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The Losers of automation.
How the introduction of robotics changed the European occupational class structure

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Abstract

This paper examines the occupational and social impact of labour-replacing technologies in Western European countries. Our study combines data on job tasks created with O*Net 3.0, information on regional robots exposure created with data from the International Federation of Robotics, and microdata from the EU-LFS from 1997 to 2017 that were longitudinalised by applying pseudo-panel models.

We investigate unemployment risks associated with the introduction of labour-saving technologies as well as changes in workforce composition and possible modifications to the occupational stratification of European societies caused by the introduction of these new technologies. In addition, we examine the “shrinking-middle-class” hypothesis as we are interested in analysing the impact of robotics on social stratification in Europe.

Our results reveal that the degree to which the process of technological innovation is embedded in institutions is highly relevant to understanding the stratification effects of robotics. This finding calls into question the deterministic – that is, the intrinsically functionalistic – perspective that underlies the economic approach of SBTC/RBTC theories. Overall, we find that a process of technical change lies at the root of different upgrading scenarios in Europe, with Northern Europe demonstrating the most positive effects of this process. Central Europe appears more stable, and technology here currently seems to be inducing only mild growth in non-manual and non-routine jobs, a reduction in unemployment risks, and an overall “upgrading” of employment- and class structure. The “losers” of the process of technological change appear to be the Southern European countries, which are currently experiencing a reduction in employment levels for low- and mid-educated male workers as well as an overall downgrading of occupational and class structures. Overall, our results do not confirm any convergent trend of technological unemployment or of “hollowing out the middle class”.

1. Introduction

The introduction of new and powerful labour-replacing technologies has historically incited public concern regarding the risk of mass unemployment and a jobless future. Indeed, concern about automation is not a new phenomenon and can be traced back to the dawn of the first industrial revolution (Hobsbawn, 1952; Braverman, 1974; Mokyr, Vickers and Ziebarth, 2015). However, despite two centuries of unrelenting technological progress, employment rates in Western political economies have continued to grow (Autor, 2015). In addition to eliminating jobs, each technological leap has been accompanied by new employment opportunities and has spurred transformations in the type and quality of occupations available, even if the substitution of traditional jobs with new ones has not always been seamless (Frey, 2019).

Scholars have documented massive processes of occupational polarisation or occupational upgrading in almost every advanced economy in the past thirty years in terms of the distribution of income or employment composition (Milanovic, 2016; Oesch and Menés, 2011; Goos, Manning and Salomons, 2009; Autor, Levy and Murnane, 2003). Technological change has been largely recognised as the most important factor behind these long-term processes and is responsible for changing employment- and class structures (Green, 2012; Green, Felstead and Gallie, 2003) because the automating technologies introduced in recent decades are good substitutes for routine-task jobs, which are concentrated at the middle and bottom levels of occupational structure. Similarly, the idea of a “middle-class squeeze” or a “shrinking middle-class” has significantly increased in popularity in the social science literature (Scott and Pressman, 2011; Pressman, 2007, 2009), notwithstanding the feeble empirical support for the concept in countries other than US (Brandolini, Gambacorta and Rosolia, 2018; Dallinger, 2013).

However, one of the problems with a task-based perspective is that it conceives the relation between technological change and labour market dynamics (in terms of both employment levels and employment composition) as being strongly deterministic and mainly defined by the technical capabilities of machinery. However, processes (and consequences) of automation do not take place in a vacuum; rather, they are embedded in historically defined national institutional arrangements. Actors in different political economies face different sets of incentives and constraints, which first affect the introduction of technology and eventually shape strategies in response to restructuring processes that are prompted by technological change. As a result, technology may have very dissimilar consequences for employment- and class structure across countries, and these consequences are defined by different contextual and institutional arrangements. Hence, comprehensively evaluating the spillovers of labour-replacing technology into the employment- and class structure would ideally require an institutional theory of stratification, the creation of which would go well beyond the scope of this paper. Indeed, our focus lies on a specific micro-technical mechanism that is embedded in different institutional settings. We investigate the existence of a heterogeneous relation between automation, employment composition, and class structure by examining the adoption of robotics across Western European countries from 1997 to 2017, and we adopt a cluster-based

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1 Dallinger (2013) used LIS data on 19 countries covering the 1985–2005 period and found little change in the income position of the (income-defined) middle classes with respect to both market- and disposable incomes. Market incomes in the top quintile increased remarkably in most countries during this period, while the bottom quintile group lost out. Thus, if some “crisis” affected the “intermediate” occupational positions, this was only in relative terms in comparison with the top positions. Notably, such “retrenchment” was not dramatic enough to modify the social stratification hierarchy.
comparative perspective in order to highlight the importance of cross-country institutional and contextual differences in mediating the consequences of robotisation. More specifically, in line with the literature on the institutional embeddedness of the labour market (Boeri, Conde-Ruiz and Galasso, 2012; Boeri, 2011; Eichhorst and Marx, 2010; Estevez-Abe, Iversen and Soskice, 2001; Esping-Andersen and Regini, 2000), we consider two kinds of labour market institutions: labour market (de)regulatory practices on the one hand and educational and training systems on the other hand. Combining these two dimensions yields the trade-off dualist labour market/skill provision (Palier and Thelen, 2008). The positions of different countries along this trade-off represent different stable political-economy equilibria, or skill regimes (Estevez-Abe, Iversen and Soskice, 2001).2

Countries and skill regimes with a more segmented and dualised labour market, a more compressed wage structure, and usually a less-developed and less-universalistic unemployment benefit (UB) system (Boeri et al., 2012) display relatively higher levels of EPL and develop industry- or firm-specific skill regimes. On the other hand, countries with less-dualised labour markets display a relatively lower-EPL & higher-skills equilibrium, more dispersed wage structures, and progressive UB systems and thus develop occupation-specific skill regimes. Accordingly, we consider three skill regimes that have figured prominently in the literature on comparative political economy: Nordic, Continental, and Southern European countries (Gallie, 2011; Edlund and Grönlund, 2008; Iversen and Stephens, 2008) – or, to use a different labelling that emphasises the endogenous roots of the differences between the Continental European groups: Nordic, Corporatist, and Dualist “settlements” (Goldthorpe, 1984).

The present article contributes to the existing literature on automation and occupational change in three ways:

First, our findings suggest that far from being a deterministic process, the relation between automation and employment is mediated by the specific institutional context in which technology is introduced. Our results thus do not confirm any convergent trend in the transformation of employment structure that could be responsible for a ubiquitous dynamic of technological unemployment or for “hollowing out the middle class”. By taking a clearly defined and comparable indicator of automation – namely, industrial robots – we instead highlight how the very same technology may have very different impacts on employment- and class structures. Indeed, our results reveal that robotics is associated with an upgrading of employment structure in the Nordic as well as (to a lesser extent) in the Continental countries (the “Corporatist” countries) but with a downgrading of employment structure in the Southern European countries (the most dualised countries).

