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Industrial robots and workers' well-being in Europe

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Abstract: In the 21st century, advancements in technologies such as industrial robots have raised concerns about their impact on employment and wages, prompting extensive research. However, their effects on workers' subjective well-being remain underexplored. This study addresses this gap ¬by examining whether workers experience a decline in well-being due to a loss of agency or maintain it by leveraging human skills to adapt to automation. Using data from the International Federation of Robotics, Eurostat, and the European Social Survey (2002–2018), we link robot density at the country-industry-year level to workers' life satisfaction, happiness, job influence, and health. Employing an instrumental variables approach, we find that robot adoption negatively affects medium-educated workers' well-being, particularly its eudaimonic dimension, supporting the decreasing agency thesis. In contrast, low- and highly educated workers experience positive effects. These impacts are more pronounced among women and weaker in countries with robust compensatory social policies.

Keywords: industrial robots, well-being, life satisfaction, Europe, education

JEL codes: I31, O33

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1. Introduction

Concerns that automation will lead to widespread job losses date back at least two centuries to the onset of the Industrial Revolution (Mokyr et al., 2015). Although the Industrial Revolution initially had severe consequences for large segments of the population, it did not result in a long-term rise in aggregate unemployment (Frey, 2019). However, its benefits were unevenly distributed, primarily favouring those at the top of the wealth distribution (West, 2018; Iversen & Soskice, 2019; Acemoglu & Johnson, 2023).

In the twenty-first century, a new wave of anxiety over job displacement has emerged, driven by advancements in artificial intelligence and robotics (Brynjolfsson & McAfee, 2014). While several major international organisations (e.g. ILO, OECD, UNDP) have expressed concerns about the adoption of advanced industrial robots (Grimshaw, 2020), little is known about how technological change affects workers' well-being.

On the one hand, workers may recognise the disruptive potential of labour-displacing technologies and fear technological unemployment; on the other, they might also perceive new technologies as beneficial (Gallego et al., 2022). Against this backdrop, this study aims to enhance understanding of the effects of technological change on workers' well-being.

In line with this growing interest and the need to keep pace with real-world developments, this study focuses on a specific technology: industrial robots. More than other machines, robots embody technological innovation and serve as a key marker of contemporary technological change. Designed to perform versatile tasks without human intervention, industrial robots have been widely deployed in manufacturing and other industrial sectors. Their adoption has grown rapidly in Europe since the 1990s (see Figure 1) and remained resilient even during crises such as the Great Recession and the COVID-19 pandemic (Müller, 2024).

While the debate continues, considerable attention has been given to the economic winners and losers of robotization, particularly in terms of employment (Hötte & Theodorakopoulos, 2023). The displacement effect of robots—where tasks previously performed by human labour are substituted—has received empirical support in Europe (Graetz & Michaels, 2018), the United States (Acemoglu & Restrepo, 2020), and several Latin American countries (Carbonero et al., 2018; Brambilla et al., 2023). However, recent studies present more nuanced findings, reporting neutral effects (Dauth et al., 2021; Focacci, 2021) or even positive aggregate outcomes

(Acemoglu et al., 2020; Chung & Lee, 2023). Regarding employability, research suggests that robot exposure initially reduces employment but later fosters job creation.

Recently, scholars have adopted a more nuanced approach, examining the broader socioeconomic impacts of robots. Key areas of focus include their effects on the gender wage gap (Aksoy et al., 2021), fertility (Anelli et al., 2021b; Matysiak et al., 2023), mortality (O'Brien et al., 2022), support for the radical right (Anelli et al., 2021a), policy preferences (Gallego et al., 2022), and, more recently, workers' physical and mental health (Gihleb et al., 2022; Abeliansky et al., 2024) as well as substance abuse (Lu & Fan, 2024). Comparative studies highlight significant heterogeneities based on workers' education levels (e.g. Acemoglu & Restrepo, 2020), gender (e.g. Anelli et al., 2021), and institutional contexts (e.g. Matysiak et al., 2023).

Despite extensive research on the objective outcomes of robotization, its impact on workers' subjective well-being remains relatively underexplored (Martin & Hauret, 2020; Antón et al., 2023). This gap is somewhat surprising (Berg et al., 2023), given that workers increasingly interact with innovative technologies—particularly automation, industrial robots, and AI—experiencing significant non-monetary effects, including on subjective well-being. Understanding the subjective well-being of workers exposed to robotization, whether directly or indirectly, is crucial for both research and policy. These interactions shape individual and organizational outcomes, such as workplace performance and productivity, while also influencing broader social and political dynamics (Bliese et al., 2017). Indeed, these effects extend into the domestic sphere, affecting families, communities, and society at large (Chari et al., 2018).

This study seeks to address this gap by providing novel and complementary evidence on the implications of industrial robot adoption for workers' subjective well-being. A well-established relationship exists between the work environment and well-being (see Eurofound, 2019, for a review). Extensive evidence supports the spillover effect from work to overall life satisfaction, as work is not fully separate from other aspects of life (e.g. Sirgy et al., 2001; Green et al., 2024). Research indicates that workers' well-being extends beyond task performance and financial compensation. It also encompasses meaningful work, social connection, identity, workplace safety, health, and job security (e.g. Budd & Spencer, 2015).

Building on literature examining the well-being implications of technological change, we argue that robots affect various life domains that, in turn, influence workers' well-being, regardless of whether their adoption leads to aggregate job losses or employment growth. This argument is grounded in two competing perspectives on the impact of robotization on employed workers (i.e. those who are neither unemployed nor inactive, the focus of this study).

The first, which we term the *human leverage effect*, emphasises workers' superior capabilities over robots. Workers may experience—or anticipate—a comparative advantage due to their greater flexibility in performing new, more meaningful tasks, while robots take over physically demanding and hazardous work. Consequently, robotization is expected to enhance workers' well-being.

The second, which we call *decreasing workers' agency*, highlights the negative effects of robotization on job autonomy and the sense of purpose derived from work. Industrial robots may render certain jobs and skills obsolete, fostering anxiety about job security and diminishing workers' well-being (Dekker et al., 2017).

We expect that the relationship between robot adoption and workers' well-being depends on both individual characteristics and social context. In particular, and central to our contribution, we argue that the effects of robotization vary by workers' educational level. While significant attention has been given to the winners and losers of technological change in terms of education (Chiacchio et al., 2018; Dauth et al., 2021), less is known about the educational gradient of well-being outcomes. A key implication is that our analysis will be education-differentiated.

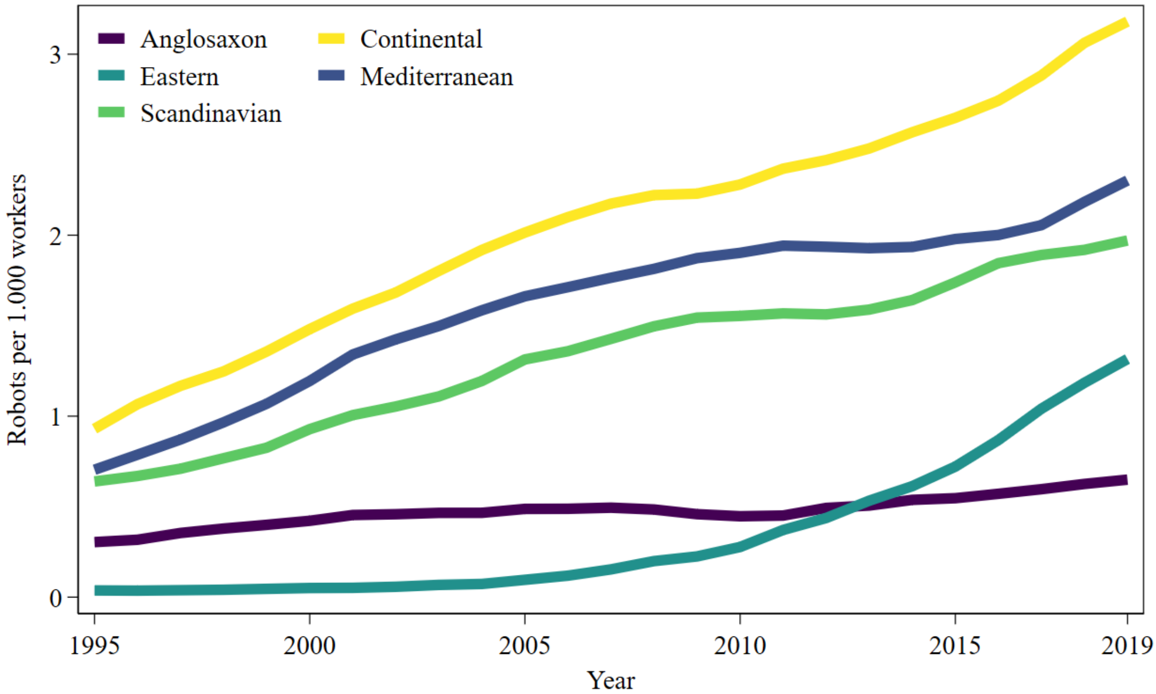
Beyond education, we contribute to the literature on the well-being effects of robotization by examining demographic disparities, specifically gender and age differences. Regarding gender, research indicates that women are overrepresented in medium-skilled jobs—those most vulnerable to technological change—at least in Europe (Brussevich et al., 2019; Piasna & Drahokoupil, 2017). Women also tend to perceive automation, including robotization, as less fair than men (Borwein et al., 2024) and have benefited less from robot-driven productivity gains (Aksoy et al., 2021).

