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DISCUSSION PAPER SERIES

IZA DP No. 17864

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APRIL 2025

ISSN: 2365-9793

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ABSTRACT

Robots Replacing Trade Unions: Novel Data and Evidence from Western Europe*

Labor unions play a crucial role in liberal democracies by influencing labor market and political dynamics, organizing workers' demands and linking them to parties. However, their importance has progressively diminished in the last decades. We suggest that technological change—and industrial robotization in particular—has contributed to weakening the role of unions. We produce novel granular data on union density at the sub-national and industry level for 15 countries of western Europe over 2002-2018. Employing these data, we estimate the impact of industrial robot adoption on unionization rates. We find that regions more exposed to automation experience a decrease in union density. The decline in unionization occurs via a compositional effect, i.e., a reallocation of employment away from traditionally unionized industries towards less unionized ones. On the other hand, there is no clear evidence of a systematic reduction in union density within industries more exposed to automation.

JEL Classification: J5, J2, O3, P0
Keywords: labor unions, automation, robots, Europe, regions

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* We thank Catherine de Vries, Pablo Beramendi, Tito Boeri, Silja Häusermann, Herbert Kitschelt, Alessia Matano, Paolo Naticchioni, and seminar participants at the 2024 APSA Comparative Labor Workshop, Bank of Italy, Bocconi University, Duke University, California Institute of Technology, EPSA 2023, European Society for Population Economics Conference 2024, International Political Economy Society Conference 2024, Joint Research Centre, MPSA 2022, Scuola Normale Superiore, SPSA 2024, Turin University, University of North Carolina at Chapel Hill, Verona University, Yale University and Zurich University for insightful comments. We gratefully acknowledge funding from the Fondazione CARIPLO Science and Technology Grant. Andrea Cancellieri, Giovanni Della Seta, Simone Foresti, Juan David Garcia Gonzalez, Maria Elena Lasiu, Mariadolores Schiavone, Fabrizio Viti and Jakob Wall provided excellent research assistance. The usual disclaimer applies.

1 Introduction

Throughout the 20th century, trade unions have played a central role in liberal democracies, influencing labor market dynamics and channeling workers' political demands into an organized voice (Ahlquist, 2017). By negotiating wages and working conditions, unions influenced how the benefits of economic progress were distributed, contributing to limit the rise in inequalities (e.g., Farber et al., 2021). By mobilizing workers in support of redistributive policies, unions served as a link between workers' constituencies and pro-redistribution parties, especially of the mainstream left (e.g., Häusermann and Kitschelt, 2023; Przeworski and Sprague, 1986). Yet, in recent decades, unions have experienced a decline in membership, paired with diminished relevance in the democratic process (Rosenfeld, 2014). This phenomenon is consequential for electoral dynamics (e.g. Kitschelt, 2012; Rennwald and Pontusson, 2021).

In this article, we provide the first evidence on unionization dynamics at the granular region and industry level covering 15 countries of western Europe, over 2002-2018. Using these novel data, we show that technological change is a key determinant of the decline in unionization. Specifically, we focus on the surge of industrial robot adoption in manufacturing, which has been identified as a main dimension of structural change over the period of analysis (e.g., Boix, 2019; Gallego and Kurer, 2022).

Automation through robots has been found to produce aggregate welfare gains with significant distributional effects. Workers that are more vulnerable to substitution by robots, and regions where these workers are more concentrated, are relative losers of this phenomenon (e.g., Acemoglu and Restrepo, 2020; Dauth et al., 2021). The unequal economic consequences of automation, in turn, have been shown to be politically consequential. In particular, automation losers have been found to turn towards radical parties, especially of the right (e.g., Anelli et al., 2021; Milner, 2021). The impact of automation on unionization has instead remained largely underexplored, with the notable exception of Balcazar (2024).

Yet trade unions are potentially key actors shaping the implications of technological change, both in terms of distributional effects on the labor market, and in terms of the ensuing political consequences. By investigating the link between automation and unionization, this article aims at furthering the general understanding of the economic and political implications of structural change.

Thus far, comparative research on trade unions has been hindered by data limitations. In fact, the only available source of comparable data across countries, the database by Visser (2019), only provides information on the overall unionization rate at the country-year level. For most European countries, in fact, these are also the only available data on unionization. Aggregate figures obscure critical sub-national and sectoral variation, and the lack of granular data makes it essentially impossible to study the determinants of unionization in a causally identified way (Ahlquist, 2017; Lipset, 1983).

In light of this, the first contribution of this paper is to assemble a novel database on region- and industry-level unionization rates across 15 western European countries.[1] To this purpose, we combine data from the European Social Survey (ESS) with country censuses over two decades (2002-2018), and use dynamic multilevel regressions with post-stratification (MrP, Park et al., 2004; Gelman et al., 2019). Intuitively, we first estimate the predicted probability of unionization for different types of individuals, defined as combinations of age, gender, education, occupation, industry, and region of residence, based on ESS data. Then, we compute the union density at, for instance, the regional level, by taking a weighted average of the unionization rates for different types. The weights represent the relative share of each type of individuals out of the population of the region, based on census data. This is an innovative application of the methodology initially proposed by Park et al. (2004), which has mostly been used thus far for predicting public opinion at the sub-national level in single-country contexts.

[1]The complete database containing granular unionization data will be made publicly available for the research community upon publication of this paper, at the following dedicated website: www.uniondata.info.

This approach allows us to obtain union density estimates that are representative at the sub-national and industry level, and comparable across countries. We validate these unionization estimates with administrative data from the handful of countries where such granular data are available. Moreover, when aggregating our estimates at the country-year level for all sample countries, we retrieve patterns that are highly consistent with those obtained from the Visser (2019) database.

We show that automation is a significant determinant of unionization decline. In particular, regions that are more exposed to robot adoption witness a decrease in union density. The effect of automation is not only statistically but also substantively significant: a one standard deviation increase in robot exposure leads to a decrease in union density by around 34.4% of a standard deviation, accounting for country-year and region fixed effects. The decline in unionization occurs via a compositional effect, i.e., a reallocation of employment away from traditionally unionized industries—that are on average more exposed to automation—towards less unionized ones. Conversely, there is no clear evidence of a systematic reduction in union density within industries where robot adoption is higher. Overall, our results speak to the importance of unionization as a contextual factor that may influence electoral dynamics at the local level, shaping the political repercussions of automation.

2 Background and conceptual framework

In this section we present the conceptual framework of the analysis. First, we discuss the political significance of trade unions and their decline over recent decades, which has been shown to be politically consequential. Then, we propose technological change, and chiefly robotization, as a driver of this decline. Finally, we connect our work to existing literature that has investigated other factors of unionization decline, clarifying and highlighting our novel contribution.

2.1 The political significance of trade unions

From an economic perspective, trade unions have historically played an important role in terms of wage setting and, more generally, in terms of bargaining over working conditions (e.g., Freeman and Medoff, 1984). Unions influence distributional outcomes by shaping how the welfare gains of economic progress are distributed. Unionization is generally associated with reduced wage inequality among unionized workers (Rosenfeld, 2014). Moreover, unions' influence on labor compensation extends beyond their immediate membership (Western and Rosenfeld, 2011). In fact, public policies often expand the reach of union-negotiated wage agreements to non-unionized workers ("union coverage effects"), and employers may independently increase wages to deter further unionization ("union threat effect"). Overall, through a combination of direct and indirect channels, rising unionization tends to reduce inequality (Farber et al., 2021), and declining unionization tends to increase it (Western and Rosenfeld, 2011).

Beyond their economic significance, labor unions also play a central role from a political perspective, in a number of ways. At a first level of analysis, unions enhance political participation by providing information and fostering engagement. Union members are more politically knowledgeable and engage more in political discussion (Iversen and Soskice, 2015). In line with that, unions have a positive influence on voter turnout (Becher and Stegmueller, 2019; Leighley and Nagler, 2007; Radcliff and Davis, 2000), an empirical regularity known as the "union vote premium". Unions also enable working-class citizens to exercise political power (Lipset, 1983; Marks, 1982). In fact, they provide workers with political training and support pathways to careers in politics. Union members and leaders frequently transition into elected or appointed government roles, and serving as a union officer is often a stepping stone to public office. This is an important factor fostering the presence of workers in politics (Mach et al., 2024).

Besides the impact on political participation, and related to that, unions organize workers' demands and frame the political discourse around distributional issues. Trade unions shape workers' policy views, making them think in terms of class interest and class conflict rather than cultural or ethnic conflict (Frymer and Grumbach, 2021; Kim and Margalit, 2017). At the same time, they foster the relevance of workers' interests in the electoral arena. On the one hand, they do so by inducing political parties to focus on distributional economic issues that are relevant to workers (Pontusson and Rueda, 2010). On the other hand, they mobilize workers in support of parties that adopt pro-redistribution stances, especially within the mainstream left (Chang, 2001; Dark, 2018; Schlozman, 2015). Labor unions also significantly influence the behavior of elected politicians, raising political responsiveness and legislative support for redistributive policies. In particular, strong union presence increases responsiveness to lower-income constituents, narrowing disparities in representation across income groups (Becher and Stegmueller, 2020). Overall, from the perspective of power resource theory (Esping-Andersen, 1985; Korpi, 1983, 1986), unions are key political actors driving redistribution and social policy.

Importantly, much of the evidence suggests that labor unions have a *contextual* impact that extends beyond their direct membership. The presence and strength of unions can generate spillovers that affect non-members. This is true both in industrial relations—where collective agreements often cover non-unionized workers—and in politics, where unions act as intermediaries for social constituencies that are broader than their membership (Freeman and Medoff, 1984). For instance, Ahlquist and Levi (2013) highlight how union leaders inspire collective actions that transcend narrow self-interest, underscoring the outward-facing nature of unions' political engagement. Union presence in workplaces and their integration into communities can shape political behavior even among non-members, and play a critical role in local political campaigns (Lyon and Schaffner, 2021; Lopez, 2004). Such contextual effects may be as impactful as the direct effects of union membership.

Overall, these considerations call for studying unions as contextually consequential actors. Empirically, this requires a shift away from focusing solely on individual union membership in surveys, moving to considering regional- and industry-level unionization measures. This type of research has thus far been hindered by data limitations. Yet, some indirect evidence on the contextual role of unions exists. For instance, the size of the workplace in which people are employed is one of the most commonly cited factors affecting union membership (e.g., Oesch, 2006). That is, unionization rates tend to be higher in larger plants, which provide a more fertile ground for unions' activities. In parallel, relating to the political repercussions of unionization, Arndt and Rennwald (2017) document how workers in larger plants are less likely to support the radical right, suggesting that this is related to higher unionization. Along the same lines, at the country level, the employment share of large plants is positively correlated with social democratic parties' vote shares (Pontusson, 1995). One of the main contributions of this study is to provide novel granular data enabling a more direct analysis of the contextual role of unions at both the sub-national and industry level.

Our novel data also allow to uncover the dynamics underlying the phenomenon of unionization decline observed in recent decades across most Western countries. In the United States, for instance, private sector unionization dropped dramatically between 1973 and 2007, falling from 34% to 8% among men, and from 16% to 6% among women (Western and Rosenfeld, 2011). Similar declines have been observed in Europe, even in Scandinavian countries that were traditionally characterized by relatively high unionization rates. Comparative analyses of unionization trends in OECD countries, based on country-level data, indicate that the 1980s marked a critical turning point (e.g., Western, 1997; Wallerstein and Western, 2000). Unionization started a decline that persisted in most cases into the 21st century. As a result, union density is now at historically low levels (Rosenfeld, 2014).

Not surprisingly, given the political significance of unions, the decline of unionization has been shown to be politically consequential. In the US, Feigenbaum et al. (2018) show that the weakening of unions reduces Democratic vote share and turnout. Moreover, it also affects who runs for office: as declining unionization forces unions to prioritize membership recruitment and retention, they allocate fewer resources to campaign contributions and political activity. Along similar lines, Carnes (2013) finds that diminishing unionization has contributed to reducing the number of legislators with working-class backgrounds, weakening the political representation of these groups. Weaker unions have also been found to be associated with increased legislative support for trade deregulation and reduced support for workers' compensatory measures (Becher and Stegmueller, 2024). According to Kitschelt (2012), the decline of unionization may have also contributed to the shift of social-democratic parties towards more centrist positions on redistribution, as they sought to attract middle-class constituencies drawn to their cosmopolitan stances on non-economic issues. The political significance of declining unionization makes it important to investigate the drivers of this phenomenon. In this article, we argue for the role of automation as a key structural factor. In the next section, we develop the conceptual framework linking automation and unionization.

2.2 The role of automation

Historically, technological progress has always generated aggregate welfare gains paired with substantial distributional consequences (Goldin and Katz, 1998). Technological innovations create new opportunities for workers whose skills are complementary to the new technologies, while posing challenges to workers that are more substitutable. This creates winners and losers of technological change, at least in relative terms.

The computer revolution that took place from the 1980s onwards, with the widespread adoption of IT and computer-based technologies, has been identified as a main driver of rising wage inequality and educational premia both in the US and in Europe (e.g., Acemoglu and Autor, 2011). Computerization has mainly substituted workers in jobs involving mostly routine tasks, both cognitive and manual, while it has complemented workers in jobs involving mostly non-routine tasks. Since routine jobs were predominantly middle-skill and middle-income occupations, this technological shift has led to a phenomenon known as "labor market polarization". In essence, employment has grown at both ends of the wage and skill spectrum, while the traditional middle class has contracted. This trend has been well-documented in both the United States and Europe (Autor and Dorn, 2013; Goos et al., 2014).

Computerization has eliminated many decently paid clerical and blue-collar jobs, with displaced workers largely absorbed into lower-wage, non-routine service roles (e.g., drivers and personal care workers). In terms of wage gains, the main winners of computerization have been high-skill, typically college-educated workers employed in non-routine cognitive jobs. They have been strongly complemented by the new technologies, and their incomes have diverged from those of the declining middle class. The latter falls into the group of losers, along with low-skill workers, who have benefited less from technological advances, and faced additional wage compression due to competition from displaced middle-skill workers (Autor, 2015).

