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Milena Nikolova
University of Groningen, Brookings Institution and IZA

Anthony Lepinteur
University of Luxembourg and IZA

Femke Cnossen
University of Groningen

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Just Another Cog in the Machine? A Worker-Level View of Robotization and Tasks*

Using survey data from 20 European countries, we construct novel worker-level indices of routine, abstract, social, and physical tasks, which we combine with industry-level robotization exposure. Our conceptual framework builds on the insight that robotization simultaneously replaces, creates, and modifies workers' tasks and studies how these forces impact workers' job content. We rely on instrumental variable techniques and show that robotization reduces physically demanding activities. Yet, this reduction in manual work does not coincide with a shift to more challenging and interesting tasks. Instead, robotization makes workers' tasks more routine, while diminishing the opportunities for cognitively challenging work and human contact. The adverse impact of robotization on social tasks is particularly pronounced for highly skilled and educated workers. Our study offers a unique worker-centric viewpoint on the interplay between technology and tasks, highlighting nuances that macro-level indicators overlook. As such, it sheds light on the mechanisms underpinning the impact of robotization on labor markets.

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

Keywords: robotization, technological change, worker-level data, tasks

Corresponding author:
Milena Nikolova
University of Groningen
Nettelbosje 2
9747 AE Groningen
The Netherlands
E-mail: m.v.nikolova@rug.nl

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1. Introduction

Over the past few decades, significant technological advancements, including the rise of robots, have profoundly impacted overall labor demand and brought about increased labor and total factor productivity (Graetz & Michaels, 2018), as well as a decline in the aggregate share of routine manual jobs across many industrialized economies (de Vries, Gentile, Miroudot, & Wacker, 2020).

Economic models describing the implications of recent technological advancements in the labor market suggest that robots can replace humans in specific tasks, particularly those that are manual and/or routine-intensive, such as repetitive physical activities that can be standardized into a set of procedures. Robots and computers are relatively less able to handle tasks that demand "tacit knowledge, flexibility, judgment, and common sense," as emphasized by Autor (2014). This is rapidly changing with the adoption of robots that have Artificial Intelligence (AI) capabilities, but our analysis period and data precede these most recent developments.

In addition to its displacement effects, robotization creates new work or modifies existing tasks (Acemoglu & Restrepo, 2019; Autor, Chin, Salomons, & Seegmiller, 2022). Yet, until recently, the public discourse, and much of academic scholarship, focused on exploring whether automation has labor-saving aspects or not in terms of total employment (i.e., displacement effect) (e.g., Acemoglu & Restrepo, 2020; Jestl, 2022; Dinlersoz & Wolf, 2023; Dixon, Hong, & Wu, 2021; Mann & Püttmann, 2021). The evidence in terms of massive job loss due to automation has been less than clear-cut, especially looking at the European context (see Acemoglu, Koster, & Ozgen, 2023, for an overview).

At the same time, the consequences of automation at the individual level, and especially those related to the tasks and activities workers do, are less well-understood. Studies in the European context find that the modest employment declines in manufacturing are (partially) offset by job creation in other sectors (e.g., Dauth *et al.*, 2021; Jestl, 2022). What is less understood is how these changes happen at the individual level and how they affect the job content of individual workers. As robots are integrated into workplaces, they take over tasks previously executed by humans, leading to potential displacement for some workers. Other workers may find continued employment within the same company or industry or switch jobs. In the context of Europe, which has robust employment protection schemes, the threat of job loss due to the adoption of robots is limited but workers may see their task set altered, as suggested by the results in Germany of Dauth *et al.*, 2021. Therefore, the central question of this paper is the direction in which workers' tasks change following robotization. Does their work become more interesting or more mundane?

The research examining how technological change affects *individual*-level tasks is hindered by a scarcity of datasets with detailed individual-level information on the job content and activities that workers do. Much of the robotization literature relies on task content measures based on coarse occupational classifications (e.g., ISCO) or occupational dictionaries, such as the Dictionary of Occupational Titles (DOT) and the Occupational Information Network (O*NET). Despite their widespread use, these approaches overlook the nuanced distinctions in job tasks within a specific occupation, both over time and across different countries. The modification and creation of new tasks within occupations are easy to overlook with this approach. Consequently, studies using occupations as indicators for job tasks can only present average shifts in the occupational distribution due to technological advancements, without capturing precisely how the daily tasks of workers within these occupations evolve with increased exposure to technology. This detailed examination of activities within occupations is particularly crucial for understanding the effects of technological progress on the individual work experiences of workers. This is the research gap that the present paper addresses.

Our theoretical framework centers on the impact of robotization on job content provided that workers retain their positions. The key predictions stem from two distinct scenarios: i) robots having full autonomy in executing routine or physical tasks, allowing humans to specialize in other tasks (i.e., *human advantage effect*), and ii) robots only partially automating tasks and the process (i.e., *Polanyi effect*).

Given that robotization has primarily impacted routine tasks, it is reasonable to conjecture that there has been a reduction in routine tasks at the individual level. Moreover, individuals exposed to robotization may experience a decrease in monotonous and physical tasks, allowing them to allocate more time to focus on abstract and socially-oriented tasks.

Nevertheless, workers might also face a decline in the overall task load as a result of robotization, potentially leading to reduced task variety and heightened feelings of monotony or repetitiveness. Additionally, the activities facilitated by new technologies are not inherently more abstract or intricate and may result in an alienating experience. Ultimately, the overall impact of robotization on job tasks at the worker level remains ambiguous and is likely to vary at a granular level.

The main contribution of this paper is to examine how robotization impacts workers' tasks by capturing important dynamics that macro-level task data often overlook. To do so, we use the European Working Conditions Survey (EWCS) for 2010 and 2015 containing information on workers' descriptions of multiple aspects of their work to build four individual-level task indices: routine, abstract, social, and physical. Furthermore, our measure of robot exposure is based on information from the International Federation of Robotics (IFR) and the EUKLEMS and reflects changes in robot adoption per 10,000 workers in 14 industries and 20 countries between 2005 and 2009 and 2015-2019.[1] We combine this robotization measure with the individual-level tasks and worker information by using the industry of employment of each worker in the EWCS data. We address endogeneity issues using an instrumental variable approach based on the adoption of robots in the same industries in other countries (as in 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; Nikolova, Cnossen & Nikolaev, 2022).

We show that robotization makes workers' tasks less physically demanding, which is in line with previous work on the health consequences of robotization and reduction in manual tasks (e.g., Gihleb *et al.*, 2022; Gunadi & Ryu, 2021). At the same time, we find that robotization increases the routineness and decreases the cognitively challenging and human contact activities of workers. Our results are in line with the *Polanyi effect*, whereby automation leaves some aspects of the production process for humans, but those aspects are more mundane and routine. Our OLS and 2SLS results are qualitatively similar and survive a battery of sensitivity checks.

[1] In this paper, we use the terms 'industrial robotization', 'robotization', and 'automation' interchangeably.

Moreover, we demonstrate that the impact of robotization varies among different skill and education groups, with the most notable difference being for abstract tasks. Specifically, robotization amplifies the negative effect of robotization on tasks for high-skilled and highly educated workers, thus making their jobs even more devoid of human interaction and supervision activities.

Our results directly contribute to two literature strands. First, they complement the extant evidence about the impact of robotization on the labor market. Unlike much of the existing literature focusing on macro-level data, shifts between occupations and aggregate job task definitions (Autor, Levy & Murnane, 2003; Autor & Dorn, 2013; Cortes *et al.*, 2017; Goos, Manning & Salomons, 2014), our study concentrates on individual-level data and focuses on workers experiencing changes at their workplace due to robotization. This approach unveils changes in job tasks that aggregate task measures at the occupation or industry level miss. We also build upon and extend the growing literature relying on worker-level survey data to measure tasks (Autor and Handel, 2013; Cassidy, 2017; Akçomak, Kok and Rojas-Romagosa, 2016; Sebastian and Biagi, 2018; De La Rica, Gortazar and Lewandowski, 2020; Lewandowski, Park, Hardy, Du, and Wu, 2022; Cnossen, 2022; Arntz, Gregory & Zierahn, 2017). While worker-based task indices are increasingly common, we validate our measure by comparing it with other widely used task measures. On average, our indices strongly align with standard occupation-based task indices (Acemoglu and Autor, 2011), with the added advantage of tapping into within-occupation variation.

Second, our study adds to the literature examining the effects of robotization on job quality, which remains relatively limited (see Nikolova *et al.*, 2022 and Rohenkohl & Clarke, 2023, for comprehensive reviews). Our results may help us understand why some studies reveal an adverse effect of automation on job satisfaction (Schwabe & Castellacci, 2020) and diminished perceived work meaningfulness and autonomy (Nikolova *et al.*, 2022).

