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The impact of robots on workplace injuries and deaths: Empirical evidence from Europe

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The impact of robots on workplace injuries and deaths: Empirical evidence from Europe

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Abstract

This paper examines the impact of robotisation on workplace safety in EU manufacturing sectors between 2011 and 2019. To address endogeneity concerns, we employ an instrumental variable approach and find that robot adoption reduces both injuries and fatalities. Specifically, a 10% increase in robot adoption is associated with a 0.066% reduction in fatalities and a 1.96% decrease in injuries. Our findings highlight the context-dependent nature of these effects. The safety benefits of robotisation materialise only in high-tech sectors and in countries where industrial relations provide strong worker protections. In contrast, in traditional industries and countries with weaker institutional frameworks, these benefits remain largely unrealised. The results are robust to several sensitivity tests.

Keywords: EU, robotisation, technology, workplace safety, injuries, fatalities, industrial relations

JEL Codes: J01, J08, J28, J50, J81, L60, O33

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1 Introduction

Every 15 seconds, a worker dies as a result of a work-related accident or occupational disease, while 153 workers experience an injury. Annually, 317 million workplace accidents occur, resulting in long periods of absence from work. The human cost of these tragedies is immense, while, according to the ILO, the economic burden of inadequate workplace safety amounts to 4% of global GDP each year (ILO, 2023). As a result, improving workplace safety is a fundamental policy concern. In the EU, occupational health and safety (H&S) is included among the 20 principles of the 'Pillar of Social Rights', as European workers are expected to benefit from 'a high level of protection of their health and safety at work.' Key policy actions include: criminal and financial penalties for non-compliance with safety protocols (e.g., companies failing to adopt legally required preventive and protective measures, workers failing to use personal protective equipment); mandatory safety plans at the plant-level; increased inspections by H&S authorities and compulsory H&S-related training (Uguina and Ruiz, 2019).

Technological and organisational change are key to reducing the risk of hazardous events (Shah and Mishra, 2024). First of all, process innovations are expected to increase efficiency. This implies modernising the production-technological apparatus by making it more transparent and controllable; reducing the risk of machine breakdowns and malfunctions (Karwowski et al., 1988); and redefining organisational practices, minimising unforeseen circumstances, including accidents, which may hinder production activities. In this respect, automation technologies and, in particular, robots can play an important role. By replacing workers in risky and physically demanding tasks, robots may reduce the number of work-related accidents. Likewise, they can help workers to perform complex tasks and improve the ergonomics of production equipment and tools. More specifically, robots can replace workers carrying out repetitive tasks (Gunadi and Ryu, 2021), reducing the incidence of musculoskeletal problems (Schneider and Irastorza, 2010).

Yet, the positive impact of robots on H&S is not guaranteed. In the absence of firm-

specific investments allowing to increase organisational efficiency (e.g., updating workflows, communication and worker-machine interaction protocols) and, most importantly, lacking adequate training programs, the impact of robots might be minimal or even negative (Sanders et al., 2024).¹ On the other hand, robotisation could accelerate the pace of work (Giuntella et al., 2025), contributing to the fragmentation of the production process and reducing workers' awareness regarding the various stages of production and their purposes (Braverman, 1974; Liu, 2023; Giuntella et al., 2023). If this is the case, the outcome can be worsening working conditions and increasing H&S risks. Heterogeneity matters, too. Robotisation-driven efficiency gains leading to organisational upgrading and improvements in terms of H&S are likely to materialise in high-tech industries and value chain segments where competitive strategies are based on product quality, improving skills and enhancing the company's reputation (Pianta, 2001). Conversely, if process innovations are primarily aimed at disciplining workers and reducing wages, as it is often the case in low-tech industries, this may lead to poorer working conditions and greater H&S-related risks (Cetrulo et al., 2019; Reljic et al., 2021a). Likewise, industrial relations may shape the robotisation-H&S relationship. For instance, if robotisation implies a concrete threat of technological unemployment and, relatedly, a reduction in workers' bargaining power, this may adversely affect firms' propensity to invest in training and, more generally, to use robots to make production safer (Staccioli and Virgillito, 2024).

Despite the growing diffusion of industrial robots and extensive research on their labour market effects (?), their impact on workplace H&S remains largely unexplored. This is particularly true in the European case. The only exception is Gihleb et al. (2022), focusing on Germany. The remaining available evidence is mostly country-specific, including studies assessing the Chinese (Luo et al., 2025; Yang et al., 2022) and the US case (Gunadi and

¹Layne (2023) reported 41 robot-related fatalities in the US between 1992 and 2017, while Kim et al. (2021) noted that industrial robots accounted for 5% of workplace deaths in South Korea between 2014 and 2018. Malm et al. (2010) analysed 25 severe robot-related injuries in Finland, showing that 60% of the accidents occurred during maintenance tasks due to insufficient instructions, many of which could have been prevented through better design (Sanders et al., 2024).

Ryu, 2021; Li and Singleton, 2021). Moreover, no contributions have so far assessed whether the robot-H&S relationship varies across industries with different techno-organisational characteristics and according to the nature of industrial relations (e.g., degree of unionisation, importance of work councils).

This paper aims at filling this research gap by providing novel evidence on the impact of robots on workplace injuries and deaths in Europe. The study is based on a sample that includes 15 manufacturing industries across 18 European countries observed between 2011 and 2019.

The analysis shows that robots significantly reduce workplace injuries and fatalities. Specifically, a 10% increase in the number of robots per 1,000 workers is associated with a 0.066% reduction in fatalities and a 1.96% decrease in injuries. However, this effect is limited to technology-intensive industries where competitive strategies rely on innovation, idiosyncratic competences and tacit knowledge, as well as in EU Member States with strong industrial relations that provide protection against socio-economic and H&S risks.

The paper is structured as follows. Section 2 provides a brief review of the literature analysing the relationship between technological change and occupational H&S. Section 3 illustrates the main research questions (RQs) and discusses theoretical expectations. Section 4 describes data (Section 4.1) and methodology (Section 4.2). Descriptive evidence on the robotisation-H&S nexus is provided in Section 5, while Section 6 reports the main results and Section 7 a set of robustness checks. Section 8 concludes.

2 Literature review: Robotisation vs occupational H&S

The technology-employment nexus is an evergreen in economics. Since the Classics—Smith, Ricardo and Marx—economists have questioned whether machines inevitably displace workers or make jobs more alienating and exhausting. The recent wave of robotisation has brought this issue back to the forefront, leading to a growing body of research quantifying its impact on employment and wages (Bisio et al., 2025; Grigoli et al., 2020; Reljic et al., 2023). Many studies examine these effects not only in aggregate but also across different worker groups, considering variations in skills, tasks, age and gender (Aksoy et al., 2021; Albinowski and Lewandowski, 2024; Dauth et al., 2021; De Vries et al., 2020). For a comprehensive review, see Guarascio et al. (2024), who provide a meta-analysis synthesising the existing evidence on how robotisation shapes employment and wages.

However, little is known about the impact that robots may have on occupational H&S. The existing evidence in this domain is limited and most contributions are based on qualitative studies. Overall, when it comes to factors affecting H&S, the literature identifies several elements playing a relevant role (Cornelissen et al., 2017): i) technological characteristics of industries, firms and plants; ii) organisational factors such as pace of work, managerial strategies and hierarchical structures; iii) institutional set-up, including the strength of work-place H&S regulations and the degree of unionisation. Against this background, robots may affect occupational H&S in different ways, potentially reducing accidents and fatalities but also posing new risks. In this respect, technological and institutional heterogeneity is crucial to determine their ultimate impact.

A few contributions, primarily based on US data, have examined the impact of robotisation on occupational H&S. For instance, Gunadi and Ryu (2021) exploit the variation in industrial employment distribution across US cities and differences in robot adoption by sector to assess its impact on workers' health. According to their findings, a 10% increase in robots per 1000 workers leads to a 10% reduction in the share of low-skilled individuals reporting poor health. This is explained by the reduction of the share of physical tasks carried out by this category of workers. Similar evidence is provided by Gihleb et al. (2022), focusing on US commuting zones and relying on establishment-level data to assess the relationship between the adoption of industrial robots and workplace injuries. These authors show that one standard deviation increase in robot exposure reduces work-related annual injury rates by approximately 1.2 cases per 100 workers. These results are in line with those of Li and Singleton (2021), using US commuting zones data regarding the 2000-2007 period. As before, an increase in robot exposure leads to a 15.1% reduction in the accident rate.