Second, our findings highlight the potential role of technological change as a source of context-specific social stratification. This article documents cross-country heterogeneity in

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2 A merely supply-sided perspective would consider agents heterogeneous along the dimensions of employment status (insider/outsider – i.e. employment in the primary vs secondary labour market) and skills (low vs high). However, in our schema, the outcome of the process of technological innovation is mediated by incentives and disincentives, which are defined at the macro-institutional level. In such a scenario, labour supply and demand are both involved and must be considered in order to understand the response of the whole economic system to technological change. J. Goldthorpe (1984, ch.13) argues that during a period of sustained economic turmoil, some Continental European “Corporatist” countries (CMEs) would go the route of “dualism”. Dualistic tendencies imply “the enlargement of certain areas of the economy within which market forces and associated relations of authority and control are able to operate more freely than in others, and in fact in such a way as to compensate for the rigidities that prevail elsewhere”. Put differently, we stress that Southern Europe constitutes a model in and of itself that is derived from a conjunction of supply factors (“insiders/outsiders” and low skill) and demand factors (labour market segmentation) in which institutions disincentivise the production of skills while rewarding the situation rent of insiders and firms resort to the secondary labour market for their low-road competition strategy.
gender- and educational asymmetries across occupations. National institutional arrangements appear decisive in mediating this process, and a clear North–South divide emerges. Indeed, robotics appears to improve occupational opportunities for every group in the Nordic countries, to foster the occupational prospects of skilled workers in the Continental countries, and to significantly increase unemployment risks for low- and mid-educated male workers in the Southern European countries.

Finally, this article stresses the importance of the skills and competences of the labour force in mediating the impact of automation on employment structures and inequalities. In contexts characterised by relatively lower EPL levels, a highly skilled labour supply, and extensive training provisions (even for low-skilled workers), labour-replacing technologies appear to have far more positive outcomes and to go hand in hand with fewer pronounced consequences in terms of inequality between groups.

2. Theoretical background: automation, employment, and class structure

The relation between industrialisation and changing class structures in Western societies has long been a central topic of classical research on social stratification and mobility (Golden, 1957; Soares, 1966; Treiman, 1970; Erikson et al. 1979). According to the so-called liberal theory of industrialisation, processes of automation have deeply transformed the occupational and class distribution of Western political economies by decreasing the proportion of people engaged in agriculture, shifting the occupational distribution from the production of goods to the provision of services, and generating entirely new occupations (Bell, 1973; Treiman, 1970; Kuznets, 1957).

Similarly, economic research suggests that the technological change that began in the 1970s has been largely “skill-biased”, thereby increasing the opportunity and demand for highly skilled workers and eventually leading to an upgrading of employment structure (Autor, Katz, Krueger 1999; Goldin and Katz, 2007). De Vries et al. (2020) have observed that in high-income countries, an increase in the adoption of robots is associated with a decrease in the employment share of routine manual task-intensive jobs. Despite important differences, both liberal- and skill-biased technological change (SBTC) theories predict that a burst of new technology will cause an increase in the demand for highly skilled workers and should – in turn – lead to an overall upgrading of occupational structure by shifting employment from low-level, routine-intensive occupations to high-level, knowledge-intensive occupations. The increase in earnings inequality is a necessary corollary of this trend.

These expectations have not gone unchallenged, with socio-economic research having been quick to point out that the SBTC framework ignores differences in the pace of technological change across industries and that several Western economies have experienced an increase in the proportion of workers employed not only at the top but also at the bottom level of occupational structure (Card and Di Nardo, 2002; Goos, Manning and Salomons, 2014; Autor and Dorn, 2013). The theory of Routine-Biased Technological Change (RBTC) has become prominent in the study of the relation between technological change and occupational structure. RBTC argues that technologies that have been introduced in recent decades have served as good substitutes for explicit and codifiable “routine-task” operations (Acemoglu and Autor, 2011; Autor, Levy and Murnane, 2003) and that several tasks exist that require manual and intellectual flexibility, judgment, and common sense in addition to high-level reasoning and for which technological substitution has been limited.
RBTC theory further suggests that occupations that constitute routine tasks are mainly concentrated in mid-level occupations, such as with production workers and clerks. More precisely, Autor et al. (2003) group occupations into different categories defined by their content (ranging from manual to interactive/analytical) and their degree of routinisation: non-routine cognitive analytical content, non-routine cognitive interactive content, routine cognitive content, routine manual content, and non-routine manual content. By reducing the demand for routine-intensive occupations at the middle level of employment structure and creating incentives for the growing demand for non-routine occupations at the top and/or bottom level, automation has led to overall changes in employment structures in the form of occupational polarisation. Therefore, unlike previous theories, RBTC suggests that automation is related to a reduction in employment shares in mid-level occupations and to increased numbers of shares in both high- and low-level jobs. These dynamics point in the same direction as Breen’s early considerations (1997), which considered organisational processes within companies to represent the key to understanding middle-class weakening. Breen has stressed that changes in technology and new methods of work monitoring worsen the position of intermediary jobs, with routine non-manual employees, lower-grade technicians, and supervisors of manual workers being especially affected by these new processes.

While RBTC offers important insight into understanding the relation between technological change and employment composition, less attention has been paid to its implications for socio-economic inequalities. Robotics stands out as a clear example of routine labour-replacing technology, and in Western European countries, routine-intensive occupations have traditionally been unevenly distributed among workers of different genders and cohorts and with different educational backgrounds. It follows that robotics can act as a stratification factor to the extent that it implies a non-neutral distribution of changing employment opportunities, unemployment risks, and wage consequences for distinct social groups.

These implications are clearly relevant for understanding the transformation of Western class structures. Indeed, the distribution of tasks among the workforce closely reflects occupational stratification (Rose and Harrison, 2007; Erikson, Goldthorpe and Portocarero, 1979), with manual tasks – both routine and non-routine – predominantly performed by the working classes and with abstract cognitive tasks concentrated in the highest ISCO categories and ESeC classes (Figures 1.A and 2.A, web appendix). Consequently, a task-based approach would lead to different and less-positive implications as compared with a liberal industrialist approach. RBTC somehow echoes Esping-Andersen’s expectation that a “service proletariat” should emerge in the transition to a post-industrial society (1993), with no major signs of overall upgrading of social structure and instead an increase in the proportion of low-level service workers within working-class groups. RBTC thus forecasts an occupational polarisation of employment structure in advanced societies due to technological innovation, with a likely reduction in routine mid-low positions.