Industrial robots represent the next spurt of automation, made possible by the expansion of the capabilities of computer based technologies. As highlighted by Frey and Osborne (2017), the novel aspect of robotization compared to earlier computerization is the extension of automation also to non-routine tasks, which were previously relatively unaffected. For instance, mobile robotics extends automation from routine assembly line operations to non-routine, more complex production activities, and to new domains such as maintenance of industrial plants, demolition and construction, and mining. According to data from the International Federation of Robotics (IFR), the stock of operational robots at the global level has grown exponentially from the mid-1990s onwards, with an acceleration from the mid-2000s. Importantly, the robotization shock comes after the peak of the so-called "China shock", i.e., the displacement driven by surging imports from China from the end of the 1980s until the Great Financial Crisis of 2007. At the same time, robotization precedes the widespread adoption of AI tools, which began gaining momentum in 2022. As a result, robotization stands out as the primary driver of structural change during the period of analysis (2002–2018), providing a key motivation for our focus.

A growing literature has provided evidence on the economic effects of automation through robots. Most studies adopt a regional level approach to focus on robot exposure, akin to the one adopted for evaluating the impact of the China shock (Autor et al., 2013). In this approach, stronger exposure to robotization is attributed to areas that were ex-ante specialized in industries witnessing higher robot adoption in subsequent years. In the US, Acemoglu and Restrepo (2020) find that stronger automation exposure reduces both employment and average wages at the commuting-zone level. The negative impact on employment is stronger in the manufacturing sector, particularly in industries such as automotive that are more exposed to robotization. Yet, it also extends to non-manufacturing sectors such as construction, personal services, and retail. The effect is more pronounced for workers with no college degree, for men in general, and for blue-collar workers employed in routine manual jobs, assembly, and related occupations. The negative effect of robotization on wages is mainly felt in the lower half of the wage distribution, thus contributing to the rise in wage inequality. Similar results for the US are also obtained by Borjas and Freeman (2019). Cross-country evidence of negative employment effects of robotization are found by Chiacchio et al. (2018) on 6 European countries, and by Carbonero et al. (2020) and Chen and Nabar (2018) on larger sets of countries including both advanced and emerging economies. Graetz and Michaels (2018), focusing on a sample of 17 industrialized countries, find that robot adoption increases productivity but reduces the share of hours worked by low-skill workers.

In Germany, Dauth et al. (2021) observe automation-induced job losses in manufacturing that are offset by employment gains elsewhere, especially in business services. Workers who are forced to switch plants, industries, or leave the manufacturing sector incur significant earnings losses. Overall, automation increases wage inequality by benefiting workers employed in occupations that are complementary to robots, such as managers and technical scientists, and penalizing substitutable workers like machine operators. Similar evidence is found by Bessen et al. (2023) for the Netherlands, and Dottori (2021) for Italy.

Overall, the surge in robotization has driven substantial distributional consequences, favoring mostly high-skill individuals vis-à-vis others. The losers of robotization tend to be concentrated in specific manufacturing industries, and in geographic areas where such industries were historically concentrated. In turn, these distributional effects have been found to be politically consequential. In the US, Frey et al. (2018) find that support for the Republican candidate Donald Trump in the 2016 presidential election was higher in local labor markets more exposed to robot adoption. In Europe, higher exposure to robotization at the regional level has been found to determine higher support for radical-right parties (Anelli et al., 2019; Dal Bó et al., 2023; Caselli et al., 2021; Milner, 2021). Similar results have been found at the individual level. For instance, Anelli et al. (2021) find that individuals more exposed to robot adoption, based on their positioning in the labor market, are more likely to support radical-right parties. Analogous evidence has been obtained measuring automation exposure through the automatability of one's occupation (e.g., Gingrich, 2019; Im et al., 2019; Milner, 2021).

While much is known about the economic and political effects of robotization, the impact on unionization has remained largely underexplored. Yet labor unions may play a crucial role in shaping the implications of automation, both in terms of distributional effects on the labor market, and in terms of the ensuing political consequences. From an economic perspective, Kristal (2013) and Kristal and Cohen (2015) find that computerization in the US increased wage inequality—and decreased the overall labor share in favor of the capital share of income—not only through direct labor market effects, but also through weakening unions. From a political perspective, Kitschelt (2012) suggests that the turn to the radical right of blue-collar constituencies experiencing economic distress may be partly explained by the decline of trade unions. Unionization decline may help make sense of a puzzle that has been often pointed out in the literature: why constituencies most penalized by automation (and globalization) are turning towards radical-right forces, rather than supporting parties with clearly redistributive stances (e.g., Kitschelt, 2012; Betz, 1993, 1994; Betz and Meret, 2012).

Radical-right parties are skeptical, or at a minimum ambiguous about redistribution (Kitschelt and McGann, 1997; Rovny, 2013); they are unsupportive of active labor market policies (Enggist and Pinggera, 2022), and of workers' rights more in general (Greilinger and Mudde, 2024; Rathgeb and Busemeyer, 2022). Unionization decline may explain why these parties are nevertheless successful at attracting the losers of structural economic changes such as automation. In fact, Rennwald and Mosimann (2023) have documented that non-unionized workers are less inclined to support parties that cater to their redistributive needs, and more likely to realign their vote based on cultural preferences. As observed by Colantone and Stanig (2018), the weakening of the link between blue-collar constituencies and left-wing parties opened the space for options that assign a central role to economic nationalism and nativism rather than the welfare state. Levi (2017) underscores that "the decline of labor unions has also facilitated the rise of populism by eliminating a source for a framework for understanding the situation of workers". Along these lines, Frymer and Grumbach (2021) discuss the feedback loop between union decline and racial prejudice. Overall, investigating the link between robotization and unionization is key to improve the understanding of both the economic and the political implications of automation.

From a theoretical standpoint, a main way in which robotization may reduce unionization is through a compositional effect in the labor market. The available evidence (e.g., Acemoglu and Restrepo, 2020; Dauth et al., 2021) suggests that robot adoption is higher in traditionally unionized manufacturing industries (e.g., automotive), and tends to shift employment towards less unionized industries (e.g., in logistics and personal care services), where it is also more difficult for unions to make inroads among workers. The result is a compositional change in employment that reduces overall unionization. This is likely to be visible not only at the country level but also at the sub-national level. The regional level is in fact most interesting for the purpose of our analysis, as it is where the role of unions as *contextual* factors may be particularly consequential, both economically and politically.

Besides this compositional effect, robotization may also reduce unionization within industries that are relatively more exposed to it. This could happen for at least three reasons. First, as suggested by Meyer (2019) in a study on computerization, the shift in the composition of the workforce induced by robots—i.e., relatively fewer blue-collar workers and more high-skill technical scientists and managers—may increase skill heterogeneity among workers, reducing their incentives for collective action. Relatedly, Checchi et al. (2010) suggest that rising earning inequality contributes to unionization decline by eroding solidarity among workers. Second, robotization may reduce the overall size of the workforce employed at each given plant; in turn, we know that unionization tends to be lower at smaller establishments (e.g., Oesch, 2006). Third, as suggested by Kristal (2013) for computerization, robotization may structurally diminish the bargaining power of workers, and thus inherently reduce their incentives to unionize. In our empirical analysis, we investigate the impact of robotization on unionization both at the regional level and at the industry level.

2.3 Automation and other factors of unionization decline

Our work is related to other streams of research that have investigated different factors of unionization decline. Brady (2007) categorizes these factors into three main families: institutional, solidaristic, and economic.

Institutional explanations argue that cross-national differences in unionization levels, as well as their trends, are largely shaped by institutional arrangements. These include union access to workplace representation, selective incentives such as union-administered unemployment schemes, recognition of employers through corporatist institutions, and closed-shop arrangements mandating union membership (Ebbinghaus and Visser, 1999). Government policies aimed at improving work security can also influence workers' incentives to join unions (Checchi and Lucifora, 2002). In the US, shifts in public policy seem to have played a key role in the decline of unionization rates (Feigenbaum et al., 2018; Farber, 2005; Hacker and Pierson, 2010; Lichtenstein, 2013).

Solidaristic explanations for unionization decline focus on the shift from class-based politics to identity- and status-oriented politics (Brady, 2007). For instance, Hechter (2004) argues that the expansion of welfare states has reduced the need for unions, as general welfare provisions now provide the social insurance that unions once offered exclusively to their members, leading to a decline in unionization and class consciousness.

Economic explanations consider both the short-term effects of business cycle fluctuations, and the long-term role of structural transformations such as de-industrialization (Brady, 2007). Studies that are most closely related to our work have investigated the link between globalization and unionization. Globalization entails easier international trade and capital mobility. Employers can exploit globalization to weaken workers' bargaining power, using the threat of production offshoring to countries with lower labor costs and lower unionization. According to Becher and Stegmueller (2020), economic shocks from global markets weaken labor unions, diminishing their influence on political representation and legislative support for compensatory policies, exacerbating inequality and heightening dissatisfaction with democratic processes. Slaughter (2007) finds a strong correlation between rising foreign direct investment and falling unionization in the US. Becher and Stegmueller (2024) find that import competition reduces district-level unionization, which in turn decreases legislative support for policies compensating economic losers and weakens opposition to trade deregulation. Ahlquist and Downey (2023) show that stronger import competition from China leads to a slight decline in unionization within manufacturing, but also to an increase in union membership in other sectors, such as healthcare and education, where unions are stronger. This suggests that structural forces may operate through compositional changes in the economy.

Technological progress, and in particular robotization, is the most important structural economic change taking place over the period we study. The consequences of robotization on labor unions are understudied. This study contributes to the literature on the economic drivers of unionization by focusing on this key dimension of structural change. In a study parallel to ours, Balcazar (2024) investigates the impact of robot adoption on unionization in the US. He finds that higher robotization at the level of congressional districts is related to lower unionization rates, and to lower responsiveness of elected representatives with respect to unions' interests, particularly on policies aimed at compensating the losers from international competition. Along similar lines, Agnolin (2025) finds that in areas of the US witnessing higher robot adoption candidates are less likely to come from a working-class background. This may contribute to weaken the representation of workers' interests in the democratic process.

3 Novel data on union density

Comparative research on labor unions has long been hampered by data limitations. As early as the beginning of the 1980s, Lipset (1983) observed that "a comparative analysis of working class movements in western society is limited by an obvious methodological problem: too many variables and too few cases". As Ahlquist (2017) aptly notes, "we have too many explanations chasing too few data points that are themselves interdependent in both time and space", and therefore recommends "research designs explicitly taking advantage of heterogeneity in context and population". To pursue such paths, better disaggregated data are required (Pontusson and Rueda, 2010).

At present, the only available source of comparable data on unionization across countries is the Visser (2019) dataset (ICTWSS). This is based on information collected and compiled by third parties within each country.[2] The main limitation of this dataset is that it only provides information on the overall unionization rate at the country-year level. Such aggregate data constitute an important constraint to unionization research. A sub-national

[2]Since 2021, the Visser (2019) database has been maintained as the OECD/AIAS ICTWSS database, reflecting a collaborative effort between the OECD and AIAS to ensure its continuation following Professor Visser's retirement. This version builds upon and consolidates earlier editions of the ICTWSS database and is publicly accessible at www.oecd.org/employment/ictwss-database.htm.

and sectoral analysis is in fact required not only to achieve clean identification of causal effects of unionization factors, but even just to address descriptive questions on unionization decline.

In the US, researchers have leveraged more fine-grained unionization data available via the Current Population Survey, where large samples of individual observations allow for meaningful aggregation at the sub-national and industry level (see, for instance, Ahlquist and Downey, 2023; Farber et al., 2021). Recently, a growing stream of research has also utilized the fine-grained data compiled by Becher et al. (2018) based on administrative records, with Balcazar (2024) and Becher and Stegmueller (2020, 2024) being notable examples.

For most European countries, instead, the national-level figures provided by the Visser (2019) database are the only available data on unionization. In fact, official national statistics only rarely collect or provide data on union density at any level, and administrative sources allow to retrieve such information only in a few contexts. While trade unions generally maintain records of their membership numbers, these records are often based on varying collection procedures, definitions of union membership, criteria for including students and retirees, and update frequencies. Moreover, statistics derived from the main trade unions' records do not account for the presence of union members in smaller trade unions.

Against this backdrop, the first contribution of this paper is to assemble a novel database on region- and industry-level unionization rates across 15 western European countries.[3] We obtain these unionization figures combining data from the European Social Survey (ESS) with country censuses over the period 2002-2018, using dynamic multilevel regressions with post-stratification (MRP, Park et al., 2004; Gelman et al., 2019). Our approach is very intuitive. First, we employ ESS data to estimate the predicted probability of unionization for

[3]These are Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK.

different types of individuals, defined as combinations of age, gender, education, occupation, industry, and region of residence. Then, we compute the unionization rate at the regional level by taking a weighted average of unionization probabilities for different types of individuals. The weights are given by the share of each type of individuals out of the regional population, as obtained from census data. Similarly, we obtain industry-level figures by using as weights the share of each type of individuals out of all workers employed in a given industry, within each country.

This methodological approach allows us to obtain unionization estimates that are representative at the sub-national and industry level, and comparable across countries. It is an innovative application of the methodology initially proposed by Gelman and Little (1997) and Park et al. (2004), and popularized in applied political science research by Lax and Phillips (2009).[4] Thus far, this approach has mostly been used for predicting public opinion at the sub-national level in the US. We provide a novel cross-country application in the European context, focusing on unionization as an outcome.