Concerning age, studies suggest that younger workers may be more adversely affected by new technologies. In industries with a high incidence of robots, middle-educated youth face a longer adaptation period for acquiring new skills (Dauth et al., 2021; Lewandowski et al., 2020), bearing the cost of labour market adjustments. In contrast, older workers may be more engaged in task complementarity processes (Albinowski & Lewandowski, 2024).

Finally, we examine heterogeneity across countries. Few multi-country studies have investigated the effects of robots on sociodemographic dimensions, but those that have (e.g. Carbonero et al., 2020; Matysiak et al., 2023) reveal considerable variation, which is unsurprising given differences in institutional contexts. Figure 1 illustrates the distribution of robots across a selection of developed countries, with Germany (Continental) and Italy (Mediterranean) standing out due to their large automotive sectors. Although the automotive sector is a significant outlier in terms of robot adoption, similar upward trends are evident in other industries. This variation suggests that robotization rates are highly industry-specific, with national totals being heavily influenced by each country's industrial composition.

We find strong evidence supporting the *decreasing workers' agency* perspective among middle-skilled workers. Specifically, an increase in robot adoption adversely affects multiple dimensions of well-being among middle-educated workers, suggesting growing discontent within the middle class regarding technological innovation in the workplace. Moreover, our findings reveal that this educational gradient is accompanied by a gender disparity: the negative effects of robot adoption on well-being are significantly stronger for women, while for men they are smaller and largely statistically insignificant. In contrast, the impact of age is negligible. Finally, we highlight the crucial role of country-level institutional settings. The decline in life satisfaction among middle-educated workers is particularly pronounced in the UK and Eastern European countries, where weaker compensatory social policies, low union coverage, and decentralised labour unions may exacerbate these effects.

Figure 1. Robot density in Europe by country group and calendar year.



Notes: Calculated by dividing total robot stocks by employees in thousands in all industries. Country groups include countries listed in Table A1.
Sources: International Federation of Robotics (IFR) and Eurostat.

The remainder of the paper is structured as follows. Section 2 introduces the theoretical framework, while Section 3 outlines the moderating effects central to our analysis. Section 4 describes the data and provides descriptive evidence on the relationship between robotization and well-being across educational groups. Section 5 details our identification strategy and analytical methodology. In Section 6, we present our results, quantify the impact of robot adoption on the well-being of various demographic groups within different institutional contexts, and conduct robustness checks. Finally, Section 7 concludes.

2. The educational gradient in the link between robotization and well-being: theoretical framework

Subjective well-being has been conceptualised as comprising three distinct yet interrelated dimensions (Diener, 1984; Nikolova & Graham, 2020): evaluative well-being, which refers to an overall assessment of one's life and circumstances (life satisfaction); eudaimonic well-being, associated with a sense of purpose and autonomy; and hedonic well-being, which pertains to momentary feelings (happiness). Given that work constitutes a significant part of life, its influence necessarily spills over into these dimensions of subjective well-being (Green et al., 2024).

Life satisfaction, the first dimension of well-being, is closely associated with an individual's overall evaluation of their life. Among workers, studies have demonstrated that working conditions—such as job quality and job security—account for a significant proportion of the variation in life satisfaction (e.g. Drobnič et al., 2010; Williams et al., 2020). However, focusing exclusively on job satisfaction may not fully capture the broader relationship between employment and overall well-being (Rohenkohl & Clarke, 2023; Bellani & Bogusz, 2024).

The theoretical literature on the relationship between technological change (such as robotization) and life satisfaction has traditionally emphasised workers' skill levels and education as key factors. Proponents of the upskilling theory argue that automation increases the demand for highly skilled positions needed to manage the complexity of new technologies (Adler, 1992; Attewell, 1992). Similarly, the initial formulation of the skill-biased technological change (SBTC) framework posits that, in a simplified labour market model with three skill levels—low, medium, and high (Autor et al., 2003)—only low-educated workers suffer displacement effects, underemployment, and declining job quality, as technology tends to replace low-skilled labour (Katz & Murphy, 1992). More recently, proponents of routinization theory, who focus on the content of work, contend that routine manual (low-skilled) workers are less affected by new technologies, as automation does not typically substitute or complement the low-paying service jobs in which many less-educated workers are employed (Autor et al., 1998; Autor, 2015). Consequently, it is the middle of the skill distribution that faces the greatest potential for job destruction, owing to the high risk of substitution of routine tasks, which are generally the easiest to automate (Autor et al., 2003; Goos & Manning, 2007). These routine tasks are commonly performed by middle-skilled workers in sectors such as manufacturing, clerical occupations, and sales, which are often accessible to non-college-educated individuals (Autor et al., 2003). Collectively, these processes are predicted to result in employment and wage losses for workers with medium education (Goos et al., 2014). For some, this may entail finding a new job if they are displaced by robot adoption and experience qualification downgrading (Dahlin, 2019; Cuccu & Royuela, 2024); for those who remain employed, it requires acquiring new skills to adapt to plant-level restructuring driven by robotization (Cirillo et al., 2021). Either scenario can incur significant harms, generating substantial long-term job insecurity (Furman, 2019). Moreover, adapting to robotics technology, as in other automation processes, may induce excessive cognitive load, thereby reducing job satisfaction (Nazareno & Schiff, 2021). Overall, middle-educated workers are likely to experience a decline in life satisfaction.

We now turn to the second dimension of well-being, the eudaimonic aspect. Robots can influence the meaningfulness and fulfilment derived from work by affecting workers' autonomy and discretion over their tasks, and by shaping their perception of having choices and authority over their actions (Nikolova & Cnossen, 2020). These factors provide intrinsic benefits to job quality (e.g. Green, 2005) and, by extension, to overall well-being. When considering the relationship between robot adoption and workers' eudaimonic well-being, two competing theoretical perspectives emerge.

Even when workers are not immediately unemployed, robots can potentially reduce employees' control over work content and processes (Artuc et al., 2023). Likewise, workers' ability to choose when and how to apply their skills and capabilities may be hindered (Gombolay et al., 2015). By taking over tasks traditionally performed by humans or reducing task diversity, robots could increase the risk of heteronomy—a condition in which individuals perceive their work as governed by externally imposed forces (Nikolova & Cnossen, 2020). Replacing tasks without affording workers control over these processes can diminish their sense of autonomy. Moreover, if task replacement is not accompanied by a top-down shift towards more meaningful work, workers may experience a reduced sense of purpose and a diminished perception of their agency. According to this perspective, the creative destruction inherent in robotization is likely to particularly affect those workers whose skills are most vulnerable to becoming heteronomous.

Recent sociological perspectives, however, challenge the notion that work—particularly assembly work—is becoming less meaningful and that workers are increasingly marginalised from managerial decision-making when robots are adopted (Vrontis et al., 2023). Drawing on Polanyi's concept of living human capacity (Polanyi, 1958), several scholars emphasise the importance of human capabilities in increasingly complex manufacturing processes driven by robotization and other technological advancements. Workers' tacit knowledge—comprising skills and expertise that are difficult to replicate in robots—plays a crucial role in maintaining autonomy and control during the adoption of new technologies (Lei, 2022). Researchers analysing the electronics and manufacturing industries highlight that certain tasks remain difficult for robots lacking artificial intelligence (AI) to replicate, given their limited capacity to operate in unpredictable environments—especially in roles that involve human interaction (Webb, 2020). Dahlin (2019) argues that while easily automatable manufacturing jobs have already been replaced, the remaining occupations foster a degree of symbiosis between humans and robots. Acemoglu and Restrepo (2020) further suggest that these technologies may replace human labour in certain tasks, yet they do not result in significant productivity gains. Collins (2010) notes that tasks requiring collective tacit knowledge and autonomy—attributes possessed not only by highly skilled workers but also by technicians and medium-skilled workers—are particularly resistant to automation. Certain tasks, such as those requiring dexterity, remain difficult for robots to perform (Lei, 2022). This, in turn, reinforces the agency of workers most directly exposed to robotization—particularly those with a medium level of education—in influencing managerial decisions (Vrontis et al., 2022). Consequently, workers' participation in the social organization of work and their involvement in decision-making regarding adjustments to the division of labour between humans and machines are likely to be enhanced, leading to increased job meaningfulness and autonomy.