In their study, Gihleb et al. (2022) provide additional evidence on the German case, exploiting data stemming from the Socio Economic Panel, which includes information on work-related accidents and disabilities. The authors document that a one standard deviation change in robot exposure led to a 4% decline in physical job intensity and a 5% decline in disability. Nonetheless, they find no significant results concerning the relationship between robotisation, mental health and work and life satisfaction.

Another set of contributions focuses on China, providing mixed results. According to Luo et al. (2025), robot adoption improves workplace safety, generating estimated cost savings of about 31.2 billion USD annually. On the other hand, analysing data on the Guangdong Province, Yang et al. (2022) show that, in the short run, robotisation tends to increase the injury rate. Yet, a reduction in the same rate is documented after two years. Such an inconsistency might be explained by the time lag required for techno-organisational upgrading to occur; as well as by the time required for new production techniques (e.g., robot-worker interactions) to be learned.

Finally, the positive effect detected concerning both the US and the German case is confirmed when it comes to South Korea. Taking advantage of administrative data on workplace injuries, Kim (2023) show that one standard deviation increase in robot exposure reduces workplace injuries by 8%. The effect turns out to be strong for more severe cases leading to permanent disability (-16.9%). Like Gunadi and Ryu (2021), the author argues that the reduction in workplace injuries is explained by the reallocation of workers towards less physically intensive tasks.

However, while automation can enhance safety with respect to physical hazard, this might not be case regarding work-related stress (Brod, 1984). If robot adoption spreads fear of job replacement, especially in the case of those performing manual and repetitive tasks (Dekker et al., 2017), this may have negative implications in terms of job satisfaction and mental health (Nikolova et al., 2024; Antón et al., 2023). Such a negative effect is not uniform across workers, though. According to Blasco et al. (2022)—analysing the French case—and Abeliansky et al. (2024)—focusing on Germany—automation-related stress and its negative implications in terms of mental health are more likely to materialise among aged, lowskilled workers and routine-intensive occupations. Interestingly enough, recent contributions focusing on China document a positive impact of robotisation on job satisfaction and mental health, highlighting the importance of country-level heterogeneities (Kouming et al., 2024; Du et al., 2024).

This brief literature review sends two main messages. First, the robotisation-occupational H&S relationship is a complex one. Overall, a negative linkage between robot adoption, workplace injuries and deaths seems to emerge. Yet, a number of heterogeneity sources—i.e., country-specific institutions, productive-technological specialisation, skill-level and age—may lead to a different outcome. Second, despite the growing empirical literature on automation and labour markets, much remains to be understood. Regarding the European case, such a literature gap is particularly large—only one contribution providing evidence on Germany (Gihleb et al., 2022)—and clashes with the importance that EU policy makers attach to this specific issue. Against this background, the next section outlines the main research questions on which the empirical analysis is based.

3 Research Questions

The first research question (RQ1) concerns the impact of robot adoption on occupational H&S. It reads as follows:

RQ1 - What is the impact of robots on workplace injuries and fatalities in Europe?

The main theoretical expectation is that robotisation improves techno-organisational efficiency, thereby reducing both injury and fatality rates. More specifically, there are four channels potentially shaping the relationship at stake. First, a *reallocation effect*: robots are expected to take over humans in carrying out the most hazardous and physically demanding tasks (Acemoglu and Restrepo, 2019), thereby reducing workers' exposure to the number of dangerous circumstances and the incidence of workplace accidents. Second, an *ergonomics effect*: modernising the production process—particularly through the introduction of automation technologies and robots—can improve the adaptability and flexibility of machines and working tools, increasing not only workers' comfort but reducing the risk of accidents (Gualtieri et al., 2021). Third, a *productivity effect*: if robotisation boosts productivity, this may result in reduced working hours and, thus, lower probability of running into an accident. On the other hand, robot adoption may also have adverse implications if it increases *work intensity* and/or reduces workers' understanding of production processes and objectives, potentially heightening the risk of workplace injuries (Grande et al., 2020).

As argued, the impact of robots may vary substantially according to industry-specific technological and organisational characteristics. In particular, in industries where there is a strong innovation-skills complementarity—i.e., industries where prevalent competitive strategies are based on product quality, firm-specific skills and continuous improvements in terms of organisational efficiency—a positive relationship between robotisation and work-place safety is expected to materialise. This type of industries are normally included in the 'Science Based' and 'Specialised Suppliers' categories of the Pavitt (1984) taxonomy. In turn, in industries where innovation is primarily aimed at containing costs (especially labour costs), the search for higher margins could coincide with a higher risk of injuries and deaths (Reljic et al., 2021b). Concerning the Pavitt taxonomy, such industries can be found in the 'Scale Intensive' and 'Supplier Dominated' categories. Therefore, our second research question (RQ2) is formulated as follows:

RQ2 - To what extent the robotisation-occupational H&S relationship is influenced by sectoral and technological heterogeneity?

Finally, we want to assess whether the nature of institutions and, in particular, the heterogeneous industrial relations characterising EU Member States affect the robot-workplace safety nexus. In terms of expectations, countries characterised by labour market laws providing robust safeguards and, no less relevant, where unions are strong enough to ensure oversight on H&S-related issues and encourage firms to invest in training are expected to benefit the most from the introduction of new technologies, including robots. On the other hand, countries with weaker labour market institutions and poor unionisation are likely to benefit less or even experience a negative effect of robotisation. This leads to our third and final research question (RQ3):

RQ3 - Do countries with stronger labour market institutions and trade unions benefit more from robotisation in terms of workplace safety?

The next section illustrates the data and empirical strategy employed to address these three RQs. Before presenting descriptive evidence on workplace fatalities and injuries across EU countries and industries, we illustrate in detail our identification strategy and the methodology used to explore technological and institutional heterogeneity.

4 Empirical strategy

4.1 Data

The empirical analysis is conducted at the country-industry level, merging data from various sources for 15 NACE Rev.2 manufacturing industries across 18 European countries observed between 2011 and 2019. The list of countries (Table A1) and industries (Table A2) is provided in Appendix A.

Data on workplace injuries and fatalities are sourced from Eurostat, while robot stock data are obtained from the International Federation of Robotics (IFR). Labour market data come from the European Labour Force Survey (EU-LFS). We further integrate these with Eurostat's annual enterprise statistics to obtain sectoral structural and economic information, and with OECD's inter-country input-output tables to construct trade variables. A detailed description of all variables, including definitions and data sources, is provided in Table A3 in Appendix A.

4.2 Methodology

We examine the impact of industrial robots on workplace fatalities and injuries (RQ1) by estimating the following model:

$$y_{ijt} = \alpha_0 + \beta_1 robot_{ij,t-1} + lab'_{ij,t-1}\gamma + econ'_{ij,t-1}\phi + trade'_{ij,t-1}\mu + \omega_i + \delta_j + \lambda_t + \epsilon_{ijt}$$
(1)

where the incidence of workplace fatalities or injuries per 1,000 workers (y) in country i, industry j and time t is expressed as a function of robot density, defined as the stock of industrial robots per 1,000 workers. The main variables of interest are log-transformed, meaning that the coefficient β_1 represents the elasticity of y with respect to robot adoptioni.e., the percentage change in y for a 1% change in robot density, holding all else constant.

To account for potential confounders, we include a set of lagged control variables (t - 1), capturing key industry and labour market characteristics (Antón et al., 2023; Li and Singleton, 2021; Gihleb et al., 2022). These include: (i) workforce characteristics (*lab*), such as gender, age, education, contract type and ISCO occupational groups; (ii) economic and structural variables (*econ*), comprising sectoral turnover, sectoral share of firms within the manufacturing sector and investment share in gross value added; and (iii) trade-related factors (*trade*), including broad and narrow offshoring (Feenstra, Robert C. and Hanson, Gordon H., 1999). We also control for country (δ) and industry (ω) fixed effects to account for unobservable time-invariant differences across countries and industries that may influence our outcomes of interest, such as varying under-reporting practices across countries and the fact that some sectors are inherently more hazardous. Additionally, we include time fixed effects (λ) to account for potential trends in our outcomes. The constant term is denoted by α , while ϵ represents the error term.