3.1 Unionization estimates and validation

In the first step of the MRP approach, we employ individual-level data from nine rounds of the European Social Survey to estimate the probability of unionization for different types of individuals. As a starting point, we estimate models of the following general form:

$$Pr(Union_i = 1) = \; F(\text{gender}, \text{age}, \text{edu}, \text{occupation}, \text{industry}, \text{region}, \text{round}, \boldsymbol{X_r}) \quad (1)$$

where $Union_i$ is an indicator variable for whether the respondent is a union member, and $F(\cdot)$ is the probit link. The probability of unionization is modeled as a function of several individual characteristics: gender, age, education, occupation (ISCO 2-digit),

[4]See also Leemann and Wasserfallen (2020) for a textbook treatment.

industry (NACE 2-digit), and region of residence (NUTS 2-digit).[5] In addition, we include information on time—i.e., the ESS round in which the individual is observed—and a vector $\boldsymbol{X_r}$ of regional, pre-sample variables. This includes: the employment share of low- and medium-skill workers, the employment share of services, the employment share of low- and medium-tech industries, the employment share of primary sector, the employment share of finance and business services, and the share of foreign-born workers.[6] Importantly, we estimate the probit models separately for each sample country.

We explore a rich space of sixteen alternative specifications for the probit function $F(\cdot)$ in Equation 1, following the dynamic MRP approach developed by Gelman et al. (2019) to model time variation. These specifications feature different combinations of random effects and time trends based on the whole set of predictors. The full list of models can be found in Online Appendix A. The baseline model, selected via cross-validation, has the following form:

$$\Pr(Union_i = 1) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{occ} + \alpha^{ind} + \alpha^{region} + \alpha^{occ\_1d,\ edu} + \beta \cdot round + \xi \cdot \boldsymbol{X_r}) \quad (2)$$

where the α terms are random effects for gender, age category, education level, occupation, industry of employment, region of residence, and the combination of (ISCO 1-digit) occupation and education level. The specification includes also a time trend, captured by the ESS *round* variable, and the vector $\boldsymbol{X_r}$ of variables controlling for cross-regional differences in pre-sample conditions.

The baseline model outlined in Equation 2 is chosen through cross-validation in order to optimize the predictive performance at the region and industry level. In practice, in each country we: randomly split the sample into $K = 10$ folds; estimate each model on the training set (i.e., excluding fold k); form unionization predictions for fold k; and iterate over folds to obtain a vector of predictions for all observations. We then evaluate the accuracy of

[5] Industries are classified according to the Revision 1.1 of the NACE classification. Regions are at the NUTS-2 level for all countries except Germany and the UK, where data are only available at the NUTS-1 level due country-specific privacy limitations.

[6] Low-skill workers have up to lower secondary education. Medium-skill workers have upper secondary and post-secondary non-tertiary education.

predictions for each relevant group of observations, i.e., regions and industries within each country.

We denote as Ω_g the set of N_g observations in a given group g (e.g., region Île-de-France, or textile industry in France). The average predicted probability for group g is $\hat{P}_g = \frac{\sum_{i \in \Omega_g} \hat{P}_i}{N_g}$. Analogously, the observed empirical frequency in the ESS data is given by $F_g = \frac{\sum_{i \in \Omega_g} \mathbb{1}(Union_i = 1)}{N_g}$. The group-wise calibration RMSE based on the whole set of groups G within a given country is $\text{RMSE}_\text{G} = \left(\frac{\sum_g (\hat{P}_g - F_g)^2}{G} \right)^{\frac{1}{2}}$. This metric compares the (cross-validated) predicted probabilities for each region or industry g with the empirical frequency of unionization among survey respondents from that region or industry. We then rank specifications according to their RMSE performance within each country. The baseline specification in Equation 2 is the model that ranks on average best across all countries in the study.[7]

Our main results on the impact of robotization on unionization are robust to employing union density figures obtained from any of the sixteen different probit specifications. For ease of exposition, in the tables we only report two sets of robustness checks. First, we show that results are robust to using the highest ranked prediction model by country. In fact, the baseline model is not necessarily the best performing within each country. In this respect, Figure A1 of the Online Appendix displays the ranking of the different models in all sample countries. Second, we show results that rely on an alternative model we chose on conceptual grounds, to allow for sector-specific differential time trends. The specification is:

$$\Pr(\text{Union}_i = 1) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{occ} + \alpha^{ind} + \alpha^{region} + \beta \cdot round + \gamma^{ind\_sector} \cdot round + \boldsymbol{\xi} \cdot \boldsymbol{X_r}) \tag{3}$$

were $\gamma^{ind\_sector} \cdot round$ denotes time trends that are specific to NACE sub-sections, i.e., aggregations of 2-digit industries.

From the probit estimates, we compute predicted probabilities of unionization for each

[7]Full details on the cross-validation approach are provided in Online Appendix A.

socio-demographic type of individuals, in each country. Types, denoted by λ, are defined by combinations of gender, age group, education level, occupation, industry, and region of residence, at a given point in time (i.e., ESS round). The probability of unionization for each type is denoted by θ_λ. To illustrate, we can retrieve the probability of unionization for women in their 30s, with a MSc degree, working as doctors, in the healthcare industry, in the Paris region (Île-de-France), in each ESS round.

In the second step of the MRP approach, we obtain unionization rates at the region (or industry) level through post-stratification of the predicted probabilities of unionization for the different types of individuals. To do so, we employ as weights the frequency of each type within each region (or industry), obtained from census data.[8]

Specifically, the unionization rate of region r at time t is obtained as:

$$\text{Union Density}_{rt} = \sum_{\lambda \in \Lambda_{rt}} \left(\frac{N_\lambda}{N_{rt}} \right) \theta_\lambda$$

where Λ_{rt} is the set of types in region r at time t; N_λ is the number of λ-type individuals in the region, and N_{rt} is the total population in the region, based on census data. The unionization rate represents the share of workers in the region that are union members.[9]

The unionization rate of industry j, in country c, at time t is:

$$\text{Union Density}_{jct} = \sum_{\lambda \in \Lambda_{jct}} \left(\frac{N_\lambda}{N_{jct}} \right) \theta_\lambda$$

where Λ_{jct} is the set of types in industry j of country c at time t; N_λ is the number of λ-type individuals working in the industry, and N_{jct} is the total number of individuals working in the industry, based on census data. The unionization rate represents the share of workers in the industry that are union members.

[8] Full details about the sources of census data, and their harmonization for the construction of the weights, are available in Online Appendix B.

[9] For the computation, we consider all workers in the labor force of the region—i.e., employed plus unemployed—excluding self-employed workers.

3.2 External validation and granular evidence on unionization decline

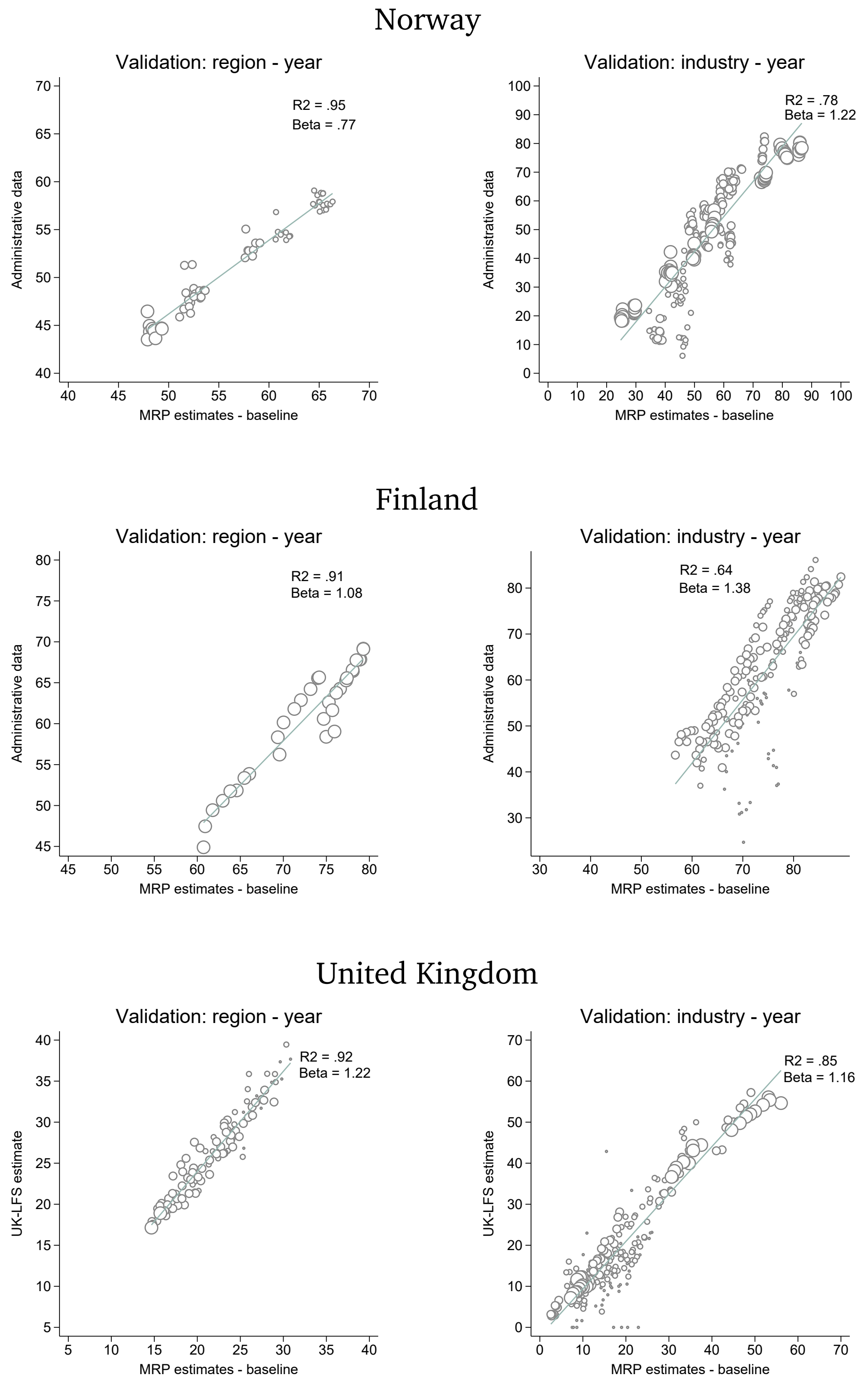
We validate the unionization estimates against official figures for Norway and Finland, two countries that provide administrative records of unionization at the sub-national and industry level. We perform a similar comparison for the UK, relying on data from the UK Labor Force Survey, that is representative at the granular level. This external validation exercise is presented in Figure 1. The left panels compare unionization rates at the region-year level, while the right panels focus on the industry-year level, with industries aggregated at the NACE sub-section level. In all panels, the horizontal axis reports the MRP unionization estimates, as obtained through the baseline model, while the vertical axis reports the external data. It is important to remark that neither the administrative records for Norway and Finland, nor the information about union membership in the UK-LFS survey data, were employed as inputs in the MRP estimation. Hence, the MRP estimates and these external benchmarks are entirely independent.

The correlation between our unionization estimates and the external data is very high. In particular, focusing on the regional figures, a regression of external data on MRP estimates yields R-squared values of 0.95 in Norway, 0.91 in Finland, and 0.92 in the UK. For industry-level variation, the R-squared values are slightly smaller, yet the overall convergence between the MRP estimates and the external data is still tight.

As a further validation exercise, we aggregate our sub-national estimates at the country-year level, and compare the resulting unionization figures with data from the Visser (2019) dataset. Reassuringly, the correlation between our aggregated data and Visser's data is very high: 0.96. Based on Visser's data, the average annual decline in unionization across the 15 western European countries in our sample was 0.384 percentage points between 2002 and 2018. Our data replicate closely this trend, showing an yearly average decline of 0.378 percentage points.

The advantage of our data is that they allow us to provide evidence of unionization

Figure 1: External validation



Note: Each observation in the chart corresponds to either a region (left panels) or an industry (right panels) in a specific survey year. The size of the circles is proportional to group size (regional population or industry employment). External validation data are from administrative records provided by Statistics Norway and Statistics Finland, and from the UK Labor Force Survey.

decline also at the region and industry level. This is done in Table 1. Specifically, in column 1 we regress the unionization rate in a given region and year on a time trend, controlling for the unionization rate of the region at the beginning of the sample (i.e., 2002), and absorbing average differences in unionization across countries through country fixed effects. The estimated coefficient on the time trend, -0.384, points to a strong decline in unionization over time, by around 3.84 percentage points on average every ten years. This is in line with the macro-level figures in Visser (2019). In column 2, we show that the declining trend is steeper in those regions that were initially more unionized. For instance, in a region with 80% initial unionization (e.g., East Middle Sweden or North and East Finland), the trend is expected to be around 5.4 percentage points every ten years, while it is around 3.3 p.p. in a region starting at 10% unionization rate (e.g., Lorraine, or Franche-Comté). In columns 3-4, we replicate the same analysis on unionization by country-industry (NACE 2-digit). Also in this case, we find evidence of a significant declining trend, by around 3.66 percentage points on average every ten years. The decline is more pronounced in country-industries that were initially more unionized.

The map in Figure 2 presents the regional change in union density based on our data over the sample period. The decline in unionization is widespread across all European regions, with significant variation both between and within countries. In the empirical analysis, we will connect within-country variation in unionization dynamics with regional variation in automation exposure, absorbing between-country variation through country-year fixed effects.

3.3 Regional variation in union density and electoral outcomes

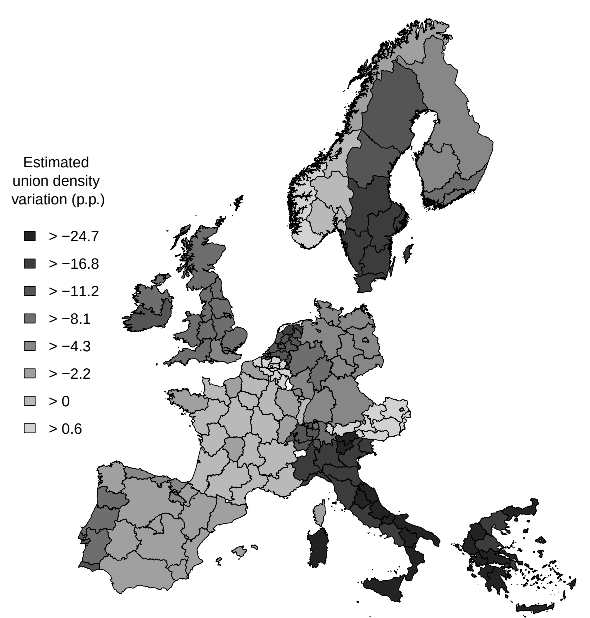
Besides describing unionization decline at the granular level, our sub-national unionization data also allow us to document, for the first time, the association between union density and electoral outcomes across European regions. For instance, we can provide empirical insights into the long-assumed positive correlation between unionization and support for mainstream left parties at the electoral-district level.