To the best of our knowledge, the empirical evidence in this regard is both scarce and mixed. One study examining European data over the decade 1995–2005 finds no effect of robotization on workers' discretion (Anton et al., 2023), while another study, based on data from a limited number of years (2010, 2015 and 2021), reports that the introduction of robots negatively affects work meaningfulness and autonomy (Nikolova et al., 2024).

The third dimension, hedonic subjective well-being, refers to feelings typically associated with short-term circumstances—such as happiness, anxiety, and stress—and pertains to mood rather than an overall life evaluation (Steptoe et al., 2015). As studies have shown, this dimension can be influenced by technological change processes (Tirabeni, 2024), including robot adoption. On one hand, exposure to robotization is likely to increase uncertainty among workers, thereby intensifying their feelings of stress and anxiety. Workers may be concerned about the disruptive potential of technological advances (Innocenti & Golin, 2022); this fear of robotization can significantly decrease their happiness. In a country-specific study, Schwabe and Castellacci (2020) observed that, from 2016 to 2019, the introduction of industrial robots in local labour markets in Norway increased workers' fear of machine replacement. Moreover, workers might feel threatened by robots even in sectors where they have not yet been introduced (Yam et al., 2021). On the other hand, by replacing dangerous or dirty tasks and reducing physically demanding work and job intensity (Gunadi & Ryu, 2021; Gihleb et al., 2022), robots can potentially improve subjective health and other correlates of happiness (Spencer, 2018). Thus, the hedonic dimension, alongside perceived health, can significantly influence workers' overall well-being, particularly among those more directly exposed to robotization—namely, those in the middle of the skill distribution.

Given the multifaceted nature of well-being, we expect to observe the impacts of robot adoption across various outcomes, including life satisfaction, job influence, happiness, and subjective health. Our guiding hypothesis integrates two competing frameworks—the *human leverage effect* and *decreasing workers' agency*. Under the *human leverage effect*, industrial robot adoption is anticipated to enhance well-being, whereas decreased workers' agency is expected to diminish it. We hypothesize that workers in the middle of the skill distribution, being most directly involved in these processes, will be particularly affected.

It is also important to note that, consistent with the socio-tropic framework (e.g. Kinder & Kiewiet, 1981; Mansfield & Mutz, 2009), technological innovation such as robot adoption can shape the attitudes and well-being of those not directly involved. This occurs because individuals' perceptions and anxieties regarding economic shocks are informed by collective-level information rather than solely by personal self-interest. Indeed, workers may express concern about technology-induced shocks even if they are not personally exposed, provided that their collective (e.g. educational group) is exposed. Borwein and colleagues (2024) report that education is more influential in addressing individuals' anxieties than, for example, skill level.

3. Moderating factors

The debate surrounding the effects of industrial robots on well-being indicates that the mixed results in studies arise because robot adoption produces contrasting experiences for different workers. These variations depend not only on educational level but also on factors characterising the broader socio-economic environment (Nikolova et al., 2024). Consequently, it is essential to consider the role of crucial moderating factors, such as sociodemographics, industrial sectors, and institutional settings.

3.1 Gender and age

The educational gradient of the impact of robots on workers' well-being can differ by gender. Scholars have explored various mechanisms through which gender inequality in well-being may emerge when technological changes occur. On the one hand, some scholars argue that female workers are at a higher risk of job displacement during robotization because they are generally assigned more routine tasks—characterised by less flexibility, fewer learning opportunities, and greater repetitiveness—and perform fewer tasks that require analytical, interpersonal, or physical skills compared with men (Aksoy et al., 2021). This expectation is also supported by Brussevich et al. (2019) and Piasna & Drahokoupil (2017), who indicate that women in Europe are more frequently employed in medium-skilled, routine jobs, which are among the most vulnerable to robotization. Accordingly, one could expect a negative impact on life satisfaction, particularly among middle-educated women.

Following the same reasoning, scholars expect that women may experience a decrease in autonomy and a diminished sense of self-determination amid robotization, whereas men's perceptions of their competencies and the meaningfulness of their work may be enhanced (Nikolova et al., 2024). Additionally, women may perceive technological change differently, which in turn significantly influences the hedonic dimension of well-being. This issue was recently explored by Borwein et al. (2024), who argue that, because women are more sensitive to economic volatility and labour market shocks, they exhibit a less positive orientation towards workplace automation. Empirically, they show that, in a sample of 10 developed countries, women tend to perceive the fairness of automation more negatively than men.

In addition, the impact of robot adoption on well-being can differ considerably across worker age groups (Dauth et al., 2021; Deng et al., 2024). On the one hand, young workers are better positioned to adapt to the tasks demanded by new technologies (Bosma et al., 2003). On the other hand, younger production workers may be particularly vulnerable, as they often perform relatively simple routine tasks that can be easily automated (Acemoglu & Restrepo, 2020).

Empirical evidence from Deng et al. (2024) indicates that employment for young workers increases with robot adoption primarily among low- and middle-skilled individuals, whereas gains for technicians, engineers, and managers are predominantly observed among middle-aged and older workers. Accordingly, it is expected that increased robot adoption will be associated with higher levels of well-being among young workers who are middle- or high-skilled.

3.2 Industries

Another moderating factor essential for unpacking the relationship between robotization and well-being is the industrial sector in which workers are employed. In theory, the impact of robot adoption should be more straightforward for workers in the manufacturing sector, who directly experience its effects on productivity, displacement, and the creation of new tasks (Chung & Lee, 2023). Empirically, Acemoglu and Restrepo (2020) and Chung and Lee (2023) have demonstrated that, in the United States, the employment effects of robots are concentrated primarily in the automotive industry. Moreover, scholars have shown that workers in sectors such as manufacturing and mining are typically middle-skilled and engaged in high-intensity routine and manual tasks—areas particularly susceptible to robotization (Hardy et al., 2018). The automotive sector, along with logistics activities, is also more prone to the so-called 'business stealing effect', whereby innovative adopters gain market share at the expense of non-innovators. In summary, robotization can affect manufacturing and non-manufacturing industries differently, generating heterogeneous spill-over (or cross-over) effects on well-being.

3.3 Institutional context

The relationship between robot adoption and well-being is expected to vary across societal contexts. Comparative welfare state research suggests that robot adoption has a less detrimental impact on workers in countries where institutions buffer the negative side effects of technological change. This is the case in nations where welfare states are more protective of workers' conditions and compensate for adverse effects, and where organised labour and collective bargaining have the power to mitigate a direct association between technological shocks and declining socio-economic conditions (Parolin, 2020).

During periods of rapid technological change, welfare state policies—particularly compensatory social policies (such as unemployment benefits) and protective regulatory policies (such as Employment Protection Legislation (EPL) and the minimum wage)—are expected to influence the relationship between large-scale labour market transformations and workers' conditions (Vlandas et al., 2022; Buseymer & Tober, 2023). In line with this reasoning, one could argue that compensatory social policies, which reduce the costs associated with realised risks, together with protective policies, which prevent or mitigate the materialization of risks, can alleviate the adverse effects of robot adoption on well-being. These policies not only protect individuals facing objective risks but also mitigate the perception of risk—for example, by reducing anxiety about the potential impact of robotization.

Concerning compensatory social policies, the literature indicates that more generous unemployment benefits are associated with a nuanced impact on job loss resulting from technological change and a lower level of perceived job insecurity (Dekker et al., 2017). In countries with large, well-developed welfare states (e.g. Scandinavian countries) (Esping-Andersen, 1990), substantial unemployment benefits are likely to mitigate the adverse effects of job loss by reducing reliance on the labour market for economic survival. This may explain why individuals report lower levels of perceived job insecurity in environments characterised by higher public social spending (Mau et al., 2012).