2. Conceptual framework: The implications of robotization on the tasks performed by workers

Macro-level evidence suggests that technological change leads to i) a decline in the proportion of routine occupations in favor of more abstract ones (Autor et al., 2003; Dustmann, Ludsteck, & Schönberg, 2009; Goos & Manning, 2007; Goos, Manning, & Salomons, 2014; Acemoglu & Autor, 2011; Autor, 2014; Böhm, 2020) and ii) an overall decrease in the routine-intensity of jobs within occupations (Spitz-Oener, 2006). As routine occupations are disappearing at the aggregate level, cognitive and interactive ones are emerging. However, examining these patterns at an aggregate level potentially overlooks the worker-level experience of those remaining in employment: does one's job become more or less routine following robotization?

Building on Autor *et al.* (2003) and Acemoglu and Restrepo (2019), we propose a framework in which each worker's bundle of tasks consists of a combination of social, abstract, routine, and physical tasks. Social and abstract tasks are activities in which humans have a significant comparative advantage over robots (i.e., human advantage tasks). Routine and physical activities are susceptible to various types of automation. Of these two, physical tasks are most likely to be automated by robots, as shown by empirical evidence by Webb (2019) based on the overlap between robot-patent data and occupational tasks. Evidence from the United States also suggests that robotization reduced the physical tasks of low-skilled US and German workers (Gihleb et al., 2022; Gunadi & Ryu, 2020).

Our theoretical framework focuses on how robotization affects job content, conditional on workers keeping their jobs. The main predicted effects stem from two scenarios: i) robots having full autonomy in executing routine or physical tasks, allowing humans to specialize in other tasks (i.e., *human advantage effect*), and ii) robots only partially automating tasks and the process (i.e., *Polanyi effect*).

First, if robots can autonomously complete a set of routine or physically demanding tasks, humans can shift towards tasks that play to human strengths. By reducing the routine and physical strength tasks for workers, robotization may leave workers with more scope and time to engage with their customers or colleagues and focus on tasks that the machines cannot yet do – such as problem-solving and complex tasks and actions requiring "common sense" judgment. For instance, pharmacists might emphasize social interaction, and warehouse workers may concentrate on enhancing workflow optimization through problem-solving. Consequently, workers transition to tasks where humans have a comparative advantage. These new responsibilities can prove more engaging, as the routine and physical aspects of jobs have been automated. For instance, a case study illustrates how the introduction of a drug-dispensing robot enabled pharmacists to dedicate more attention to client interaction (Barrett, Oborn, Orlikowski & Yates, 2011). Similar patterns have been observed in other case studies, particularly among workers with higher education (Smids, Nyholm & Berkers, 2020; Berkers, Rispens & Le Blanc, 2023). There is some aggregate evidence for this mechanism in German manufacturing industries (Dauth et al., 2021). Specifically, based on aggregate analyses, within manufacturing, robotization increases the share of abstract and manual and decreases the share of routine tasks (relative to all other tasks in manufacturing in the local labor market). According to Dauth et al. (2021), most workers who keep their jobs following automation shift into tasks that are less routine and more abstract.

Second, the change in tasks can take an entirely different trajectory due to task replacement and task creation. Due to robotization's task replacement aspects, workers might find themselves performing only segments of the task bundles they were previously responsible for, or they may be required to accompany a robot and take over tasks when the robot is unable to execute them. Some tasks or processes may not be entirely reducible to a set of procedures at the outset. The remaining components of routine activities may demand actions or judgments that are challenging to systematize. This explanation closely aligns with the so-called Polanyi paradox, which implies that because humans generally do not know how much they can do, engineers may also not be able to design a robot that replaces the complete set of tasks involved in a production process (Autor, 2014). For instance, although robots mount windshields onto cars in automobile factories, it is human technicians who must replace the windshields if they are damaged. This is due to the complexity of the task, which involves removing a defective or shattered windshield and installing a new one, a process too intricate for a robot to perform (Autor, 2014). However, from the worker's perspective, who previously dealt with a range of tasks associated with installing and replacing windshields, the introduction of robots may result in a reduction of task variety, leading them to perceive their work as more routine. A pertinent illustration of this is evident in the proliferation of robots in warehouses, where certain robots diminish the variety of tasks, leaving workers to handle small, mundane tasks that the robots cannot yet undertake. Consequently, workers may lose an overarching understanding of the complete work process, reminiscent of the principles of Taylorism, a method of scientific management emphasizing efficiency where each worker is accountable for their designated segment (Berkers et al., 2023;

Li & Liu, 2016). The robot may be installed, but the worker still needs to be present while it operates, thereby being dependent on the machine's work pace and activities – rendering their work more routine-intensive, less challenging, and less interactive. Despite the robot installation, the worker must still be present during its operation, thus depending on the machine's work pace and activities. This situation makes their work more focused on routine tasks, less challenging, and less interactive.

Automation's task-creation aspects can also increase the routine and decrease the social and abstract activities of workers, giving rise to a different version of the *Polanyi effect*. Within occupations, technology creates new tasks – for example, by having machines check in passengers at airports, gate agents can focus on dealing with rebooking flights or issuing new tickets (Autor, 2013). When machines create novel tasks through new production modes or demand for new products and services, these new tasks are first assigned to humans. As some of these tasks can be further codified, they are then susceptible to automation, leaving more mundane tasks for humans (Autor, 2013). Humans are flexible and adaptable, and because of that, they can initially perform the new tasks that technology generates in the economy. With the mastery of the tasks, however, comes the ability to codify tasks and potentially turn these tasks over to machines. In other words, in the medium and long run, even the task-creating aspects of technology can leave humans with more mundane and less interesting tasks. Workers performing these new tasks may not necessarily experience declines in wages, at least in the short or medium run, as the overall productivity goes up, but they may lose the comparative advantage in the tasks that they were previously doing.

The relative importance of the *human advantage* vs. the *Polanyi* effect determines the direction the worker-level impact of robots on the task content of jobs goes into, conditional upon workers keeping their jobs. The first, the *human advantage effect,* leads to the hypothesis that the human-advantage tasks will increase following robotization: incumbent workers will perform fewer physical tasks due to task replacement and instead perform more abstract and social tasks, and their tasks may also become less routine.

The *Polanyi effect* gives rise to the hypotheses that abstract and social tasks will *decrease* and routine tasks will *increase* as the work becomes more focused on working with the machine or performing the last few tasks that cannot yet be automated. This reduces the freedom people experience at work and the variety of tasks and directly affects the task content of their jobs.

Ex ante, it is unclear which of these two channels dominates and in which circumstances. Therefore, we conduct an empirical exercise to test whether robotization leads to more mundane jobs – if the Polanyi effect is dominant - or more interesting ones – if the human advantage effect is dominant.

3. Measuring tasks

The extant literature offers three main approaches to measuring the content of workers' tasks (Autor, 2013). First, researchers have relied on higher-level occupational groupings from available occupational classifications such as ISCO as proxies of job tasks. Occupations are grouped into broad categories, such as "managerial," "production," or "service," based on which the task content of jobs is inferred. This approach is rather crude as it fails to account for similarities between routine and non-routine tasks across different occupations (Autor, 2013). For example, both office clerks and supermarket cashiers perform functions that can be easily codifiable and replaced with software and machines, and both teachers and nurses perform activities that require flexibility and judgment to adapt to changing circumstances, empathy, and interactive skills, which are difficult to codify.

A second approach includes categorizing tasks based on grouping occupational descriptions detailed in occupational dictionaries, such as the Dictionary of Occupational Titles (DOT) and the Occupational Information Network (O*NET) in the US (Handel, 2016). This approach closely maps the existing job descriptions of the occupations in O*NET with the framework in Autor *et al.* (2003) related to the intensity of non-routine analytic, non-routine interactive, routine cognitive, routine manual, and non-routine manual activities.

The main advantage of this method is the ability to rely on descriptions of the job activities provided by statistical agencies (Autor, 2013). These measures also cover all occupations and at a high level of detail (Fernández-Macías and Bisello, 2022). Yet, the method does not allow for heterogeneity in job tasks within an occupation. For example, two general managers can have a very different set of activities. However, the researcher assigning the tasks to the occupation only sees the fixed definition in O*NET rather than the actual tasks performed by the worker. As Autor (2013, p. 190) notes, "[...] at best, occupation level task measures provide a rough approximation to the microeconomic assignment process." In addition, the task assignments based on O*NET definitions ignore the dynamics related to task reshuffling and optimization resulting from automation.

The third approach to measuring tasks, which we adopt in this paper, collects job and task descriptions from surveys that also elicit information on demographics, job characteristics, and job quality (Fernández-Macías & Bisello, 2022). The main advantage of this approach is that it offers information at the level of workers rather than occupations and allows studying nuances in the task content *within* and *between* occupations and over time. Despite the limitations of self-reported data, worker-level measures have proved relevant for research in the literature on task-biased technological change. In a seminal paper based on the German Qualification and Career Survey, Spitz-Oener (2006) documents that German occupations in 1999 required more complex tasks than in 1979 and that these changes were due to changes within occupations rather than between occupations.[2]

4. Data and key variables

We use three main data sources: i) information on the adoption of industrial robots from the International Federation of Robotics (IFR); ii) data on the number of employees per industry and information on fixed capital stock in computing, communications, computer software, and databases (i.e., ICT) from the EU KLEMS database; and iii) worker-level data from 2010 and 2015 from 20 European countries working in 14 industries from the European Working Conditions Surveys (EWCS).