To conclude, research results on the “disappearance of the middle class/es” as a consequence of technological change are mixed since robotics does not threaten all groups of workers in the same way. Institutions clearly play a role in determining the outcomes of the connection between production technologies, occupational opportunities, and class structures.

3. Institutions: labour market (de)regulation, educational systems, and skill regimes
We have seen how a task-based perspective often conceptualises automation as a strongly deterministic process. Indeed, connecting the introduction of labour-replacing technologies with labour market outcomes through mechanisms based solely on the technical capabilities (and related price) of machinery (Autor, Levy and Murnane, 2003) goes hand in hand with assuming a functionalist perspective based on the ineluctability of industrialism and modernisation (“convergent trends”) as opposed to the “political economy of capitalism” (Goldthorpe 1984) and thus disregards important contextual factors that shape actors’ responses to automation (Bailey and Leonardi, 2015). In fact, the socio-economic literature has revealed that patterns of occupational change differ across countries despite very similar evolutions of technological equipment (Oesch and Piccitto, 2019; Fernández-Macias and Hurley, 2017; Oesch, 2015; Fernández-macias, 2012; Oesch and Menés, 2011).

We consider three kinds of institutional processes that mediate the impact of technological innovation on occupational and social structures and therefore also on inequality: labour market deregulation, the characteristics of the educational system, and the characteristics of the skill regime.

The kind of flexibilisation implemented – which is more or less “two-tiered” – may prompt a process of dualisation (Emmenegger et al., 2012; Palier and Thelen, 2010) between a protected core workforce and a peripheral, less-skilled, less-trained (Cutuli and Guetto, 2013), and less-paid (Barbieri, Cutuli, 2018) workforce that has fewer social and labour rights (Barbieri, Cutuli and Passaretta, 2018; Barbieri and Cutuli, 2016; Polavieja, 2003). The presence of such a secondary labour market represents an opportunity for firms that are oriented towards low-road competition strategies, which are implemented by eschewing the introduction of high-value-added technological innovations.

In addition to labour market dualisation, the characteristics of educational and training systems can be expected to play a crucial role in influencing the impact of automation on employment structures and inequality. Indeed, the levels of formal education and competencies among the labour force can shape responses to technological change from both employers and employees. On the demand side, the interaction between labour market dualisation and skill is pivotal since firms adapt and define their production and employment strategies on the basis of the availability of input factors in the context in which they operate (Murphy and Oesch, 2018; Hall and Soskice, 2001). When taking advantage of new opportunities that stem from higher technological capabilities and growing product demand, employers who face a highly qualified labour force and operate in labour markets that do not incentivise the use of a secondary workforce are more likely to increase their demand for high-level occupations. The supply of a highly educated workforce is thus crucial since it influences the availability and relative cost of highly qualified labour (McCollum and Findlay, 2015; Korpi and Tåhlin, 2009). As a result, a process of technological change in the context of a highly qualified labour supply can lead to a high-road employment- and production strategy and an overall occupational upgrading. This result is especially relevant with a labour supply comprised of highly educated women entering the labour market (Murphy and Oesch, 2018). On the other hand, when firms face a high supply of low-educated workers, they may find incentives to increase low-skilled, labour-intensive productions. In Southern Europe, where the average educational level of the labour force is close to the bottom and segmented labour markets have been institutionally nurtured (Barbieri and Cutuli, 2016; Palier and Thelen, 2010), a strategy of labour-cost competition based on a selected core workforce of skilled insider workers as opposed to a buffer of low-qualified secondary labour market workers may prove convenient (Brunello and Wruuck, 2019).
On the supply side, workers equipped with suitable skills can more easily transition to new occupations that emerge from the process of technological change, thereby reducing individual risks and losses that arise from the automation of their traditional occupational domains. The opposite holds for poorly educated and untrained/un trainable workers.

However, the skill and supply of human capital in a specific labour market is not represented by average levels of formal educational competencies alone. The literature on comparative political economy stresses the importance of the type and specificity of skills in shaping employers’ production strategies and patterns of inequality (Estevez-Abe, Iversen and Soskice, 2001; Hall and Soskice, 2001), thereby highlighting the relevance of national vocational and training systems and leading to the definition of distinctive skill regimes.

In one of the earliest categorisations of this kind, authors within the varieties-of-capitalism (VoC) framework distinguished between two possible skill regimes: liberal and coordinated market economies. The former relied primarily on general and transferable skills, the latter on industry- and/or firm-specific skills. The original distinction was conceived as being mainly rooted in pre-labour-market-entry vocational training, and less attention was paid to other instruments of skill formation, such as on-the-job training policies and the lifelong learning schemes of the workforce. The original dichotomous categorisation has thus been criticised for its oversimplification, and subsequent literature has called for a further division of coordinated market economies into a Nordic and a Continental Cluster. The distinction between these two clusters is based on the assumption that deliberative institutions and centre-left government coalitions help to foster universalistic policies in the Nordic countries more than in the Continental ones, which has implications for skill formation.

As a result, the Nordic countries are characterised by high levels of spending not only on vocational training but also on general education and active labour market policies. The result is a skill supply characterised by high levels of occupation-specific skills and general educational competencies, particularly at the median and bottom levels of skill distribution, because even active people with low levels of education may undergo extensive training both on the job and through state-promoted programs. Consequently, the Nordic countries are characterised by generally lower EPL and a higher and more compressed skill distribution, thereby allowing firms in these countries to develop high-value-added production strategies and to increase the demand for high-level- and knowledge-intensive occupations. On the other hand, the Continental countries are characterised by high levels of vocational education and smaller investments in both tertiary education and active labour market policies, thereby resulting in a large supply of industry-specific skills and only moderately high levels of general skills at the bottom level of skill distribution. The relative absence of strong general skills – especially among less-qualified workers – is not favourable to the development of new service jobs and inhibits the expansion of new occupations.

A further distinction between the Continental and Southern European countries came later. The kind of skill regime that is distinctive of Southern Europe is characterised by a “generic” educational system that provides close to the lowest level of vocational education, a scarcity of additional training institutions, and a supply of firm-specific skills coupled with low levels of on-the-job training after entering employment. The combination of a high supply of low-skilled workers and low levels of general skills at the bottom level of skill distribution in a context of highly dualised labour markets means that firms have few options but to adopt low-road, labour-intensive, neo-Fordist production strategies that foster employment growth at the bottom level of the occupational and class structure (Edlund and Grönlund, 2008; Iversen and Stephens, 2008; Soskice, 2007).
Put differently, the redistributive propensity of the different skill regimes is crucial in defining the impact of automation on occupational inequalities. High levels of provision and investments in training policies and the lifelong learning schemes of the workforce appear decisive, especially since these factors allow skill obsolescence to be limited for workers whose formal educational composition is pre-determined and largely unchangeable. Since an unequal distribution of the risk of automation across skill- and educational levels suggests that low-skilled workers are the most vulnerable category, adult learning and continuous training emerge as crucial policy instruments for retraining and upskilling poorly educated and unskilled manual workers, whose jobs are most at risk of being replaced by automation (Bosch, 1992; Mahnkopf, 1992). Skill-based (and class-) inequalities thus can be mitigated through an encompassing vocational and training system that is capable of providing even low-educated workers with the right skills to cope with technological change.