Regarding regulatory protective policies, as conceptualised by Levy-Faur (2013, 2014), scholars have demonstrated that such measures can buffer the negative side effects of technological change (e.g. Cutuli & Tomelleri, 2023). Research suggests that employees in countries with stronger employment protection laws—such as those in Continental nations compared with Eastern or Anglosaxon countries—tend to feel more secure in their jobs (Anderson & Pontusson, 2007), as restrictive Employment Protection Legislation (EPL) prevents employers from dismissing workers (Vlandas & Halikiopoulou, 2022). However, this protective effect may not extend to contexts where welfare provision is generous only for insiders, potentially leading to precariousness for others (e.g. in Germany, France, Italy and Spain). These considerations are crucial for understanding the heterogeneous effects that the institutional context may have on well-being.

A recent study has shown that middle-educated workers who fear that their jobs will be lost due to technological change demand short-term compensatory and protective policies, such as increased unemployment benefits (Busemeyer et al., 2023). Thus, workers residing in more residual welfare states—namely, liberal and Eastern European countries—are likely to be more apprehensive about labour market risks induced by technological change and more concerned about their broader economic impact, with subsequent adverse effects on their well-being (Thewissen & Rueda, 2019).

Moreover, the literature suggests that another form of regulatory protection concerns labour relations (Anderson & Pountsson, 2007). Higher rates of union membership—and its spill-over effects on non-unionised workers—are likely to safeguard workers' conditions in the face of technological shocks (Lordan & Neumark, 2017). The adoption of robotics and other advanced digital tools, as well as the pace of their implementation, is significantly influenced by the presence of employee representation mechanisms, such as unions and works councils (Doellgast et al., 2009; Haapanala et al., 2022). Research has demonstrated that trade unions can mitigate significant occupational and structural shifts induced by technological advancements (Fernandez, 2001; Kristal & Cohen, 2017; Kristal & Edler, 2021). For example, the bargaining power of trade unions in negotiations with major automotive companies is vital for ensuring the reassignment of displaced workers, for instance by facilitating internal flexibility (Streeck, 1984). Studies indicate that employee representation increases the likelihood of receiving employer-funded training (e.g. Adolfsson et al., 2022), thereby facilitating the reallocation of tasks. Furthermore, research in Europe has shown that the presence of trade unions promotes specific work systems and practices—such as training, time management, and information-sharing—that complement the adoption of new technologies (Belloc et al., 2023). In contexts where trade unions are particularly influential, such as in Scandinavian and Western European countries, coordinated wage bargaining and the development of firm-specific skills foster incremental product innovations while maintaining a degree of job security even amidst technological advancements (Bosch & Schmitz-Kießler, 2020; Haipeter, 2020). Greater union coverage also translates into increased bargaining power in negotiations with the government and other social partners during industrial transformations.

We recognize that cross-country differences in the association between robot adoption and well-being may stem from factors beyond welfare state arrangements, such as variations in national discourses surrounding robotization and differences in the balance of objective and perceived risks associated with this transformation (e.g. Arntz et al., 2016). However, we expect that the institutional context—characterised by compensatory social policies, protective regulatory policies, and effective labour organisation—will be the most salient factor in explaining cross-national differences (see also Busemeyer & Tober, 2023). We argue that the institutional mixture is particularly influential when individuals evaluate the potential impact of robotization on their life circumstances. Therefore, we propose that a country's welfare state context—defined by its overall generosity and the balance between social investment and compensatory measures, as well as organised labour—plays a key role in workers' well-being (Di Tella et al., 2003), especially in times of technological shocks.

Given that the survey data in this study covers 24 countries with diverse welfare state arrangements, we can assess the extent to which existing institutional contexts influence individual-level well-being patterns, although a detailed quantitative analysis of cross-country differences is not feasible due to the limited number of cases. More specifically, Scandinavian countries are characterised by generous compensatory social policies and relatively lower regulatory protective policies (offset by a high prevalence of active labour market policies) alongside high to medium union density. Continental countries, in contrast, are marked by lower levels of compensatory social policies and higher levels of regulatory protective policies—particularly in terms of Employment Protection Legislation (EPL) for permanent workers—and, in some cases, minimum wage legislation (with Austria and Switzerland notably lacking a statutory minimum wage), combined with medium-high union coverage. Mediterranean countries exhibit a dualistic pattern regarding both EPL and compensatory social policies, with insiders receiving greater benefits, and generally maintain medium levels of union coverage. Finally, liberal and Eastern European countries are characterised by low levels of both compensatory and regulatory protective policies as well as generally low union coverage (Zwysen & Drahokoupil, 2024), with such policies also being fully decentralised (Haapanala et al., 2022).

4. Data

Our study utilises individual-level data from the European Social Survey (ESS ERIC, 2018a, 2018b, 2023a-2023g), a cross-sectional survey with a representative sample conducted biennially since 2002, which has involved participation from 39 countries at least once. All survey waves include consistent questions on well-being, thereby enabling a pseudo-panel analysis. We focus on the first nine rounds of the survey (2002–2018) to exclude the impacts of the COVID-19 pandemic.

To merge the individual-level ESS data with robot density—constructed using industry-level data from the International Federation of Robotics and Eurostat—we limit our ESS sample to countries that report robot stocks to the International Federation of Robotics. This approach encompasses all countries that participated in the ESS at least once, totalling 24 countries (see Table A1 in the Appendix). We restrict our sample to employed individuals aged 15 to 64, ensuring that gender, age, nationality, and the ESS-constructed analytic weights are non-missing (with less than 1% of observations discarded). Our final sample comprises 236,151 observations, with some data missing at random (up to 19% of observations, depending on the variable). To address this, we apply multiple imputation with chained equations (MICE).

We operationalize the three dimensions of well-being using distinct indicators. For the evaluative dimension, we focus on life satisfaction, while for the hedonic dimension, we focus on happiness. Both are assessed on an ordinal scale from 0 to 10, with higher scores indicating greater well-being. Respondents are asked: “How satisfied are you with life as a whole?” and “How happy are you?”. Additionally, we include an indicator of subjective health—self-reported health—which is originally measured on a Likert scale from 1 to 5 (with 1 denoting “very good” and 5 indicating “very bad”). We reverse this scale to facilitate interpretation of results.

For the eudaimonic dimension, we draw on a measure of work autonomy from the ESS. In the survey, job control is assessed by the statement: "I'm allowed to influence policy decisions about activities of the organisation," and is measured on an ordinal scale from 0 to 10, where 0 indicates no influence and 10 indicates complete control. This indicator reflects the degree of influence or power that workers have over the policy decisions within their organisations (see Huijts et al., 2017; Warr, 2017).

