We Were The Robots: Automation and Voting Behavior in Western Europe *

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Abstract

The increasing success of nationalist and radical-right parties is one of the most remarkable developments in the politics of advanced democracies. We investigate the impact of industrial robot adoption on electoral outcomes in 14 Western European countries, between 1993 and 2016, employing official election results at the district level and individual-level voting data, combined with party ideology scores from the Manifesto Project, and measures of exposure to automation at the regional and individual level. Higher exposure to robot adoption increases support for nationalist and radical-right parties. Unveiling some potential transmission channels, higher

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robot exposure at the individual level leads to poorer perceived economic conditions and well-being, lower satisfaction with the government and democracy, and a reduction in perceived political self-efficacy. Structural changes in the economy, and in particular the decline of manufacturing employment, play a significant part in the success of nationalist and radical-right parties in Western Europe.

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Introduction

Nationalist and radical-right parties and candidates have become increasingly successful in Western democracies over the past three decades. While part of the literature focuses on the cultural drivers of such political developments, a growing body of research relates them to structural changes in the economy (Franzese 2019). In this paper, we contribute to this literature by studying the role automation plays in the success of the radical right. We focus on the effects of industrial robot adoption in fourteen Western European countries, between the early 1990s and 2016. This wave of automation led to productivity and welfare gains, but it has also produced substantial distributional effects, imposing stronger adjustment costs in regions that were historically specialized in industries adopting more robots, and penalizing individuals whose skills were substituted rather than complemented by the new technologies.

We rely on two empirical strategies to estimate the causal impact of automation on voting behavior. The first strategy exploits district-level election returns and regional variation in exposure to robot adoption based on the ex-ante industry specialization, following the measurement approach developed by Acemoglu and Restrepo (2018). In the second strategy, we introduce a novel measure of individual exposure to automation, based on individual characteristics such as age, gender, and education, and on the historical employment patterns in the region of residence, dating before the latest automation wave. This measure assigns stronger exposure to automation to more vulnerable individuals, whose characteristics would have made them more likely, in the past, to work in occupations that are more subject to automation. Our empirical approach builds upon the idea that automation not only affected workers initially employed in specific occupations, but might have also reduced job opportunities for prospective workers with certain characteristics. For instance, we can capture the fact that, due to automation, some workers who would have been likely to obtain a well-paid job in the automotive industry in the past –according to their individual characteristics and the historical employment pattern of their region– find themselves unemployed today, or employed in low-wage service occupations. This analysis leverages individual-level data from the European Social Survey (ESS) and the EU Labor Force Survey.

We find that automation shocks have political effects on aggregate election returns at the district-level, leading to a tilt in favor of nationalist parties promoting an anti-cosmopolitan agenda, and in favor of radical-right parties. Consistently, the individual-level findings show that individuals that are more exposed to automation are substantially more likely to vote for radical-right parties, and tend to support parties with more nationalist platforms. Unveiling some potential transmission channels, higher robot exposure at the individual level leads to poorer perceived economic conditions and well-being, lower satisfaction with the government and democracy, and a reduction in perceived political self-efficacy.

Technology and the labor market

Shifts in technology determine distributional consequences by affecting labor market dynamics. New opportunities arise for workers endowed with skills that are complementary to new technologies, while more substitutable workers lose out. In simple words, technological innovation produces winners and losers, at least in relative terms. The identity of such winners and losers varies depending on the nature of technological changes (Goldin and Katz 1998).

Computers and computer-based machines can perform routine, codifiable tasks, but are much less capable of performing non-routine tasks requiring abstract thinking, creativity, social interaction, and the manual ability to work in irregular environments. Hence, the diffusion of computer-based technologies has penalized workers performing routine tasks, while jobs involving mostly non-routine tasks have been complemented. Since routine jobs –both manual and cognitive– were mostly middle-income and middle-skill jobs, a polarization of the labor market has been documented both in the US and in Europe during the 1980s and 1990s (Autor and Dorn 2013; Goos et al. 2014). Polarization involves an increase in employment at the two tails of the wage and skill distribution, along with a shrinkage of the traditional middle class. Workers (both actual and prospective) substituted by computer-based technology have been largely absorbed by the service sector in non-routine jobs, typically at lower wages and with less favorable contractual conditions (e.g., drivers and fast-food workers). The main computerization winners have been the high-skill (college-educated) workers in cognitive occupations: their incomes have been diverging from those of the impoverished middle class, which has been falling in the group of losers together with low-skill workers. The latter, even if employed in non-routine tasks, have been complemented by the new technologies much less than the high-skilled, and their wage dynamics have been compressed by the additional supply of displaced middle-skill workers competing for the same jobs (Autor 2015).