Equation 1 is estimated using pooled ordinary least squares (OLS) and fixed effects (FE). However, the relationship between robots and H&S may be subject to endogeneity, particularly reverse causality. Workplace safety constitutes a cost component for firms (e.g., investments in protective equipment, worker training and expenses related to injuries or fatalities), which could incentivise a higher robot adoption in sectors where safety costs are more significant. If this is the case, standard OLS estimates may be biased. To address this concern, we adopt an instrumental variable (IV) approach \dot{a} la Acemoglu and Restrepo (2020), consistent with the existing literature (Dauth et al., 2021; Gihleb et al., 2022; Reljic et al., 2023). Specifically, we instrument robot density using industry-level robot stock per 1,000 workers in the US.² The key underlying assumption is that robot adoption in the US is primarily driven by global technological progress and supply-side factors—such as declining automation costs and improvements in robot capabilities—rather than by industryspecific workplace safety conditions in EU countries. This implies that variation in US robot adoption is exogenous to workplace fatalities and injuries in the EU and affects them only through its impact on domestic robot adoption, thereby satisfying the exclusion restriction. All estimations are weighted by 2011 employment levels to account for sectoral size.³ and standard errors are robust to heteroscedasticity and clustered at the country-industry level to address serial correlation.

To further explore the relationship between robotisation and workplace H&S, we extend the analysis in two directions (RQ2 and RQ3).

We first test for heterogeneous effects across sectors using the Pavitt taxonomy (Pavitt, 1984; Bogliacino and Pianta, 2010). Specifically, we split industries into three groups based on their technological regimes: *Science-Based and Specialised Suppliers* (high-tech sectors) (e.g., electronics), characterised by strong in-house R&D investment, significant patenting activity and a prevalence of product innovation; *Scale-Intensive sectors* (e.g., automotive),

 $^{^{2}}$ Alternatively, robot density in Japan is used as an instrument, yielding qualitatively similar results (see Table D2).

³Unweighted estimates produce qualitatively similar results (see Table D1).

marked by economies of scale, oligopolistic markets and a combination of incremental product and process innovation; *Supplier Dominated sectors* (e.g., textile industry), depicted by low internal R&D activity, many small firms and process innovation, primarily through acquisition of machinery. See Table A2 in Appendix A for a detailed list of sectors in each Pavitt class.

Second, we examine cross-country heterogeneity by dividing countries into three groups low (Czechia, Greece, Lithuania, Slovakia, Estonia, Hungary, Poland, Netherlands), medium (Austria, Germany, France, Ireland, Italy, Sweden) and high (Finland, Denmark, Belgium) based on the strength of industrial relations (IR) and workers' bargaining power. This allows us to assess whether bargaining power mediates the impact of robotisation on workplace H&S outcomes. This grouping is determined by identifying discontinuities in the IR index distribution, which is constructed using principal component analysis (PCA), incorporating industrial relations indicators and broader institutional characteristics. See Appendix C for a detailed discussion.

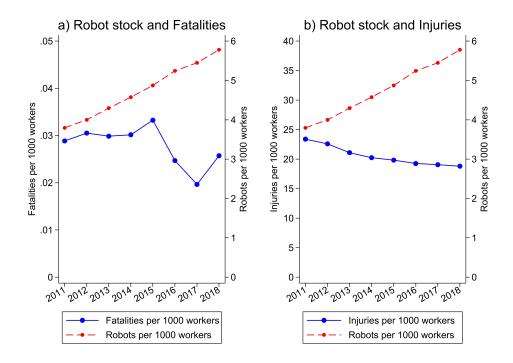
5 Descriptive evidence

In what follows, we highlight key trends in robot adoption and workplace injuries and fatalities. Figure 1 presents the average annual incidence of fatalities and injuries per 1,000 workers, alongside robot density, between 2011 and 2018. The number of industrial robots in the EU increased steadily over this period, reflecting the broader adoption of automation technologies across industries, as widely documented in the literature (Macías et al., 2021; Reljic et al., 2023). Panel (a) shows that fatalities initially follow a similar trend, remaining relatively stable until 2015, after which they decline significantly.⁴ In contrast, panel (b) shows a steady downward trend in injuries per 1,000 workers throughout the 2011-2018 period. The divergence between these patterns suggests that automation, as reflected in

⁴This marked drop coincides with a period of robust employment growth, which mechanically reduces the denominator in normalised terms (see Figure B1 in Appendix B).

rising robot adoption, could be associated with reductions in injury rates, potentially due to the substitution of hazardous manual tasks. Nevertheless, the observed improvements in workplace safety are likely influenced by additional factors, including sectoral composition effects, regulatory changes or broader advancements in workplace safety practices.

Figure 1: Evolution of fatalities, injuries and industrial robots per 1,000 workers



Source: Own elaborations based on Eurostat and IFR data

Figure 2 highlights significant cross-country heterogeneities. Panel (a) shows that while fatalities are somewhat evenly distributed, they are particularly concentrated in Eastern European countries, with Czechia, Slovakia, and Hungary exhibiting the highest rates. However, the ranking differs for injuries, as shown in panel (b) and Figure B2 in Appendix B, where Slovakia and Czechia appear to be among the 'safest' countries for workers. This inconsistency likely indicates under-reporting of injuries, a phenomenon documented in the Eurogip Report (2023), which highlights a high percentage of under-reporting in Eastern European countries.

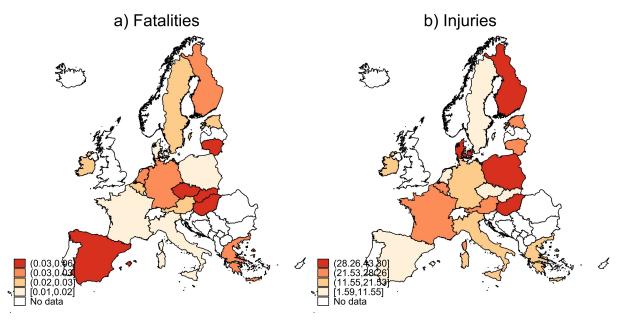


Figure 2: Workplace fatalities and injuries across EU countries

Source: Own elaborations based on Eurostat data

The variation in workplace incidents across countries is likely driven by differences in their sectoral specialisation and institutional frameworks. Countries with higher concentrations of hazardous industries are more likely to have higher rate of workplace injuries and fatalities due to the inherent risks in these sectors. At the same time, institutional factors, such as the strength of labour protection, enforcement of workplace safety regulation and reporting practices, play a critical role in shaping workplace safety outcomes. For instance, stronger bargaining power of workers and industrial relations may reduce the incidence of workplace accidents.

Indeed, we observe significant heterogeneity in fatalities and injuries across sectors, as reflected in the Pavitt taxonomy (Figure 3). Supplier dominated industries exhibit the highest rates of both fatalities and injuries, with fatalities reaching approximately 0.04 per 1,000 workers (Panel a) and injuries close to 30 per 1,000 workers (Panel b), which is more than double the rates in high-tech sectors. This highlights the high occupational risks associated with traditional, less technologically advanced sectors. A case in point is the manufacturing of wood, cork and furniture, which emerges as the sector with the highest incidence of both fatalities and injuries (see Figure B3 in Appendix B).

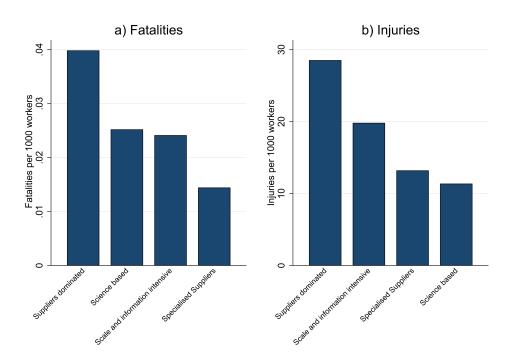


Figure 3: Workplace fatalities and injuries by Pavitt classes

Source: Own elaborations based on Eurostat data

Scale-intensive industries follow, particularly in terms of injuries, where the rate is nearly 20 per 1,000 workers. These industries rely on large-scale production processes, commonly associated with manual, repetitive and potentially hazardous tasks. Notable examples are the manufacturing of non-metallic mineral products and the printing and reproduction of recorded media, which rank high in terms of fatalities and injuries, respectively.

In contrast, Science-Based and Specialised Supplier industries report comparatively lower rates, with fatalities below 0.02 and injuries below 15 per 1,000 workers. It is unsurprising that high-tech sectors represent less hazardous environments for workers. A case in point is the electronics industry, which exhibits the lowest fatality and injury rates. Nonetheless, it is important to highlight that the repair and installation of machinery sector ranks third in terms of fatalities, suggesting that robotisation might also pose safety risks in these sectors, especially in the absence of adequate safety systems or when workers lack sufficient training to interact with robots and perform maintenance tasks (Sanders et al., 2024).