Table 1: Unionization decline

Dep. Var.:	Union Density			
	(1)	(2)	(3)	(4)
Analytical Unit:	Region		Industry	
Year	-0.384***	-0.300***	-0.366***	-0.304***
	[0.035]	[0.048]	[0.016]	[0.023]
Initial Union Density	0.911***	6.835**	0.927***	4.676***
	[0.021]	[2.880]	[0.008]	[1.235]
Initial Union Density X Year		-0.003**		-0.002***
		[0.001]		[0.001]
Country FE	X	X	X	X
Observations	1,467	1,467	6,270	6,270
R-squared	0.984	0.984	0.985	0.985

Note: In columns 1-2, the dependent variable is the unionization rate at the region-year level; in columns 3-4, the dependent variable is the unionization rate at the country-industry-year level. Unionization estimates are obtained through MRP employing the baseline model. Initial union density refers to 2002. The models are estimated by OLS and include country fixed effects. Standard errors are clustered by region in columns 1-2, and by country-industry in columns 3-4.
*** p<0.01, ** p<0.05, * p<0.1

Figure 2: Union density variation 2002-2018



Specifically, we relate regional unionization figures to support for different party families at the district level, estimating specifications of the following form:

$$\text{Share}_{\ell dt} = \alpha + \beta \text{ Union Density}_{r(d)t} + \eta_{ct} + \epsilon_{\ell dt}, \tag{4}$$

where $\text{Share}_{\ell dt}$ denotes the cumulative vote share for parties belonging to family ℓ, in electoral district d, in country c, in the election taking place in year t. The sample includes elections held between 2002 and 2018. $\text{Union Density}_{\mathrm{r(d)t}}$ is the unionization rate in the (NUTS-2) region r where district d is located, as measured in year t.[10] η_{ct} are country-year fixed effects, which are equivalent to election fixed effects. Standard errors are clustered at the region-year level.

We focus on six party families: radical left, mainstream left, mainstream right, radical right, ethno-regionalist, and other, single-issue parties. Parties are assigned to a given family based on the Manifesto Project classification (Volkens et al., 2016), except for the radical left and right families, which are identified based on consensus in the literature.[11]

Results are presented in Table 2. Consistent with the expectations, we detect a positive association between unionization and support for parties of the mainstream left. There is also a positive correlation between unionization and support for ethno-regionalist parties. Conversely, union density is uncorrelated with support for single-issue parties, and negatively associated with support for the other party families.

4 Automation and unionization

We investigate the impact of automation exposure on unionization at the regional level estimating regressions of the following form:

[10] In many cases, a district is itself a NUTS-2 region. In other cases, a given region may contain two or more districts. Importantly, a district is always fully contained within the boundaries of one single NUTS-2 region, with no overlaps.

[11] See Online Appendix C for full details on party classification. Some residual parties are not included in the analysis, as they are too small to be coded by the Manifesto Project. The same applies to three "agrarian" parties from Norway, Sweden, and Finland.

Table 2: Unionization and voting

	(1) Radical Left	(2) Mainstr. Left	(3) Mainstr. Right	(4) Radical Right	(5) Ethno-Region.	(6) Other Single
Union Density	-0.211***	0.861***	-1.034***	-0.104**	0.494***	-0.023
	[0.055]	[0.176]	[0.189]	[0.049]	[0.171]	[0.027]
Country-year FE	X	X	X	X	X	X
Observations	7,157	7,157	7,157	7,157	7,157	7,157
R-squared	0.530	0.324	0.362	0.731	0.169	0.889
Std dev. Y	4.939	11.94	13.52	4.102	6.501	2.009
Std dev. X	9.617	9.617	9.617	9.617	9.617	9.617
Magnitude	-0.412	0.693	-0.735	-0.244	0.731	-0.110

Note: The dependent variable is the cumulative vote share for parties belonging to a given party family at the electoral-district level. Unionization estimates are obtained through MRP employing the baseline model. The model is estimated by OLS and includes country-year fixed effects. The table reports the standard deviation of the dependent variable and of the unionization rate, along with the magnitude of their relationship, after residualizing with respect to country-year fixed effects. Standard errors are clustered by region-year.
*** p<0.01, ** p<0.05, * p<0.1

$$\text{Union Density}_{\text{rt}} = \alpha + \beta \text{ Regional Robot Exposure}_{\text{rt}} + \eta_{ct} + \eta_r + \epsilon_{rt}, \tag{5}$$

where r indexes (NUTS-2) regions, and t years. Union $\text{Density}_{\text{rt}}$ is the unionization rate in region r and year t. The terms η_{ct} and η_r are country-year and region fixed effects, respectively. Regional Robot $\text{Exposure}_{\text{rt}}$ is the exposure to industrial robot adoption in region r, evaluated in year t. Following Acemoglu and Restrepo (2020), this is measured as:

$$\text{Regional Robot Exposure}_{\text{rt}} = \sum_j \frac{L_{rj}^{\text{pre}-\text{sample}}}{L_r^{\text{pre}-\text{sample}}} * \frac{R_{cj}^{t-1} - R_{cj}^{t-k}}{L_{cj}^{\text{pre}-\text{sample}}}, \tag{6}$$

where r indexes regions, j manufacturing industries, c countries, and t years. $R_{cj}^{t-1} - R_{cj}^{t-k}$ is the change in the operational stock of industrial robots over the past k years, in country c and industry j. In the baseline analysis, $k = 3$. This change is normalized by the pre-sample number of workers employed in the same country and industry, $L_{cj}^{\text{pre}-\text{sample}}$, yielding a ratio that measures the intensity of robot adoption at the industry level.

The regional-level exposure is a weighted summation of the industry-level changes, where the weights capture the historical importance of each industry in the region. Specifically, each weight is the ratio between the number of workers employed in a given region and industry, $L_{rj}^{\text{pre-sample}}$, and the total number of workers employed in the same region, $L_{r}^{\text{pre-sample}}$. Weights are based on pre-sample figures, dating before the surge in the adoption of industrial robots observed from the mid-1990s onwards. Intuitively, regions that were initially specialized in industries in which the adoption of robots has later been faster are assigned stronger exposure to automation.

Data on robot adoption by industry are sourced from the International Federation of Robotics (IFR). They refer to eleven industries encompassing the whole manufacturing sector. These correspond mostly to NACE Rev. 1.1 sub-sections (details in Table D.1 of the Online Appendix). Employment data are from national sources or Eurostat. Detailed information on all data sources employed to measure automation exposure can be found in Online Appendix D.

To address potential endogeneity concerns, we employ an overidentified model with three instrumental variables capturing complementary aspects of technological progress that are relevant for robots. These instrumental variables exploit: the producer price index of computers, sourced from Federal Reserve Economic Data (FRED, US Bureau of Labor Statistics, 2023); and two indexes of advances in computing, specifically single-thread performance and number of transistors per microprocessor, both sourced from Rupp (2021). For each of these variables, we compute the instrument as follows:

$$\text{IV Regional Robot Exposure}_{\text{rt}} = \sum_{j} \frac{L_{rj}^{\text{pre-sample}}}{L_{r}^{\text{pre-sample}}} * Rep_j * \Delta Index_{t-1,t-k}, \tag{7}$$

where $\Delta Index_{t-1,t-k}$ is the change in the relevant variable between $t-1$ and $t-k$, and Rep_j is an industry-level replaceability index—i.e., the share of hours worked within industry j in occupations replaceable by robots—as computed by Graetz and Michaels (2018) based on US Census data of 1980. These instruments are designed to capture the role of plausibly exogenous global technological shifts in robotics and computing (i.e., $\Delta Index_{t-1,t-k}$), which vary over time and are common across countries. These shifts have differential effects across industries based on their ex-ante predisposition to robotization (i.e., Rep_j). In turn, the impact on regions depends on the pre-sample composition of employment across industries (i.e., the terms $\frac{L_{rj}^{\text{pre-sample}}}{L_r^{\text{pre-sample}}}$).

Columns 1-2 of Table 3 display the baseline estimates of Equation 5. The first column reports ordinary least squares (OLS) estimates, while the second shows instrumental variables (IV) results, where regional exposure to robot adoption is instrumented as described above. In these regressions, we employ the baseline unionization estimates, obtained through MRP according to Equation 2. The coefficient on regional robot exposure is negative and precisely estimated in both columns, pointing to a negative effect of automation on unionization. The IV estimate is larger than the OLS one in absolute value. This is consistent with there being unobserved factors related at the same time with both higher automation and higher unionization. For instance, the presence of stronger unions may raise company incentives to accelerate automation to replace workers. In terms of magnitudes, according to the IV estimate in column 2, a one standard deviation increase in robot exposure (i.e., 17 robots per 100,000 workers) leads to a reduction in regional union density by 34.4% of a standard deviation. This figure is obtained net of country-year and region fixed effects, as per the Mummolo and Peterson (2018) approach.

These results are robust to employing union density figures obtained from any of the other 15 probit specifications used in the MRP approach. For ease of exposition, in Table 3 we only report two robustness checks. Specifically, in columns 3-4 we use unionization estimates obtained from the highest ranked prediction model by country. In columns 4-5, we employ unionization estimates based on the model outlined in Equation 3, which allows for sector-specific differential time trends. The results are very similar to the baseline

Table 3: Regional robot exposure and unionization

Dep. Var.:	Regional Union Density					
	(1)	(2)	(3)	(4)	(5)	(6)
MRP Model:	Baseline		Best by country		Sector trends	
Regional Robot Exposure	-0.177***	-0.430**	-0.184***	-0.466***	-0.176***	-0.347**
	[0.051]	[0.171]	[0.052]	[0.177]	[0.048]	[0.161]
Country-year FE	X	X	X	X	X	X
Region FE	X	X	X	X	X	X
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
Observations	1,413	1,413	1,413	1,413	1,413	1,413
Std dev. Y	0.526	0.526	0.533	0.533	0.521	0.521
Std dev. X	0.421	0.421	0.421	0.421	0.421	0.421
Magnitude	-0.141	-0.344	-0.145	-0.368	-0.143	-0.281
First stage F-stat		15.45		15.45		15.45

Note: The dependent variable is the union density at the regional level, estimated through MRP according to the model indicated on top. The table reports the standard deviation of the dependent variable and of robot exposure, along with the magnitude of their relationship, after residualizing with respect to country-year and region fixed effects. Robust standard errors in brackets.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

evidence of columns 1-2, in terms of both statistical and substantive significance. Hence, for the next battery of robustness checks we only focus on the baseline unionization estimates.

Table 4 reports twelve robustness checks on the baseline IV result of column 2 in Table 3, which is replicated in the first row for convenience. Each row refers to a different estimation, and reports the coefficient and standard error on regional robot exposure. In rows 2-6, we augment the baseline specification with interactions between the year dummies and a number of initial regional conditions, measured pre-sample and specified in each row. By doing this, we control for differential regional trajectories—as related to the initial characteristics of the labor force—which might be confounded with exposure to automation. The results are not significantly affected.

In rows 7-10, we replicate the baseline regressions excluding the largest regions, which might arguably provide a sub-optimal approximation of the local labor market concept behind the theoretical and measurement approach by Acemoglu and Restrepo (2020). We drop, alternatively, regions in the top 10% or 25% of the distribution in terms of geographical area, either within each country (rows 7-8) or overall (rows 9-10). The results remain close to the baseline. In rows 11-13, we exclude from the computation of the instruments three industries that are particularly relevant for robotization. These are the automotive industry, which is the most robot-intensive, and the electronics and metal industries, which provide key robot inputs.[12] Results do not hinge on the inclusion of any one of these industries, thus corroborating the robustness of our findings.

Finally, we assess whether the estimated effect of automation is sensitive to the choice of different lags for the computation of regional robot exposure. In the baseline specification we consider the change in the operational stock of robots over the previous three years, i.e., between $t-1$ and $t-3$. In Figure E1 of the Online Appendix, we show that results are robust to considering alternative time periods, ranging from the previous two to six years.

5 Potential channels underlying the main effect

The main finding of the analysis, thus far, is that higher exposure to robotization reduces unionization at the regional level. This result could be driven by two non-mutually exclusive channels, as outlined in Section 2.2. First, there could be a systematic reduction of unionization *within* industries where robot adoption is higher. Second, automation may induce a reallocation of workers *between* industries, shifting employment from highly unionized industries towards less unionized ones. In this section, we explore both channels.

We begin by investigating the within-industry impact of automation on unionization, estimating the following specification:

$$\text{Union Density}_{\text{cjt}} = \alpha + \beta \, \frac{R_{cj}^{t-1} - R_{cj}^{t-k}}{L_{cj}^{\text{pre-sample}}} + \eta_{ct} + \eta_j + \epsilon_{cjt}, \tag{8}$$

where c indexes countries, j industries, and t years. η_{ct} and η_j are country-year and industry fixed effects, respectively. Union Density$_{\text{cjt}}$ is the unionization rate in industry

[12] In particular, we exclude the NACE sub-sections DM (manufacture of transport equipment), DL (manufacture of electrical and optical equipment) and DI-DJ (manufacture of other non-metallic mineral products and manufacture of basic metals and fabricated metal).