4.1. IFR data and robotization

We source robot stock data from the IFR, which is an association of major robot producers. Data are available at the industry level within countries, and no company data are available. Our measure of robotization is similar to that of Aksoy *et al.* (2021) and Nikolova *et al.* (2022). Like Aksoy *et al.* (2021), we do not make an adjustment related to the depreciation rate and use the original IFR data, which assumes a service life of 12 years and no operation of the robot after that. By a robot, we mean an

[2] For example, shift-share analyses in Spitz-Oener (2006) demonstrate that about 15% of the total changes in the analytical task measure can be attributed to between-occupational shifts, while 85% - to within-occupational ones.

"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). A robot, therefore, is fully autonomous and, does not require a human worker to operate it and can be re-programmed to perform different tasks (Jurkat, Klump, & Schneider, 2022). The dataset excludes industrial robots, such as automated storage and retrieval systems controlled by machines. A detailed overview of the dataset and its limitations is available in Jurkat *et al.* (2022).

The IFR data are available in principle starting in 1995 for certain countries and industries. Nevertheless, there are many missing entries in the early years. We, therefore, use the IFR data post-2005 due to the gaps in data availability prior to that year that would have required many imputations. Furthermore, our EWCS data also have a NACE classification code that we can only use starting in 2005 due to the revision of the codes, which makes 2005 an opportune starting year for investigation. Note that, like other papers in the literature (e.g., Graetz & Michaels, 2018), we still needed to impute the data for 2005 for Bulgaria, Greece, and Lithuania.

Our measure of robotization is expressed in terms of changes and is specified like in Nikolova *et al.* (2022). For each industry j in country c and year t:

$$Robotization_{j,c,t} = IHS\left[\frac{number\ \ robots_{j,c,t-1}}{10{,}000\ employees\ _{j,c,2000}} - \frac{number\ \ robots_{j,c,t-5}}{10{,}000\ employees_{j,c,2000}}\right] \tag{1}$$

where $Robotization_{j,c,t}$ is the change in robotization between t-1 and t-5 in industry j in country c. We use a 4-year gap to compute the changes and lag it one year to reflect the interval between consecutive EWCS survey waves. Lagging the variable helps with reverse causality issues in the OLS specifications and also allows us to better match the timing of the survey responses with the reference period for robot stocks. Finally, the denominator contains the number of workers in the year 2000, sourced from the EUKLEMS -INTANProd data, rather than current employee numbers to ensure that changes in robotization are not influenced by changes in the number of employees in that particular industry.

Additionally, we address the challenge posed by the highly skewed distribution of changes in robotization (Bekhtiar, Bittschi, & Sellner, 2021) by applying an inverse hyperbolic sine (IHS) transformation to these changes (Bellemare & Wichman, 2020).

Like Aksoy *et al.* (2021), we choose the IHS method over alternative transformations, such as taking the logarithm or using percentile rankings for changes in robotization. The latter over-emphasizes minor differences between changes in robotization at the top of the distribution and under-emphasizes significant differences at the bottom. The IHS method resembles logarithmic transformation but retains accuracy for zeros and negative values. However, it does come with the drawback that coefficients are not immediately interpretable without conversion into elasticities. We provide elasticity values where possible.

4.2. Worker-level information on tasks

We rely on the 2010 and 2015 EWCS from the European Working Conditions Survey Integrated File 1991-2015 (Eurofound, 2023a). The EWCS offers rich, nationally representative information collected via face-to-face interviews with workers in European countries. Respondents aged 16 and older who work at least one hour per week are eligible to answer the questionnaires. Each survey wave polls unique workers, and the dataset is cross-sectional.

The EWCS dataset is the best available source for our analyses for several reasons. In Appendix B, we detail the other extant datasets and explain their advantages and disadvantages. First, the EWCS asked individuals a plethora of questions about their daily activities and experiences at work. Second, the survey provides information about the industry of employment (NACE Rev 2, two-digit), which allows us to merge the data from the IFR and EUKLEMS with the EWCS. The NACE Rev 2 information is only available from 2010 onwards (a different classification was used in earlier years). This is the reason why our analysis does not make use of pre-2010 EWCS survey waves. Finally, the richness of the dataset allows us to include a range of control variables, such as age, gender, occupation, work hours, education, and firm size.

EWCS respondents are asked to precisely describe the tasks they are doing in their job. To reduce the dimensionality of the type of tasks performed by workers, we take inspiration from O*NET-based task indices and construct four indices related to routine, abstract, client interaction (social), and physical tasks. We create all indices using the first polychoric principal component (Olsson, 1979) and standardize the indices to have a standard deviation of 1 and a mean of 0. We also standardized all variables comprising the indices before including them in the index. Table 1 details the items used in constructing the indices and how these relate to the O*NET-based task indices.

Our routine measure is based on the following seven items: i) whether the job involves repetitive arm movements, ii) whether it involves monotonous tasks, iii) whether the work pace is dependent on the automatic speed of a machine, iv) the performance of short repetitive tasks of less than 1 minute and v) less than 10 minutes, vi) whether the respondent is able to change or choose the order of tasks and vii) the speed or rate of work. The Cronbach's alpha is 0.66, and the Kaiser-Meyer-Olkin measure of sampling accuracy is 0.70. The first principal component accounts for 37% of the variation. For comparison, the survey-based routine index in Autor in Handel (2013), which is based on the Princeton Data Improvement Initiative (PIID) survey dataset described in Section 3 in their paper, accounts for 56% of the variation in the variables they include.

The abstract index is based on three items capturing i) whether the respondent's main paid job involves solving unforeseen problems on their own, ii) complex tasks, and iii) learning new things. The Cronbach's alpha is 0.63, the KMO measure is 0.68, and the first principal component accounts for 58% of the total variance. In Autor and Handel's abstract index, it is 41%.

Our social index is based on variables capturing whether i) the respondent's work pace is dependent on people, such as customers, passengers, students, patients; ii) whether the respondent's main paid job involves handling angry clients, customers, patients, pupils, iii) whether the respondent deals directly with people who are not employees at the workplace, such as customers, passengers, pupils, and patients, and iv) whether the respondent supervises others. In this sense, our index comprises both tasks that fit in the social perceptiveness definition (non-routine manual interpersonal tasks) of O*NET, i.e., being aware of how others are reacting and why they are reacting the way that they do and also non-routine cognitive functions related to coaching and supervising others. The Cronbach's alpha is 0.57, the KMO measure of sampling accuracy is 0.63. The first principal component explains 47% of the total variance. A comparison with Autor and Handel is impossible as they have no analogous index.

Finally, the physical tasks index is based on whether the respondent works in tiring and painful positions and carries or moves heavy loads. These variables capture physical stamina and the physical labor content of tasks. The Cronbach's alpha is 0.69, and the KMO measure of sampling accuracy is 0.50. The first principal component has an eigenvalue of 1.7 and explains 83% of the total variance. The possible analogous index in Autor and Handel would be the manual tasks, but it is just a simple item based on the *"proportion of the workday spent performing physical tasks such as standing, operating machinery or vehicles, or making or fixing things by hand"* (p. S71).

The last column of Table 1 details the correlations (computed by collapsing all data at the 2-digit ISCO occupation level) between the indices that we create and those that are "off-the-shelf" and most commonly used in the literature (i.e., the O*NET indices in Acemoglu and Autor, 2011).[3] The correlation coefficients in all cases are relatively high, suggesting that our indices are valid representations of the concepts we are trying to capture. The correlation coefficients are of similar magnitudes as those reported by Sebastian and Biagi (2018), who also use the EWCS to construct indices related to abstract, routine, and manual tasks. The correlation coefficients are slightly lower when we limit the number of observations to our analysis sample, which excludes the "other non-manufacturing industries."

Table 2 details the correlation coefficients between the task indices that we constructed. The highest correlation is between abstract and social tasks (0.35) and routine and physical activities (0.34). Nevertheless, it is clear from the items reported in Table 1 that these indices are not tautological but rather capture distinct task aspects and activities at work.

In Table 3, we explore whether the task indices we created plausibly correlate with individual monthly earnings (in PPP and log-transformed) and whether the correlations remain once we control for the O*NET task indices, in the spirit of Autor and Handel (2013). Model (1) only includes the EWCS task indices and country and year dummies. Model (2) includes individual controls and occupation and industry

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[3] The data on task indices are available on Daron Acemoglu's website, which provides replication files and data: https://economics.mit.edu/people/faculty/daron-acemoglu/data-archive. To merge the task data from the Acemoglu and Autor's paper that uses the SOC occupational classification to the EWCS, which uses the ISCO classification, we used the correspondence tables prepared by the Institute for Structural Research (IBS), provided here: https://ibs.org.pl/en/resources/occupation-classifications-crosswalks-from-onet-soc-to-isco/.

dummies. As expected, the routine and physical indices are consistently associated with lower earnings, while abstract activities are positively contributing to income. The association between earnings and the social index is positive and turns statistically significant after including the individual-level controls and industry and occupation dummies in Model (2).