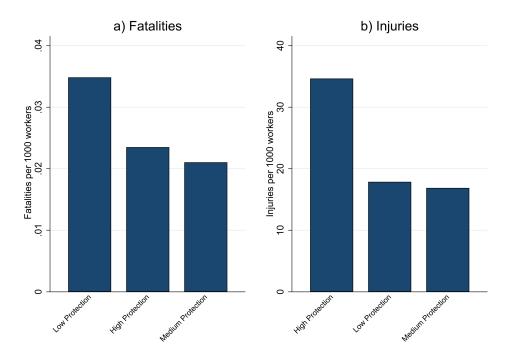


Figure 4: Workplace fatalities and injuries by the IR taxonomy

Source: Own elaborations based on Eurostat and ICTWSS data

Similarly, fatality and injury rates vary according to the nature of IR. Panel (a) in Figure 4 shows that fatalities are more prevalent in countries with weaker protection (including Czechia, Greece, Lithuania, Slovakia, Estonia, Hungary, Poland, Netherlands), as expected. In contrast, Panel (b) reveals a higher concentration of injuries in countries with stronger IR (e.g., Finland, Denmark, Belgium). This pattern likely reflects the impact of under-reporting, which tends to affect injuries rather than fatalities, as the latter are nearly impossible to conceal. As a result, under-reporting in countries with weaker IR systems may mask the true extent of workplace injuries.

These descriptive findings reveal notable patterns: fatalities have fallen sharply since

2015, while injuries have declined steadily over the period 2011–2018. However, significant disparities remain. Cross-country comparisons highlight inconsistencies, with high fatality rates but relatively low reported injury rates in Eastern European countries, likely reflecting under-reporting. At the sectoral level, workers in traditional (supplier dominated) industries face the highest risks, whereas those in high-tech industries appear to be less exposed to workplace injuries and fatalities. These patterns highlight the importance of considering institutional and structural factors when examining the relationship between technology and workplace H&S.

6 Results

The results are organised as follows. Section 6.1 presents and discusses the baseline estimates. Section 6.2 examines sectoral heterogeneity by performing sample-splitting based on Pavitt groups, while Section 6.3 investigates cross-country heterogeneity through sample-splitting according to the IR index.

6.1 Baseline

We report the results of our model estimating the impact of robotisation on workplace fatalities and injuries in Tables 1 and 2, respectively. Columns (1) and (2) present OLS estimates, first without controls and then with country, year, and Pavitt (sector) fixed effects (FEs). Column (3) extends the specification by incorporating interactions between countryyear and country-Pavitt (sector) FEs. The former accounts for time-varying national shocks that affect industries differently across countries, such as changes in labour regulations; while the latter captures time-invariant country-industry-specific characteristics. These interaction terms ensure that our estimates are not confounded by broader economic or policy shifts at the country or industry level, nor by changes over time. Column (4) further introduces control variables, including labour force characteristics, economic and structural variables, and offshoring, to account for additional factors driving variation in workplace fatalities and injuries. Finally, the last two columns present IV estimations, with and without controls, respectively.

| | (1) OLS 1 | (2) OLS 2 | (3) FE 1 | (4) FE 2 | (5) IV 1 | (6) IV 2 |
|-----------------------------|-------------------------------|------------------------------|--|-------------------------------|-------------------------------|-------------------------------|
| | 0 00000*** | 0.0000=** | 0.000.00*** | 0.00402*** | 0.00500*** | 0.00000*** |
| Robot density $(t-1)$ | -0.00292^{***} (0.00107) | -0.00327^{**} (0.00135) | $\begin{array}{c} -0.00348^{***} \\ (0.00127) \end{array}$ | -0.00496^{***} (0.00139) | -0.00506^{***} (0.00148) | -0.00663^{***} (0.00186) |
| Year | no | yes | yes | yes | yes | yes |
| Country | no | yes | yes | yes | yes | yes |
| Pavitt | no | yes | yes | yes | yes | yes |
| Year x Country | no | no | yes | yes | yes | yes |
| Country x Pavitt | no | no | yes | yes | yes | yes |
| Controls | no | no | no | yes | no | yes |
| Constant | 0.0253*** | 0.0226*** | 0.00274 | 0.174^{***} | 0.00251 | 0.182*** |
| | (0.00272) | (0.00837) | (0.00976) | (0.0462) | (0.00935) | (0.0454) |
| Kleibergen-Paap F statistic | | | | | 267.022 | 185.173 |
| Observations | 2,017 | 2,017 | 2,017 | 1,871 | 2,017 | 1,871 |
| R2 adjusted | 0.012 | 0.118 | 0.205 | 0.239 | 0.203 | 0.238 |

Table 1: Workplace fatalities per 1,000 workers

Notes: Robust standard errors clustered at the country-industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All estimates are weighted for the size of sectoral employment in 2011; Both variables are log-transformed. *Source:* Own elaboration

The results indicate that robotisation consistently reduces workplace fatalities across all model specifications (see Table 1). Specifically, a 10% increase in the number of robots per 1,000 workers reduces fatality rate by approximately 0.07% (Column 6, Table 1). However, its impact on workplace injuries becomes both statistically significant and larger in magnitude only when the IV approach is adopted (see Table 2, Columns 5 and 6). This is likely due to reverse causality, where firms and industries with higher injury rates adopt robots to improve safety, biasing OLS estimates toward zero. IV estimation addresses this by isolating exogenous variation in robot adoption—such as that driven by global technological progress—which is unrelated to injury rates, thereby uncovering the 'true' negative effect. Specifically, a 10% increase in the number of robots per 1,000 workers reduces injury rate by approximately 1.96% (Column 6, Table 2). Moreover, the first-stage F-statistic is well above conventional thresholds, indicating that the instrument (i.e., robot density in the US) is sufficiently strong.

| | (1) OLS 1 | (2) OLS 2 | (3) FE 1 | (4) FE 2 | (5) IV 1 | ${}^{(6)}_{ m IV 2}$ |
|-------------------------------------|---------------------------|--------------------------|--------------------------|--------------------------|--------------------------|---|
| Robot density $_{(t-1)}$ | -0.0385 (0.0434) | -0.0219 (0.0468) | -0.0111 (0.0479) | -0.0157 (0.0399) | -0.117** (0.0510) | -0.196^{***} (0.0573) |
| Year | no | yes | yes | yes | yes | yes |
| Country | no | yes | yes | yes | yes | yes |
| Pavitt | no | yes | yes | yes | yes | yes |
| Year x Country | no | no | yes | yes | yes | yes |
| Country x Pavitt | no | no | yes | yes | yes | yes |
| Controls | no | no | no | yes | no | yes |
| Constant | 2.684^{***} (0.0938) | 2.998^{***} (0.233) | 2.375^{***} (0.418) | 4.066^{***} (1.053) | 2.360^{***} (0.302) | $\begin{array}{c} 4.967^{***} \\ (1.052) \end{array}$ |
| Kleibergen-Paap rk Wald F statistic | | | | | 267.022 | 185.173 |
| Observations | 2.017 | 2,017 | 2.017 | 1.871 | 2.017.022 2.017 | 1.871 |
| R2 adjusted | 0.004 | 0.554 | 0.646 | 0.726 | 0.630 | 0.706 |

Table 2: Workplace injuries per 1,000 workers

Notes: Robust standard errors clustered at the country-industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All estimates are weighted for the size of sectoral employment in 2011; Both variables are log-transformed. Source: Own elaboration

Overall, our findings suggest that the adoption of industrial robots enhances workplace H&S in the EU by reducing both fatalities and injuries per 1,000 workers, providing an affirmative answer to RQ1. This aligns with earlier country-specific studies on China (Luo et al., 2025), the US (Gihleb et al., 2022) and South Korea (Kim, 2023). However, to the best of our knowledge, this is the first providing a systematic cross-country analysis of the impact of robotisation on workplace safety. Our results are robust to several sensitivity checks discussed in Section 7 and reported in Appendix D. In what follows, we address RQ2 and RQ3.

6.2 Sectoral heterogeneity

We extend our analysis to examine whether structural differences influence the relationship between robotisation and workplace H&S. To this end, we divide industries into three groups based on the Pavitt Taxonomy (Pavitt, 1984).⁵ The results are presented in Table 3 for fatalities and Table 4 for injuries.