Table 4: Additional robustness checks

Dep. Var.:	Regional Union Density
1) Baseline	-0.430** [0.171]
2) Year dummies * Initial share low-skill workers	-0.427** [0.176]
3) Year dummies * Initial share med-skill workers	-0.406** [0.174]
4) Year dummies * Initial share high-skill workers	-0.401** [0.174]
5) Year dummies * Initial share foreign workers	-0.431** [0.178]
6) Year dummies * Initial stock foreign workers	-0.417** [0.178]
7) Excluding largest 10% regions by country	-0.424** [0.193]
8) Excluding largest 25% regions by country	-0.414* [0.232]
9) Excluding largest 10% regions overall	-0.521*** [0.178]
10) Excluding largest 25% regions overall	-0.708*** [0.210]
11) Excluding automotive industry	-0.419* [0.228]
12) Excluding electronics industry	-0.397** [0.177]
13) Excluding metals and minerals industries	-0.434*** [0.163]

Note: All reported coefficients refer to regional robot exposure. All models include country-year and region fixed effects. Robust standard errors in brackets.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

j, country c, and year t. This is regressed on the industry-level exposure to automation, $\frac{R_{cj}^{t-1}-R_{cj}^{t-k}}{L_{cj}^{\text{pre-sample}}}$, with $k = 3$. Note that this is the same measure of industry exposure that is used as an input in Equation 6 to compute regional robot exposure.[13]

We instrument automation exposure using the same three indexes of technological progress employed in the regional analysis. Specifically, the three instrumental variables are defined as follows:

$$\text{IV Industry Robot Exposure}_{jt} = Rep_j * \Delta Index_{t-1,t-k}, \tag{9}$$

where Rep_j is the labor replaceability of industry j, and $\Delta Index_{t-1,t-k}$ is the change in one of the three indexes employed for the computation of regional instruments in Equation 7. In fact, the industry-level instruments are the inputs used for the computation of the instrumental variables at the regional level.

Table 5 shows the estimation results of Equation 8. The estimated coefficients on robot exposure are not statistically different from zero at the 5% level in either column. Coefficient estimates are also small in magnitude. In particular, according to the IV specification in column 2, a one standard deviation increase in robot exposure would yield an effect as small as -0.4% of a standard deviation in union density. These results are based on the baseline estimates of unionization. Findings are very similar when employing alternative unionization estimates, as reported in Table E.1 of the Online Appendix. Overall, the analysis does not support the conclusion that automation significantly alters unionization rates within industries. While the first-stage F-statistic is lower for industry variation than for regional variation, the comparison with the clearly detected regional-level relationship between automation and unionization suggests that the null results at the industry level are likely to reflect a genuinely weak or ambiguous effect.

[13] Industrial robot adoption is recorded for 11 manufacturing industries, mostly at the NACE sub-section level, as presented in Table D.1 of the Online Appendix. Non-manufacturing industries are included in the analysis at the NACE 2-digit level of disaggregation, and have zero exposure to robot adoption. Results are substantially unchanged when excluding these industries from the analysis.

Table 5: Industry-level analysis

Dep. Var.:	Industry Union Density	
	(1)	(2)
Industry Robot Exposure	0.150*	-0.029
	[0.081]	[0.641]
Country-year FE	X	X
Industry FE	X	X
Estimator	OLS	2SLS
Observations	5,943	5,943
Std dev. Y	6.568	6.568
Std dev. X	0.873	0.873
Magnitude	0.020	-0.004
First stage F-stat		5.457

Note: The dependent variable is the unionization rate at the country-industry-year level. Unionization estimates are obtained through MRP employing the baseline model. The table reports the standard deviation of the dependent variable and of robot exposure, along with the magnitude of their relationship, after residualizing with respect to country-year and industry fixed effects. Robust standard errors in brackets.
*** p<0.01, ** p<0.05, * p<0.1.

Lack of evidence in favor of the within-industry channel is not surprising in light of the empirical studies on the employment effects of automation in Europe (e.g., Dauth et al., 2021; Dottori, 2021). In fact, these studies suggest that employment declines in automated manufacturing industries occur primarily through reduced hiring rather than layoffs. Since incumbent workers are more likely to be unionized than new hires, halting turnover may not necessarily decrease union density, even as automation may lower incentives to unionize, as discussed in Section 2.2.

Next, we examine the second potential channel underlying the main region-level results, i.e., an automation-induced compositional change in the labor market, with a relative shift in employment from more to less unionized industries. For this channel to be relevant, two conditions must hold: (1) industries that are relatively more exposed to automation witness a relative decline in employment; and (2) automation exposure is higher in industries that were more unionized at the beginning of the sample period. In Table 6, we provide evidence consistent with these two conditions.

In columns 1-2, we regress the national share of workers employed in a given industry on exposure to robotization. The instrumental variable results indicate that industries with higher exposure to robot adoption experience a decline in their employment share. Specifically, a one standard deviation increase in automation exposure determines a decrease of the industry employment share by about 7.3% of a standard deviation.

Columns 3-4 of Table 6 display linear regressions where the dependent variable is the average automation exposure by country-industry over the whole sample period (2002-2018), and the predictor is the initial unionization rate at the country-industry level, measured in 2002. Column 3 includes all industries, both manufacturing and non-manufacturing, while column 4 considers only manufacturing industries. These purely descriptive regressions indicate that industries that were initially more unionized experienced greater automation over time.[14] Taken together, the results presented in Table 6 point to automation-induced reallocation of employment as the main channel underlying the negative impact of robotization on unionization identified at the regional level.

This pattern plausibly reflects systematic processes with an economic and social logic. Robots have primarily automated activities at industrial plants, i.e., contained environments where most manufacturing workers were concentrated, facilitating union organization and collective action. In contrast, automation has spurred employment growth in sectors that are more challenging to unionize, where collective action is harder to coordinate. Logistics, for example, has expanded significantly due to increased productivity and lower production costs driven by automation. However, logistics workers often operate in isolation, and services are frequently outsourced to companies that are detached from production and easily replaceable. Such factors create substantial barriers to unionization and hinder

Table 6: Automation, employment share, and initial unionization

Panel A Automation and Empl. Share			**Panel B** Initial Unionization and Automation		
Dep. Var.	Employment share		Dep. Var.	Avg. robot exposure	
	(1)	(2)		(3)	(4)
Industry robot exposure	0.0003 [0.0002]	-0.001** [0.0003]	Initial union density	0.010*** [0.004]	0.117*** [0.038]
Country FE	X	X	Country FE	X	X
Industry FE	X	X			
Estimator	OLS	2SLS	Estimator	OLS	OLS
Industries	All	All	Industries	All	Manuf.
Observations	5,937	5,937	Observations	701	160
Std dev. Y	0.0101	0.0101	Std dev. Y	0.762	1.443
Std dev. X	0.883	0.883	Std dev. X	9.663	5.031
Magnitude	0.0250	-0.0725	Magnitude	0.124	0.409
First stage F-stat		6.755			

Note: In Panel A: the dependent variable is the share of workers employed in a given country-industry-year relative to the total number of employed workers in the corresponding country-year; the reported coefficients refer to industry robot exposure. In Panel B: the dependent variable is the average industry-level robot exposure over 2002-2018, measured at the country-industry level; the reported coefficients refer to initial union density in 2002, based on baseline MRP unionization estimates. Standard errors are clustered at the country-year level in Panel A, while robust standard errors are reported in Panel B.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

effective collective action in the expanding industries.

6 Conclusion

Technological change generates economic distributional consequences that have been shown to be politically consequential. Labor unions are potentially key actors shaping both the economic and the political implications of technological change. Yet the impact of technological change on unionization has remained largely underexplored. This study offers new insight on this issue.

We assemble a novel dataset with unionization data at the region and industry level, encompassing fifteen western European countries over two decades (2002-2018). These data allow us to document for the first time the decline of unionization in Europe at the granular level. We also shed empirical light on the long-assumed positive association between unionization and support for mainstream left parties at the local level.

We provide comprehensive evidence that technological change, in the form of robotization of manufacturing activities, has been a significant driver of unionization decline. Specifically, we find that an increase in exposure to robotization decreases the unionization rate at the regional level. The decline in unionization is driven by a compositional effect in the labor market: automation induces a reallocation of employment from traditionally unionized industries, where robotization is more intensive, towards less unionized ones. Conversely, there is no evidence of a systematic reduction of unionization within industries that are relatively more exposed to automation.

These findings speak to the role of unionization as a contextual factor that may shape electoral dynamics at the local level, influencing the political repercussions of automation. For instance, as proposed by Kitschelt (2012), the decline of labor unions may be a key factor behind the rise of radical right support among the losers of structural change in advanced democracies. In fact, labor unions are intermediary organizations that historically

[14] See also Figure E2 for additional descriptive evidence pointing in the same direction.

connected blue-collar constituencies to mainstream parties, in particular of the left. These organizations not only linked workers to parties but also framed their interests in terms of class antagonism rather than ethno-national identities. As automation displaces workers and weakens trade unions, the capacity of unions to mobilize working-class voters and serve as political intermediaries for social-democratic parties diminishes. Economic grievances among the losers of structural change are then increasingly intercepted by nationalist and radical-right forces. The novel dataset developed in this study will enable further research on these topics, and more broadly on the social, and political implications of labor unions, whose significance is difficult to overstate.

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Robots Replacing Trade Unions: Novel Data and Evidence from Western Europe

Online Appendix

Contents

A MRP prediction models

At the core of estimations based on Multilevel Regression with Post-stratification (MRP) is a multilevel (or hierarchical) response model in which the outcome is the variable of interest (Leemann and Wasserfallen, 2020). In our case, the outcome variable indicates whether the respondent is currently a member of a trade union and is a function of individual-level characteristics such as gender, age, educational attainment, occupation, region of residence and industry, modeled as random intercepts, so that the intercept for each category of a given variable is modeled as a draw from a common normal distribution. A full list of the categories used for each variable is provided in Section B. The model yields estimates for the realization of the random effects, which allows to predict the probability of trade union membership for every possible combination of the included covariate categories.

In addition to these individual-level effects, we account for time trends, following the dynamic MRP approach developed by Gelman et al. (2019). Specifically, we include a term for the survey round as a linear trend ($\beta \cdot round$). To capture heterogeneous time trends, we also allow the time effect to vary across groups defined by a given individual-level characteristic. For example, the effect of time may differ by age group ($\gamma^{age} \cdot round$): these age-specific time trends are modeled as random slopes.

Industries (*ind*) and occupation (*occ*) variables are defined at the 2-digit level of the NACE Rev. 1.1 and ISCO-88 classifications, respectively. When allowing for specific time trends, we employ the more aggregated NACE sub-section (*ind_sector*), as well as ISCO-88 1-digit (*occ_1d*) categories. The same is done in models that include interaction effects for combinations of variables. For instance, we include random intercepts for specific occupation–sector combinations ($\alpha^{occ\_1d,\ ind\_sector}$), allowing for more flexible patterns of variation across individual profiles.

Finally, we model contextual (regional-level) effects by including both random intercepts for regions and linear effects for regional characteristics. That is, alongside the random intercept for each region, α^{region}, we include fixed coefficients $\boldsymbol{\xi}$ for region-level predictors $\boldsymbol{X_r}$. These pre-sample predictors include: the employment share of low- and medium-skill workers, the employment share of services, the employment share of low- and medium-tech industries, the employment share of primary sector, the employment share of finance and business services, and the share of foreign-born workers.

This structure allows us to account for both individual-level and contextual heterogeneity in trade union membership, while modeling its evolution over time. We employ the following list of sixteen alternative specifications:

1. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \gamma^{ind\_sector} \cdot round + \boldsymbol{\xi} \cdot \boldsymbol{X_r})$
2. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \boldsymbol{\xi} \cdot \boldsymbol{X_r})$
3. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \gamma^{occ\_1d} \cdot round + \boldsymbol{\xi} \cdot \boldsymbol{X_r})$

4. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \gamma^{age} \cdot round + \boldsymbol{\xi \cdot X_r})$

5. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \gamma^{edu} \cdot round + \boldsymbol{\xi \cdot X_r})$

6. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{edu} + \alpha^{age} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \gamma^{gndr} \cdot round + \boldsymbol{\xi \cdot X_r})$

7. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \alpha^{occ\_1d,\ ind\_sector} + \boldsymbol{\xi \cdot X_r})$

8. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \alpha^{occ\_1d,\ reg} + \boldsymbol{\xi \cdot X_r})$

9. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \alpha^{occ\_1d,\ age} + \boldsymbol{\xi \cdot X_r})$

10. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \alpha^{occ\_1d,\ gndr} + \boldsymbol{\xi \cdot X_r})$

11. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \alpha^{occ\_1d,\ edu} + \boldsymbol{\xi \cdot X_r})$

12. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \alpha^{ind\_sector,\ reg} + \boldsymbol{\xi \cdot X_r})$

13. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \alpha^{ind\_sector,\ age} + \boldsymbol{\xi \cdot X_r})$

14. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \alpha^{ind\_sector,\ gndr} + \boldsymbol{\xi \cdot X_r})$

15. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \beta \cdot round + \alpha^{ind\_sector,\ edu} + \boldsymbol{\xi \cdot X_r})$

16. $Pr(\text{Union}_i) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{ind} + \alpha^{occ} + \alpha^{region} + \alpha^{round} + \beta \cdot round + \boldsymbol{\xi \cdot X_r})$

Specification 1 reflects our preferred approach on conceptual grounds, as it allows for sector-specific differential time trends. Specification 2 provides a more parsimonious alternative, relying only on a common time trend. Specifications 3 through 6 replicate the structure of specification 1 incorporating differential time trends for individual characteristics (occupation, age, education, gender). Specifications 7 through 15 include interaction effects for pairwise combinations of occupation (1-digit) or sector and each of the other individual-level variables. These models allow the joint effect of two variables to vary flexibly across grouping levels by estimating separate random intercepts for each combination. For instance, specification 15 includes random intercepts for sector-education, capturing variation across the 27 industry sub-sections (plus a category for the unemployed) crossed with three levels of educational attainment. Specification 16 adds a random intercept for survey round (α^{round}) alongside a linear time trend ($\beta \cdot round$). While we generally avoid modeling round-specific effects due to the risk of overfitting wave-specific idiosyncrasies, this specification is included to assess MRP performance under an alternative strategy for modeling temporal heterogeneity.