Model (3) in Table 3 incorporates the O*NET task indices as supplementary controls. The patterns in terms of associations with income of the routine, abstract, and physical indices we devised and those from the O*NET are comparable, reinforcing the credibility of our indices. However, the estimates related to the social indices present a difference, with our EWCS-based social index positively correlating with earnings, while that of the O*NET correlates negatively. A closer examination of the sub-components of the indices suggests that this discrepancy is because our social index puts more weight on tasks associated with greater earnings than the O*NET index. This is why Model (4) breaks the social indices into their ingredients – "Interactions with non-employees," "Dealing with angry clients," "Customer-driven work-pace," and "Employee supervision" in the case of EWCS, and "non-routine cognitive interpersonal" and "non-routine manual interpersonal skills" for the O*NET index. Essentially, in the O*NET, the manual interpersonal index (social perceptiveness, e.g., counseling depressed patients) is negatively correlated with earnings, while the cognitive component of the O*NET social index is positively correlated. Three items in the EWCS-based social index have positive and statistically significant estimates, with the largest coefficient estimate being for "Employee supervision," which reflects a cognitive aspect of the EWCS-based social index. Meanwhile, "Interactions with non-employees" only attracts a marginally negative coefficient. All in all, our indices plausibly correlate with existing measures in the literature and show plausible correlations with income.

4.3. Analysis sample construction

We merge information from the EWCS, IFR, and EUKLEMS based on the NACE Rev 2 industry information available in all three sources. Consequently, we drop from the sample workers with missing information on the industry of employment.

Our analysis sample has information on individuals working in 14 industries and 20 countries in 2010 and 2015. We follow the existing literature (e.g., Aksoy *et al.*, 2021; Graetz & Michaels, 2018) and exclude the “all other non-manufacturing” industry even though it represents about 63% of the EWCS. We do so because this category comprises mainly service industries that do not employ industrial robots. Finally, we drop the armed forces’ occupation from the analyses because they only comprise a handful of observations. Our final analysis sample contains 16,862 observations.

Appendix Table A1 details the construction of all the key variables used in the analyses, which are similar to those in Nikolova *et al.* (2022) and Aksoy *et al.* (2021). Table 4 provides detailed summary statistics of our estimation sample.

5. Empirical Strategy

We rely first on OLS estimations and bring causal inference via two-stage least squares (2SLS) regressions. Our analyses dovetail with and combine strategies explored in the extant literature (Acemoglu & Restrepo, 2020; Adachi *et al.*, 2020; Aksoy *et al.*, 2021; Anelli, Giuntella, & Stanig, 2021; Anelli, Colantone & Stanig, 2021; Dauth *et al.*, 2021; de Vries *et al.*, 2020; Graetz & Michaels, 2018; Nikolova *et al.*, 2022).

5.1. Main Model

Our main model assumes that the job activities T of individual i, living in country c and working in industry j in year t is:

$$T_{i,c,t} = \alpha_0 + \alpha_1 Robotization_{j,c,t} + \alpha_2 ICT_{j,c,t} + X_{i,c,t}\varphi + \pi_c + \tau_t + \varepsilon_{i,j,c,t} \tag{2}$$

whereby *Robotization* is the change in robot density in country c and industry j between years *t-1* and *t-5* (see the technical details behind the construction of this variable in Section 2.2. – Equation (1)). $ICT_{j,c,t}$ is the change in fixed capital stock in computing, communications, computer software, and databases per 10,000 workers. Like Jestl (2022), we consider ICT a different type of automation technology. The “computerization” wave lasted from the 1960s (pre-computer age) to the end of the 1990s (diffusion of the internet) (Frey & Osborne, 2017; Martin & Hauret, 2022). It was followed by Digitalization Wave 3.0, marked by the rise of robotization and inducing routine-biased technological change (Martin & Hauret, 2022). Both $Robotization_{j,c,t}$ and $ICT_{j,c,t}$ are IHS-transformed to account for their skewed distributions.

We include standard control variables, denoted by $X_{i,c,t}$ and including age group, gender, working hours, tenure, company size, education, having other jobs, and ISCO-08 occupation detailed in Section 2 above, π_c and τ_t denote country and time dummies (i.e., survey year 2010 or 2015), respectively, and $\varepsilon_{i,c,j,t}$ is the error term. The country fixed effects take into account any cultural differences in providing answers to survey questions and capture institutional factors, such as labor market institutions, to the extent that they do not change over time. Time dummies take into account shocks that are common across all countries.

We cluster the standard errors at the country*industry level and weigh all regressions using the survey weight. In the Appendix, we also report results using weights calculated using the within-country industry employment shares of employment hours (Aksoy *et al.*, 2021; Graetz & Michaels, 2018) that provide more importance to industries with larger employment shares. Where possible, we report the estimates related to the coefficient estimate of the robotization variable in terms of elasticities, following the computation formulas from Bellemare and Wichman (2020).

5.2. Addressing the endogeneity of robotization

We identify two main threats to causal identification. First, omitted shocks may both affect the propensity of specific industries to adopt robots and influence workers' tasks. For instance, a labor shortage in a particular industry may both cause the adoption of more robots and the re-shuffling of tasks among existing workers. Second, specific workers may non-randomly sort into industries that get more or less robotization exposure (e.g., workers who are open to technology may be more likely to work in industries with high robotization exposure and perform certain tasks).

Most existing papers offer credible ways of dealing with the first issue related to omitted industry-specific shocks by employing instrumental variable techniques. Following those studies, we instrument robotization in a particular country and industry with information on the automation in the same industry from all other countries in the sample except the respondent's (as in Anelli *et al.*, 2021; Nikolova *et al.*, 2021). The logic of the instrument is that the robotization pace in the same industry in all other countries captures the same trends and shocks in technological progress and robotization (i.e., the "technological frontier of robots" of Acemoglu & Restrepo, 2020). This technological frontier of robots in other countries, which is correlated with domestic robot adoption, is exogenous to the tasks that individual workers do in a particular country. The instrument would be invalid if robotization in the same industry but in other countries is correlated with other shocks, such as import competition and rising wages, which affect the robot adoption of the same industries across countries at the same time (Acemoglu & Restrepo, 2020). The existing cross-country research on the effects of automation has mainly relied on two instruments developed by Graetz and Michaels (2018) - "replaceable hours" and “robot arms.” These instruments capture the percentage of replaceable employment hours and the proportion of physical tasks related to reaching and handling in US industries in 1980. However, these instruments have some limitations, such as being based on the US industrial structure and violating the monotonicity assumption, which affects their accuracy and reliability (Bekhtiar et al., 2021). Nonetheless, for completeness, we also present the results obtained from using these instruments but warn readers to interpret them with caution.

Addressing self-selection is a more complex endeavor: employing a panel data setup would enable the use of individual fixed effects, which, can help alleviate concerns by netting out the impact of time-invariant unobserved traits. Our dataset comprises pooled cross-sections, with different individuals surveyed across the waves, precluding the use of individual fixed effects. Although we cannot entirely rule out the issue of self-selection into industry, we adopt a mitigation strategy that includes sequentially control variables to document the extent to which robotization is orthogonal to individual characteristics.

6. Results

6.1. Main results

Table 5 details our main results. In the first Column, we report the OLS coefficient estimates and corresponding elasticities for the change in robot density from a regression where we only control for year and country fixed effects. An increase in robot density appears to correlate negatively with the abstract index and social index but is positively associated with the routine index. When we control for the change in ICT stock in Column (2), the coefficient estimates remain virtually the same, suggesting that the results do not confound trends related to ICT adoption and computerization.

Although informative, the estimates in Column (1) and (2) in Table 5 are not causal. As mentioned above, one of the two major threats to our identification is the endogenous selection of workers into industries. We mitigate this problem by augmenting our Model with several control variables that determine the selection process. We report the results in Column (3). While the sign of the coefficient estimates remains the same, their magnitude is lower, suggesting that some worker-level self-selection bias is at play.

Omitted variables could explain both the speed of robot adoption and workers' tasks. For this reason, we appeal to the instrumental variable approach described in Subsection 4.2 and report the results in Column (4). The 2SLS estimates suggest first that robotization decreases the physical burden on workers – i.e., tasks related to carrying heavy loads and working in tiring positions. Second, as already revealed by the OLS estimates, the IV results confirm that robotization increases individual-level routine work and decreases workers' abstract and social tasks.