Column (1) reports the baseline estimation, which includes controls, as well as country,

⁵See Table A2 in Appendix A for details on the sectors included in each Pavitt class.

sector, and year fixed effects (FEs), along with country-year FEs. In Column (2), we combine the Science-Based (SB) and Specialised Suppliers (SS) classes into a single category to better capture the effect of robotisation in technologically advanced sectors while simultaneously increasing the statistical power of our estimates by expanding the number of observations. Column (3) presents the estimates for the Scale and Information-Intensive (SII) class, while Column (4) reports the effects for the Supplier Dominated (SD) class.

| | (1) | (2) | (3) | (4) |
|-----------------------------|-------------|-----------|-------------|-----------|
| | IV | SB&SS | SII | SD |
| | | | | |
| Robot density $(t-1)$ | -0.00738*** | -0.0228** | -0.00737*** | 0.00008 |
| | (0.00217) | (0.00920) | (0.00199) | (0.00708) |
| Year | yes | yes | yes | yes |
| Country | yes | yes | yes | yes |
| Pavitt | yes | no | no | no |
| Year x Country | yes | yes | yes | yes |
| Controls | yes | yes | yes | yes |
| Constant | 0.211*** | 0.128 | 0.104 | 0.215** |
| | (0.0494) | (0.142) | (0.0675) | (0.0861) |
| Kleibergen-Paap F statistic | 170.894 | 25.575 | 96.21 | 23.38 |
| Observations | 1,871 | 636 | 611 | 624 |
| R2 adjusted | 0.193 | 0.262 | 0.375 | 0.379 |

Table 3: Workplace fatalities per 1,000 workers

Notes: Robust standard errors clustered at the country-industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All estimates are weighted for the size of sectoral employment in 2011; Both variables are log-transformed. Source: Own elaboration

Our findings indicate that the positive impact of robotisation on workplace H&S is not uniform across sectors but is concentrated in high-tech industries—specifically, SB and SS—where process innovations enhance workplace safety. This effect may stem from competitive strategies focusing on quality of products, accumulation of knowledge and corporate reputation (Pianta, 2001). Compared to the baseline model, the reduction in fatalities in these sectors is three times greater (0.22% vs. 0.07%), while the decrease in injuries is nearly five times larger (9.98% vs. 1.96%).

In contrast, traditional sectors, which exhibit a higher incidence of workplace injuries and fatalities per 1,000 workers (see Section 5), do not experience comparable safety benefits from robotisation. In these industries, the estimated coefficient is even positive, albeit statistically insignificant, suggesting that automation alone may not be sufficient to improve workplace safety.

| | (1) IV | (2) SB&SS | (3) SII | (4) SD |
|--|---------------------------------|--------------------------------|--------------------------------|--------------------------------|
| Robot $density_{(t-1)}$ | -0.207^{***} (0.0581) | -0.996^{***} (0.286) | -0.0459 (0.0422) | 0.128 (0.110) |
| Year Country Pavitt Year x Country Controls | yes yes yes yes yes | yes yes no yes yes | yes yes no yes yes | yes yes no yes yes |
| Constant | 6.205^{***} (0.969) | 10.20^{***} (2.801) | 3.631^{**} (1.497) | $1.344 \\ (1.549)$ |
| Kleibergen-Paap F statistic Observations R2 adjusted | $170.894 \\ 1,871 \\ 0.671$ | $25.575 \\ 636 \\ 0.457$ | $96.21 \\ 611 \\ 0.805$ | $23.38 \\ 624 \\ 0.846$ |

Table 4: Workplace injuries per 1,000 workers

Notes: Robust standard errors clustered at the country-industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All estimates are weighted for the size of sectoral employment in 2011; Both variables are log-transformed. Source: Own elaboration

6.3 Institutional Heterogeneity

A second exercise examines whether workers' bargaining power mediates the effect of robotisation on workplace H&S outcomes. Specifically, we test for heterogeneity across EU countries based on the nature of their industrial relations. To do so, we classify countries into three groups according to their IR index: low (Czechia, Greece, Lithuania, Slovakia, Estonia, Hungary, Poland, Netherlands), medium (Austria, Germany, France, Ireland, Italy, Sweden), and high protection (Finland, Denmark, Belgium) (see Appendix C for more details). The results are presented in Table 5 for fatalities and Table 6 for injuries.

Column (1) reports the baseline estimation, which includes controls, as well as country, sector, time and country-year FEs. In Column (2), we estimate the effect of robotisation in high-protection countries, while Columns (3) and (4) present the results for medium- and low-protection countries, respectively. The findings suggest that countries whose industrial relations systems provide greater protection to workers tend to benefit more in terms of

H&S. In other words, 'labour-friendly' institutions (e.g., trades unions, work councils) can amplify the benefits of automation in terms of reduction of work-related accidents.

| | (1) IV | (2) high | (3) medium | (4) low |
|--|-------------------------------|--------------------------|------------------------------|------------------------|
| | 1 V | mgn | mearum | low |
| Robot $\text{density}_{(t-1)}$ | -0.00738^{***} (0.00217) | -0.0115*** (0.00446) | -0.00715^{**} (0.00328) | -0.00290 (0.00357) |
| Year | yes | yes | yes | yes |
| Country | yes | yes | yes | yes |
| Pavitt | yes | yes | yes | yes |
| Year x Country | yes | yes | yes | yes |
| Controls | yes | yes | yes | yes |
| Constant | 0.211^{***} (0.0494) | -0.0122 (0.0410) | 0.238^{***} (0.0606) | 0.114 (0.0726) |
| Kleibergen-Paap F statistic observations R2 adjusted | $170.894 \\ 1,871 \\ 0.193$ | $60.739 \\ 321 \\ 0.280$ | 106.28 769 0.199 | 83.927 781 0.227 |

Table 5: Workplace fatalities per 1,000 workers

Notes: Robust standard errors clustered at the country-industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All estimates are weighted for the size of sectoral employment in 2011; Both variables are log-transformed. Source: Own elaboration

In countries with higher protection, a 10% increase in robot density leads to a 0.115% and 4.84% reduction in the fatality and injury rates, correspondingly. Although the effect on injuries is positive across all three country groups, its magnitude diminishes as the IR index decreases. Specifically, the reduction in injuries is twice as large in high-protection countries—where the incidence of precarious jobs is relatively lower and workers enjoy a stronger institutional support—compared to medium- and low-protection ones. On the other hand, in low-protection countries (e.g., Eastern Europe)—characterised by low union density, decentralised wage bargaining, limited expenditure on training and minimal support for passive labour market policies—the potential safety benefits of robotisation remain largely unrealised.

| | (1) IV | (2)high | (3) medium | (4) low |
|--|---------------------------------|---|---------------------------------|---------------------------------|
| Robot density $_{(t-1)}$ | -0.207^{***} (0.0581) | -0.484^{***} (0.122) | -0.248^{***} (0.0694) | -0.216^{***} (0.0598) |
| Year Country Pavitt Year x Country Controls | yes yes yes yes yes | yes yes yes yes yes | yes yes yes yes yes | yes yes yes yes yes |
| constant | 6.205^{***} (0.969) | 2.571^{**} (1.219) | $7.874^{***} \\ (1.433)$ | 2.491^{*} (1.483) |
| Kleibergen-Paap F statistic observations R2 adjusted | $170.894 \\ 1,871 \\ 0.671$ | $\begin{array}{c} 60.739 \\ 321 \\ 0.547 \end{array}$ | 106.28 769 0.646 | 83.927 781 0.752 |

Table 6: Workplace injuries per 1,000 workers

Notes: Robust standard errors clustered at the country-industry level in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1; All estimates are weighted for the size of sectoral employment in 2011; Both variables are log-transformed. Source: Own elaboration

7 Robustness Checks

We conduct a series of robustness checks to assess the sensitivity of our results to changes in the estimation method, sample composition and IR taxonomy. The results, reported in Appendix D, include: (1) unweighted estimations; (2) using Japan's robot density as an alternative IV; (3) excluding sectors with the highest incidence of fatalities and injuries (i.e., sector 16: manufacturing of wood, cork, and furniture); (4) excluding countries with relatively high fatality rates, specifically Czechia, Slovakia, and Hungary; (5) addressing potential outliers by trimming the bottom and top 2% observations in terms of fatalities, injuries and robot density; and (6) disaggregating the IR taxonomy to four groups: i) *high protection* (Belgium, Denmark, Finland) with the IR index between 70 and 100 ii) medium*high protection* (Austria, Germany, Spain, France, Irland, Italy, Sweden) with IR index between 50-69 iii) medium-low protection (Estonia, Greece, Lithuania, Netherlands) with the IR index between 30-49 and iv) low-protection (Czechia, Hungary, Poland and Slovakia) with the IR index between 0 and 48.

Overall, our findings remain robust across all sensitivity tests, confirming the negative

impact of robotisation on workplace fatalities and injuries.