A.1 RMSE and assessment of prediction models

To evaluate the relative predictive performance of each model specification, we compute, for each model, a group-wise calibration Root Mean Square Error (RMSE). In this section, we first outline how this metric is constructed, then describe its distribution across models, and finally explain the procedure used to rank models based on their RMSE scores.

First, we implement a 10-fold cross-validation procedure (within each sample country). We randomly split the sample into $K = 10$ folds, then iteratively estimate the model on the training set (excluding fold k), and generate predicted probabilities of union membership for the held-out fold k. This process is repeated across all folds, yielding a complete vector of out-of-sample predictions.

We assess calibration at relevant levels of aggregation, i.e., regions and industries within each country, summarized by computing a group-level root mean squared (RMSE) metric. This metric summarizes departures of the observed frequencies by region from the average of the predicted probabilities by region; and the same for industries. A well-calibrated model will display empirical frequencies by group in line with the predicted probabilities. The metric we adopt takes the squared discrepancies between frequencies and predicted probabilities in each group, averages them, and then moves back to the original scale by taking the square root.

Formally, let Ω_g denote the set of N_g observations in a given group $g = 1, 2, \ldots, G$. A group is defined either as a region or an industry within each country. We first calculate the average predicted probability of union membership $\hat{P}_g$ for group g as:

$$\hat{P}_g = \frac{\sum_{i \in \Omega_g} \hat{P}_i}{N_g} \tag{10}$$

The observed empirical frequency F_g in the ESS data is given by:

$$F_g = \frac{\sum_{i \in \Omega_g} \mathbb{1}(Union_i = 1)}{N_g} \tag{11}$$

The RMSE for a given level of aggregation (region or industry) within a given country is then defined as:

$$\text{RMSE}_\text{G} = \left(\frac{\sum_g (\hat{P}_g - F_g)^2}{G} \right)^{\frac{1}{2}} \tag{12}$$

This metric compares the (cross-validated) predicted probabilities for each region or industry g with the empirical frequency of unionization among survey respondents from region or industry g.

To facilitate meaningful comparisons across countries with different levels of unionization, we rescale the RMSE by the observed range of unionization rates across groups. That is, we divide the raw RMSE by the range of the observed group-level unionization rates:

$$\text{Rescaled RMSE}_G = \frac{\text{RMSE}_G}{\max_g F_g - \min_g F_g} \tag{13}$$

Finally, because our interest lies in assessing model calibration across both geographic and industry dimensions, we create an overall metric as the sum of the rescaled RMSEs for regions and industries:

$$\text{RMSE} = \text{Rescaled RMSE}_{region} + \text{Rescaled RMSE}_{industry} \tag{14}$$

This measure captures how well each model reproduces the observed spatial and industry variation in unionization in the survey data, and allows us to compare the predictive accuracy of alternative specifications.

Figure A1 displays the relative performance of each model specification by country, based on RMSE. To facilitate comparison, RMSE values are expressed as a percentage of the highest (i.e., worst) RMSE within each country. Since RMSE values are close in absolute terms, this approach highlights relative differences in model performance. For example, in Austria, specification 8 yields the lowest RMSE, which is approximately 12% lower than the highest RMSE for the country, observed in specification 16.

We then rank the different model specifications by their RMSE performance within each country. Specifically, we assign a rank to each model in every country based on its RMSE value. For example, model 1 is the top-performing model in France, the Netherlands, Sweden, and the UK, while it ranks 15th in Portugal and Spain. To compare overall performance across models, we consider the average ranking by country. That is, we prioritize models that, even if not consistently the best in every country, tend to perform well relative to others on average.

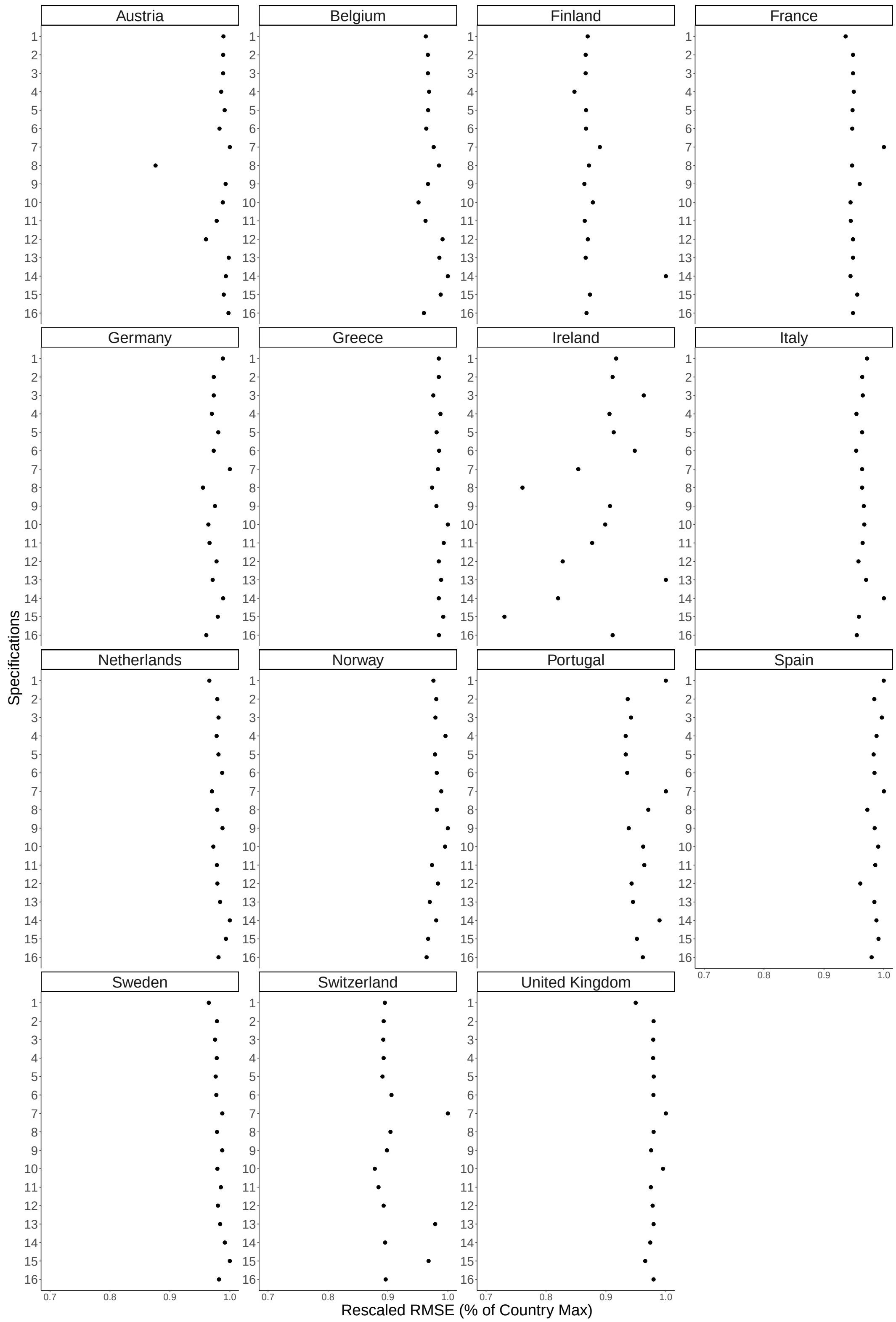
According to this criterion, model 11 emerges as the best-performing model overall. While this is not the top-ranked model in any single country, it consistently achieves high rankings across most countries. We therefore adopt specification 11 as the baseline model. Its functional form is:

$$\Pr(Union_i = 1) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{occ} + \alpha^{ind} + \alpha^{region} + \alpha^{occ\_1d,\ edu} + \beta \cdot round + \xi \cdot \boldsymbol{X_r}) \tag{15}$$

where the α terms are random effects for gender, age category, education level, occupation, industry of employment, region of residence, and the combination of (1-digit) occupation and education level. The specification includes also a linear time trend, captured by the ESS *round* variable, and the vector $\boldsymbol{X_r}$ of variables controlling for cross-regional differences in pre-sample conditions.

Our main results on the impact of robotization on unionization are robust to employing union density figures obtained from any of the sixteen different probit specifications. Throughout the paper, for ease of exposition we only show results based on two alternative approaches to model selection. The first is to use the best-performing model within each country. This leads us to select different models for different countries. Under this approach,

Figure A1: Prediction models performance by country



Note: The figure plots RMSE values rescaled within each country, expressed as a percentage of the highest RMSE observed in that country. For each country, the model with the highest RMSE is set to 1, and all other values are expressed relative to it.

we would choose specification 1 for France, the Netherlands, Sweden, and the UK; specification 4 for Finland and Portugal; specification 6 for Italy; specification 8 for Austria, Germany, and Greece; specification 10 for Belgium and Switzerland; specification 12 for Spain; specification 15 for Ireland; and specification 16 for Norway.

The second alternative approach relies on conceptual considerations and adopts specification 1, which incorporates sector-specific differential time trends. The model is defined as follows.

$$\Pr(\text{Union}_i = 1) = \text{Probit}(\alpha^{gndr} + \alpha^{age} + \alpha^{edu} + \alpha^{occ} + \alpha^{ind} + \alpha^{region} + \beta \cdot round + \gamma^{ind\_sector} \cdot round + \boldsymbol{\xi} \cdot \boldsymbol{X_r})$$

were $\gamma^{ind\_sector} \cdot round$ denotes time trends that are specific to NACE sub-sections, i.e., aggregations of 2-digit industries.

B Data sources and harmonization of data across countries

In Table B.1, we report the data sources used for each country in both the prediction and post-stratification stages of the MRP estimation procedure. While the prediction stage relies exclusively on the European Social Survey (ESS), post-stratification draws on national census or registry data wherever available. In countries where recent census data are unavailable or access is highly restricted, we instead rely on Labor Force Surveys. The last column shows the external validation data, available only for Finland, Norway, and the UK.

Table B.1: Data sources

Country	Prediction data	Post-stratification data	External validation data available
Austria	ESS	Mikrozensus (Statistics Austria)	-
Belgium	ESS	National LFS (Statbel)	-
Finland	ESS	Registry Data (Statistics Finland)	Registry Data (Statistics Finland)
France	ESS	Census (IPUMS)	-
Germany	ESS	Mikrozensus (Statistisches Bundesamt)	-
Greece	ESS	Census (IPUMS)	-
Ireland	ESS	Census (IPUMS)	-
Italy	ESS	National LFS (ISTAT)	-
The Netherlands	ESS	Survey Workforce New Series EEBnw (CBS)	-
Norway	ESS	Registry Data (Statistics Norway)	Registry Data (Statistics Norway)
Spain	ESS	Census (IPUMS)	-
Sweden	ESS	Registry Data (Statistics Sweden)	-
Switzerland	ESS	EU-LFS (FSO - Eurostat) + Admnistrative data	-
Portugal	ESS	Census (IPUMS)	-
United Kingdom	ESS	Office for national statistics (National LFS)	National LFS

To ensure consistent application of the MRP estimation across space and time, for each country we harmonized six key variables present in both the ESS and the post-stratification datasets. These harmonized variables are listed, along with their categories, in Table B.2 and include age, education, region, industry, occupation, and gender.

For the regional variable, we adopt the NUTS 2-digit classification for all countries except the UK and Germany, for which the data we use are available only at the NUTS 1-digit level. The dataset excludes Northern Ireland, Ceuta and Melilla, and the French overseas territories.

The education variable is categorized into three levels: "less than secondary education", "secondary education", and "tertiary education or more". Occupation is classified using the ISCO-88 scheme at the 2-digit level. When original data use different classification systems (e.g. ISCO-08, SOC, or national classifications), we apply crosswalks to convert them to ISCO-88.

Table B.2: Summary of harmonized variables and categories

Variable	Categories
Gender	Male, Female
Education	Less than secondary education, Secondary education, Tertiary education or more
Age	Below 25, 25-34, 35-44, 45-54, 55-64, Over 65
Region	NUTS 2-digit (NUTS 1-digit UK, DE)
Occupation	ISCO-88 2-digit
Industry	NACE Rev. 1.1. 2-digit

The industry variable follows the NACE Rev. 1.1 classification, at the 2-digit level. When original industry data are based on other systems (mainly NACE Rev. 2, and in some cases SIC or national classifications), we convert them using crosswalks. The mapping from NACE Rev. 2 to NACE Rev. 1.1 is detailed in the next section. Unemployed individuals are classified under a residual, fictitious industry category to reflect their temporary lack of affiliation with any specific industry.

Throughout the data harmonization process, for both the ESS and post-stratification datasets, we identify and exclude individuals who are out of the labor force, such as retirees and those not actively seeking employment. Additionally, we exclude self-employed individuals.

When post-stratification data for a given country-year are unavailable—due to census data being collected only every 5 or 10 years, or limited temporal coverage of registry data—we adopt two strategies based on informed assumptions. We either rely on the weights calculated with data from the following available year (e.g., we use 2004 weights for the year 2002) or estimate the missing data through interpolation or conditional extrapolation from surrounding years. In the case of conditional extrapolation, we project the region-industry employment frequencies while preserving the relative demographic composition within each industry-region cell, as observed in the closest available year (e.g., we extrapolate the number of workers in a given industry-region for years after the latest census, preserving the gender, age, education, occupation composition characterizing that industry-region in the latest census). The complete list of imputations and interpolations/extrapolations, by country, is provided in Section B.2.