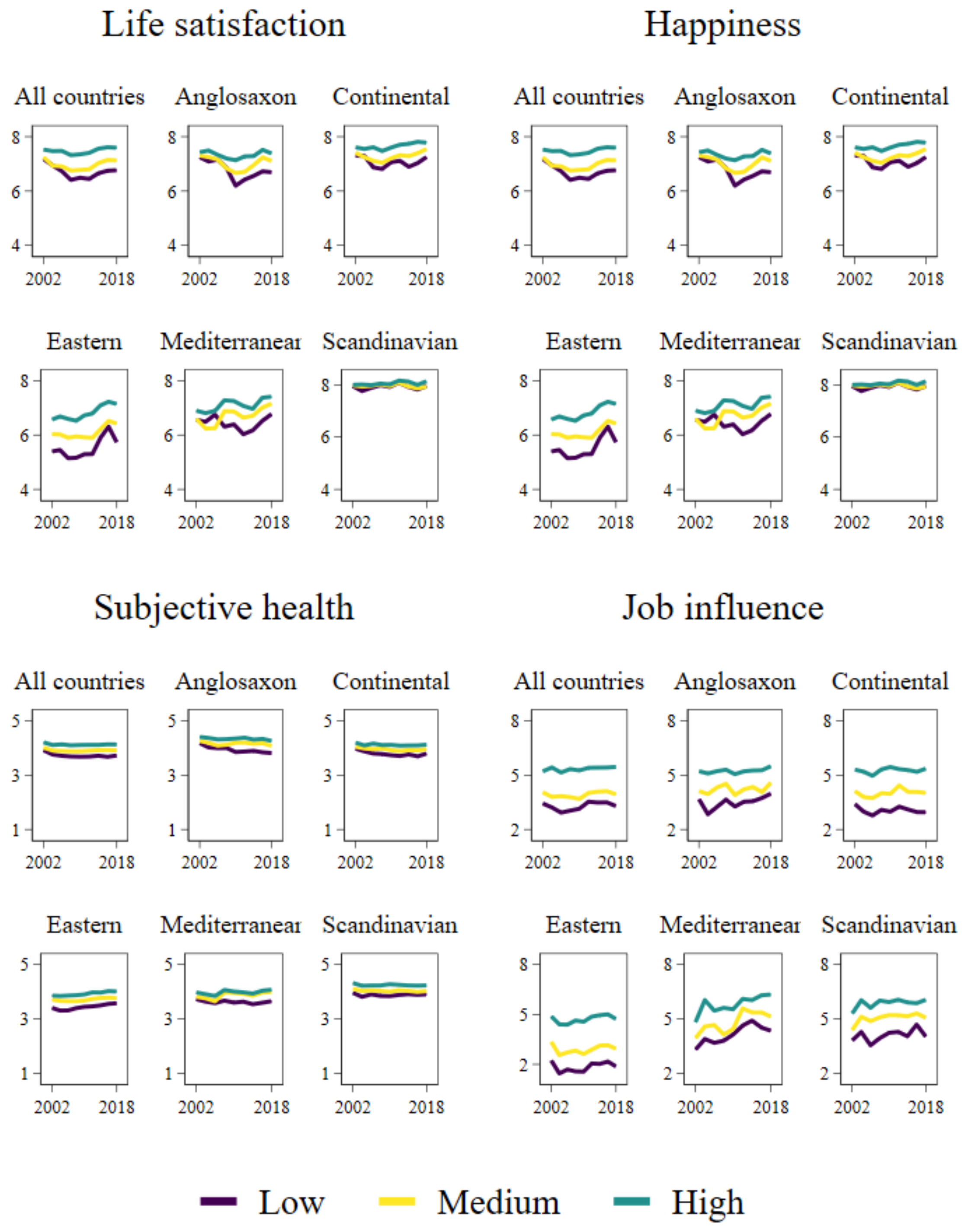
Using four measures enables us to capture the multifaceted nature of subjective well-being and confers methodological advantages. Single-measure methodologies have been criticised because variations stemming from question wording cannot be isolated (Diener, 1984). Consequently, results based on a single measure may be susceptible to biases such as acquiescence or social desirability.

Additionally, we include the following sociodemographic control variables: gender (binary, male or female, as reported in the ESS); age and age squared (in years); education (measured using ISCED and aggregated into low, medium, and high levels) as a proxy for skill (see, for example, Nikolova et al., 2024); and migration background (indicated by domestic or foreign citizenship). Education is also included as a moderator.

Figure 2 presents the average responses to the four dimensions of well-being, segmented by education level, country group, and calendar year. All measures of well-being are stratified by education level: highly educated workers report the highest levels of well-being, followed by middle-educated and then low-educated individuals. These disparities are least pronounced in Scandinavian countries, which also report the highest overall well-being among all welfare regimes (Easterlin & O'Connor, 2022). In contrast, Eastern European countries exhibit the lowest, albeit increasing, levels of well-being. Moreover, we observe a decline in certain dimensions of workers' well-being—namely life satisfaction and happiness—in Anglo-Saxon and Mediterranean countries during the Great Recession, particularly among low-educated individuals in Italy, Portugal, and Spain. This trend aligns with expectations given the rising unemployment and inactivity in these countries during the economic crisis (Biegert & Ebbinghaus, 2022; Bozio et al., 2015). Continental countries display stable trends for middle- and highly educated workers, although a noticeable decline for low-educated workers coincides with the onset of the Great Recession.

To compute robot density—a measure of workers' exposure to automation (see details in Section 5)—we utilize robot stocks data from the International Federation of Robotics (IFR). The IFR provides annual data on the operational stock of industrial robots by country and industry from 1993 to 2019 (International Federation of Robotics, 2020). Industries are classified according to the International Standard Industrial Classification (ISIC) of All Economic Activities (United Nations, 2008). This comprehensive dataset includes robot stock records at the 1-digit level for various industries, including agriculture, forestry, mining, manufacturing, electricity, gas, water supply, construction, and services. We link the robot data to employment structures by industry using the methodology detailed in Section 6. Eurostat has publicly provided country-level employment structures by 1-digit industry codes—classified according to NACE Rev. 1.1 (for periods prior to 2008)—since 1993 (Eurostat, 2023). We reclassify these data to the ISIC framework to ensure consistency with the robot stocks data.

Figure 2. Well-being of workers by measure, education, welfare regime, and calendar period.



Notes: Country groups include countries listed in Table A1.
Sources: European Social Survey 2002-2018.

5. Methods

Our methodology relies on regressing measures of well-being on robot density and a set of sociodemographic controls (as detailed in Section 4) for a sample of 24 European countries. We then perform separate analyses for each country group—Anglosaxon, Continental, Eastern

European, Mediterranean, and Scandinavian—to examine how the relationship between robot density and well-being varies across different welfare regimes.

We construct robot density at the country-industry-year level as a measure of workers' exposure to automation. Most studies on the labour market consequences of robotization rely on regional analyses, quantifying robot adoption through a Bartik instrument that decomposes country-industry robot stocks onto regions using regional employment structures (e.g. Acemoglu & Restrepo, 2020; Dauth et al., 2021). However, the measurement of workers' exposure to automation is not limited to regional analyses; for example, Graetz and Michaels (2018) employ a country-industry measure. This approach can also be applied in our study, where well-being is measured at the individual level, allowing us to merge robot density data with survey responses by country, year, and the industry in which the worker is employed.

To calculate robot density, we utilize robot stocks from the International Federation of Robotics and aggregate employment data from Eurostat. Robot density is defined as the number of industrial robots installed in a specific country *c*, in industry *i*, in a given year *t*, divided by the number of workers (in thousands) in that country-industry during a baseline period *t0*—which corresponds to the 1990s or early 2000s, depending on the country. Mathematically, this is expressed as:

$$\text{robot density}_t^{c,i} = \frac{\text{robot stocks}_t^{c,i}}{\frac{\text{workers}_{t0}^{c,i}}{1000}}.$$

This formulation provides a measure of workers' exposure to automation by standardising robot stocks relative to the employment size in the corresponding industry and country at the onset of robotization. Similarly to the regional-level Bartik instrument, the employment structure used in calculating robot density is measured before the onset of robotization, ensuring that the only potentially endogenous component is the robot stocks. We set *t0* to the earliest point in time for which employment data by country and industry are available from Eurostat. For early robot adopters such as Germany or Italy, this baseline is 1993, whereas for late adopters like Poland—where earlier industry-level employment data are unavailable—the baseline is set at 2002.

A further concern regarding the endogeneity of robot density arises if external factors simultaneously affect both robot adoption and workers' well-being. Such shocks may be continental (e.g. recession), domestic (e.g. country-level policies), regional (e.g. changes in employment structure), or sectoral (e.g. increased unionisation). To address this issue, we instrument robot density in European countries using two measures, whereby we divide robot stocks in Japan and South Korea by employment in Europe:

$$\text{instrument}_t^{\text{JP,i}} = \frac{\text{robot stocks}_t^{\text{JP,i}}}{\frac{\text{workers}_{t0}^{c,i}}{1000}};$$

$$\text{instrument}_t^{\text{KR,i}} = \frac{\text{robot stocks}_t^{\text{KR,i}}}{\frac{\text{workers}_{t0}^{c,i}}{1000}}.$$

This strategy for addressing the endogeneity of workers' exposure to robots was introduced by Acemoglu and Restrepo (2020) and has been widely adopted in other studies on robot adoption (e.g. Graetz & Michaels, 2018; Matysiak et al., 2023). We use robot stocks in Japan and South Korea because these countries (together with Germany) are forerunners of robot adoption worldwide, and robot implementation in Europe is theoretically expected to follow their patterns. At the same time, robot stocks in these countries are unlikely to have a direct impact on workers' well-being in Europe. In our methodology, we follow Dauth et al. (2021) to construct an overidentified IV model using these two instruments.