In the past twenty years, mobile robotics has made possible the automation of an expanding array of non-routine manual tasks involving not only assembly line operations in factories, but also demolition and construction, maintenance of industrial plants, logistic services, transportation, and mining activities. A growing literature investigates the economic effects of this latest automation wave, from the mid-1990s onwards. These studies exploit data on the adoption of industrial robots at the industry level, made available for many countries by the International Federation of Robotics. According to these data, the stock of operational robots in advanced economies has increased exponentially between 1993 and 2016, a phenomenon commonly referred to as the “robot shock”.

Focusing on the US, Acemoglu and Restrepo (2018) find that, at the level of commuting zones, a stronger exposure to the robot shock has a negative effect on local employment rates and wages. To illustrate, the adoption of one extra robot in a commuting-zone reduces employment by around 6 workers. The negative effect of robots on employment is stronger in the manufacturing sector, and especially in industries that are most exposed to robots. Moreover, it is more pronounced for workers with less than college education, for blue collars employed in routine manual tasks and assembling, for machinists and transport workers, and for men in general. The negative effect of robots on wages is concentrated in the bottom half of the wage distribution, contributing to the increase in wage inequality. Chiacchio et al. (2018) focus on six European countries and find a negative effect of robot adoption on employment at the level of local labor markets. Dauth et al. (2018), based on German data, find that the adoption of robots leads to job losses in manufacturing, which are compensated by employment gains elsewhere, mostly in the business service sector. Importantly, fewer manufacturing jobs become available for new entrants in the labor market. Overall, automation increases wage inequality: it benefits managers and high-skill workers performing abstract tasks, while low- and medium-skill workers see their earnings decrease, leading to a general decline in the labor share of income.

Automation and politics

In order to understand the theoretical link between automation and voting, we move from reckoning that automation represents a source of structural change in the economy that generates aggregate gains but with winners and losers. As we have just documented, losers tend to be concentrated in vulnerable manufacturing regions and in specific social segments, encompassing low-skill workers that are most substitutable by robots, but also sizable segments of the traditional middle class.

There are multiple reasons why individuals negatively affected by automation might turn to nationalist, anti-cosmopolitan, and radical-right parties. First of all, these political forces are perceived as a clear alternative to traditional mainstream parties. Economic insecurity is associated with less trust in political institutions (Algan et al. 2017; Guiso et al. 2017). To the extent that economic distress leads not only to anti-incumbent sentiments as per standard economic vote results, but also to discontent with the system at large, these parties –with their critical stance towards representative liberal democracy– provide an attractive option for dissatisfied voters.

Moving beyond the simple anti-incumbent motivation, it is important to recognize the appeal of the political platforms offered by nationalist and radical-right forces for automation losers. Earlier work has identified "economic nationalism" as a fundamental trait of these parties (Bornschier 2005; Colantone and Stanig 2018a; Kriesi et al. 2006). Besides a strong nationalist rhetoric, economic nationalist platforms place a strong emphasis on the protection of workers. Thus far, the growing appeal of these platforms has been mostly linked to globalization-induced economic distress (Bornschier 2005; Kriesi et al. 2006; Swank and Betz 2003; Zaslove 2008); in particular, import competition in advanced countries has been shown to tilt voters towards radical-right parties and candidates (Autor et al. 2016; Colantone and Stanig 2018a, 2018b; Dippel et al. 2015; Guiso et al. 2017; Jensen et al. 2017; Malgouyres 2014; Margalit 2011). The underlying idea is that globalization –similarly to automation– generates aggregate welfare gains but with winners and losers, who might then turn to the radical right. Although globalization and automation tend to affect different sectors and regions, their economic consequences are difficult to tease out from each other for voters. For instance, there is evidence that protectionism is the preferred response of individuals to labor-market shocks, "even when job losses are due to non-trade factors such as technology and demand shocks" (Di Tella and Rodrik 2019, 3).

Nationalist and radical-right platforms are particularly appealing in the wake of structural transformations of the economy as they offer a very generic promise of protection. This crucially involves the broad idea of “taking back control” of the country from global impersonal forces –such as those behind international trade and technological change– and the defense of a traditional way of life that supposedly characterized the nation before globalization, computers, and robots had a disruptive impact on society. Nostalgia for a mythical (recent) past has indeed been shown to play a significant role in radical-right support (Bornschier and Kriesi 2013; Gest et al. 2018; Steenvoorden and Harteveld 2018). The rhetoric typically involves an emphasis on traditional family structure, with a strong role for the male head of household empowered by a well-paid and stable job (Akkerman 2015; Spierings and Zaslove 2015).