Although the dependent and independent variables are standardized, the interpretation of the coefficients in Table 5 is not straightforward due to the IHS transformation of the robotization variable, which is why we report the elasticities. For example, Column (4) suggests that doubling robotization increases the routineness of workers' tasks by 6%, and reduces the abstract and social tasks by 5% and 7%, respectively.

The fact that robotization decreases the frequency of performing physically demanding tasks is in line with existing studies (e.g., Gihleb *et al.,* 2022; Gunadi & Ryu, 2021), especially given that robots are most successful in replacing these activities (Webb, 2019).

Our results indicate that the Polanyi paradox effects dominate, considering the result that robotization makes tasks more routine. The fact that robotization also leads to fewer social and abstract tasks suggests that all job content becomes more mundane and less interesting. In other words, our results indicate that the increase in routine work is not compensated by an increase in abstract or social work.

We offer several robustness checks that increase confidence in the validity of our results. First, we check whether the results we report depend on the weights we use for the analyses. Instead of the survey weights, in Appendix Table A2, we use industry employment shares as weights – giving more importance to larger industries. The results are in line with our main specifications in Table 6. We also check whether the results are robust to using the Graetz and Michaels (2018) instruments commonly used in the literature, even though these instruments have several limitations we described earlier in the paper. The F-statistics related to the first-stage regressions are much smaller than those in the main analyses. The results are consistent with those in the main analyses (Table 6), though the magnitudes are higher.

Appendix Tables A4 to A7 detail how robotization affects each of the components of the indices using our 2SLS approach. We conduct this analysis to ensure that our indices do not hide nuanced changes within the variables comprising the indices. Our results suggest this is not the case for most indices. The coefficient estimates for robotization as related to all components of the routine index are positive, suggesting that greater exposure to robots does increase all aspects of routines reported in EWCS. The same applies to Appendix Table A5 and Table A7, where all the components of the abstract and physical index decrease with robotization. Appendix Table A6 displays the effect of robotization on the components of the social index, and the results are somewhat more nuanced. Robotization strongly decreases the frequency of interactions with non-employees but does not change the probability of employee supervision. These two components already behaved in opposite ways in Table 3. Combining our results in Appendix Table A6 and Table 3, it seems that robotization mostly reduces tasks that could be affiliated with the non-routine manual interpersonal O*NET classification of social tasks.

6.2. Heterogeneity Analysis

Our introduction highlighted two examples demonstrating the dynamic relationship between robotization and workers' tasks. The first example focused on a robotic drug dispensing device, showcasing the positive aspect of robotization. In this scenario, the robot assumes the most repetitive and physically demanding tasks, enabling pharmacists to dedicate their time and energy to cognitively and socially challenging responsibilities. Simultaneously, some pharmacy workers saw a decrease in the complexity and an increase in the routine intensity of their work (Barrett *et al.*, 2011). Similarly, the second example of robots in a logistic warehouse highlighted that a novel addition of a robot to an originally physical-task-intensive industry may contribute to an environment of alienation for workers who are already engaged in tasks alongside various other machines (Berlers *et al.*, 2023).

The main findings of our study align with a more pessimistic view of robotization on average. However, it is important to acknowledge that these conclusions are based on average results, and the impact of robotization may vary among workers. To explore this further, we examine whether the effects of increased exposure to robotization are consistent across different worker circumstances and socio-demographic groups. To this end, we use our 2SLS Model and introduce an interaction term between robot exposure and i) education levels (Table 6), ii) occupation levels (Table 7), and job tenure (Table 8).

First, Table 6 details that having a higher education degree does not seem to moderate the relationship between physical and routine tasks. Nevertheless, it significantly cushions the negative effect of robotization on abstract tasks and amplifies the negative effect of robotization on social tasks. In other words, the highly educated working in industries hit by robotization seem to be doing even fewer social tasks as a result. This could be due to the task modification aspects of technology - Industrial robots are capable of taking over tasks that include aspects of customer and client interaction. For example, in the automotive industry, robots not only assemble parts but can also perform quality checks that would have required skilled human oversight, thereby reducing the need for interaction between workers and clients. Alternatively, with robots taking over more tasks, there might be less need for collaboration among workers, which traditionally involves a high degree of social interaction.

Next, in Table 7, we include a binary variable representing high-skilled occupations (i.e., occupations falling within the first three one-digit ISCO occupational categories – managers, professionals, technicians, and associate professionals). Specifically, the impact on routine tasks is mitigated for workers in high-skilled occupations. Conversely, like with education, robotization appears to make tasks even less interactive for those with high-skilled occupations. We detect no significant moderation effects of working in a high-skilled occupation for physical or abstract tasks.

Finally, in Table 8, we show that robotization affects the tasks of both newcomers (i.e., those with less than one year on the job) and more established workers in the same way. This finding seems to point to the conclusion that worker self-selection into industries that would end up being automated does not seem to be the main driver of our findings. What we cannot fully rule out with this analysis is the potential for job switching between industries and the extent to which it drives our results. The potential for job switching across industries is arguably limited due to industry-specific human capital. For example, in a sample of about 9000 individuals in German worker-level data, Heß et al. (2023), find that 390 individuals switch out of high-automation potential occupations and 301 switch into high-automation potential occupations. Nevertheless, we acknowledge this possibility and we hope that future work can address it with access to finer-grained data.

7. Conclusion and discussion

This paper represents the first attempt to offer a worker-focused viewpoint on the impact of robotization on tasks, utilizing detailed information on workers' job content in conjunction with industry-level robotization data. Our findings indicate that robotization shifts workers' activities, making their jobs more routine and less abstract and social, but less physically demanding. Our results align with the so-called Polanyi effect, whereby robots partially replace workers' tasks, leaving the last bit of routine tasks to humans and making their jobs even more mundane. Taking a worker-level perspective provides more nuance and leads to a different conclusion about the implications of automation for tasks than looking at aggregate-level analyses (e.g., de Vries et al., 2021).

Specifically, while robots reduce the share of routine jobs in the economy as a whole and in the long run, for individual workers who keep their jobs, the tasks that remain to be done following robotization are less interesting and challenging, more routine, and less meaningful. Our findings complement recent work that suggests that robotization has decreased the physical burden of jobs (Gihleb *et al.*, 2022; Gunadi & Ruy, 2021). At the same time, robotization has made work more intense (Antón, Fernández-Macías, & Winter-Ebmer, 2023) and less meaningful and autonomous (Nikolova *et al.*, 2022), despite economy-wide increases in productivity (Graetz & Michaels, 2018; Gregory, Salomons & Zierahn, 2021). In addition, recent research suggests that robotization leads to a decline in training and lower acquisition of IT and soft business skills (Heß *et al.*,2023). Taken together, this evidence suggests that robotization negatively impacts job content, job quality, and training opportunities for workers, which paints a rather glum picture of the future of work. At the same time, our results and those of related papers show the *immediate to medium-run* consequences of automation on the task content of workers' jobs, while the long-run effects may differ. In other words, our results likely capture better the task displacement effects of technology while task creation aspects of technology and full worker adaptation have not yet taken place.

These results have important implications for labor market arrangements and the future of work, given the rise of new technologies related to Artificial Intelligence and Machine Learning, which have the potential to automate high-skilled jobs (Webb, 2019). As machines become more sophisticated, they will likely be able to perform tasks that were once considered highly skilled. This means that even high-skilled workers may be at risk of being displaced by automation, and the tasks that remain for workers may become even more routine and less fulfilling.

By using worker-level data, our empirical analysis enables a nuanced analysis of how robotization transforms the workplace, avoiding the limitations of broad task classifications based on occupational dictionaries. Our approach not only captures the granular heterogeneity in task content within occupations over time but emphasizes the significance of adopting a worker-centered viewpoint to gain a more comprehensive understanding of the labor market implications of automation, surpassing the constraints of occupational dictionaries.

At the same time, our paper leaves several opportune avenues for future research. Panel data tracking the same workers over time, documenting their tasks and employment history, would improve understanding of how workers adjust to technological shocks through job/industry switching or retraining/reskilling, and the subsequent adaptations in their tasks. In addition, employer-employee datasets that could also contribute information on company and management practices could further help shed light on the mechanisms underpinning our findings. Future analyses should also prioritize the incorporation and analysis of new technologies, such as AI. Our dataset has detailed information on tasks only until 2015, at which point AI was not a prominent technology. Furthermore, our dataset offers a limited time frame for studying the consequences of robotization. Alternative datasets, discussed in

Appendix B also have multiple limitations, related to the time span, country coverage, and task measures. Future data collection efforts are urgently needed to facilitate future explorations of how technology affects workers' tasks and how these experiences relate to the overall effects of technology in the economy.