One further concern is that Japan and South Korea primarily adopt robots in the electronics sector, whereas most European countries install robots mainly in the automotive industry. However, robot adoption in electronics has been increasing in Europe (International Federation of Robotics, 2020). Moreover, identifying a suitable instrument for robot density in Europe is challenging, as most countries with similar cultural and developmental profiles—such as the United States, Canada or Australia—adopt industrial robots to a much smaller extent than European countries (International Federation of Robotics, 2020). One strategy documented in the literature is to estimate models for each European country separately, using robot adoption in other European countries as an instrument for robotization (e.g. Matysiak et al., 2023). However, such an approach is not feasible when estimating models across multiple European countries, and one of the objectives of this paper is to compare country groups. Although it remains unclear whether Europe will indeed follow the robot adoption patterns of the two Asian forerunners, we demonstrate in the online supplementary material that these instruments are both relevant and strong in our IV regressions. To test the instruments' relevance, we compute the Kleibergen–Paap rk Wald F statistic (Kleibergen & Paap, 2006).

Our model takes the following form:

$$Y = \alpha + \beta\ (\text{robot density}\ \times\ \text{education}) + \gamma\ \text{robot density} + \delta\ \text{education} + \theta\, X + \varepsilon,$$

where X represents a set of control variables, including age, age squared, gender, migration background (native or migrant), as well as country and year fixed effects. We estimate this model using two-stage least squares (2SLS/IV) regression. The dependent variable Y denotes each of the following well-being measures—life satisfaction, job influence, happiness, and subjective health—and we estimate separate models for each outcome.

We interact robot density with education (categorised as low, medium and high) to test our hypothesis that robots exert a heterogeneous effect on workers according to their skill level. Next, we re-estimate the model separately for women, men, younger and older workers, as well as for those employed in manufacturing. This approach enables us to test expectations drawn from the literature—that women and younger workers are more affected by industrial robot adoption than men and older workers, and that the impact of automation is larger in the manufacturing sector. Finally, we run the model separately for each welfare state type to verify whether institutional safety nets can mitigate the adverse impact of robots on well-being.

6. Results

Tables 1 and 2 present the coefficients for the interaction between robot density and education. We observe a stratified impact of robot density on workers' well-being, with effects varying by education level. In a 2SLS model estimated on the full sample of countries, an increase of one robot per 1,000 workers is associated with a decrease in life satisfaction among middle-educated workers of –0.012 (SE = 0.005) on a scale from 0 to 10. The corresponding negative effects on happiness and subjective health are –0.008 (SE = 0.005) and –0.005 (SE = 0.002), respectively, while the impact on job influence is considerably larger at –0.184 (SE = 0.02).

In contrast, one additional robot per 1,000 workers increases life satisfaction and happiness among low-educated workers by 0.019 (SE = 0.005) and 0.014 (SE = 0.003), respectively, and among highly educated workers by 0.005 (SE = 0.005) and 0.003 (SE = 0.005). Moreover, an additional robot per 1,000 workers raises the subjective health of highly educated workers by 0.004 (SE = 0.002) and their job influence by 0.158 (SE = 0.019). We do not, however, find statistically significant effects of robot adoption on subjective health and job influence among low-educated workers. In summary, both high- and low-educated workers tend to experience a more favourable impact on well-being relative to middle-educated workers, holding all else constant.

These results support the hypothesis of a U-shaped relationship between robot adoption and well-being across education levels. In particular, the evidence for middle-educated workers is consistent with the *decreasing workers' agency* hypothesis: this group—whether directly or indirectly exposed to robotization, as suggested by the socio-tropic perspective—suffers more in terms of well-being. Furthermore, the effects are slightly larger for life satisfaction than for happiness or subjective health, suggesting that the implications of robot adoption extend beyond immediate economic outcomes. Notably, the effect on job influence is an order of magnitude larger, which indicates that robot adoption may substantially undermine the eudaimonic dimension of well-being among medium-skilled workers by reducing their job control and limiting their participation in the social organization of work.

Next, we investigate gender differences in the impact of robot density on well-being. The results for the overall sample are consistent with the main models, with statistical significance evident for women (see Table 1). Specifically, one additional robot per 1,000 workers is associated with a decrease in life satisfaction among medium-educated women (coefficient = –0.034, SE = 0.004). Conversely, for low-educated and highly-educated women, robot density is associated with increases in life satisfaction by 0.04 (SE = 0.004) and 0.025 (SE = 0.003), respectively. This U-shaped relationship is also observed for the other three well-being dimensions among women. In contrast, the corresponding estimates for men are generally smaller and not statistically significant, with the exception of job influence. Among middle-educated workers, the effect on job influence for men is approximately half that observed for women, although it remains significant at the 1% level. Overall, these findings suggest that middle-educated women are more sensitive to increases in robot adoption. The most pronounced gender differences are related to subjective health and, especially, life satisfaction—indicating that evaluative well-being is the primary driver of the U-shaped relationship observed in the data.

Moreover, we observe that the educational gradient does not vary substantially by age (Table 1). For all four well-being dimensions examined, medium-educated workers report a decrease in well-being with increased robot adoption, regardless of age group. Specifically, both younger workers (under 35) and older workers (35 or more) exhibit declines in job influence of a similar magnitude (–0.174 with SE = 0.015 for those under 35, and –0.188 with SE = 0.023 for those aged 35 or older), while the impact on the other well-being domains is marginally larger for the younger cohort. Notably, highly-educated workers who are relatively young also report a significant negative coefficient with respect to life satisfaction. This finding is consistent with the idea that the benefits of robotization may accrue primarily to highly skilled workers with more work experience.

Next, we restrict our sample to workers employed in manufacturing (Table 1), which represents approximately 16% of the total sample. In this sector, we observe negative effects of increased robot adoption on job influence and happiness for medium-educated workers, while no significant effects emerge for the other educational groups. In particular, for the dimension of job influence, the coefficient for medium-educated workers in the manufacturing sector is –0.174 (SE = 0.072), compared to –0.184 (SE = 0.020) for the overall sample. These findings suggest that medium-educated workers, who are arguably the most vulnerable to robotization in a sector highly susceptible to technological change, experience a substantial reduction in work autonomy. Moreover, this group reports a significant decline in the hedonic dimension of well-being, which may be explained by an upsurge in negative feelings such as stress and pain. Notably, we do not find statistically significant effects for medium-educated workers in manufacturing with respect to the other two well-being domains, namely life satisfaction and subjective health.

Finally, we examine how the overall effects of robot density on workers' well-being vary by institutional context, revealing notable heterogeneities (Table 2). With respect to the evaluative dimension, our analysis shows that robots exert a negative and statistically significant effect on the life satisfaction of middle-educated workers in Anglosaxon (–0.026) and Eastern countries (–0.028). A negative, albeit smaller, coefficient is observed in Scandinavian countries (–0.01) and in Continental countries (–0.003, not significant). In Mediterranean countries, however, the effect is positive and statistically significant for middle-educated workers (0.013), but negative for highly-educated workers (–0.021).

A clearer pattern emerges for the eudaimonic dimension: the U-shaped relationship associated with the educational gradient is evident across all country groups, with larger coefficients in Anglosaxon and Eastern European countries. In general, the U-shaped pattern also holds for the hedonic dimension. However, for highly-educated workers in Mediterranean countries, we observe a decrease in hedonic well-being, whereas middle-educated workers experience the opposite effect. This suggests that highly-educated workers in strongly dualistic labour markets may suffer a decline in hedonic well-being as robot adoption increases.

Additional analyses by age (Table A3) indicate that the non-negative effects observed in Mediterranean and Continental countries are driven primarily by workers aged under 35. In these groups, the coefficients for robot density are generally larger for younger workers than for older workers, which is consistent with previous studies reporting that labour market entrants are more affected by robot adoption. In Continental and Mediterranean countries, the impact of robot adoption on the well-being of middle-educated workers under 35 is positive, contrasting with the effects observed in other country groups. Notably, these two country groups also exhibit the highest robot density rates in our sample (see Figure 1).

A recent study by Chung and Lee (2023) demonstrated that robot adoption increases employment at advanced stages of technological progress by creating new tasks—particularly in the automotive industry, where most robots are installed in Continental and Mediterranean countries. Similarly, Deng et al. (2024) reported that young workers are most likely to benefit from the reinstatement effect of robot adoption. We interpret these findings as indicating that the positive effect of robot density on the well-being of middle-educated workers in Continental and Mediterranean countries may reflect the higher employment and task-reallocation opportunities afforded to young workers in sectors with high levels of robot adoption.

The results for the subjective health dimension generally follow the overall educational gradient, although the effects are more mixed in more liberal economies. In these contexts, highly-educated workers tend to experience a negative impact from an increase in robot adoption, whereas middle-educated workers exhibit the opposite pattern.