An important question that naturally arises is why automation losers would not turn to left parties running on platforms of redistribution and compensation of losers. Two recent studies show that workers employed in occupations more at risk of automation report preferences for a bigger role for government in reducing inequality (Thewissen and Rueda 2019; van Hoorn 2018). These findings resonate with an established literature showing how exposure to economic distress, including higher perceived risk of unemployment, increases support for redistribution (e.g., Cusack et al. 2006; Margalit 2013; Rehm 2009; see also Margalit 2019). Van Hoorn (2018) also shows that respondents more exposed to automation support government intervention in favor of declining industries. These automation-induced preferences for more redistribution and government intervention should orient voters towards left parties. Yet, we find that exposure to automation does not lead to any electoral gain for left parties; if anything, we detect negative effects for mainstream left parties.

Several factors might contribute to this response by voters. Promises of redistribution and compensation of losers have become less appealing and credible over time, due to the fiscal constraints faced by governments, especially since the financial crisis. The significant convergence between mainstream left and mainstream right in terms of redistribution and welfare state policies weakened the link between social democratic parties and working class constituencies, opening the space for new parties on the fringes of the political spectrum (Hall and Evans 2019). Blue-collar constituencies have become increasingly important in the electorate of the radical right (Betz 1993, 1994; Betz and Meret 2012; Oskarson and Demker 2015; Spies and Frantzmann 2011). At the same time, moderating the economic platforms helped the mainstream left capture more economically centrist voters, especially the so-called socio-cultural (semi-)professionals, attracted to left parties mostly because of their stances in terms of cosmopolitan values (Keman 2011; Kitschelt 2012; Kriesi 1998).

In addition, globalization and technological change weakened the role of labor unions. Automation in manufacturing disrupts the established patterns of shop-floor organization, making it harder for unions to retain their central role. By reducing employment in manufacturing and tilting it towards the service sector, automation also reduces the number of workers that are unionized or easily reached by unions. Labor unions have historically provided an important link between left parties and blue-collar constituencies; therefore, as suggested by Kitschelt (2012), their reduced importance might be a reason why losers from structural changes have turned towards nationalist and radical-right forces rather than left parties.

Radical-right parties tend to propose platforms that are not particularly redistributive, as initially understood by Kitschelt and McGann (1997), and more recently documented by Colantone and Stanig (2018a) and Cantoni et al. (2019). According to what was dubbed the “winning formula”, radical-right parties were able to assemble a coalition of the petty bourgeoisie and blue-collar workers, where the middle class was more attracted by economic conservatism and the promise of low taxes, while the working class was more attracted by authoritarianism and nativism. Some automation losers might then be pushed towards the radical right *in spite of* its economic conservatism, for reasons that have more to do with a shift in attitudes.

This consideration leads to a set of deeper factors, related to low-level psychological reactions, that contribute to explain why the radical right has been more successful at channeling the demands that emerge from the automation shock. Several papers show how economic distress, induced for instance by import shocks, can tilt individual orientations in a nativist and authoritarian direction (Ballard-Rosa et al. 2018, 2019; Gennaioli and Tabellini 2018). Recent work in psychology shows more directly that there is a robust association, in the U.S. and in Europe, between concerns for automation and opposition to immigration. In addition, experimental subjects propose to lay off more immigrant workers when layoffs are motivated by the adoption of labor-saving automation than when layoffs are due to a generic "company restructuring" (Gamez-Djokic and Waytz 2019). This type of reaction would naturally push voters towards nationalist and radical-right parties, while creating a disadvantage for left parties, that have a reputation of egalitarianism and working class internationalism (Betz and Meret 2012, Kriesi et al. 2012). In fact, nativism is a prominent facet of the agenda of radical-right parties, and has often been proposed as a main explanation for their success (Arzheimer 2009; Golder 2003).

This evidence points to an interaction between economic and cultural factors in explaining the form the political backlash has taken. Gidron and Hall (2017) provide the most complete line of argumentation in this direction, claiming that the effects of economic and cultural changes are channeled by social status. The reduction of well-paid jobs in manufacturing means that an increasing number of low- and medium-skill workers end up in jobs that offer poorer pay and less security. Due to the spatial concentration of economic opportunities in the knowledge economy around urban centers, the structural changes also give rise to a sense of entire regions being "left behind", with a failure of representation compounding the failure of compensation, as Frieden (2018) notes. The same structural changes are accompanied by a cultural shift: less social value is assigned to "hard work", a source of status for low- and middle-skill workers, and more value is assigned to knowledge and entrepreneurship. In line with this view, Gidron and Hall (2017) find that, between the late 1980s and 2014, less educated males saw their perceived relative status decline compared to previous generations. In turn, self-reported social status is found to be significantly associated with support for the radical right.