Cross-country differences in human capital- and educational systems are therefore important in explaining the heterogeneous effect of automation across countries and across groups of workers within countries. Throughout the analysed years, European countries strongly differ in the educational composition of their labour force (Figs 3–4.A, web appendix) as well as in the severity of their labour market dualisation. The most visible pattern is a clear North–South divide. Indeed, compared with the rest of Europe, the Southern European countries are characterised by a substantively higher supply of low-educated workers and by a higher degree of labour market dualisation, which triggers a strong insider–outsider divide (Boeri, Conde-Ruiz and Galasso, 2012).

4. Research hypothesis

In light of the previous discussion, we expected automation to generate an overall upgrading of employment/class structure in Northern European countries, a moderate upgrading in the Continental countries, and a downgrading in the Southern European countries (Hypothesis 1). The contextual characteristics of the Nordic countries (again, the countries have a high supply of tertiary-educated workers as well as vocational and training systems that promote high levels of specific and general skills, even at the bottom level of skill distribution) create incentives for pursuing high-value-added production strategies that make extensive use of high-skill, knowledge-intensive occupations. The Continental countries are defined by relatively high average educational credentials among employees; however, their vocational and training systems are much more strongly oriented towards providing industry-specific skills – through a dual-educational system, pre-labour market entry, and strong apprenticeship programs – but only moderate levels of general skills, especially for low-educated workers. While a large supply of highly skilled workers and the presence of strong technical qualifications among semi-skilled workers allow for a shift to higher-level occupations in the Continental countries, this is less so than in the Northern European countries, where high levels of both occupation-specific skills and general competencies are available across the entire workforce.

Finally, the Southern European countries are characterised both by a high supply of low-skilled workers (below secondary education) with no vocational qualifications and by few investments in subsequent training or active labour market policies. In Southern Europe, firms have greater incentives to adopt production- and employment strategies that profit from the presence of a highly segmented labour market (with a cheaper workforce), thereby fostering
the demand for low-skilled, labour-intensive occupations. Automation and technological change lead to a risk of downward mobility for low-skilled workers and inhibit status upgrading for most groups since skill distribution discourages the development of new, high-level occupations. In Southern Europe, low-educated male workers face a significant risk of technological unemployment due to the absence of training opportunities and the presence of fiercer competition.

However, we expected the opportunity for workers to be able to retrain and acquire new skills to increase their ability to cope with (i.e. mediate the consequences of) technological change and to thereby enhance their likelihood of transitioning to better, higher-level positions and to reduce their risk of unemployment (Hypothesis 2).

In terms of the impact of robotics and technological innovation on general class structure and social stratification dynamics, the diffusion of robotics was expected to impact not only the skill structure of our country clusters but also the same occupational class structure (Hypothesis 3). Of course, skills and occupational classes are not strictly collinear, and classes may be more heterogeneous than are closed occupational groups. However, decades of literature has revealed that skill- and class structures are indeed associated (Williams and Bol, 2018; Erikson, Goldthorpe and Hällsten, 2012; Jonsson et al., 2009; Rose and Harrison, 2007; Weeden and Grusky, 2005; Ganzeboom and Treiman, 2003; Oesch, 2003; Esping-Andersen, 1993; Goldthorpe and Hope, 1974). It follows that productive and skill changes may well impact the social stratification structures of advanced capitalist countries and modify the composition of the different classes yet not the entire social hierarchy (Goldthorpe, 2007). Therefore, following Breen (1997), we expected robotics to exert some “prospective” impact on the social stratification of our country clusters in favour of expanding the upper classes in Northern Europe, consolidating the mid-upper classes in the Continental countries, and diminishing the upper classes while expanding the manual classes in Southern Europe.

5. Data, methods, and variables

Microdata came from the EU-LFS from 1997 to 2017.³ Task indices were created using O*Net 3.0, and information on the adoption of robots was taken from the International Federation of Robotics. We adopted a regional-level approach and connected indicators of technological exposure at the regional level to regional and individual indicators of employment, occupational level, class composition, and performed tasks. We took regions – rather than countries – as the main units of analysis since subnational areas are not equally exposed to automation due to regional sectoral specialisation and/or industrial and economic development. Similarly, regions within countries differ in their training policies and levels of participation in training. Thus, a regional approach allowed us to better account for sub-national variation (Barbieri et al., 2019).

The analysis was structured on two levels. First, on the regional level, we used 50 nuts-1 European regions from 10 European countries observed over 21 years as the unit of analysis.

³ Germany entered the analysis beginning in 2002 since EU-LFS microdata do not include information on region of residence before this year.
and subsequently grouped the regions into three clusters. We connected indicators of regional employment, class structure, and task composition to an indicator of regional robotics exposure.

Second, in order to investigate diverse effects across gender- and educational groups, we aggregated individuals from the EU-LFS into pseudo-individuals defined by their time-invariant characteristics (region of residence, three ISCED educational levels, and gender). We computed time-varying averages of the variables of interest (Barbieri and Cutuli, 2016; Deaton, 1985) and followed the group values of each unit over time while treating them as conventional panel observations. In this way, we could connect longitudinal variation in the response variables for each (regional, gender-, and educational) group to the variation of the specific regional level of robotics exposure.

To connect our indicator of regional robotics exposure to changes in both regional occupational composition and pseudo-individual outcomes, we exploited the longitudinal dimension of the data and applied group-level fixed-effects models. In this way, we could control for time-constant unobserved heterogeneity between regions and pseudo-individuals.

For the regional-level analysis (Equation 1), we separately regressed three sets of variables \( (Y_{rt}) \) on the regional indicator of robotics exposure \( (Rbt_{rt}) \).

\[
Y_{rt} = \sum_{c=1}^{C} \beta_c Rbt_{rt} \times Cluster_c + \sum_{c=1}^{C} \theta_c X_{rt} \times Cluster_c + \varphi \gamma + u_t + \epsilon_{rt}
\]

The first set of dependent variables refers to the impact on unemployment- and employment structures, the second set of variables refers to the regional class composition, and the third set of variables refers to the task composition of the labour force (see next section for variable descriptions). Models also included year fixed effects \( (\varphi_{r}) \) to control for exogenous common shocks across regions and a vector of time-varying regional features \( (X_{rt}) \) as well as the corresponding vector of coefficients \( (\theta_c) \), which included the youth unemployment rate and the supply of highly skilled workers (the share of university graduates over the active population).