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Table 1: Task indices – comparison between our measures and Autor and Dorn (O*NET)

<table>
<tr><th></th><th>Nikolova, Lepinteur and Cnossen, EWCS</th><th>Acemoglu and Autor (2011), O*NET</th><th>Correlation coefficients</th></tr>
<tr><td>Physical</td><td>1. Working in tiring or painful positions
2. Carrying or moving heavy loads</td><td>Non-routine manual physical
1. Operating vehicles, mechanized devices, or equipment
2. Spend time using hands to handle, control or feel objects, tools or controls
3. Manual dexterity
4. Spatial orientation</td><td>Full sample: 0.81
Analysis sample: 0.84</td></tr>
<tr><td>Routine</td><td>1. Frequency of repetitive hand or arm movements
2. Monotonous tasks
3. Work pace dependence on the automatic speed of a machine or movement of a product
4. Short repetitive tasks of less than 1 minute
5. short repetitive tasks of less than 10 minutes
6. Inability to choose or change the order of tasks
7. Inability to choose or change the speed or rate of work</td><td>Routine cognitive
1. Importance of repeating the same tasks
2. Importance of being exact or accurate
3. Structured v. Unstructured work (reverse)

Routine manual
1. Pace determined by the speed of equipment
2. Controlling machines and processes
3. Spend time making repetitive motions</td><td>Full sample: 0.72
Analysis sample: 0.61</td></tr>
<tr><td>Abstract</td><td>1. Solving unforeseen problems
2. Complex tasks
3. Learning new things
4. Frequency of applying own ideas at work</td><td>Non-routine cognitive: Analytical
1. Analyzing data/information
2. Thinking creatively
3. Interpreting information for others</td><td>Full sample: 0.76
Analysis sample: 0.81</td></tr>
<tr><td>Social</td><td>1. Frequency of dealing directly with non-employees, such as customers, pupils, passengers, patients, etc.
2. Handling angry clients, customers, patients, pupils, etc.
3. Work pace dependence on the demands of customers, pupils, patients, etc.
4. Supervising other employees</td><td>Non-routine cognitive: Interpersonal
1. Establishing and maintaining personal relationships
2. Guiding, directing, and motivating subordinates
3. Coaching/developing others
Non-routine manual: Interpersonal
1. Social perceptiveness (aware of others' reactions and understanding why they react as they do)</td><td>Full sample: 0.79
Analysis sample: 0.73</td></tr>
</table>

Notes: The table presents the variables used for creating the task indices in this paper (based on the EWCS) and those based on the O*NET in Acemoglu and Autor's replication files (2011). Data from the replication files from Autor and Dorn (2013), merged with correspondence tables between O*NET SOC occupation codes and ISCO-08, was used to compute the correlations between the indices in this paper and those in Acemoglu and Autor (2011). The IBS (Institute for Structural Research) prepared the correspondence tables. The correlations were computed at the 2-digit ISCO-08 level (i.e., the data was collapsed at the ISCO-08 level, and then the correlations were computed). The routine, abstract, social, and physical task indices in this paper are standardized at the European level prior to collapsing the data.

Table 2: Correlation matrix between the task indices for the analysis sample

	Physical	*Routine*	*Abstract*	*Social*
Physical	1.000			
Routine	0.343	1.000		
Abstract	-0.092	-0.177	1.000	
Social	-0.103	-0.191	0.347	1.000

Notes: N=16,862. The correlations are based on the individual analysis sample and using the sample weights

Table 3: OLS Wage Regressions of Log Monthly Earnings and Task Measures from EWCS and O*NET, at the worker level

	Log Monthly Earnings			
	(1)	(2)	(3)	(4)
Physical index EWCS	-0.032***	-0.016***	-0.015***	-0.014***
	(0.007)	(0.004)	(0.004)	(0.004)
Routine index EWCS	-0.036***	-0.018***	-0.017***	-0.017***
	(0.006)	(0.004)	(0.004)	(0.004)
Abstract index EWCS	0.157***	0.046***	0.045***	0.041***
	(0.010)	(0.004)	(0.004)	(0.004)
Social index EWCS	0.007	0.012***	0.016***	
	(0.008)	(0.004)	(0.004)	
Interactions with non-employees				-0.008*
				(0.004)
Dealing with angry clients				0.008*
				(0.004)
Customer-driven work-pace				0.006*
				(0.004)
Employee supervision				0.059***
				(0.004)
Physical index O*NET			-0.005	-0.020
			(0.015)	(0.016)
Routine index O*NET			-0.025*	-0.010
			(0.013)	(0.015)
Abstract index O*NET			0.120***	0.077***
			(0.018)	(0.021)
Social index O*NET			-0.039***	
			(0.012)	
Non-routine cognitive interpersonal O*NET				0.059**
				(0.024)
Non-routine manual interpersonal O*NET				-0.055***
				(0.014)
Individual controls	N	Y	Y	Y
Industry and occupation FE	N	Y	Y	Y
Country and year FE	Y	Y	Y	Y
Observations	35,769	35,769	35,769	35,769
Adj. R-squared	0.879	0.918	0.918	0.918

Notes: Standard errors in parentheses are clustered on the country*occupation level (200 categories). The monthly earnings are PPP-adjusted and log-transformed. All models include a constant and are weighted using the sampling weights. Models (2) and (3) include individual controls for age, gender, working hours, job tenure, company size, education, and industry and occupation fixed effects. See Tables 1-2 for variable definitions. All indices are standardized to have a mean of 0 and standard deviation of 1. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Summary statistics, analysis sample

Variable	Mean	Std. Dev	Min	Max
Physical index	-0.002	1.002	-1.081	1.301
Social index	0.013	1.000	-1.229	3.259
Abstract index	0.003	0.997	-2.395	1.015
Routine index	-0.009	0.997	-1.941	2.696
Robotization (IHS-transformed)	0.714	1.680	-5.836	6.727
ICT (IHS-transformed)	1.713	2.132	-7.310	8.919
Age group				
15-35	0.259	0.438	0	1
36-45	0.270	0.444	0	1
45-60	0.390	0.488	0	1
Over 60	0.076	0.265	0	1
Missing	0.004	0.064	0	1
Biological sex				
Female	0.405	0.491	0	1
Male	0.595	0.491	0	1
Quartile of hours worked				
Lowest	0.425	0.494	0	1
Q2	0.211	0.408	0	1
Q3	0.137	0.344	0	1
Q4	0.199	0.399	0	1
Missing	0.027	0.163	0	1
Education				
Primary or less	0.060	0.238	0	1
Secondary	0.547	0.498	0	1
Post-secondary/tertiary	0.355	0.478	0	1
Missing	0.038	0.191	0	1
Occupation				
Managers	0.055	0.228	0	1
Professional	0.215	0.411	0	1
Technicians and associate professionals	0.081	0.273	0	1
Clerical support workers	0.055	0.228	0	1
Service and sales workers	0.052	0.221	0	1
Skilled agricultural, forestry, and fishery workers	0.074	0.262	0	1
Craft related trades workers	0.267	0.442	0	1
Plant and machine operators and assemblers	0.102	0.303	0	1
Elementary occupations	0.095	0.293	0	1
Missing	0.003	0.053	0	1

Company size				
Less than 250 employees	0.633	0.482	0	1
250 or more employees	0.092	0.289	0	1
Missing	0.276	0.447	0	1
Job tenure				
1 year or less	0.138	0.345	0	1
2-5 years	0.254	0.435	0	1
6-10 years	0.192	0.394	0	1
11 or more years	0.395	0.489	0	1
Missing	0.021	0.143	0	1
Other jobs				
No	0.922	0.269	0	1
Yes	0.076	0.265	0	1
Missing	0.002	0.050	0	1

Notes: The table provides summary statistics for the variables used in the analyses. N=16,862. See Tables 1 and 2 for variable definitions.

Table 5: The effect of robotization on individual job tasks

	Physical Index			
	(1)	(2)	(3)	(4)
Change in Robot Density (per 10000 workers - IHS)	0.011	0.014	-0.006	-0.029**
	(0.012)	(0.012)	(0.005)	(0.014)
Change in ICT stock (per 10,000 workers)	.	Yes	Yes	Yes
Individual controls	.	.	Yes	Yes
KP Wald F-statistics	.	.	.	94.132
Elasticity	0.010	0.013	-0.006	-0.026
Observations	16,862	16,862	16,862	16,862
	Routine Index			
	(1)	(2)	(3)	(4)
Change in Robot Density (per 10000 workers - IHS)	0.083***	0.084***	0.042***	0.114***
	(0.013)	(0.013)	(0.008)	(0.015)
Change in ICT stock (per 10,000 workers)	.	Yes	Yes	Yes
Individual controls	.	.	Yes	Yes
KP Wald F-statistics	.	.	.	94.132
Elasticity	0.042	0.042	0.021	0.057
Observations	16,862	16,862	16,862	16,862
	Abstract Index			
	(1)	(2)	(3)	(4)
Change in Robot Density (per 10000 workers - IHS)	-0.038***	-0.039***	-0.020***	-0.052***
	(0.009)	(0.009)	(0.007)	(0.014)
Change in ICT stock (per 10,000 workers)	.	Yes	Yes	Yes
Individual controls	.	.	Yes	Yes
KP Wald F-statistics	.	.	.	94.132
Elasticity	-0.015	-0.016	-0.008	-0.021
Observations	16,862	16,862	16,862	16,862
	Social Index			
	(1)	(2)	(3)	(4)
Change in Robot Density (per 10000 workers - IHS)	-0.059***	-0.060***	-0.028***	-0.094***
	(0.013)	(0.013)	(0.008)	(0.019)
Change in ICT stock (per 10,000 workers)	.	Yes	Yes	Yes
Individual controls	.	.	Yes	Yes
KP Wald F-statistics	.	.	.	94.132
Elasticity	-0.046	-0.047	-0.022	-0.074
Observations	16,862	16,862	16,862	16,862

Notes: Standard errors in parentheses are clustered at the industry*country level. All dependent variables are standardized, with a mean of 0 and a standard deviation of 1. Columns (1) to (3) are OLS regressions, and Column (4) is a 2SLS regression where the instrument is the change in robot density in the same industry in all other countries except respondent's. All regressions include year and country FE. Individual controls are gender, age groups, education dummies, company size, working hours, having other jobs, occupation dummies, and tenure. The elasticity is computed based on the non-standardized dependent variables.

