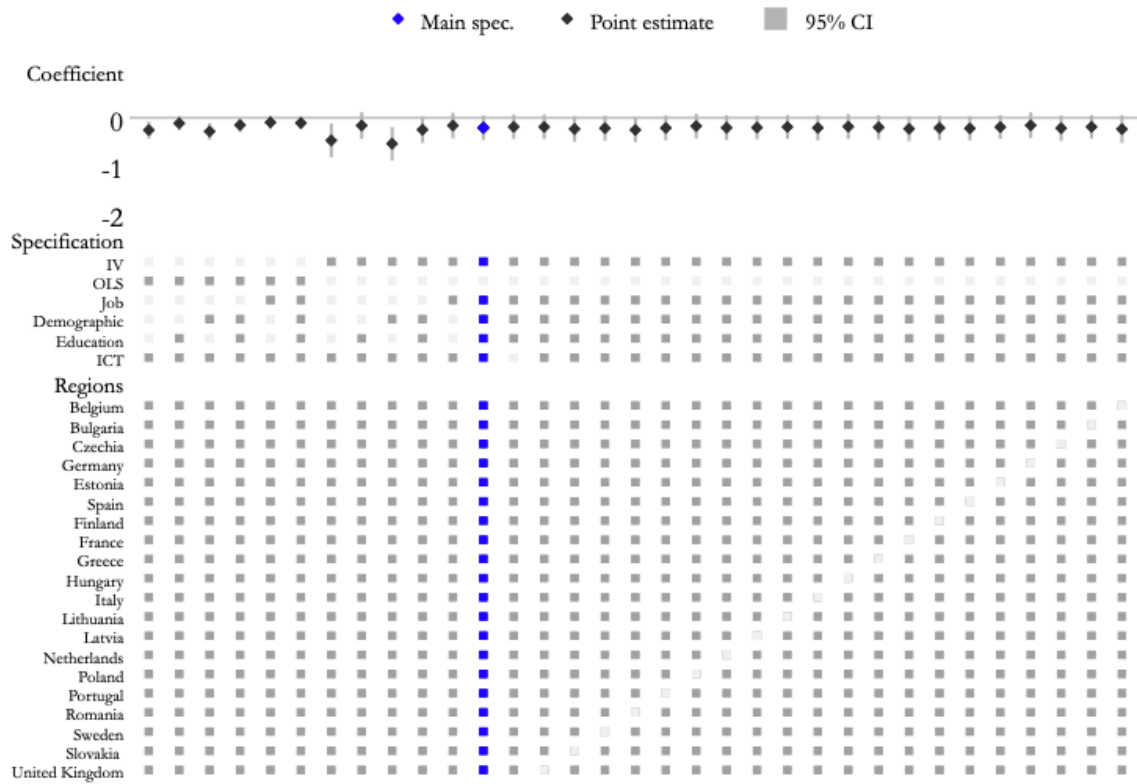
Figure 7: Specification curve analysis, autonomy



Source: Authors' calculations based on IFR and EUKLEMS

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.