These processes lead to an opposition to the cosmopolitan agenda that encompasses technological progress and globalization, but also lifestyle choices, individual freedoms, and immigration. For EU countries, European integration itself is an important and easily identifiable component of the cosmopolitan agenda, which is cast by nationalist and radical-right parties in opposition to a supposedly homogenous national culture (Betz and Meret 2009; De Vries 2018; Hooghe and Marks 2018; Margalit 2012). Indeed, Euroskepticism is a defining trait of the radical right in the EU.

There is limited evidence, thus far, on the consequences of the most recent spurts of technological change on political behavior. We are aware of four contributions that, like ours, directly link recent technological developments to voting behavior. Gallego et al. (2018) show that one facet of the IT revolution, namely computerization, has detectable political implications in the UK. Their focus is mainly on the winners of these changes: educated workers in IT-heavy sectors, who become more likely to vote Conservative and less likely to vote Labour. Studying the 2016 US presidential election, Frey et al. (2018) show how voters in regions more affected by robotization in manufacturing were more supportive of the Republican candidate, Donald Trump, who was running on a nationalist platform akin to those of the European radical right, both in economic and in identitarian terms. Im et al. (2019), using data on eleven countries from the ESS, show that workers in occupations at higher risk of automation are more prone to vote for radical-right parties. Finally, Dal Bó et al. (2018) show that the share of automation-vulnerable workers in a municipality robustly correlates with support for the Sweden Democrats in local elections.

Measurement of exposure to automation

In what follows, we introduce our measures of exposure to robot adoption, first at the regional level, then at the individual level.

Regional exposure

Following Acemoglu and Restrepo (2018), we measure the time-varying exposure to automation at the regional level as:

$$\text{Regional Exposure}_{crt} = \sum_{j} \frac{L_{crj}^{\text{pre-sample}}}{L_{cr}^{\text{pre-sample}}} * \frac{R_{cj}^{t-1} - R_{cj}^{t-n}}{L_{cj}^{\text{pre-sample}}}, \tag{1}$$

where c indexes countries, r NUTS-2 regions, j manufacturing industries, and t years.

$R_{cj}^{t-1} - R_{cj}^{t-n}$ is the change in the operational stock of industrial robots between year $t-1$ and $t-n$, in country c and industry j. This change is normalized by the pre-sample number of workers employed in the same country and industry, $L_{cj}^{\text{pre-sample}}$. This ratio provides a measure of the intensity of robot adoption at the industry level. To retrieve the regional-level exposure, we take a weighted summation of the industry-level changes, where the weights capture the relative importance of each industry in each region. Specifically, each weight is the ratio between the number of workers employed in a given region and industry ($L_{crj}^{\text{pre-sample}}$), and the total number of workers employed in the same region ($L_{cr}^{\text{pre-sample}}$). Importantly, 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.

This measure is based on a theoretical model developed by Acemoglu and Restrepo (2018), where robots can displace workers in supplying tasks to the local labor market, but also produce positive spillovers on local employment and wages through increased productivity. The overall local labor market effects of automation are thus determined by whether the displacement effect prevails on the positive spillover one.

We compute the regional exposure to automation by combining data from different sources. We retrieve employment data for 192 NUTS-2 administrative regions from national sources and Eurostat. Table A1 in the Online Appendix reports year and source for each of the fourteen sample countries.[1] Yearly data on the stock of operational robots by country and industry are sourced from the International Federation of Robotics. We focus on eleven industries encompassing the whole manufacturing sector. These correspond mostly to NACE Rev. 1.1 subsections (details in Table A2 of the Online Appendix).[2] The average yearly change in the stock of operational robots in our sample is an increase

[1]For Germany, data are only available at the more aggregated NUTS-1 level; hence, 16 out of 192 sample regions are NUTS-1.

[2]For the Netherlands, Belgium, Austria, Portugal, Switzerland, and Greece, robot data in some initial years are not disaggregated by industry. We have allocated the total number of robots to industries based on the average country-industry share of total robots in years with full information.

of 7.6 robots for every 100,000 workers in the region, with a standard deviation of 10. In some regions and years, the yearly increase in the number of robots has been as much as 94 for every 100,000 workers.