In other instances, one or more variables used to post-stratify are only available at a higher level of aggregation than our standard. For instance, industry data may be available only at the sub-section level of the NACE classification, rather than the preferred 2-digit level. In such cases, we adopt an approach inspired by the multilevel regression with synthetic post-stratification (MrsP) method introduced by Leemann and Wasserfallen (2017). This method allows us to reconstruct post-stratification frequency weights at the target granular level by combining coarse joint-distribution data with more granular marginal distributions for one variable. A concrete example of this approach in our study concerns Switzerland. For this country, we rely on detailed post-stratification data from the national version of the EU Labor Force Survey, which provides cell frequencies defined by gender, education, age, region, occupation, and industry. However, industry information is available only at the sub-section level of NACE Rev. 1.1. To refine this to the 2-digit level, we draw Eurostat data that detail employment shares across NACE 2-digit categories within each region-year and NACE sub-section group. Specifically, for each region and year, we compute the share of employees in each 2-digit NACE category relative to the total employment in the corresponding sub-section-level category. These shares are then used to proportionally allocate individuals from the Swiss EU-LFS data—classified by demographic characteristics, region and sub-section—into the more detailed 2-digit NACE categories. A detailed list of instances where this method is used is also included in Section B.2.

The next section describes the mapping procedure from NACE Rev. 2 to NACE Rev. 1.1. The following section provides a comprehensive list of country-specific adjustments to the general harmonization approach, due to data limitations such as those described above.

B.1 Industry classification and harmonization to NACE Rev 1.1

The data in our study span the period 2002-2018, during which time the European classification system for economic activities underwent a substantial revision. In particular, Eurostat and other statistical agencies coordinated the transition from NACE Revision 1.1, introduced in 1993, to NACE Revision 2, adopted in December 2006 and implemented from January 1, 2008, onwards. This transition involved significant changes to the coding system, including at the 2-digit level. To ensure temporal consistency in our analysis, it was essential to harmonize all industry data to a common standard. For this purpose, we constructed a deterministic crosswalk from NACE Revision 2 to NACE Revision 1.1, at the 2-digit level. This means that each Rev. 2 industry is uniquely associated with a single Rev. 1.1 industry category.

The mapping was based on a close reading of official Eurostat documentation (Eurostat, 2008). In cases where a Rev. 2 industry could reasonably be linked to multiple Rev. 1.1 industries, we adopted a majority principle: the Rev. 2 industry was assigned to the Rev. 1.1 industry employing the largest share of its workforce (see Perani et al., 2015).

To further improve temporal consistency and account for structural changes in the classification system, we combined a few NACE Rev. 1.1 2-digit industries. Specifically:

- NACE Rev. 1.1 – 12 (Mining of uranium and thorium ores) was incorporated into NACE Rev. 1.1 – 13 (Mining of metal ores)
- NACE Rev. 1.1 – 30 (Manufacture of office machinery and computers) was incorporated into NACE Rev. 1.1 – 32 (Manufacture of radio, television and communication equipment and apparatus)
- NACE Rev. 1.1 – 33 (Repair, maintenance and installation of machinery and equipment) was incorporated into NACE Rev. 1.1 – 36 (Manufacture of furniture; manufacturing n.e.c.)
- NACE Rev. 1.1 – 37 (Recycling) was incorporated into NACE Rev. 1.1 – 90 (Sewage and refuse disposal, sanitation and similar activities)

The complete crosswalk from NACE Rev. 2 to NACE Rev. 1.1 is presented in Table B.3.

Table B.3: Correspondence table mapping NACE Rev. 2 to NACE Rev. 1.1

NACE Rev. 2	Industry Name	NACE Rev. 1.1	Industry Name
01	Agriculture, farming of animals, hunting and related service activities	01	Agriculture, hunting and related service activities
02	Forestry and logging	02	Forestry, logging and related service activities
03	Fishing and aquaculture	05	Fishing, fish farming and related service activities
05	Mining of coal and lignite	10	Mining of coal and lignite; extraction of peat
06	Extraction of crude petroleum and natural gas	11	Extraction of crude petroleum and natural gas; service activities incidental to oil and gas extraction, excluding surveying
07	Mining and preparation of metal ores	13 (+12)	Mining of metal ores (+12: Mining of uranium and thorium ores)
08	Other mining and quarrying	14	Other mining and quarrying
09	Mining and quarrying related service activities	11	Extraction of crude petroleum and natural gas; service activities incidental to oil and gas extraction, excluding surveying
10	Manufacture of food products	15	Manufacture of food products and beverages
11	Manufacture of beverages	15	Manufacture of food products and beverages
12	Manufacture of tobacco products	16	Manufacture of tobacco products
13	Manufacture of textiles	17	Manufacture of textiles
14	Manufacture of wearing apparel	18	Manufacture of wearing apparel; dressing and dyeing of fur
15	Manufacture of leather and related products	19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products	21	Manufacture of pulp, paper and paper products
18	Printing and reproduction of recorded media	22	Publishing, printing and reproduction of recorded media

NACE Rev. 2	Industry Name	NACE Rev. 1.1	Industry Name
19	Manufacture of coke, refined petroleum products and fuels briquettes	23	Manufacture of coke, refined petroleum products and nuclear fuel
20	Manufacture of chemicals, chemical products and man-made fibres, except pharmaceutical products	24	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	24	Manufacture of chemicals and chemical products
22	Manufacture of rubber and plastic products	25	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products	26	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals	27	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment	28	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, communication equipment, electronic and optical products	32 (+30)	Manufacture of radio, television and communication equipment and apparatus (+30: Manufacture of office machinery and computers)
27	Manufacture of electrical equipment	31	Manufacture of electrical machinery and apparatus n.e.c.
28	Manufacture of machinery and equipment n.e.c.	29	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers, semi-trailers and parts and accessories for motor vehicles	34	Manufacture of transport equipment
30	Manufacture of other transport equipment	35	Manufacture of other transport equipment
31	Manufacture of furniture	36 (+33)	Manufacture of furniture; manufacturing n.e.c. (+33: Repair, maintenance and installation of machinery and equipment)
32	Other manufacturing activities	36 (+33)	Manufacture of furniture; manufacturing n.e.c. (+33: Repair, maintenance and installation of machinery and equipment)
33	Repair, maintenance and installation of machinery and equipment	29	Manufacture of machinery and equipment n.e.c.
35	Electricity, gas, steam, cold and hot water and cold air	40	Electricity, gas, steam and hot water supply
36	Water collection, treatment and distribution	41	Collection, purification and distribution of water
37	Collection, drainage and treatment of sewage	90 (+37)	Sewage and refuse disposal, sanitation and similar activities (+37: Recycling)
38	Waste collection, treatment and disposal activities; materials recovery	90 (+37)	Sewage and refuse disposal, sanitation and similar activities (+37: Recycling)
39	Remediation and similar activities	90 (+37)	Sewage and refuse disposal, sanitation and similar activities (+37: Recycling)
41	Development of building projects; Construction of buildings	45	Construction
42	Civil engineering	45	Construction
43	Specialised construction activities	45	Construction
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	50	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods
46	Wholesale trade (include commission trade), except of motor vehicles and motorcycles	51	Wholesale trade and commission trade, except of motor vehicles and motorcycles
47	Retail trade, except of motor vehicles and motorcycles	52	Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods
49	Land transport and transport via pipelines	60	Land transport, transport via pipelines
50	Water transport	61	Water transport
51	Air transport	62	Air transport
52	Warehousing and support activities for transportation (include cargo handling)	63	Supporting and auxiliary transport activities; activities of travel agencies
53	Postal and courier activities	64	Post and telecommunications
55	Accommodation	55	Hotels and restaurants
56	Food and beverage service activities	55	Hotels and restaurants
58	Publishing activities	22	Publishing, printing and reproduction of recorded media

NACE Rev. 2	Industry Name	NACE Rev. 1.1	Industry Name
59	Motion picture, video and television programme production, sound recording and music publishing activities	92	Recreational, cultural and sporting activities
60	Radio and television activities	92	Recreational, cultural and sporting activities
61	Telecommunications	64	Post and telecommunications
62	Computer programming, consultancy and related activities	72	Computer and related activities
63	Information service activities	72	Computer and related activities
64	Financial service activities, except insurance and pension funding	65	Financial intermediation, except insurance and pension funding
65	Insurance, reinsurance and pension funding, except compulsory social security	66	Insurance and pension funding, except compulsory social security
66	Activities auxiliary to financial services and insurance activities	67	Activities auxiliary to financial intermediation
68	Real estate activities	70	Real estate activities
69	Legal and accounting activities	74	Other business activities
70	Activities of head offices; management consultancy activities	74	Other business activities
71	Architectural, engineering and related technical activities; technical testing and analysis	74	Other business activities
72	Scientific research and development	73	Research and development
73	Advertising, market research and public opinion polling	74	Other business activities
74	Other consultancy, scientific and technical activities	74	Other business activities
75	Veterinary activities	85	Health and social work
77	Renting activities	71	Renting of machinery and equipment without operator and of personal and household goods
78	Employment activities	74	Other business activities
79	Travel agency, tour operator, reservation service and related activities	63	Supporting and auxiliary transport activities; activities of travel agencies
80	Security and investigation activities	74	Other business activities
81	Services to buildings and landscape activities	74	Other business activities
82	Office administrative, office support and other business support activities	74	Other business activities
84	Public administration and defence; compulsory social security	75	Public administration and defence; compulsory social security
85	Education	80	Education
86	Human health activities	85	Health and social work
87	Residential care activities	85	Health and social work
88	Social work activities without accommodation	85	Health and social work
90	Creative, arts and entertainment activities	92	Recreational, cultural and sporting activities
91	Libraries, archives, museums and other cultural activities	92	Recreational, cultural and sporting activities
92	Gambling and betting activities	92	Recreational, cultural and sporting activities
93	Sports activities and amusement and recreation activities	92	Recreational, cultural and sporting activities
94	Activities of membership organizations	91	Activities of membership organizations n.e.c.
95	Repair of computers and personal and household goods	52	Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods
96	Other personal service activities	93	Other service activities
97	Activities of households as employers of domestic personnel	95	Activities of households as employers of domestic staff
98	Undifferentiated goods- and services-producing activities of private households for own use	97	Undifferentiated services producing activities of private households for own use
99	Activities of extraterritorial organizations and bodies	99	Extra-territorial organizations and bodies

B.2 Country-level adjustments to the harmonization procedure

Table B.4 provides details on country-specific adjustments to the harmonization of post-stratification data due to data availability constraints.

Table B.4: Country-specific adjustments

Country	Notes
Austria	Micro-census data for 2002 are incomplete; hence, we replicate the values from 2004 for that year.
Belgium	While the joint distributions are estimated using national LFS data from Statbel, we further disaggregate them by self-employed versus the rest of the labor force. This breakdown relies on additional EU-LFS data on the distribution of self-employed and non-self-employed individuals by year, sector (NACE sub-section), region, and occupation (ISCO-88, 2-digit), following the MRSP approach (Leemann and Wasserfallen, 2017) described in the first section of Appendix B. This allows us to identify and exclude the self-employed from the dataset, consistent with the approach used for the other countries.
	Data on context-level variables are estimated at the NUTS 1-digit level; post-stratification data are at the NUTS 2-digit level.
Finland	Registry data for 2002 are incomplete; hence, we replicate the values from 2004 for that year.
France	Data between 2006 and 2011 are linearly interpolated using the full joint distribution available for those two years. For years prior to 2006 and after 2011, we extrapolate region-industry frequencies, while holding constant the relative demographic composition within each industry–region cell at the 2006 and 2011 levels, respectively, as described in the first section of Appendix B.
Germany	Data are available only at the NUTS 1-digit level.
Greece	Data between 2001 and 2011 are linearly interpolated using the full joint distribution available for those two years. For years after 2011, we extrapolate region-industry frequencies, while holding constant the relative demographic composition within each industry–region cell at the 2011 levels.
Ireland	Occupation data are classified at the ISCO-88 1-digit level instead of the 2-digit level.
	For the year 2016, the NACE 2-digit level breakdown is unavailable. Hence, we compute the NACE 2-digit industry distribution within each NACE sub-section, and use it to proportionally allocate individuals with each given demographic combination into the more-detailed 2-digit NACE categories. The shares of 2-digit NACE employment among industry subsections in 2016 are derived from the Labor Force Survey (LFS) of the United Kingdom for the same year. The choice of using UK data is made because a similar survey is not available for Ireland in 2016.
	Data for the years between 2006 and 2011, and between 2011 and 2016 are linearly interpolated using the full joint distribution available for each respective pair of years. Data for 2018 are unavailable; hence, we replicate the values from 2016 for that year.
Italy	Data for the years between 2006 and 2012, 2012 and 2016, and 2016 and 2018 are linearly interpolated using the full joint distribution available for each respective pair of years. For the years prior to 2004, we extrapolate region-industry frequencies, while holding constant the relative demographic composition within each industry–region cell at the 2004 level.
Netherlands	Data for 2002 are unavailable; hence, we impute the values of 2003 for that year.
Norway	Data for 2002 are incomplete; hence, we impute the values of 2003 for that year.
Portugal	Data between 2001 and 2011 are linearly interpolated using the full joint distribution available for those two years. For years after 2011, we extrapolate by adjusting weights at the region–industry level, while holding constant the relative distribution within each industry–region cell at the 2011 levels.
Spain	Data between 2001 and 2011 are linearly interpolated using the full joint distribution available for those two years. For years after 2011, we extrapolate region-industry frequencies, while holding constant the relative demographic composition within each industry–region cell at the 2011 levels.
Sweden	No specific adjustments.
Switzerland	While frequency weights are estimated using national EU-LFS data, the industry variable is initially at the NACE sub-section level. We refine the industry variable from NACE Rev. 1.1 sub-section to the 2-digit level using Eurostat data, following an approach inspired by the MRSP method of Leemann and Wasserfallen (2017). For each region and year, we compute the share of employees in each 2-digit NACE category relative to the total employment in the corresponding sub-section category. These shares are then used to proportionally allocate individuals from the Swiss EU-LFS data—classified by demographic characteristics, region and sub-section-level—into the more detailed 2-digit NACE categories.
UK	Data are available only at the NUTS 1-digit level. For observations with unspecified qualifications, we impute educational attainment based on the individual's age at the time of education completion.