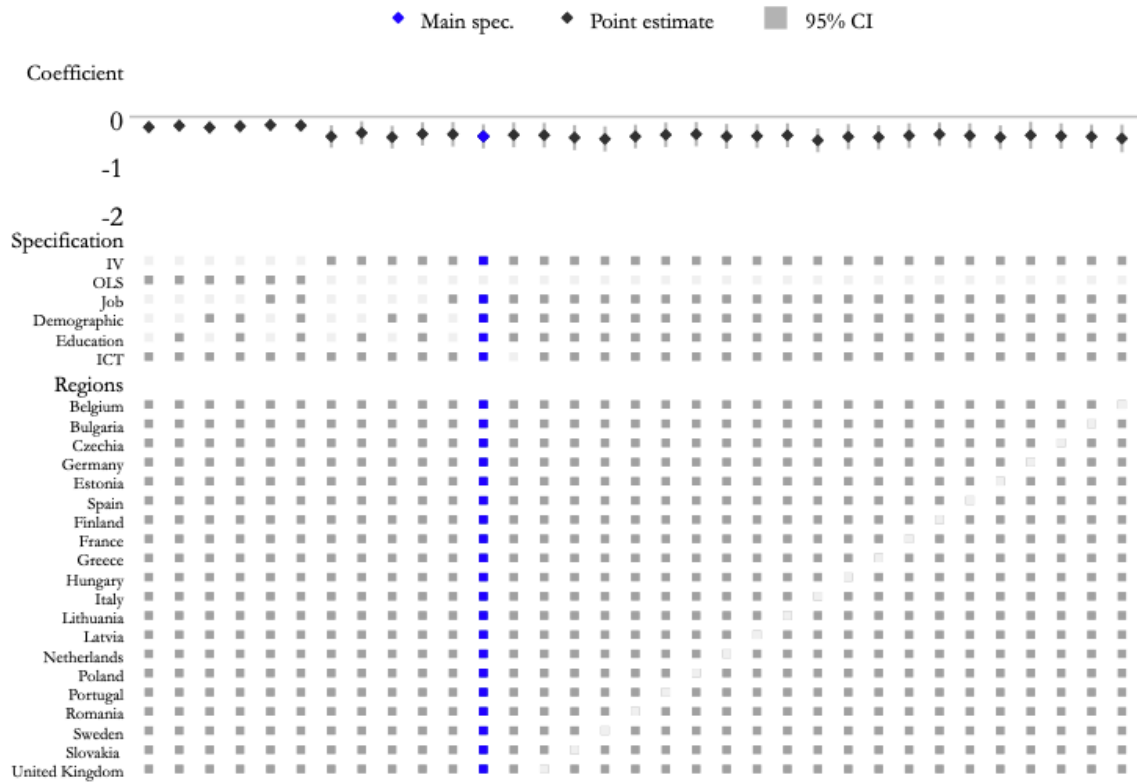
Figure 8: Specification curve analysis, competence



Source: Authors' calculations based on IFR and EUKLEMS

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.

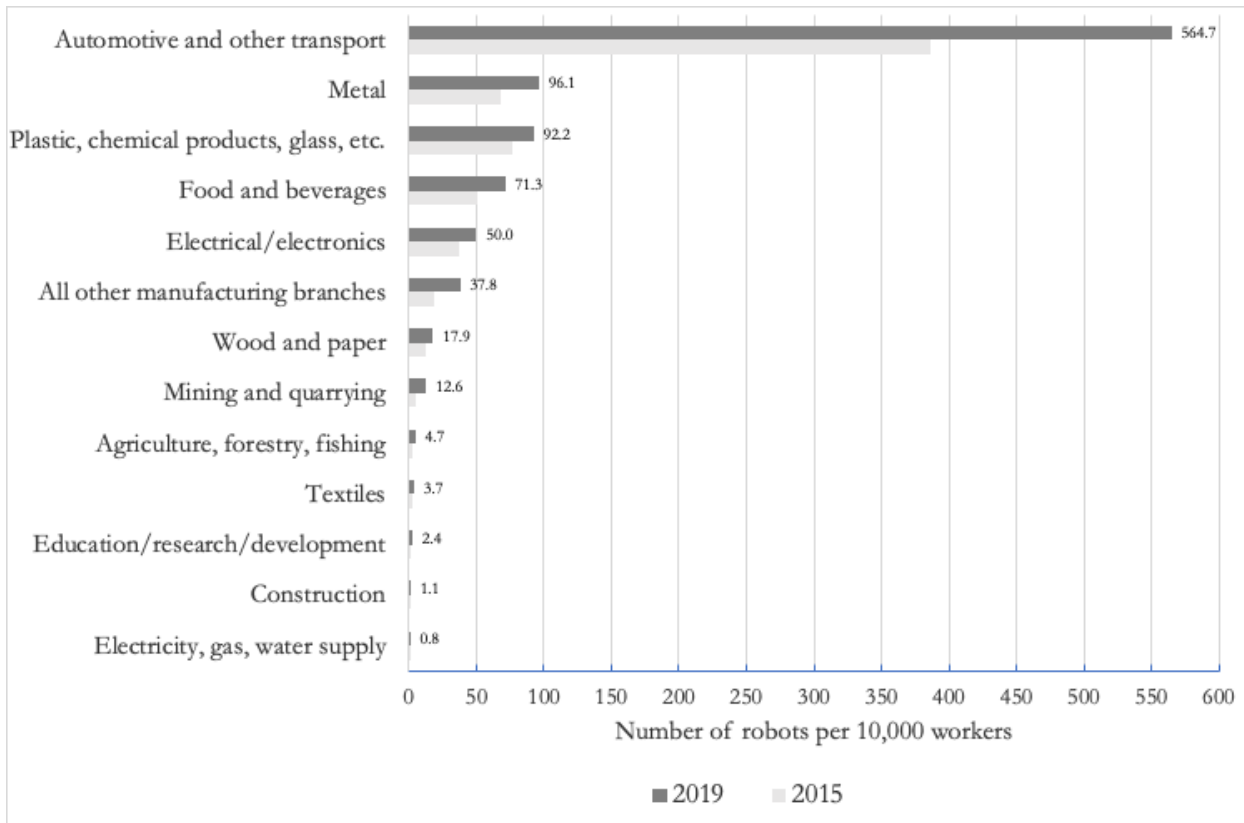
Figure 8: Specification curve analysis, relatedness