Table 6: The effect of robotization on individual job tasks, by skill level

	Physical (1)	Routine (2)	Abstract (3)	Social (4)
Change in Robot Density (per 10000 workers - IHS)	-0.050***	0.159***	-0.069***	-0.070***
	(0.019)	(0.021)	(0.020)	(0.023)
High-skilled Occupation* Change in Robot density	0.006	-0.061**	0.039	-0.064**
	(0.025)	(0.029)	(0.024)	(0.028)
High-skilled Occupation	-0.632***	-0.444***	0.461***	0.589***
	(0.042)	(0.037)	(0.039)	(0.043)
Change in ICT stock (per 10,000 workers)	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Observations	16,862	16,862	16,862	16,862

Notes: Standard errors in parentheses are clustered at the industry*country level. All regressions are based on a 2SLS estimation. All dependent variables are standardized, with a mean of 0 and a standard deviation of 1. All regressions include year and country FE. Individual controls are gender, age groups, education dummies, company size, working hours, having other jobs, and tenure. High-skilled occupations are Managers, Professional, and Technicians, and associate professionals. All other ISCO-08 occupations are coded as non-high-skilled.

Table 7: The effect of robotization on individual job tasks, by education levels

	Physical (1)	Routine (2)	Abstract (3)	Social (4)
Change in Robot Density (per 10000 workers - IHS)	0.115***	0.115***	-0.062***	-0.077***
	(0.015)	(0.016)	(0.016)	(0.018)
Post-secondary/Tertiary education* Change in Robot density	-0.010	-0.010	0.048**	-0.082**
	(0.026)	(0.026)	(0.023)	(0.040)
Post-secondary/Tertiary education	-0.300***	-0.217***	0.166***	0.221***
	(0.034)	(0.027)	(0.031)	(0.040)
Change in ICT stock (per 10,000 workers)	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Observations	16,862	16,862	16,862	16,862

Notes: Standard errors in parentheses are clustered at the industry*country level. All regressions are based on a 2SLS estimation. All dependent variables are standardized, with a mean of 0 and a standard deviation of 1. All regressions include year and country FE. Individual controls are gender, age groups, company size, working hours, having other jobs, occupation, and tenure.

Table 8: The effect of robotization on individual job tasks, by the number of years in the same job

	Physical (1)	Routine (2)	Abstract (3)	Social (4)
Change in Robot Density (per 10000 workers - IHS)	-0.033**	0.114***	-0.096***	-0.048***
	(0.014)	(0.016)	(0.021)	(0.015)
More than 1 year on the job* Change in Robot density	0.030	0.008	0.018	-0.017
	(0.021)	(0.030)	(0.023)	(0.025)
More than one year on the job	-0.068**	0.033	-0.140***	-0.147***
	(0.028)	(0.031)	(0.030)	(0.031)
Change in ICT stock (per 10,000 workers)	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Observations	16,511	16,511	16,511	16,511

Notes: Standard errors in parentheses are clustered at the industry*country level. All regressions are based on a 2SLS estimation. All dependent variables are standardized, with a mean of 0 and a standard deviation of 1. All regressions include year and country FE. Individual controls are gender, age groups, company size, working hours, having other jobs, occupation, and education. Observations with missing information on the tenure in the company are excluded from the analysis.

APPENDIX A

Table A1: Variable definitions of the main variables in the analysis

Variable	Explanation and coding
Dependent variables	
Routine tasks index	Index based on extracting the first component of a polychoric principal component analysis (PCA) using 7 items. The index is standardized to have a mean of 0 and a standard deviation of 1. Before the polychoric PCA analysis, all items were first standardized to have a mean of 0 and a standard deviation of 1. Specifically, the following 7 items were included (1) respondent's main paid job includes "Repetitive hand or arm movements", measured on a recoded response scale of 1= Never; 2 = Almost Never; 3 = Around 1/4 of the time; 4 = Around half of the time; 5 = Around 3/4 of the time; 6 = Almost all of the time; 7 = All of the time; (2) main paid job involving "monotonous tasks," measured as 0 = No and 1 = Yes; (3) respondent's pace of work dependent on the automatic speed of a machine or movement of a product, measured as 0 = No and 1 = Yes; (4) respondent's job involves short repetitive tasks of less than 1 minute, with 0 = No and 1 = Yes; (5) respondent's job involves short repetitive tasks of less than 10 minutes, measured as 0 = No and 1 = Yes; (6) respondent unable to choose or change order of tasks, whereby 0 = No (respondent is able to change those) and 1 = Yes (respondent unable to choose those); and (7) respondent unable to choose or change speed or rate of work, whereby 0 = No (respondent is able to change those) and 1 = Yes (respondent unable to choose those);
Abstract tasks index	Index based on extracting the first component of a polychoric principal component analysis (PCA) using 4 items. The index is standardized to have a mean of 0 and a standard deviation of 1. Before the polychoric PCA analysis, all items were first standardized to have a mean of 0 and a standard deviation of 1. The following items were included and related to whether the respondent's main paid job involves (1) solving unforeseen problems on their own, (2) complex tasks, (3) learning new things, and (4) the frequency of applying their own ideas at work. All variables are coded such that 0=No, 1=Yes.
Social tasks index	Index based on extracting the first component of a polychoric principal component analysis (PCA) using 4 items. The index is standardized to have a mean of 0 and a standard deviation of 1. Before the polychoric PCA analysis, all items were first standardized to have a mean of 0 and a standard deviation of 1. Specifically, the following 4 items were included (1) respondent's main paid job includes "Dealing directly with people who are not employees at your workplace, such as customers, passengers, pupils, patients, etc." measured on a recoded response scale of 1= Never; 2 = Almost Never; 3 = Around 1/4 of the time; 4 = Around half of the time; 5 = Around 3/4 of the time; 6 = Almost all of the time; 7 = All of the time; (2) main paid job involving "handling angry clients, customers, patients, pupils, etc." measured on a recoded response scale of 1= Never; 2 = Almost Never; 3 = Around 1/4 of the time; 4 = Around half of the time; 5 = Around 3/4 of the time; 6 = Almost all of the time; 7 = All of the time; (3) work pace dependent on the direct demands from people such as customers, pupils, patients, etc., whereby 0 = No and 1 = Yes and (4) whether the respondent supervises other employees.
Physical tasks index	Index based on extracting the first component of a polychoric principal component analysis (PCA) using 2 items. The index is standardized to have a mean of 0 and a standard deviation of 1. Before the polychoric PCA analysis, all items were first

	standardized to have a mean of 0 and a standard deviation of 1. Specifically, the following 2 items were included: (1) respondent's main paid job includes tiring or painful positions and (2) carrying or moving heavy loads, measured on a recoded response scale of 1= Never; 2 = Almost Never; 3 = Around 1/4 of the time; 4 = Around half of the time; 5 = Around 3/4 of the time; 6 = Almost all of the time; 7 = All of the time;
Key independent variable	
Robotization	The inverse hyperbolic sine transformation of the change in robot stocks between year t-5 and year t-1 in each industry and country, divided 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-5 and year t-1 in each industry and country, normalized by the number of workers (in 10,000s) in 2005 in that industry and country. Missing values are based on imputations from 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); respondent has other jobs (1=no, 2 = yes, 3 = missing information); occupation dummies (ISCO 08 one-digit categories, including a missing category); year dummies; country dummies.