First, the unweighted regressions (Table D1) confirm the negative impact of robotisation, although with a larger estimated effect than the weighted model. This suggests that, if anything, our baseline estimates may slightly underestimate the true impact.

Second, using robot density in Japan as an alternative IV produces qualitatively similar results (Table D2), though the coefficients are somewhat larger. However, F-statistics indicate that the US-based instrument is stronger than the Japan-based one.

Third, excluding outliers-sectors (Table D3) and countries (Table D4) with the highest fatality rates- as well as trimming the top and bottom 2% of observations yields qualitatively similar results (Table D5).

Finally, when we refine the IR taxonomy by dividing countries into four groups (Tables D6 and D7), our findings remain consistent, with one exception. In low-medium protection countries, the negative effect of robotisation on injuries is larger than in high-medium protection countries, although it is only significant at the 10% level.

8 Concluding remarks

This work investigates the impact of robotisation on workplace fatalities and injuries across 18 European countries and 15 two-digit NACE Rev.2 manufacturing sectors observed between 2011 and 2019. Unlike previous studies that focus on single-country contexts (e.g., Luo et al. (2025) on China, Gihleb et al. (2022) on the US and Kim (2023) on South Korea), we provide, to the best of our knowledge, the first systematic cross-country analysis of robotisation's effect on workplace safety in the EU. Furthermore, we explore how this relationship varies across sectors and industrial relations regimes.

Addressing RQ1, our findings indicate that industrial robot adoption enhances workplace health and safety by reducing both fatalities and injuries per 1,000 workers. Specifically, a 10% increase in robot density is associated with a 0.07% reduction in fatalities and a 1.96% decrease in the injury rate. However, these effects are not uniform and depend on sectoral and institutional heterogeneity.

With respect to RQ2, we find that technology-intensive sectors—Science-Based and Specialised Suppliers—experience significantly larger workplace safety improvements. Compared to the baseline model, the reduction in fatalities is three times greater (0.22% vs. 0.07%), while the effect on injuries is nearly five times larger (9.98% vs. 2%). These results suggest that in industries where competitive strategies rely on innovation, firm-specific skills and continuous improvements in organisational efficiency, robot adoption translates into more substantial safety benefits. In contrast, in sectors where process innovation primarily serves (labour) cost-reduction purposes, robotisation does not reduce workplace fatalities and injuries.

Finally, in line with RQ3, our results highlight the important role of labour market institutions in shaping the relationship between robotisation and workplace safety. Countries with strong worker protections exhibit greater safety benefits from robot adoption. Specifically, in high-protection environments (e.g., Finland, Denmark, Belgium), the reduction in fatalities (0.1% vs. 0.07%) and injuries (4.84% vs. 2.07%) is nearly twice as large as in the baseline model.

The robustness of these findings is confirmed through multiple sensitivity tests, including unweighted estimation, the use of an alternative instrument (robot density in Japan), the exclusion of countries with exceptionally high fatality rates, the omission of hazardous sectors, heterogeneity analysis within industrial relations groups and adjustments for outliers.

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Appendix

A Data description

| C | Country name | | | | | |
|-----------|--------------|---------|--|--|--|--|
| Austria | Belgium | Czechia | | | | |
| Denmark | Estonia | Finland | | | | |
| France | Germany | Greece | | | | |
| Hungary | Ireland | Italy | | | | |
| Lithuania | Netherlands | Poland | | | | |
| Slovakia | Spain | Sweden | | | | |

Table A1: List of countries

| Sector Description | NACE | Pavitt |
|--|----------|-----------------------------|
| Manufacture of coke, petroleum products, chemical, and | 19,20,21 | Science Based |
| pharmaceutical products | | |
| Manufacture of computer, electronic, and optical prod- | 26 | Science Based |
| ucts | | |
| Manufacture of electrical equipment | 27 | Specialised Suppliers |
| Manufacture of machinery and equipment n.e.c. | 28 | Specialised Suppliers |
| Manufacture of other transport equipment | 30 | Specialised Suppliers |
| Manufacture of basic metals | 24 | Scale Information Intensive |
| Manufacture of motor vehicles, trailers, and semi- | 29 | Scale Information Intensive |
| trailers | | |
| Manufacture of other non-metallic mineral products | 23 | Scale Information Intensive |
| Manufacture of paper and reproduction of recorded me- | 17,18 | Scale Information Intensive |
| dia | | |
| Manufacture of rubber and plastic products | 22 | Scale Information Intensive |
| Manufacture of fabricated metal products, except ma- | 25 | Suppliers Dominated |
| chinery and equipment | | |
| Manufacture of food products, beverages, and tobacco | 10,11,12 | Suppliers Dominated |
| Manufacture of textiles, wearing apparel and leather | 13,14,15 | Suppliers Dominated |
| Manufacture of wood, cork, and furniture | 16,31 | Suppliers Dominated |
| Repair and installation of machinery and equipment and | 32,33 | Suppliers Dominated |
| other manufacturing | | |

Table A2: List of sectors

| Variables | Description | Source | | | |
|------------------------|---|-----------|--|--|--|
| Dependent Variables | | | | | |
| Fatalities (intensity) | # of workplace deaths (per $1,000$ workers) | EUROSTAT | | | |
| Injuries (intensity) | # of workplace injuries (per 1,000 workers) | EUROSTAT | | | |
| | Main Regressor | | | | |
| Robot density | robot stock per 1,000 workers | IFR | | | |
| | Controls | | | | |
| | labour market variables | | | | |
| Gender | share of female workers $(\%)$ | EU-LFS | | | |
| Low skill | share of workers with ISCED level 0-2 (%) | EU-LFS | | | |
| Medium skill | share of workers with ISCED level $3+4$ (%) | EU-LFS | | | |
| Temporary contracts | share of workers with a temporary contract $(\%)$ | EU-LFS | | | |
| Aged workers | share of workers aged $55+(\%)$ | EU-LFS | | | |
| Young workers | share of workers with age 15-24 $(\%)$ | EU-LFS | | | |
| Managers | share of managers $(\%)$ | EU-LFS | | | |
| Craft workers | share of craft workers $(\%)$ | EU-LFS | | | |
| Manual workers | share of manual workers $(\%)$ | EU-LFS | | | |
| | Economic and structural variables | | | | |
| Turnover | sectoral turnover (%) | EUROSTAT | | | |
| Firm | sectoral share of firms within manufacturing sector $(\%)$ | EUROSTAT | | | |
| Investments | investment in gross value added $(\%)$ | EUROSTAT | | | |
| | Trade-related variables | | | | |
| Broad offshoring | share of imported intermediate inputs in total inputs (%) | OECD-ICIO | | | |
| Narrow offshoring | share of imported intermediate inputs $(\%)$ within the same sector | OECD-ICIO | | | |

B Additional figures

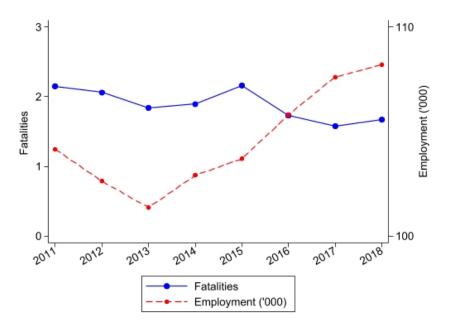
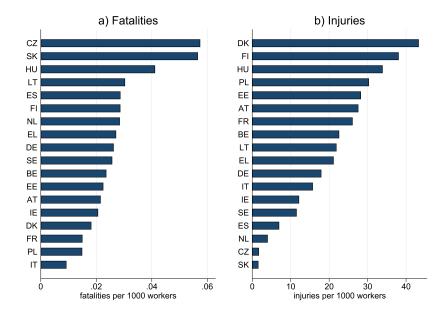


Figure B1: Workplace fatalities and total employment ('000)

Source: Own elaborations based on Eurostat data

Figure B2: Fatalities and injuries across EU countries



Source: Own elaborations based on Eurostat data

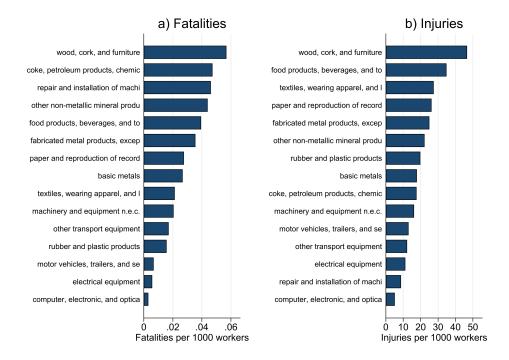


Figure B3: Fatalities and injuries across industries

Source: Own elaborations based on Eurostat data

C Industrial Relation Taxonomy

To examine the mediating role of industrial relations in the robot–workplace health and safety nexus, we classify countries into three groups based on the nature of their industrial relations (IR) systems. To this end, we first construct an IR index using principal component analysis, drawing on data from Eurostat and ICTWSS (the list of variables used in the analysis is available in Table C1). The index is then normalised to range from 0 to 100 (see Figure C1).