Source: Authors' calculations based on IFR and EUKLEMS

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.

Figure 10: Industrial robots per 10,000 workers by industry and year, 2014-2019



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 2015 and 2019. The values for 2014 are shown next to each bar. The industries Construction, Education/research/development, and Electricity, gas, water supply have very small non-zero values.

Appendix

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

	Robots per 10,000 workers, 2005	Robots per 10,000 workers, 2009	Robots per 10,000 workers, 2010	Robots per 10,000 workers, 2014	Pct. Change 2005-2009	Pct. Change 2010-2014
Electricity, gas, water supply	0.145	0.278	0.279	0.473	91.724	69.534
Construction	0.417	0.738	0.840	1.010	76.978	20.238
Education/research/d evelopment	1.408	1.378	1.336	1.653	-2.131	23.728
Agriculture, forestry, fishing	1.842	1.475	1.502	2.157	-19.924	43.609
Textiles	3.044	2.544	2.429	3.102	-16.426	27.707
Mining and quarrying	0.460	2.900	3.417	4.349	530.435	27.275
Wood and paper	8.976	10.760	10.452	12.145	19.875	16.198
All other manufacturing branches	14.958	12.378	13.369	15.669	-17.248	17.204
Electrical/electronics	32.957	30.808	30.712	36.486	-6.521	18.800
Food and beverages	17.950	31.087	33.663	46.919	73.187	39.379
Metal	29.094	48.936	49.763	61.113	68.200	22.808
Plastic, chemical products, glass, etc.	55.467	69.527	68.563	71.236	25.348	3.899
Automotive and other transport	261.238	276.571	288.021	366.461	5.869	27.234

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, and 2014, also presented in Figure 1. In addition, this table shows the percentage change in the robot density between 2005-2009 and 2010-2014 in the last two columns. The industries Construction, Education/research/development, and Electricity, gas, 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 instruments