C Details on party classification

The list of radical-right parties includes: the Austrian Freedom Party (FPÖ), the Alliance for the Future of Austria (BZÖ) and the Team Stronach for Austria in Austria; the Flemish Bloc (VB) and the Flemish Interest (VB) in Belgium; the True Finns (PS) in Finland; the National Front (FN) in France; the Alternative for Germany (AfD) in Germany; the Popular Orthodox Rally (LAOS) and Golden Dawn (XA) in Greece; the Brothers of Italy - National Centre-right (FDI-CDN), the National Alliance (AN), the Northern League (LN), and the League (L) in Italy; the Forum for Democracy (FvD), the List Pim Fortuyn (LPF) and the Party of Freedom (PVV) in the Netherlands; the Progress Party (FrP) in Norway; VOX in Spain; the Sweden Democrats (SD) in Sweden; the Swiss Democrats (SD/DS), the Federal Democratic Union (EDU/UDF), and the Swiss People's Party (SVP/UDC) in Switzerland; and the United Kingdom Independence Party (UKIP) in the United Kingdom.

The list of radical-left parties includes: the Workers' Party of Belgium (PTB/PVDA) in Belgium; the Left Front (FDG) and the French Communist Party (PCF) in France; the Left Wing Alliance (VAS) in Finland; the Party of Democratic Socialism (PDS), The Left. Party of Democratic Socialism (L-PDS), and The Left (LINKE) in Germany; the Coalition of the Radical Left (SYRIZA), the Communist Party of Greece (KKE), and the Progressive Left Coalition (SYN) in Greece; Civil Revolution (RC), the Communist Refoundation Party (PRC), the Party of Italian Communists (PdCI), and Left Ecology Freedom (SEL) in Italy; the Socialist Party (SP) in the Netherlands; the Socialist Left Party (SV) in Norway; the Left Bloc (BE) and the Unified Democratic Coalition (CDU) in Portugal; United We Can, We Can, United Left (IU), Compromís–Podemos–EUPV, the Galician Nationalist Bloc (BNG), and the Aragonist Council (CHA) in Spain; the Left Party (V) in Sweden; the Swiss Labour Party (PdAS/PdTS) in Switzerland; and We Ourselves (SF) in both the United Kingdom and Ireland.

We classify as mainstream left all the parties that, according to the Manifesto Project data (Volkens et al., 2016), belong to the Ecological, Socialist, and Social-Democratic party families, and are not classified as radical-left parties according to the list above. We classify as mainstream right all the parties that, according to (Volkens et al., 2016), belong to the Liberal, Christian-Democratic, and Conservative party families, and are not classified as radical-right parties according to the list above.

The list of ethnic and regionalist parties (following Volkens et al., 2016) includes: the New Flemish Alliance (N-VA) in Belgium; the Swedish People's Party (RKP/SFP) in Finland; the Basque Nationalist Party (PNV/EAJ), Catalan Republican Left (ERC), Canarian Coalition (CC), Convergence and Union (CiU), Democratic Convergence of Catalonia (CDC), Together for Catalonia (JxCat), Popular Unity Candidacy (CUP), and Amaiur in Spain; and the Scottish National Party (SNP) in the United Kingdom.

The list of single-issue or otherwise hard-to-classify parties includes: the Pirates in Germany; the European

Democracy (DE), List Di Pietro – Italy of Values (IdV), Popular Democratic Union for Europe (P-UDEUR), and Five Star Movement (M5S) in Italy; the 50Plus (50PLUS), Party for the Animals (PvdD), and Reformed Political Party (SGP) in the Netherlands; and the National Solidarity Party (PSN) in Portugal.

D Measure of exposure to robot adoption: data sources

To construct the measure of exposure to robot adoption, we use data on the adoption of industrial robots for the 15 European countries of interest between 1993 and 2018. For Greece and Ireland, data are only available from 1999 and 2002, respectively. In these two cases, we begin measuring robot exposure in 2006, considering that earlier data classify all robots as "unspecified" and lack variation across industries. Robot data are classified into eleven industries that cover the entire manufacturing sector, mainly corresponding to the sub-sections of Section D (i.e. Manufacturing) of the NACE Rev. 1.1 classification. These are presented in Table D.1.

Table D.1: Description of industries

Industry description	**NACE Rev. 1.1 code**
Food, beverages, tobacco	DA
Textiles and leather	DB-DC
Wood and wood products	DD
Pulp, paper, publishing and printing	DE
Coke, refined petroleum, chemicals, rubber and plastic	DF-DG-DH
Other non-metallic mineral products	DI
Basic metals and fabricated metal products	DJ
Machinery and equipment n.e.c.	DK
Electrical and optical equipment	DL
Transport equipment	DM
Manufacturing n.e.c. (furniture, toys, sports goods, etc.)	DN

Annual data on the stock of operational industrial robots by country and industry are sourced from the International Federation of Robotics (IRF), which compiles data reported by robot suppliers, with support from national robotics associations. The operational stock of robots measures the number of robots in use each year in each given country and industry, based on an assumed average service life of 12 years and immediate withdrawal from service thereafter. The IRF adopts the ISO 8373:2012 definition of an industrial robot as an "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (Müller, 2022).

The pre-sample employment data used for the computation of robotization exposure are obtained from national sources and Eurostat. They refer to an year between 1988 to 1995, depending on the country. Table D.2 provides an overview of the data sources used for each country. The data are obtained at the NUTS 2-digit level, except for Germany and the United Kingdom, where they are obtained at the NUTS 1-digit level.

For the instruments, we use annual data from 1993 to 2018 on three variables designed to capture technological shifts. The first instrument relies on the Producer Price Index for the industry "Electronic Computer Manufacturing", sourced from the Federal Reserve Bank of St. Louis's FRED Economic Data (US Bureau of Labor Statistics, 2023). The electronic computer manufacturing category includes both primary and secondary products. The former

Table D.2: Employment data sources

Country	Data Source
Austria	Eurostat Regional Employment Statistics; Austria Statistics
Belgium	National Bank of Belgium
Finland	Statistics Finland
France	National Institute of Statistics and Economic Studies (INSEE)
Germany	Federal Employment Agency
Greece	Hellenic Statistical Authority – Enterprise Census of 1988
Ireland	Eurostat Regional Employment Statistics; Central Statistics Office
Italy	National Institute for Statistics (ISTAT)
Netherlands	Statistics Netherlands (CBS)
Norway	Statistics Norway (SSB)
Portugal	Statistics Portugal (INE)
Spain	National Statistics Institute (INE)
Sweden	Statistics Sweden (SCB)
Switzerland	Swiss Statistics (SFSO)
United Kingdom	Office for National Statistics (ONS)

encompasses both single-user computers and other types of computers, including host and multiuser computers. This index is set to 100 in 2004 and reported annually without seasonal adjustments. The second instrument relies on single-thread performance (measured in SpecINT x 10^3), which reflects the speed at which a single thread (i.e., a sequence of instructions within a program) can be executed by a processor core. The third instrument relies on the number of transistors (in thousands) per microprocessor, which influences the complexity and performance of calculations. Data for the second and third instruments are sourced from Rupp (2021).

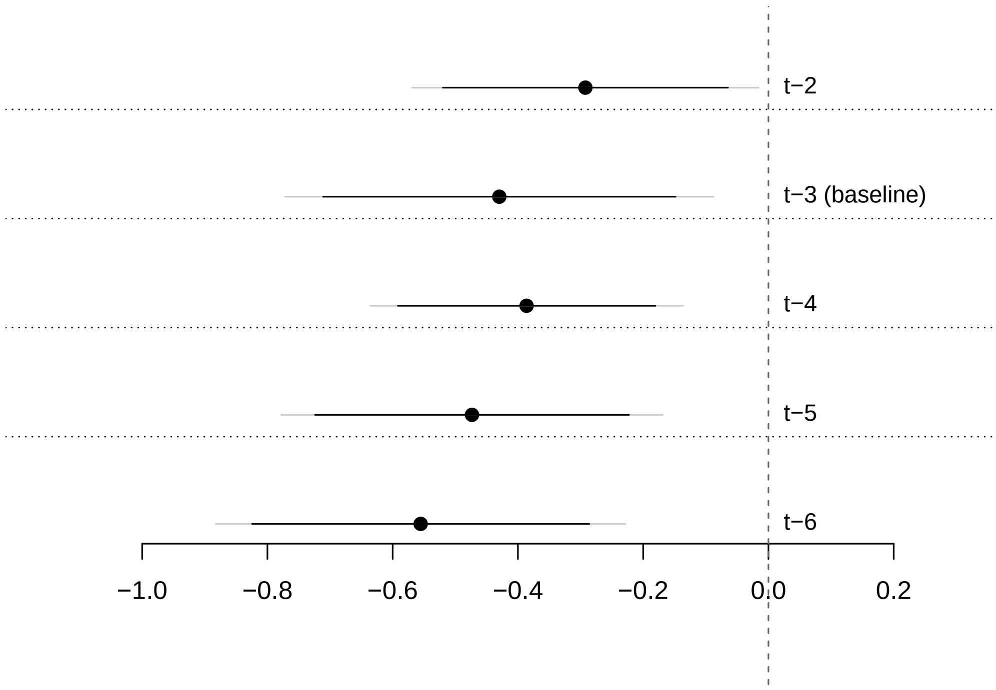
E Additional results

Table E.1: Industry-level analysis - robustness

Dep. Var.:	Industry Union Density			
	(1)	(2)	(3)	(4)
MRP Pred. Model	Best by country		Sector trends	
Estimator	OLS	2SLS	OLS	2SLS
Industry Robot Exposure	0.147*	-0.078	0.132*	-0.108
	[0.080]	[0.648]	[0.080]	[0.654]
Country-year FE	X	X	X	X
Industry FE	X	X	X	X
Observations	5,943	5,943	5,943	5,943
Std dev. Y	6.549	6.549	6.574	6.574
Std dev. X	0.873	0.873	0.873	0.873
Magnitude	0.0196	-0.0104	0.0175	-0.0143
First stage F-stat		5.457		5.457

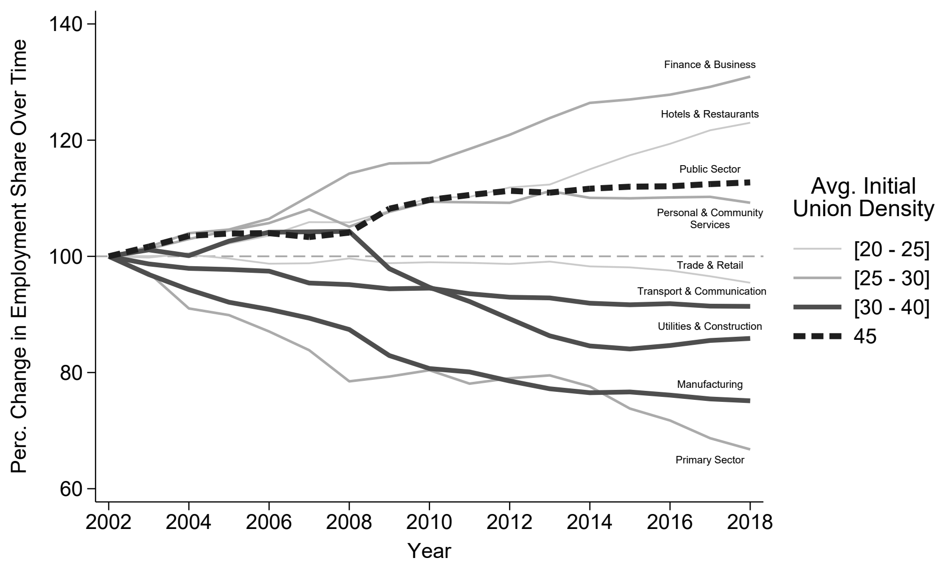
Note: The dependent variable is the unionization rate at the country-industry-year level. Unionization estimates are obtained through MRP employing the highest ranked prediction model by country in columns 1-2, while model 1 of Section A is employed in columns 3-4. The table reports the standard deviation of the dependent variable and of robot exposure, along with the magnitude of their relationship, after residualizing with respect to country-year and industry fixed effects. Robust standard errors in brackets.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure E1: Robustness: different periods



Note: The dependent variable is the unionization rate at the region-year level. Unionization estimates are obtained through MRP employing the baseline model. The coefficients reported in the plot correspond to the effect of regional robot exposure, measured over alternative time periods ranging from the previous two to six years. All models include country-year and region fixed effects. The figure displays point estimates along with 95% (dark bars) and 90% (light bars) confidence intervals, computed using robust standard errors.

Figure E2: Employment share by sector and initial union density



Note: The figure displays changes in employment shares across broad sectors from 2002 to 2018, expressed relative to their levels in 2002. Employment shares are calculated by aggregating Eurostat employment data across the fifteen countries included in the study, grouped into broad sectors: Primary Sector (NACE Rev 1.1: sections A, B, C); Manufacturing (D); Utilities and Construction (E, F); Trade and Retail (G); Hotels and Restaurants (H); Transport and Communication (I); Finance and Business (J, K); Public Sector (L, M, N, Q); and Personal and Community Services (O, P). Each country's contribution is weighted equally, so the series reflects the unweighted average sectoral composition across countries. That is, the measure captures the average relative importance of each sector within the total employed population. The figure also displays the average initial union density levels in 2002, with darker and wider lines indicating sectors with higher initial union density. The data highlights a steady decline in employment shares for traditionally unionized sectors, such as Manufacturing, Transport and Communication, Utilities and Construction, where union density initially ranged between 30% and 40%. For instance, in Manufacturing——where union density averaged around 35%——employment share fell from 18% in 2002 to 13% in 2018. The only exception among highly unionized sectors is the public sector, which has expanded in terms of employment. Conversely, sectors with lower initial union density, such as Finance and Business Services, Hotels and Restaurants, and Personal and Community Services, have increased their share of total employment over time.