It is clear that, overall, middle-educated workers in Scandinavian and Continental countries experience a smaller impact from robot adoption compared to their counterparts in other European regions. One might speculate that, in Scandinavian countries, the generosity of compensatory social policies combined with robust labour organization mitigates the effects of robotization on both affective and hedonic well-being. In Continental countries, the configuration of labour organization appears particularly effective in countering the loss of work meaningfulness associated with technological transformation, thereby ensuring that middle-educated workers are not disproportionately disadvantaged.

However, even though the magnitude of the coefficients is smaller in these regions, the effects are not negligible; certain groups may still face challenges in adapting to new forms of automation and potential shifts in well-being. By contrast, in Anglosaxon countries, middle-educated workers are the most adversely affected by robot adoption—the magnitude of the coefficients is higher than in other country groups. Notably, in these countries, highly educated workers experience the most positive impact on three out of the four well-being dimensions, with subjective health being the only exception.

Table 1. Effects of robot density on well-being of workers by education and demographic group. Estimates from instrumental variables regression (2SLS) where robot density is interacted with education.

	Life satisfaction (0-10)					
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	.019***	.007	.04***	.021***	.017***	-.019
	(.005)	(.004)	(.004)	(.005)	(.006)	(.014)
Middle-educated	-.012**	.001	-.034***	-.01	-.013***	-.069
	(.005)	(.005)	(.004)	(.006)	(.005)	(.049)
Highly-educated	.005	-.009	.025***	-.005*	.008	.024
	(.005)	(.006)	(.003)	(.003)	(.006)	(.018)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.085	.083	.087	.062	.093	.094
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	Job influence (0-10)					
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	.005	.023	-.013	.02	0	0
	(.014)	(.019)	(.011)	(.015)	(.021)	(.02)
Middle-educated	-.184***	-.171***	-.213***	-.174***	-.188***	-.174**
	(.02)	(.027)	(.013)	(.015)	(.023)	(.072)
Highly-educated	.152***	.133***	.195***	.131***	.16***	-.002
	(.019)	(.025)	(.014)	(.018)	(.02)	(.027)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.096	.097	.087	.085	.091	.135
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	Happiness (0-10)					
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	.014***	.012***	.018***	.007	.016***	-.002
	(.003)	(.003)	(.003)	(.006)	(.003)	(.012)
Middle-educated	-.008	-.001	-.017***	-.004	-.009*	-.096**
	(.005)	(.005)	(.004)	(.005)	(.005)	(.042)
Highly-educated	.003	-.006	.016***	.003	.001	.007
	(.005)	(.007)	(.003)	(.003)	(.007)	(.016)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.058	.057	.058	.04	.064	.061
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	Subjective health (1-5)					
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	0	-.003	.004***	.003	-.001	-.003
	(.002)	(.003)	(.001)	(.003)	(.002)	(.005)
Middle-educated	-.005*	0	-.011***	-.004***	-.005*	.029
	(.002)	(.004)	(.002)	(.001)	(.003)	(.018)
Highly-educated	.004*	-.001	.011***	.002***	.004	.003
	(.002)	(.004)	(.001)	(.001)	(.003)	(.007)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.123	.125	.121	.041	.101	.139
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Controls include: age, age squared, gender, migration background.

Table 2. Effects of robot density on well-being of workers by education and welfare regime. Estimates from instrumental variables regression (2SLS) where robot density is interacted with education.

	Life satisfaction (0-10)				
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	0	.007	-.021	.004	.019***
	(.022)	(.007)	(.023)	(.003)	(.002)
Middle-educated	-.026*	-.003	-.028***	.013***	-.01***
	(.015)	(.002)	(.01)	(.005)	(.002)
Highly-educated	.017***	.002	-.003	-.021***	.011***
	(.006)	(.005)	(.008)	(.005)	(.001)
Observations	26580	73057	61492	25294	43057
R-squared	.015	.084	.112	.058	.023
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
	Job influence (0-10)				
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	-.003	-.046***	-.194	-.016	-.021***
	(.018)	(.012)	(.175)	(.017)	(.003)
Middle-educated	-.54***	-.106***	-.305***	-.085***	-.111***
	(.128)	(.016)	(.032)	(.005)	(.018)
Highly-educated	.518***	.054***	.209***	.052***	.079***
	(.09)	(.01)	(.045)	(.002)	(.013)
Observations	26580	73057	61492	25294	43057
R-squared	.074	.086	.077	.083	.105
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
	Happiness (0-10)				
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	-.017	.008***	-.015	.01***	.012***
	(.017)	(.003)	(.012)	(.003)	(.002)
Middle-educated	-.007	-.002	-.013	.01**	-.005***
	(.015)	(.002)	(.009)	(.005)	(.002)
Highly-educated	.031***	-.01*	.005	-.021***	.004**
	(.006)	(.005)	(.005)	(.006)	(.001)
Observations	26580	73057	61492	25294	43057
R-squared	.015	.038	.088	.056	.017
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
	Subjective health (1-5)				
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	-.076***	-.003**	.008	.004***	.013***
	(.016)	(.001)	(.005)	(.001)	(.001)
Middle-educated	.026***	0	-.018***	-.008***	-.007***
	(.005)	(.002)	(.003)	(.002)	(.001)
Highly-educated	-.056***	.005***	-.007***	.003*	.01***
	(.01)	(.001)	(.001)	(.002)	(.001)
Observations	26580	73057	61492	25294	43057
R-squared	.064	.106	.226	.135	.068
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

*Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*
Controls include: age, age squared, gender, migration background.

7. Discussion

Industrial robot adoption has significantly altered the conditions of participation in the labour market by rendering certain jobs redundant while simultaneously creating new opportunities for other workers. Previous literature has provided extensive evidence regarding the impact of robot adoption on employment, wages, and various socioeconomic phenomena, including the gender wage gap, fertility, and voting behaviour. A notable contribution of this study is its dual focus on assessing the impact of robotization on workers' subjective well-being—a hitherto overlooked outcome—and on analysing the associated socio-demographic gradients. In particular, we have estimated the effects of robot density on different dimensions of workers' well-being, taking into account heterogeneity by skill level (proxied by education), gender, age, and institutional setting.

The theoretical literature presents two contrasting scenarios. On one hand, the *human leverage effect* emphasises the unique strengths of workers relative to robots. Humans possess a clear comparative advantage owing to their adaptability and their ability to perform innovative and meaningful tasks, even as routine physical activities are increasingly delegated to automation. On the other hand, the framework we refer to as *decreasing workers' agency* highlights the adverse effects of rising robotization on job autonomy and on the sense of fulfilment derived from work. This perspective also underscores the potential for industrial robots to render certain jobs and skills obsolete, thereby heightening fears of unemployment and job insecurity.

Our results indicate that while robot adoption tends to diminish well-being among medium-educated workers, it appears to enhance well-being for both low- and highly-educated workers. This stratified effect underscores the importance of considering skill levels when discussing the consequences of automation, reflecting the hypothesis that technological changes can yield both positive and negative outcomes within the labour market. Notably, we find relatively larger estimates of the effect of robotization on well-being for the dimension related to job autonomy, compared with the other measures (even after rescaling). The eudaimonic dimension of well-being appears to be the most affected by robotization. On the one hand, this finding suggests that industrial robots may limit workers' autonomy when robots and algorithms dictate tasks and workflow (Gombolay et al., 2015). On the other hand, it indicates that the de-unionization of the workforce and the consequent weakening of labour organisations play a crucial role in explaining this decline—particularly among medium-educated workers, who are predominantly employed in the manufacturing sector. The lack of effective top-down agreements to facilitate a transition towards more meaningful work in the context of robotization may result in workers experiencing a diminished sense of purpose and a reduced perception of their own agency. In contrast, the *human leverage effect* hypothesis is confirmed for both low- and highly-educated workers. As suggested by previous studies (Dekker et al., 2017), the robotization shock appears to boost evaluative well-being among highly-educated workers, who are likely to reap the benefits of automation—for example, by experiencing a greater sense of contribution through the adoption of robots (Nikolova et al., 2024). Similarly, the impact on well-being is positive for low-educated workers; those at the lower end of the skill distribution, who are typically engaged in services that are difficult to robotise, do not experience any direct effect on their job autonomy, and may benefit from rising earnings and increased employment shares.

Furthermore, our analysis demonstrates that women's subjective well-being is far more affected by robotization than that of men. This finding is in line with previous studies indicating that women's employment is more negatively impacted by robot adoption (e.g. Aksoy et al., 2021) and that women tend to perceive automation more negatively than men (Borwein et al., 2024).