We then define three groups based on key discontinuities in the IR index: (1) high protection (IR index between 70 and 100), (2) medium protection (IR index between 50 and 69), and (3) low protection (IR index between 0 and 49). This classification is illustrated in Figure C2.

| Variable | Description | Type | Values |
|-----------------------------------|---|-------------|--|
| Level of wage bargaining | The predominant level at which wage bargaining takes place | Categorical | 5 = central; 4 = central/industry; 3 = industry; 2 = sec- tor/enterprise; 1 = enterprise |
| Wage setting | Type of coordination of wage setting | Categorical | 6 = Government-imposed; 5 = Government-sponsored; 4 = Peak associations; 3 = Informal cen- tralisation; 2 = Pattern; 1 = Sig- nals; 0 = None |
| Work council | Status of work council | Categorical | 2 = Mandated by law; $1 =$ Voluntary; $0 =$ Exceptional or absent |
| National collective bargaining | National collective bargaining in force | Dummy | 1 = Yes; $0 = $ No |
| Sectoral collective bargaining | Sectoral collective bargaining in force | Dummy | 1 = Yes; $0 = $ No |
| Regional collective bargaining | Regional collective bargaining in force | Dummy | 1 = Yes; $0 = $ No |
| Occupational collective agreement | Occupational collective agreement in force | Dummy | 1 = Yes; $0 = $ No |
| Firm bargaining | Predominant level at which firm bar- gaining takes place | Categorical | 1 = Articulated; $2 =$ Partially articulated; $3 =$ Disarticulated |
| Government | Government intervention in wage bar- gaining | Categorical | 5 = Imposes wage settlements; 4 = Participates directly; 3 = Influ- ences indirectly; 2 = Institutional framework; 1 = None |
| Peace clause | Presence of peace clause in collective agreements | Categorical | 2 = Peace clause; 1 = Implicit; 0 = Absent |
| Favourability | Favourability rule in collective agree- ments | Categorical | 3 = Inversed; 2 = Undefined; 1 = Exceptions allowed; 0 = Strict hierarchy; |
| Minimum wage | Presence of minimum wage | Dummy | 1 = Yes; $0 = $ No |
| Union density | Proportion of unionised employees | Ratio | % |
| Training | Training expenditure | Ratio | % GDP |
| Unemployment support | Unemployment benefits expenditure | Ratio | % of GDP |
| Employment rate | Proportion of employed population | Ratio | % of total employment |
| Non-standard workers | Proportion of non-standard workers | Ratio | % of total employment |
| Workers with two or more jobs | Proportion of workers with two or more jobs | Ratio | % |

Table C1: List of variables used for PCA analysis

Source: Own elaborations based on Eurostat and ICTWSS data

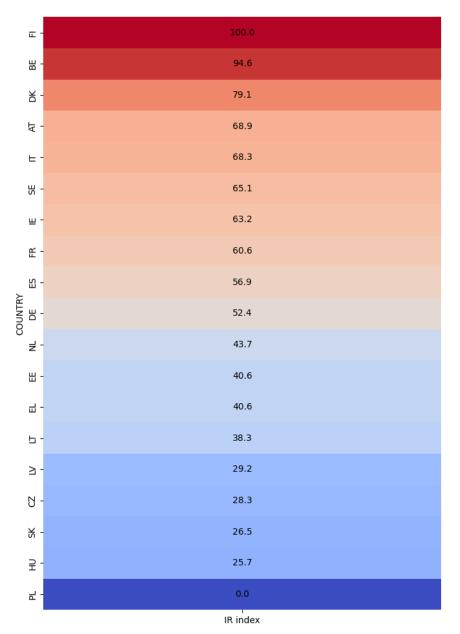


Figure C1: IR index value for each country

Source: Own elaborations based on Eurostat and ICTWSS data

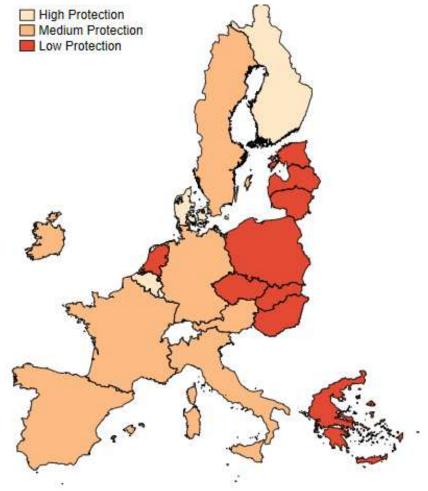


Figure C2: Regimes of industrial relations

Note: High protection (FI, DK, BE); medium protection (AT, DE, ES, FR, IE, IT, SE); low protection (CZ, EE, EL, HU, LT, PL, SK, NL); *Source:* Own elaborations

| Variables | High | Medium | Low |
|--------------------------------------|--------|--------|--------|
| Level of wage bargaining | 4.000 | 2.857 | 1.556 |
| Wage setting | 4.333 | 2.143 | 1.556 |
| Work council | 1.667 | 1.571 | 1.556 |
| National collective bargaining | 0.667 | 0.000 | 0.000 |
| Sectoral collective bargaining | 1.000 | 1.000 | 0.889 |
| Regional collective bargaining | 0.333 | 0.714 | 0.222 |
| Occupational collective agreement | 1.000 | 1.000 | 0.333 |
| Firm bargaining | 1.000 | 1.571 | 1.667 |
| Government | 3.667 | 2.000 | 2.222 |
| Peace clause | 1.333 | 1.000 | 2.000 |
| Favourability | 1.333 | 1.286 | 1.000 |
| Minimum wage | 0.333 | 0.571 | 1.000 |
| Union density $(\%)$ | 64.200 | 29.300 | 14.567 |
| Training | 0.348 | 0.255 | 0.053 |
| Uneployment support | 1.300 | 1.574 | 0.523 |
| Employment rate $(\%)$ | 67.500 | 65.157 | 61.700 |
| Non-standard workers $(\%)$ | 6.088 | 12.634 | 8.677 |
| Workers with two or more jobs $(\%)$ | 0.499 | 0.752 | 0.740 |

Table C2: Descriptive statistics by IR regime

Source: Own elaborations based on Eurostat and ICTWSS data

Robustness Checks D

| | (1) | (2) | (3) | (4) |
|-----------------------------|----------------|---------------|-------------|-----------------|
| | Fatalities per | 1,000 workers | Injuries pe | r 1,000 workers |
| Robot density $_{(t-1)}$ | -0.00770*** | -0.00909*** | -0.230*** | -0.315*** |
| (t-1) | (0.00138) | (0.00171) | (0.0356) | (0.0534) |
| Year | yes | yes | yes | yes |
| Country | yes | yes | yes | yes |
| Pavitt | yes | yes | yes | yes |
| Year \times Country | yes | yes | yes | yes |
| Country \times Pavitt | yes | yes | yes | yes |
| Controls | no | yes | no | yes |
| Constant | 0.00459 | 0.0590 | 2.288*** | 3.946*** |
| | (0.00825) | (0.0370) | (0.214) | (0.743) |
| Kleibergen-Paap F statistic | 290.733 | 234.84 | 290.733 | 234.84 |
| Observations | 2,017 | 1,871 | 2,017 | 1,871 |
| R2 adjusted | 0.177 | 0.227 | 0.668 | 0.702 |

Table D1: IV estimates, unweighted

Notes: Robust standard errors clustered at the country-industry level in parentheses *** p<0.01, ** p<0.05, * p<0.1; Both variables are log-transformed.

| | (1) | (2) | (3) | (4) |
|-----------------------------|---------------|------------------|------------|------------------|
| | Fatalities pe | er 1,000 workers | Injuries p | er 1,000 workers |
| Robot density $(t-1)$ | -0.00553** | -0.00987*** | -0.191** | -0.358*** |
| | (0.00222) | (0.00248) | (0.0918) | (0.0955) |
| Year | yes | yes | yes | yes |
| Country | yes | yes | yes | yes |
| Pavitt | yes | yes | yes | yes |
| Year x Country | yes | yes | yes | yes |
| Country x Pavitt | yes | yes | yes | yes |
| Controls | no | yes | no | yes |
| Constant | 0.00251 | 0.182*** | 2.360*** | 4.967*** |
| | (0.00935) | (0.0454) | (0.302) | (1.052) |
| Kleibergen-Paap F statistic | 80 | 66 | 80 | 66 |
| Observations | 2,017 | 1,871 | 2,017 | 1,871 |
| R2 adjusted | 0.202 | 0.232 | 0.599 | 0.652 |

Table D2: IV estimates, robot density in Japan

Notes: Robust standard errors clustered at the country-industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All estimates are weighted for the size of sectoral employment in 2011; Both variables are log-transformed.