To investigate the heterogeneous relation across contexts, we interacted each independent variable with three dummies \( (Cluster_i^c) \) that indicated the country regime to which each region belonged: Nordic, Continental, and Southern European.

To identify the “winners” and “losers” of employment restructuring spurred by automation, we regressed the unemployment rate and the ISEI level \( (Y_{irt}) \) of pseudo-individuals on the regional indicator of robotics exposure \( (Rbt_{rt}) \), as shown in Equation 2.

\[
Y_{irt} = \sum_{c=1}^{C} \sum_{E=1}^{E} \sum_{G=1}^{G} \beta_{CEG} Rbt_{rt} \times Cluster_{ir}^c \times Edu_{ir}^E \times Gen_{ir}^G + \sum_{c=1}^{C} \sum_{E=1}^{E} \sum_{G=1}^{G} \theta_{CEG} X_{rt} \times Cluster_{ir}^c \times Edu_{ir}^E \times Gen_{ir}^G + \varphi_{ir} + u_{it} + \epsilon_{it}
\]

Since pseudo-individuals were generated by intersecting region, education, and gender through fixed effects, we controlled for all time-constant unobserved heterogeneity between these units. We additionally included all the controls specified for the regional model.

In order to investigate the heterogeneous effect of robotics across institutional clusters and groups, regional robotics exposure was interacted with dummies for each of the three clusters \( (Cluster_{ir}^c) \),

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\[4\] Countries included in the analysis were Italy, Portugal, and Spain (Mediterranean Cluster); Germany, Belgium, France, and Austria (Continental Cluster); and Sweden, Finland, and Denmark (Nordic Cluster) (Gallie, 2011). We did not include countries in the Liberal Cluster (UK and Ireland) in the analysis since these countries had no variation in robotics exposure throughout the analysed years.
dummies for the three educational levels ($Edu^E_i$), and dummies for the sex of the pseudo-individuals’ ($Gen^G_i$).

As mentioned in the theoretical section, diverse effects across individuals are likely related to the skill levels and competences of the individuals, which are in part related to the individuals’ level of education and in part to the national capacity to train workers and help them adapt to changing labour markets. We therefore considered how participation in training activities had mediated the impact of automation on individuals’ unemployment risk and ISEI level. For each pseudo-individual, we took the average share of the active population between 25 and 60 years who had undergone some training activity in the four weeks preceding the interview. By interacting this measure ($Train_i$) with the indicator of automation and with dummies for individual characteristics (as in Equation 3), we could detect the heterogeneous impact of robotics for similar groups of workers in regional contexts characterised by different levels of training. In all the analyses, standard errors were clustered at the regional level.

\[ Y_{irt} = \sum_{E=1}^{3} \sum_{G=1}^{2} \beta_{EG} Rbt_{rt} \cdot Train_i \cdot Edu^E_i \cdot Gen^G_i + \sum_{E=1}^{3} \sum_{G=1}^{2} \theta_{EG} X_{rt} \cdot Train_i \cdot Edu^E_i \cdot Gen^G_i + \varphi_t + u_i + \varepsilon_{it} \]

5.1 Employment- and class structure

We defined occupational position by taking the ISEI scores of each ISCO-88 3-digit occupation and grouping them into five quintiles. The regional share of workers employed in each of these five groups represented our first set of dependent variables. Occupations were ranked such that each quintile consisted of the same occupations in each analysed country. Robotics was expected to impact occupational structures and occupational opportunities by replacing specific occupations based on their task content. The type of tasks performed in an occupation was taken as an intrinsic characteristic of the occupation per se, independent of the number of people employed in that occupation or the remuneration of the occupation in a specific country. By ranking occupations based on the Europe-wide ISEI-level distribution, we rendered occupational quintiles comparable across time and countries (see web appendix for details).

Literature on occupational change and the hollowing-out of the middle classes has almost exclusively investigated changes in the nationally ranked distribution of occupations in terms of wages or some other income indicator. However, this approach neglects important dimensions of employment relations, such as the degree of work-asset specificity and the ability to monitor work efforts and achievements, both of which are crucial to enabling a sociological understanding of the ongoing transformations. We thus extended the analyses to include occupational class composition, and we investigated how automation has changed the composition of the labour force across the analysed clusters in terms of the ESeC – a categorical socio-economic classification based on occupation, employment position, and contract type (Rose and Harrison, 2007).

We adopted a five-category definition of the ESeC and therefore created five distinct independent variables that indicate the share of workers in each of the five classes: the salariat; intermediate employees; small employers and the self-employed; lower services, sales, and clerical occupations; lower technical occupations; and routine occupations.\(^2\) We next examined which classes had grown (in terms of workforce share) and which classes had numerically decreased due to having undergone technological change, and we also investigated where this process occurred – that is, in what contexts.

\(^2\)EU-LFS data do not contain information on supervisory positions for the time period under analysis. We therefore adopted the simplified ESeC scheme with no supervisory information.
This process provided some clarity in the long-standing debate on the destiny of the “middle”, specifically in response to technological change.

5.2 Task composition

Since the relation between automation and employment structure was expected to go hand in hand with shifts in task composition, we further investigated how robotics had influenced the regional distribution of jobs as defined by the content of their tasks. We used the Occupational Information Network 3.0 (O*NET 3.0) as a source of information on the task content of the occupations. O*Net 3.0 data were collected in the US for approximately 1,000 occupations based on the SOC-2000 classification. O*Net data contain several indicators of tasks performed in each occupation in terms of the importance, level, and extent of the activity. Following Acemoglu and Autor (2011), we used the importance scale of fifteen items representing five task-content dimensions (Table 1A, web appendix). Items were standardised and then combined via an additive scale in five indices: non-routine manual (NRMN), routine manual (RTMN), routine cognitive (RTCOG), non-routine cognitive interpersonal (NRCIP), and non-routine cognitive analytical (NRCA).

To estimate the task content of jobs in each European country and region, we connected O*NET task indices to the corresponding three-digit ISCO-88 codes and ranked them in percentiles based on the distribution of occupations per each index. Each ISCO-88 three-digit occupation was assigned a number from 1 to 100 that represented its level of content in each specific task dimension.