Our study raises a policy-relevant question: what can be done to mitigate the negative well-being effects experienced by medium-skilled workers? Our analysis of the moderating influence of the institutional environment provides partial answers. On the one hand, it suggests that both compensatory social policies and regulatory protection through robust labour organisation—characteristic of Scandinavian and Continental countries—are associated with better protection and support for workers, leading to less negative well-being outcomes for medium-educated workers. However, it is important to note that even in these countries the impact of robotization remains inequitable, adversely affecting medium-educated workers while enhancing the well-being of both low- and highly-educated workers. On the other hand, our findings indicate that in liberal market economies, workers with high levels of education receive greater robotization premia in terms of well-being, whereas the other educational groups experience negative, or at times negligible, impacts. In these economies, the adoption of technology appears to boost employment at advanced stages of technological development by generating new tasks particularly suited to younger, more recently trained workers.

Based on these findings, we argue that despite recent criticisms of traditional approaches—which have been accused of overlooking the convergence of liberalising trends across different capitalist models (Baccaro & Howell, 2017)—the notion that institutional heterogeneity drives significant cross-country differences in well-being in Europe remains valid. Nonetheless, a distinct yet significant convergence is emerging, leading to a polarization of workers' well-being across all institutional contexts, primarily driven by a (perceived or objective) decline in job control.

There are several limitations to this study. First, it relies on pooled cross-sectional data, making it impossible to track the labour market status of individuals over time. Consequently, the analysis had to be restricted to employed individuals, as we lack information on the last industry in which unemployed individuals worked. Although longitudinal data would be preferable to address this issue, panel surveys rarely include questions on well-being and are usually country-specific, which hinders comparative analysis. Second, we focus on industrial robot adoption due to data availability and to benchmark our study against previous literature on automation, which frequently operationalises automation through robot use. However, this approach might underestimate the extent of actual automation in some sectors, such as mechanical engineering, where automation often relies on machine tools rather than robots. This shortcoming may be resolved as more comprehensive data become available to researchers.

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Appendix

Table A1. Countries used in the analysis by country group, years they are available in the European Social Survey, and the number of observations for those countries in the restricted sample.

Country group	Country	Years available	Observations
Anglosaxon	Ireland	All (2002-2018)	13,515
Anglosaxon	United Kingdom	All (2012-2018)	13,065
Continental	Austria	All except 2012	11,866
Continental	Belgium	All (2012-2018)	10,573
Continental	France	All (2012-2018)	10,196
Continental	Germany	All (2012-2018)	13,888
Continental	Netherlands	All (2012-2018)	11,764
Continental	Switzerland	All (2012-2018)	10,759
Eastern	Bulgaria	2006-2012, 2018	6,450
Eastern	Czech Republic	All except 2006	11,357
Eastern	Estonia	All except 2002	10,070
Eastern	Hungary	All (2012-2018)	7,433
Eastern	Lithuania	2008-2018	5,980
Eastern	Latvia	2006, 2008, 2014, 2018	1,944
Eastern	Poland	All (2012-2018)	10,340
Eastern	Romania	2006, 2008, 2018	1,126
Eastern	Slovakia	2004-2012, 2018	6,335
Mediterranean	Italy	2002, 2004, 2012, 2016, 2018	4,129
Mediterranean	Portugal	All (2012-2018)	9,331
Mediterranean	Spain	All (2012-2018)	9,894
Scandinavian	Denmark	All except 2016	8,600
Scandinavian	Finland	All (2012-2018)	11,788
Scandinavian	Norway	All (2012-2018)	10,795
Scandinavian	Sweden	All (2012-2018)	10,006

Table A2. Effects of robot density on well-being of workers by education and demographic group. Estimates from ordinary least squares (OLS) regression where robot density is interacted with education.

			Life satisfaction (0-10)			
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	.009*	.007*	.009**	.015***	.007	-.011**
	(.004)	(.003)	(.002)	(.003)	(.005)	(.005)
Middle-educated	.004	.007	.001	.007*	.003	.016*
	(.004)	(.005)	(.002)	(.003)	(.005)	(.009)
Highly-educated	.002	-.003	.007**	-.003*	.003	-.003
	(.002)	(.002)	(.002)	(.001)	(.003)	(.006)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.085	.083	.088	.063	.094	.096
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
			Job influence (0-10)			
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	-.004	.025**	-.044***	.013*	-.009	.018**
	(.007)	(.009)	(.007)	(.006)	(.01)	(.008)
Middle-educated	-.081***	-.084***	-.079***	-.066***	-.088***	-.022*
	(.006)	(.007)	(.003)	(.004)	(.007)	(.013)
Highly-educated	.044***	.036***	.065***	.024***	.05***	-.034***
	(.007)	(.008)	(.007)	(.006)	(.008)	(.009)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.103	.104	.095	.093	.098	.138
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
			Happiness (0-10)			
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	.008**	.014***	-.004**	.007**	.009**	-.002
	(.002)	(.002)	(.001)	(.002)	(.002)	(.004)
Middle-educated	.002	.003	.003*	.005**	.001	.003
	(.003)	(.004)	(.001)	(.002)	(.004)	(.008)
Highly-educated	-.004	-.005	-.005**	-.007***	-.003	-.01*
	(.003)	(.003)	(.002)	(.001)	(.004)	(.005)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.058	.057	.059	.04	.064	.066
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
			Subjective health (1-5)			
	All	Men	Women	Under 35	35 or older	Manufacturing
Low-educated	0	.003***	-.008***	.003**	-.001	-.002
	(.001)	(.001)	(0)	(.001)	(.001)	(.002)
Middle-educated	-.002	-.001	.001	0**	-.002	-.005
	(.001)	(.001)	(0)	(0)	(.001)	(.003)
Highly-educated	.003**	.004***	0	.001**	.004**	.004*
	(.001)	(.001)	(.001)	(0)	(.001)	(.002)
Observations	229480	110852	118628	73177	156303	37666
R-squared	.123	.125	.122	.042	.102	.141
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Controls include: age, age squared, gender, migration background.

Table A3. Effects of robot density on well-being of workers by education and welfare regime for workers aged under 35 years old. Estimates from instrumental variables regression (2SLS) where robot density is interacted with education.

	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Life satisfaction (0-10)					
Low-educated	.341***	.006	-.029	.003	.026***
	(.015)	(.011)	(.02)	(.009)	(.002)
Middle-educated	-.167***	.003*	-.005	.03***	-.02***
	(.024)	(.001)	(.027)	(.004)	(.004)
Highly-educated	.096***	-.004	-.034***	-.049***	.01***
	(.035)	(.005)	(.012)	(.003)	(.003)
Observations	8659	23127	18542	7983	14866
R-squared	.015	.065	.092	.042	.025
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Job influence (0-10)					
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	.099**	-.042***	-.096	.03*	-.051***
	(.041)	(.01)	(.077)	(.016)	(.005)
Middle-educated	-.438***	-.11***	-.327***	-.09***	-.078***
	(.08)	(.012)	(.03)	(.009)	(.014)
Highly-educated	.271***	.094***	.176***	-.004	.031***
	(.071)	(.012)	(.049)	(.006)	(.011)
Observations	8659	23127	18542	7983	14866
R-squared	.082	.081	.068	.072	.094
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Happiness (0-10)					
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	.263***	-.005	-.001	-.011	.001
	(.017)	(.009)	(.013)	(.007)	(.003)
Middle-educated	-.122***	.001	.02	.029***	-.011***
	(.018)	(.002)	(.019)	(.003)	(.003)
Highly-educated	.118***	-.004	-.034***	-.028***	.002
	(.04)	(.003)	(.008)	(.003)	(.003)
Observations	8659	23127	18542	7983	14866
R-squared	.013	.031	.056	.055	.016
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Subjective health (1-5)					
	Anglosaxon	Continental	Eastern	Mediterranean	Scandinavian
Low-educated	-.068***	-.003	0	-.002	.017***
	(.006)	(.005)	(.006)	(.002)	(.001)
Middle-educated	.045***	.001	-.027***	.003***	-.012***
	(.011)	(.002)	(.003)	(.001)	(.001)
Highly-educated	-.047***	.006***	-.004***	-.007***	.006***
	(.012)	(.001)	(.002)	(.001)	(.001)
Observations	8659	23127	18542	7983	14866
R-squared	.024	.049	.062	.041	.029
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

*Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Controls include: age, age squared, gender, migration background.

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