Table A2: The effect of robotization on individual job tasks, with employment shares as weights

	Physical Index			
	(1)	(2)	(3)	(4)
Change in Robot Density (per 10000 workers - IHS)	0.035*	0.040**	-0.010	-0.031***
	(0.019)	(0.019)	(0.006)	(0.012)
Change in ICT stock (per 10,000 workers)	.	Yes	Yes	Yes
Individual controls	.	.	Yes	Yes
KP Wald F-statistics				125.580
Elasticity	0.032	0.037	-0.009	-0.028
Observations	15,966	15,966	15,966	15,966
	Routine Index			
	(1)	(2)	(3)	(4)
Change in Robot Density (per 10000 workers - IHS)	0.119***	0.122***	0.058***	0.117***
	(0.015)	(0.015)	(0.010)	(0.015)
Change in ICT stock (per 10,000 workers)	.	Yes	Yes	Yes
Individual controls	.	.	Yes	Yes
KP Wald F-statistics				125.580
Elasticity	0.060	0.061	0.029	0.059
Observations	15,966	15,966	15,966	15,966
	Abstract Index			
	(1)	(2)	(3)	(4)
Change in Robot Density (per 10000 workers - IHS)	-0.056***	-0.056***	-0.027***	-0.067***
	(0.010)	(0.010)	(0.008)	(0.015)
Change in ICT stock (per 10,000 workers)	.	Yes	Yes	Yes
Individual controls	.	.	Yes	Yes
KP Wald F-statistics				125.580
Elasticity	-0.023	-0.023	-0.011	-0.027
Observations	15,966	15,966	15,966	15,966
	Social Index			
	(1)	(2)	(3)	(4)
Change in Robot Density (per 10000 workers - IHS)	-0.097***	-0.099***	-0.042***	-0.114***
	(0.015)	(0.015)	(0.010)	(0.017)
Change in ICT stock (per 10,000 workers)	.	Yes	Yes	Yes
Individual controls	.	.	Yes	Yes
KP Wald F-statistics				125.580
Elasticity	-0.074	-0.076	-0.032	-.088
Observations	15,966	15,966	15,966	15,966

Notes: Standard errors in parentheses are clustered at the industry*country level. All dependent variables are standardized, with a mean of 0 and a standard deviation of 1. Columns (1) to (3) are OLS regressions, and Column (4) is a 2SLS regression where the instrument is the change in robot density in the same industry in all other countries except respondent's. All regressions include year and country FE. Individual controls are gender, age groups, education dummies, company size, working hours, having other jobs, occupation dummies, and tenure. The elasticity is computed based on the non-standardized dependent variables. The weight used is the country-specific employment share of each industry.

Table A3: The effect of robotization on individual job tasks, with instruments from Graetz and Michaels (2018)

	Physical (1)	Routine (2)	Abstract (3)	Social (4)
Change in Robot Density (per 10000 workers - IHS)	-0.037*	0.212***	-0.068***	-0.192***
	(0.019)	(0.031)	(0.019)	(0.032)
Change in ICT stock (per 10,000 workers)	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
KP Wald F-statistics	25.874	25.874	25.874	25.874
Elasticity	-0.033	0.107	-0.028	-0.150
Observations	16,862	16,862	16,862	16,862

Notes: Standard errors in parentheses are clustered at the industry*country level. All dependent variables are standardized, with a mean of 0 and a standard deviation of 1. All results are based on 2SLS regressions, where the instruments are based on Graetz and Michaels (2018). All regressions include year and country FE. Individual controls are gender, age groups, education dummies, company size, working hours, having other jobs, occupation dummies, and tenure. The elasticity is computed based on the non-standardized dependent variables.

Table A4: The effect of robotization on individual job tasks for each sub-component of the routine index

	Repetitive Movements	Monotonous Tasks	Work Pace Linked to Machine Speed	Short Repetitive Tasks (<1 Min)	Short Repetitive Tasks (<10 Min)	Lack of Task Order Control	Lack of Work Speed Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Robot Density (per 10000 workers - IHS)	0.018 (0.011)	0.040*** (0.012)	0.157*** (0.020)	0.031** (0.014)	0.035*** (0.012)	0.056*** (0.013)	0.069*** (0.013)
Change in ICT stock (per 10000 workers)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP Wald F-statistics	94.132	94.132	94.132	94.132	94.132	94.132	94.132
Elasticity	.010	.041	.263	.052	.041	.010	.041
Observations	16,862	16862	16,862	16,862	16,862	16862	16,862

Notes: Standard errors in parentheses are clustered at the industry*country level. All regressions are based on a 2SLS estimation. All dependent variables are standardized, with a mean of 0 and a standard deviation of 1. All regressions include year and country FE. Individual controls are gender, age groups, education dummies, company size, working hours, having other jobs, occupation, and tenure. See Tables 1 and 2 for variable definitions.

Table A5: The effect of robotization on individual job tasks for each sub-component of the abstract index

	Problem -solving (1)	Complex tasks (2)	Learning (3)	Applying own ideas (4)
Change in Robot Density	-0.057***	-0.016	-0.016	-0.076***
(per 10000 workers - IHS)	(0.014)	(0.014)	(0.012)	(0.015)
Change in ICT stock (per 10,000 workers)	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
KP Wald F-statistics	94.132	94.132	94.132	94.132
Elasticity	-0.028	-0.012	-0.011	-0.028
Observations	16,862	16,862	16,862	16,862

Notes: Standard errors in parentheses are clustered at the industry*country level. All regressions are based on a 2SLS estimation. All dependent variables are standardized, with a mean of 0 and a standard deviation of 1. All regressions include year and country FE. Individual controls are gender, age groups, education dummies, company size, working hours, having other jobs, occupation, and tenure. See Tables 1 and 2 for variable definitions.

Table A6: The effect of robotization on individual job tasks for each sub-component of the social index

	Interactions with non-employees (1)	Dealing with angry clients (2)	Customer-driven work-pace (3)	Employee supervision (4)
Change in Robot Density	-0.124***	-0.076***	-0.049***	0.016
(per 10000 workers - IHS)	(0.020)	(0.016)	(0.015)	(0.012)
Change in ICT stock (per 10000 workers)	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
KP Wald F-statistics	94.132	94.132	94.132	94.132
Elasticity	-0.084	-0.058	-0.043	0.036
Observations	16,862	16,862	16,862	16,862

Notes: Standard errors in parentheses are clustered at the industry*country level. All regressions are based on a 2SLS estimation. All dependent variables are standardized, with a mean of 0 and a standard deviation of 1. All regressions include year and country FE. Individual controls are gender, age groups, education dummies, company size, working hours, having other jobs, occupation, and tenure. See Tables 1 and 2 for variable definitions.

Table A7: The effect of robotization on individual job tasks for each sub-component of the physical index

	Tiring/painful positions (1)	Heavy loads (2)
Change in Robot Density	-0.038***	-0.022
(per 10000 workers - IHS)	(0.012)	(0.014)
Change in ICT stock (per 10,000 workers)	Yes	Yes
Individual controls	Yes	Yes
KP Wald F-statistics	94.132	94.132
Elasticity	-0.024	-0.015
Observations	16,862	16,862

Notes: Standard errors in parentheses are clustered at the industry*country level. All regressions are based on a 2SLS estimation. All dependent variables are standardized, with a mean of 0 and a standard deviation of 1. All regressions include year and country FE. Individual controls are gender, age groups, education dummies, company size, working hours, occupation, and tenure. See Tables 1 and 2 for variable definitions.

APPENDIX B
Details about Survey Datasets with Information on Individual Worker Skills and Activities

We detail the main datasets used in the literature to measure worker-level tasks. Interested readers should consult the overviews in Fernández-Macíasas and Bisello (2022) and Bisselo et al. (2021). Several surveys elicit information on job tasks and the content of work, along with collecting data on demographics, job characteristics, and job quality (Bisello et al., 2021). The main advantage of such datasets is that they offer information at the level of workers, rather than occupations, and allow to study nuances in the task content *within* and *between* occupations.

First, the Qualification and Career Survey by IAB/BIBB survey conducted every 6 years in Germany asks respondents about their main job duties and the tools and machines they use (Bisello et al., 2021). One disadvantage of this dataset is that the questions changed through the survey waves, thus limiting the comparability. Another disadvantage is the single-country focus.

Additional surveys that measure tasks at the worker level include the IAB 2014 survey implemented as part of the German National Educational Panel (NEPS), which is used to operationalize the measurement of analytic, interactive, manual, routine, and autonomy-demanding tasks. Another example is the Skills, Technology, and Management Practices (STAMP) survey in the US and its revised version as part of the Princeton Data Improvement Initiative (PDII) (Autor & Handel, 2013). The two surveys have limitations in terms of being only available for a small number of observations in the case of STAMP and only in the year 2008 in the case of PDII.

The PIAAC survey (OECD Survey of Adult Skills) is about respondents' proficiency in literacy, numeracy, and problem-solving in technological environments life. The initial survey was conducted in 2011/2012 in 24 economies, then in 9 economies in 2014/2015, and then in 6 economies in 2016/2017.

A final source, which is the one we use in this paper, is the European Working Conditions Survey (EWCS) conducted by the European Commission Foundation (Eurofound). Its main advantage over the only other cross-country dataset - the PIAAC -- is that the EWCS is available for more than one time period. Compared with the STAMP, PDII, and the BIBB, the EWCS is available for multiple European countries, rather than a single country.

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