We then combined occupational scores with individual data from the EU-LFS from 1997 to 2017. In this way, each employed individual in the EU-LFS was assigned five task scores corresponding to their ISCO-88 code of occupation. Individual values were then averaged for each region-year, producing five regional-level indices of task composition. As the values of the indices for each occupation were constant over time, variation in regional scores was given exclusively by change over time in the distribution of employment across occupations, and occupational task content was held constant at the 2003 level, which Autor, Levy, and Murnane (2003) define as the “extensive margin”. Variation in regional scores was clearly not the only source of variation as several studies have documented changes in task content within occupations (Spitz-Oener, 2006; Autor, Levy and Murnane, 2003). Nevertheless, this variation in regional scores was the most pertinent to our research objective since we investigated changes in employment structures that were necessarily produced by shifts in employment between occupations. The five indices therefore measured the change in regional task composition given by the shift in employment between occupations as defined by different task specialisations.

5.3 Robotics

The regional variable of robotics exposure was constructed using data provided by the International Federation of Robotics (IFR). The IFR collects information on the introduction and stock of industrial robots – disaggregated by detailed sectors of application – for 50 countries beginning in 1993. The adoption of robots is arguably the most relevant source of industrial automation for the last 30 years. Robot sales have been steadily rising in recent decades, reaching almost 4 million by the end of 2017.

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6 O*Net data have been frequently used in studies on countries other than the US, e.g. those by Arias et al. (2014), Goos et al. (2014), Hardy et al. (2016), and Lewandowski et al. (2017). Handel (2012) has demonstrated that US-based occupational surveys and non-US skill surveys produce very similar outcomes for European countries. Furthermore, Cedefop (2013) has revealed that results from O*Net and two surveys that followed the same methodology in Italy and Czeclia yielded highly correlated results for task indices (>0.8), suggesting that it is methodologically valid to apply O*Net information to Europe.

7 Importance- and level scales are highly correlated (0.92 in O*NET 2003 and 0.96 in O*NET 2014). We therefore followed Acemoglu and Autor (2011) by applying only the importance scale.

8 The use of occupational ranking for tasks rather than the direct task values facilitated the transposition of US-based values to Europe and relaxed the assumption of a perfect correspondence in task content: this is a standard choice in the literature.
thereby rendering robotics the most salient form of technology as a replacement for physical activity. Furthermore, robotics is a clearly defined form of technology and allows for a comparable measure of automation across countries and industries. We combined IFR data with employment counts by country, industry, and year from the EU-LFS from 1997 in order to measure the number of industrial robots per thousand workers.10

Following Acemoglu and Restrepo (2017) and Dauth et al. (2018), we developed a measure of robotics exposure for each region-year as the sum of European regional industrial employment shares (EMPLrjt0/EMPLrt0) times the ratio of the national diffusion of robots in each industry over industrial employment (RBTSjt/EMPLjt0).11 The full equation is shown in [4], where \( r \) represents the European regions, \( t \) represents each year from 1997 to 2017, \( t0 \) represents levels from 1997, and \( j \) represents the reference industry.

\[
Regional\ Robotics\ Exposure_{r,t} = \sum_{j \in J} \frac{EMPL_{rj,t0}}{EMPL_{rt0}} \times \left( \frac{Robots_{rj}}{EMPL_{jt0}} \right)
\]

In other words, the national share of robots per industrial branch was assigned to each region-year based on the employment level in that regional industry during the first observed period.12 Values for all industries were then summed for each region-year, thereby yielding the overall regional robotics exposure.

6. Results: changes in employment- and class structure

Before analysing the association between industrial automation and changes in employment composition and class structure, we present some descriptive statistics throughout the analysed years and countries. Figure 1 displays the variation in the share of workers employed in each of the five ISEI quintiles for each country during the period under analysis. In line with most of the sociological literature, these descriptive statistics highlight a process of occupational upgrading rather than of polarisation in almost all European countries (Oesch and Picciotto, 2019; Oesch and Menés, 2011). In the years under analysis, the share of workers employed in top-tier occupations rose in every country, while the share of workers employed in lower- and mid-level occupations either decreased or stagnated.

[Figure 1]

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9 Robots are defined by the International Federation of Robotics as automatically controlled, multipurpose, manipulator-programmable devices rotatable around three or more axes that can be either fixed in place or mobile for use in industrial automation applications.

10 Data on national and regional employment at the NACE 2-digit level were provided by EUROSTAT through their data extraction service.

11 Acemoglu and Restrepo (2017) define it as “exposure to robots, a measure defined as the sum over industries of the national penetration of robots into each industry times the baseline employment share of that industry in the labor market”. The authors computed regional robotics exposure as the difference between the stock of industrial robots in each industry between 1990 and 2007. We used the stock of robots in each observed year and exploited all 21 time points for each region.

12 This choice avoided any mechanical correlation between robotics and overall- or industry-level employment outcomes. For instance, the introduction of robots may have increased or decreased total industrial regional and national employment levels and may thus have directly affected the denominators. Taking values at the first observed period allowed us to focus on persistent differences in the regional specialisation of different industries.
The same dynamics emerge from an exploration of the trends in class composition (ESeC), as shown in Figure 2. During the analysed years, the share of the salariat grew, whereas that of lower technical and routine workers decreased in every country observed. On the other hand, the middle classes (intermediate occupations and the self-employed) stagnated in most countries, the only exception being that of a steady decrease in the share of self-employed individuals in the Southern European countries. A sociologically informed definition of socio-economic class therefore casts some doubt on the idea of a hollowing-out of the middle-classes and instead highlights a pattern of upgrading with declining shares of working classes and growing shares of upper classes.

[Figure 2]

The patterns presented in Figures 1 and 2 are also mirrored by the composition of the labour force in terms of performed tasks. Figure 3 displays national trends in the five task indices. A clear shift in task composition from manual tasks to cognitive abstract- and interpersonal tasks emerges, which suggests that changes in employment- and class structure were driven by a shift from manual occupations to cognitive, knowledge-intensive occupations.

[Figure 3]

Figure 4 reports the average marginal effects of regional robotics exposure on the regional unemployment rate and the share of workers employed in each of the five ISEI quintiles for the three country clusters. Each bar represents the change in the regional share of unemployed (red bar) or employed (blue bars) individuals in each quintile in response to an increase of one robot per thousand workers.

Robotics does not appear to be significantly associated with the overall trends of regional unemployment in any country cluster, which is a relevant outcome as it reveals that technological innovation in manufacturing sectors is not represented solely by labour-replacing technology and thus does not necessarily lead to a jobless future. Moreover, no significant evidence of a “middle class squeeze” in terms of employment reduction can be found in any cluster. On the contrary, robotics appears to have a rather heterogeneous impact on the employment structures of different institutional clusters. While a clear pattern of upgrading emerges in the Nordic and Continental countries, with the upper two ISEI quintiles being the most favoured by a trend of employment growth, the opposite is true for the Southern European countries, where robotics is associated with growth in the share of workers employed in low-level occupations and with a small – albeit statistically significant – decrease in the number of top positions.