Source: Own elaboration

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|-------------|------------------|-------------|-----------|-------------|-----------|
| | IV 1 | IV 2 | IV 3 | IV 1 | IV 2 | IV 3 |
| | Fatali | ties per 1,000 v | vorkers | Injurie | s per 1,000 | workers |
| Robot density $_{(t-1)}$ | -0.00663*** | -0.00405*** | -0.00606*** | -0.196*** | -0.0884* | -0.195*** |
| (° 1) | (0.00186) | (0.00138) | (0.00184) | (0.0573) | (0.0527) | (0.0606) |
| Year | yes | yes | yes | yes | yes | yes |
| Country | yes | yes | yes | yes | yes | yes |
| Pavitt | yes | yes | yes | yes | yes | yes |
| Year x Country | yes | yes | yes | yes | yes | yes |
| Country x Pavitt | yes | yes | yes | yes | yes | yes |
| Controls | yes | no | yes | yes | no | yes |
| Constant | 0.182*** | 0.0261* | 0.153** | 4.967*** | 3.582*** | 3.876*** |
| | (0.0454) | (0.0146) | (0.0710) | (1.052) | (0.140) | (1.378) |
| Kleibergen-Paap F statistic | 185.173 | 436.081 | 168.868 | 185.173 | 436.081 | 168.868 |
| Observations | 1,871 | 1,896 | 1,750 | 1,871 | 1,896 | 1,750 |
| R2 adjusted | 0.238 | 0.206 | 0.242 | 0.706 | 0.631 | 0.705 |

Table D3: IV estimates, excluding manufacturing of wood and cork

Notes: Robust standard errors clustered at the country-industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All estimates are weighted for the size of sectoral employment in 2011; Both variables are log-transformed. Source: Own elaboration

| | | (| 4.5 | | | |
|-----------------------------|------------------------------|-------------|-------------|----------|--------------|-----------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | IV 1 | IV 2 | IV 3 | IV 1 | IV 2 | IV 3 |
| | Fatalities per 1,000 workers | | | Injurie | es per 1,000 | workers |
| Robot $density_{(t-1)}$ | -0.00663*** | -0.00440*** | -0.00656*** | -0.196** | -0.111* | -0.196*** |
| * (0 1) | (0.00186) | (0.00151) | (0.00187) | (0.0573) | (0.0571) | (0.0518) |
| Year | yes | yes | yes | yes | yes | yes |
| Country | yes | yes | yes | yes | yes | yes |
| Pavitt | yes | yes | yes | yes | yes | yes |
| Year x Country | yes | yes | yes | yes | yes | yes |
| Country x Pavitt | yes | yes | yes | yes | yes | yes |
| Controls | yes | no | yes | yes | no | yes |
| Constant | 0.182*** | 0.00251 | 0.165*** | 4.967*** | 2.360*** | 3.944*** |
| | (0.0454) | (0.00936) | (0.0504) | (1.052) | (0.302) | (1.104) |
| Kleibergen-Paap F statistic | 185.173 | 266.477 | 118.922 | 185.173 | 266.477 | 118.922 |
| Observations | 1,871 | 2,056 | 1,533 | 1,871 | 2,056 | 1,533 |
| R2 adjusted | 0.238 | 0.207 | 0.276 | 0.706 | 0.630 | 0.783 |

Table D4: IV estimates, excluding countries with the highest incidence of fatalities

Notes: Robust standard errors clustered at the country-industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All estimates are weighted for the size of sectoral employment in 2011; Both variables are log-transformed. Source: Own elaboration

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|--|--|--|--|--|---|
| | IV | Winsor 2% | Winsor 2% | IV | Winsor 2% | Winsor 2% |
| | Fatali | ties per 1,000 w | vorkers | Injur | ies per 1,000 v | vorkers |
| Robot $\operatorname{density}_{(t-1)}$ | -0.00663^{***} | -0.00579^{***} | -0.00548^{***} | -0.196^{***} | -0.197^{***} | -0.194^{***} |
| | (0.00186) | (0.00163) | (0.00149) | (0.0573) | (0.0574) | (0.0574) |
| Year Country Pavitt Year x Country Country x Pavitt Controls Constant | yes yes yes yes yes yes 0.182*** | yes yes yes yes no 0.176*** | yes yes yes yes yes yes 0.158*** | yes yes yes yes yes yes 4.967*** | yes yes yes yes no 5.025*** | yes yes yes yes yes 5.043*** |
| Kleibergen-Paap F statistic Observations R2 adjusted | (0.0454) 185.173 1,871 0.238 | (0.0412) 185.173 $1,871$ 0.270 | (0.0380) 185.173 1,871 0.283 | (1.052) 185.173 1,871 0.706 | (1.049) 185.173 1,871 0.706 | (1.047) 185.173 $1,871$ 0.707 |

Table D5: IV estimates, winsor

Notes: Robust standard errors clustered at the country-industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All estimates are weighted for the size of sectoral employment in 2011; Both variables are log-transformed. Source: Own elaboration

| | (1) IV | (2) high | (3) medium-high | (4) medium-low | (5) low |
|-----------------------------|-------------------------------|-------------------------|-------------------------|-----------------------|-----------------------|
| Robot $density_{(t-1)}$ | -0.00738^{***} (0.00217) | -0.0115*** (0.00446) | -0.00715** (0.00328) | -0.00748 (0.00575) | -0.00356 (0.00446) |
| Year | yes | yes | yes | yes | yes |
| Country | yes | yes | yes | yes | yes |
| Pavitt | yes | yes | yes | yes | yes |
| Year x Country | yes | yes | yes | yes | yes |
| Controls | yes | yes | yes | yes | yes |
| Constant | 0.211*** | -0.0122 | 0.238*** | 0.252* | 0.0794 |
| | (0.0494) | (0.0410) | (0.0606) | (0.129) | (0.0858) |
| Kleibergen-Paap F statistic | 170.894 | 60.739 | 106.28 | 40.045 | 47.413 |
| Observations | 1.871 | 321 | 769 | 321 | 460 |
| R2 adjusted | 0.193 | 0.280 | 0.199 | 0.184 | 0.293 |

Table D6: Workplace fatalities per 1,000 workers, four IR regimes

Notes: Robust standard errors clustered at the country-industry level in parentheses *** p<0.01, ** p<0.05, * p<0.1; All estimates are weighted for the size of sectoral employment in 2011; Both variables are log-transformed.

Source: Own elaboration

| | (1) IV | (2) high | (3) medium-high | (4) medium-low | (5) low |
|-----------------------------|------------|-------------|--------------------|-------------------|-------------|
| Robot density $_{(t-1)}$ | 0.00738*** | -0.484*** | -0.248*** | -0.372* | -0.168*** |
| (t-1) | (0.00733) | (0.122) | (0.0694) | (0.193) | (0.0620) |
| Year | yes | yes | yes | yes | yes |
| Country | yes | yes | yes | yes | yes |
| Pavitt | yes | yes | yes | yes | yes |
| Year x Country | yes | yes | yes | yes | yes |
| Controls | yes | yes | yes | yes | yes |
| Constant | 0.211*** | 2.571** | 7.874*** | 2.575 | 2.999^{*} |
| | (0.0494) | (1.219) | (1.433) | (1.952) | (1.807) |
| Kleibergen-Paap F statistic | 170.894 | 60.739 | 106.28 | 40.045 | 47.413 |
| Observations | 1,871 | 321 | 769 | 321 | 460 |
| R2 adjusted | 0.193 | 0.547 | 0.646 | 0.622 | 0.788 |

Table D7: Workplace injuries per 1,000 workers, four IR regimes

Notes: Robust standard errors clustered at the country-industry level in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1; All estimates are weighted for the size of sectoral employment in 2011; Both variables are log-transformed.