	(1)	(2)	(3)	(4)
	Robotization	Robotization	Robotization	Robotization
Panel A: IV Replaceable hours and robotic arms first stage				
Robotic arms	-5.383** (2.104)	-5.383** (2.104)	-5.383** (2.104)	-6.057*** (2.166)
Replaceable hours	7.096*** (0.993)	7.096*** (0.993)	7.096*** (0.993)	7.420*** (1.003)
1st stage F-stat	32.85	32.85	32.85	34.83
Hansen's J statistics (overidentification test)	3.185	10.14	1.559	6.654
Overidentification test p-value	0.074	0.001	0.212	0.010
Panel B: IV Replaceable hours and robotic arms second stage				
	Work meaningfulness	Autonomy	Competence	Relatedness
Robotization	-1.037*** (0.189)	-1.182*** (0.203)	-0.389** (0.161)	-0.657*** (0.166)
R ²	0.053	0.152	0.174	0.069
Elasticity	-0.020	-0.023	-0.008	-0.013
Number of observations	16,206	16,206	16,206	13,041

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

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, 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). All regressions are weighted using the survey weight. The analysis sample is based on 20 European countries and 13 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 with different weights

	(1)	(2)	(3)	(4)
	Work meaningfulness	Autonomy	Competence	Relatedness
Panel A: Ordinary Least Squares				
Robotization	-0.313*** (0.055)	-0.355*** (0.075)	-0.076 (0.070)	-0.240*** (0.086)
Elasticity	-0.006	-0.007	-0.001	-0.005
R ²	0.062	0.157	0.188	0.086
Panel B: IV Peer Robot Adoption Second Stage				
Robotization	-0.563*** (0.098)	-0.750*** (0.137)	-0.298** (0.126)	-0.337*** (0.129)
Elasticity	-0.011	-0.015	-0.006	-0.007
R ²	0.061	0.155	0.187	0.086
1st stage F-stat	142.1	142.1	142.1	139.6
Weighted number of observations	15,352	15,352	15,352	12,292
Number of observations	16,206	16,206	16,206	13,041

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

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 5 is that this table relies on different weights, namely country-specific industry employment shares. 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 in Panel B is based on the industry adoption of automation 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 13 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

	(1)	(2)	(3)	(4)
	Work meaningfulness	Autonomy	Competence	Relatedness
Panel A: Ordinary Least Squares				
Robotization	-0.235*** (0.061)	-0.304*** (0.062)	-0.090 (0.063)	-0.197*** (0.066)
Elasticity	-0.005	-0.006	-0.002	-0.004
R ²	0.075	0.175	0.183	0.080
Panel B: IV Peer Robot Adoption Second Stage				
Robotization	-0.514*** (0.125)	-0.760*** (0.133)	-0.192 (0.122)	-0.404*** (0.123)
Elasticity	-0.010	-0.015	-0.004	-0.008
R ²	0.073	0.170	0.183	0.079
1st stage F-stat	105.9	105.9	105.9	103
Number of observations	16,206	16,206	16,206	13,041

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

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 5 is that this table includes countryXyear 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, 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 in Panel B is based on the industry adoption of automation in all other countries in the sample (except that particular country). The elasticity estimate is calculated following Bellemare and Wichman (2020). All regressions are weighted using the survey weight. The analysis sample is based on 20 European countries and 13 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	-0.473*** (0.132)	-0.773*** (0.144)	-0.208 (0.132)	-0.427*** (0.124)
On the Job 1 Year of Less	-0.618 (0.458)	-1.715*** (0.373)	0.046 (0.341)	0.170 (0.440)
RobotizationX On the Job 1 Year of Less	-0.220 (0.319)	0.059 (0.303)	0.015 (0.262)	0.118 (0.342)
R ²	0.069	0.170	0.176	0.074
1st stage F-stat	52.66	52.66	52.66	51.23
Number of observations	16,206	16,206	16,206	13,041

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

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 been working 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 in Panel B is based on the industry adoption of automation in all other countries in the sample (except that particular country). The elasticity estimate is calculated following Bellemare and Wichman (2020). All regressions are weighted using the survey weight. The analysis sample is based on 20 European countries and 13 industries. See Table 3 for variable definitions.

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