As previously mentioned, the skill distribution in the Southern European countries is characterised by high levels of low-skilled workers. Our analysis reveals that the capacity of the Southern European countries to create high-level and highly skilled occupations is basically non-existent and that technological diffusion is extremely limited in these countries.

[Figure 4]

The same pattern can also be found in Figure 5, which shows the AME of robotics on the share of workers employed in each of the five ESeC classes. Taking the ESeC as an indicator of class structure allows us to further distinguish between the technologically induced processes of upgrading in the Nordic and Continental countries. In both groups of countries, robotics significantly reduces the share of workers who belong to lower technical and routine occupations. However, while employment growth in the Nordic countries occurs among the salariat, employment growth in the Continental countries occurs among the self-employed craftsmanship.

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13 The main explanation for the trend observed in Southern Europe is a decrease in traditional forms of self-employed craftsmanship.
occurs mainly among those in lower services. Indeed, this difference reflects the diverse nature of the two skill regimes. While the orientation of the Continental countries towards providing industry-specific skills favours creating cognitive and interpersonal professional occupations (e.g. shop workers and retail assistants), the high levels of general skills in the Nordic countries instead allow for knowledge-intensive and creative occupations to proliferate in the salariat class. Finally, the process of downgrading in Southern Europe can be confirmed by examining the composition of the ESfC, which reveals that robotics is associated with a decrease in the share of workers in the upper classes and with distributed increases of workers in the lower classes.

[Figure 5]

Finally, Figure 6 illustrates the AME of robotics on regional task composition. Again, what emerges is a striking difference between the Southern European countries and the rest of Europe. In Nordic and Continental Europe, in line with expectations, industrial robots reduce regional employment in manual task-intensive occupations and shift employment to more cognitive and abstract occupations. The same process is not present in the Southern European countries, where no significant pattern emerges and – if anything – the introduction of robotics appears to reinforce employment in routine manual occupations.

[Figure 6]

In conclusion, industrial automation appears to have significantly different consequences for employment- and class structures as well as for the types of jobs available in different European institutional contexts. In the Continental and Nordic countries, robotics seems to produce a crowding-out effect that leads away from mid- and low-level manual occupations and towards better cognitive occupations. These same processes appear to be inhibited in the Southern European countries, where robotics is associated with a downgrading of employment structure and an increase in manual task-intensive jobs.

Figure 7 illustrates the AME of regional robotics exposure for each of the three groups of countries on the ISEI levels of individuals as defined by their level of education and gender. The heterogeneous macro-patterns evident in the regional level results also emerge with regard to different social groups as defined in terms of gender and educational level.

The first section of Figure 7 shows the AME of robotics on the ISEI levels of males and females at different levels of education in the Nordic countries. Results reveal a positive effect of robotics for all individuals, regardless of their level of education or gender. Benefits from the strong upgrading process documented in Figures 4–6 are therefore equally distributed among all analysed groups.

The second section of the figure refers to the Continental countries, where robotics is associated with an improvement in occupational position only for mid- and highly educated workers, regardless of their gender. Inequality in occupational opportunities therefore emerges along educational lines. While automation generates incentives for creating new, high-level occupations, low-educated workers are unable to transition to these higher positions. Nevertheless, these workers do not suffer losses in terms of employment; on the contrary, Figure 8 reveals that robotics is associated with a reduction in their unemployment rates.

The last section of Figure 7 illustrates the AME of robotics on ISEI levels for different genders and levels of education in the Southern European countries. The burden of the downgrading process documented in Figure 4 can be seen to be borne mainly by women with medium and high levels of education. On the other hand, low- and mid-educated men – the group most represented in manual occupation – undergo no change in their occupational level. However, these are the only two groups that experience technological unemployment.

Figure 8 displays the average marginal effect of robotics on the unemployment risk of each group by country cluster. As evident in the last section of the graph, robotics is positively associated with the
unemployment rate of Southern European low- and mid-educated men. This finding is not surprising since these men are almost exclusively employed in occupations that are highly vulnerable to industrial automation. At the same time, these men have few retraining opportunities, and as robots continue to take over their traditional employment domain, the men are rendered unfit for the new, fast-growing technological occupations and face harsh competition in accessing the few occupations available to them.

The question therefore arises as to why robotics leads to more and better occupations for everyone in the Nordic and Continental countries while reducing job opportunities for some groups and worsening the occupational positions of others in the Southern European countries. As previously argued, the skill levels of the labour force play a crucial role in this process. The Nordic and Continental countries are characterised by a highly skilled labour force, whereas a large share of the active population in the Southern European countries in the years under analysis had not reached secondary education.

Moreover, regions in these three regimes are strongly differentiated in terms of effort and attitudes towards being promoted and participation in training. Training programs can be viewed as effective instruments in helping workers – especially low-skilled ones – transition to new types of occupations after their traditional jobs have been replaced by new technology, and participation in training can be viewed as an effective means of preserving technology-related social inequalities and thereby of avoiding technological downgrading and unemployment. Figure 9 reports the average marginal effect of robotics exposure on the ISEI level of each group of individuals at different levels of participation in training. The x-axis displays the percentage of the active population in each group – defined by region, education, and gender – that participated in some sort of training activity in the period from 1997 to 2017. The positive effect of robotics on individual ISEI levels can be seen to be substantially greater for groups of individuals who actively participated in training programs during the analysed period. This relation is particularly evident for mid-educated workers.

The opposite effect can be seen concerning unemployment. Figure 10 displays the AME of robotics on the unemployment risk for each group at different levels of participation in training. The negative effect of robotics is once again much stronger for groups of individuals who had extensively participated in training. This effect is particularly strong for low-educated individuals. The clear message that emerges from these results is that skill levels in the labour force are crucial in mediating the impact of technological change. Even if low-educated men appear to be strongly exposed to the risk of automation, their employment- and occupational prospects appear significantly better after high-quality training provisions.

7. Discussion and conclusions

A vast strand of socio-economic research suggests that technological change in recent decades has transformed the employment- and class structures of Western political economies, inducing either growing occupational polarisation or upgrading. The main mechanism connecting the two phenomena is articulated by the theory of skill-/routine-biased technical change (S/RBTC). This theory suggests that technologies introduced act as substitutes mainly for routine tasks, which are concentrated at the mid- and low levels of occupational structure, and thereby provides fodder to the fear of a disappearing middle class in advanced economies.

As claimed throughout this article, the theory of S/RBTC is highly deterministic insofar as it stresses the technical capabilities of technologies yet disregards important contextual and institutional dynamics that can ultimately shape the way in which actors respond to the introduction of new technologies. The present article underscores the relevance of contextual factors in shaping the ultimate impact of automation on employment- and class structures as well on the distribution of gains and losses stemming from the automation process.

Our results highlight the potentially disruptive and transformative power of technological change in terms of its ability to modify national occupational structures and inequalities in class-, gender-, and
educational occupational opportunities. At the same time, our results stress the relevance of national educational and training systems in mediating the impact of automation.

In terms of the overall impact of robotics on employment structure, our results demonstrate that the introduction of robotics has different effects across different contexts. In the Nordic and Central European countries, robotics appears to induce a process of occupational upgrading by shifting employment from low-level manual occupations to higher-level cognitive occupations. The opposite effect is true for the Southern European countries, where automation appears to provoke a downgrading of occupational structure, with no discernible impact on the distribution of tasks.

Three different “worlds of technological innovation” emerge upon examination of the impact of robotics on class structures, with a clear process of upgrading occurring in Northern European countries, where salariat classes are currently increasing while the middle- and lower classes are decreasing. The opposite is true for the Southern European context, where robotics is associated with a decrease in the share of individuals employed in the upper classes. Finally, in the Continental countries, automation currently seems to be inducing a moderate process of upgrading by simply shifting employment from routine manual- and lower technical occupations to lower services.

However, the process of a “middle-class squeeze” cannot be identified anywhere. The vast amount of (mainly US) literature on the “shrinking middle” and the resulting U-shaped society thus appears incapable of accounting for the European scenario in terms of either occupational or social-stratification structures. In Europe, institutions are the relevant mediator between technology on the one hand and both productive and social outcomes on the other hand. The three patterns identified in our analyses largely reflect the nature of the trade-off between the kind of labour market (de)regulatory practices implemented at the country level and the characteristics of national educational and training systems.

Indeed, the high levels of both specific and general skills – especially at the middle and bottom levels of skill distribution – in the Nordic countries allow firms to reap the benefits of better technological capabilities and to pursue high-road, knowledge-intensive production strategies. At the same time, workers in these countries are equipped with high levels of transferable and technical skills that allow them to transition to new, higher-level jobs and class positions. Pseudo-panel results reveal that in the Nordic countries, benefits from the technology-driven process of occupational upgrading are equally distributed among individuals, regardless of their gender or educational level. In these countries, workers can transition to better positions after manual-intensive, low-level occupations have been replaced by robots. Moreover, the Nordic countries generally have lower EPL levels. As EPL has a significant impact on productivity growth via its sizeable effect on labour market flows (Martin, Scarpetta 2011), it follows that lower-EPL&higher-skills equilibria can better exploit the advantages of technological change.

On the other hand, in the Continental countries, improvements in occupational levels are restricted to highly and mid-educated workers, regardless of gender. The “universalistic” upgrading process, which is evident in the Nordic countries, appears somehow inhibited in the Continental countries, which corroborates their more “conservative/meritocratic” (Esping-Andersen, 1990) pattern of social stratification. The skill supply in the Continental countries is mainly characterised by high levels of industry- and firm-specific skills in addition to high levels of tertiary-educated workers. Thus, the vocational training- and apprenticeship system restricts the possibility of developing new, knowledge-intensive occupations in emerging sectors and tends to reproduce the existing pattern of professional composition as well as the associated social stratification.

Finally, far from revealing scenarios of mass technological unemployment, our findings indicate that low- and mid-educated (male) workers in the Southern European countries are the only category of workers to experience technological unemployment in nowadays Europe. In Southern Europe, robotics appears to be quickly replacing workers who had traditionally been employed in the most automatable occupations without generating new employment opportunities. The low average educational level of the labour force in these Southern European countries – coupled with low levels of vocational education and training – is entirely impeding the creation of new, highly skilled jobs, thereby resulting in a relatively small increase of employment predominantly at the bottom level of the occupational
distribution – and in few retraining opportunities for low-educated male workers who have been pushed out of their traditional employment domains. At the same time, robotics in these countries is significantly shifting female employment to lower-level occupations.

Our results also highlight the importance of training opportunities and reveal that training is a crucial factor in mediating the impact of automation and its consequences of social stratification. Indeed, the capacity of national and local systems to provide workers with the right set of skills is one of the main factors that determine whether modern political economies are capable of reaping the unquestionable benefits of the global trend of technological change.
References


Bureau of Economic Research.


FIGURES

Figure 1: National trends in the share of workers aged 25 to 60 employed in five groups of occupations, ranked on their ISEI score (1997–2017)

Notes: Own calculations from weighted EU-LFS data from 1997 to 2017. Variables were rescaled to have mean 0 in 1997.
Figure 2: National trends in the share of workers aged 25 to 60 employed in five ESeC classes (1997–2017)

Notes: Own calculations from weighted EU-LFS data from 1997 to 2017. Variables were rescaled to have mean 0 in 1997.
Figure 3: National trends in average task content for workers aged 25 to 60 (1997–2017)

Notes: Own calculations from weighted EU-LFS data from 1997 to 2017 and O*Net 3.0. Variables were rescaled to have mean 0 in 1997.
Figure 4: Average marginal effect of robotics on regional unemployment and the regional share of workers employed in five ISEI quintiles, disaggregated by groups of countries

Notes: Fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate, and the share of the highly educated active population. Full results in Table 2.A of the web appendix.
Figure 5: Average marginal effect of robotics on the share of workers in five ESeC classes, disaggregated by groups of countries

Notes: Fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate, and the share of the highly educated active population. Full results in Table 3.A of the web appendix.
Figure 6: Average marginal effect of robotics on the regional level of tasks indexes, disaggregated by groups of countries

Notes: Fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate, and the share of the highly educated active population. Full results in Table 4.A of the web appendix.
Figure 7: Average marginal effect of robotics on the ISEI score by level of education, gender, and country cluster

Notes: Pseudo-individual fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate, and the regional share of the highly educated active population. Full results in Table 5.A of the web appendix.
Figure 8: Average marginal effect of robotics on unemployment by level of education, gender, and country cluster

Notes: Pseudo-individual fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate, and the regional share of the highly educated active population. Full results in Table 5.A of the web appendix.
Figure 9: Average marginal effect of robotics on the ISEI levels of pseudo-individuals defined by levels of education and gender at different levels of participation in training.

Notes: Pseudo-individual fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate, and the regional share of the highly educated active population. Full results in Table 6.A of the web appendix.
Figure 10: Average marginal effect of robotics on unemployment levels of pseudo-individuals defined by levels of education and gender at different levels of participation in training

Notes: Pseudo-individual fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate, and the regional share of the highly educated active population. Full results in Table 6.A of the web appendix.