We regress electoral outcomes on exposure to robots. One could be concerned with endogeneity issues, which could arise from different sources. First, robot adoption tends to be pro-cyclical: firms install more robots during periods of stronger economic growth. If economic cycles are associated with different patterns of support for given sets of parties, the OLS estimates of the impact of robots on voting would be biased. In particular, if voters in good times tend to support more mainstream parties rather than nationalist and radical-right parties, we would expect a downward bias in the OLS estimates. Second, more robots might be installed in regions with stronger employment protection legislation, which makes labor relatively more costly. Given that employment legislation is usually determined at the national level, we reduce this concern by including country-year fixed effects in our regressions. Relatedly, the pace of robot adoption in a region may also be influenced by the local strength of labor unions. To the extent that unionization is systematically associated with stronger or weaker performance of different sets of parties, we would have a confounding factor biasing OLS estimates.

To address the endogeneity concerns, similarly to Acemoglu and Restrepo (2018), we employ the following instrument:

$$\text{IV Regional Exposure}_{crt} = \sum_j \frac{L_{crj}^{\text{pre-sample}}}{L_{cr}^{\text{pre-sample}}} * \frac{\bar{R}_{-c,j}^{t-1} - \bar{R}_{-c,j}^{t-n}}{\bar{L}_{-cj}^{\text{pre-sample}}} \tag{2}$$

where c indexes countries, r NUTS-2 regions, j manufacturing industries, and t years. $\frac{\bar{R}_{-c,j}^{t-1} - \bar{R}_{-c,j}^{t-n}}{\bar{L}_{-cj}^{\text{pre-sample}}}$ is the change in the average stock of operational robots per worker in industry j across all other sample countries (i.e., excluding c), between year $t-1$ and $t-n$. This term replaces $\frac{R_{cj}^{t-1} - R_{cj}^{t-n}}{L_{cj}^{\text{pre-sample}}}$ in Equation (1): we instrument robot adoption in each country and industry by using robot adoption in the same industry but in different countries. Intuitively, our instrument is meant to exploit industry-specific trajectories in automation that are driven by technological innovations shared across countries. Its validity hinges on the fact that the adoption of robots in other countries, at the industry level, is plausibly exogenous to the political dynamics of each domestic region.

Individual exposure to automation

Assessing the individual exposure to automation poses an important challenge: the endogeneity of current occupation to automation dynamics. To illustrate, consider an individual displaced from a well-paid and stable job in manufacturing, due to robot adoption, in year $t-1$. In year t, the same individual finds a new job in services, e.g., as a janitor in a fast-food restaurant, at a lower wage and with a temporary contract. If we were to use occupation at time t to assess automation exposure, we would attribute to this individual a low score of occupational automatability. Yet, this hypothetical individual is the canonical case of an automation loser, and a measure based on current occupation would not capture it. Even worse, using current occupation would not allow us to assign an automation shock to workers who are displaced and remain unemployed: hence we would leave out of the analysis an important group of negatively affected individuals. Moreover, automation not only affects workers initially employed in specific occupations, but also reduces job opportunities for prospective workers, who might find themselves employed in second-best occupations with low automation intensity.

In order to capture the individual exposure to automation in a way that is not contaminated by the consequences of automation itself, we introduce the following measure:

$$\text{Individual Exposure}_{icrt} = \Delta R_{ct} * \underbrace{\sum_j \widehat{Pr}(o_i = j|\text{age}, \text{gender}, \text{edu}, r) * \theta_j}_{\text{Individual Vulnerability}} \tag{3}$$

where ΔR_{ct} is the national percentage change in total operational robots between year $t-1$ and $t-n$, in the country c where individual i resides, i.e., $\frac{R^{t-1}_{c(i)} - R^{t-n}_{c(i)}}{R^{t-n}_{c(i)}}$.

$\widehat{Pr}(o_i = j|\text{age}, \text{gender}, \text{edu}, r)$ is individual i's probability of working in occupation j, predicted based on age, gender, educational attainment, and region of residence. The score θ_j is an estimate of the automation threat for occupation j. Summing the product of $\widehat{Pr}(o_i = j|\text{age}, \text{gender}, \text{edu}, r)$ times θ_j over all occupations, we obtain a measure of individual vulnerability to automation for each individual i. The individual exposure to robot adoption in year t is then obtained multiplying this individual vulnerability by the national pace of robot adoption ΔR_{ct}.

An important element allows us to avoid the issue of contamination discussed above: the predicted probabilities of employment are based on the occupational patterns prevailing in each region at the beginning of the 1990s, thus before the latest spurt of automation and robot adoption. Intuitively, for a given national pace of robot adoption, our measure of individual exposure therefore assigns higher scores to individuals whose age, gender, educational profile, and region of residence would have made them more likely –in the pre-shock labor market– to work in occupations whose automatability is higher.

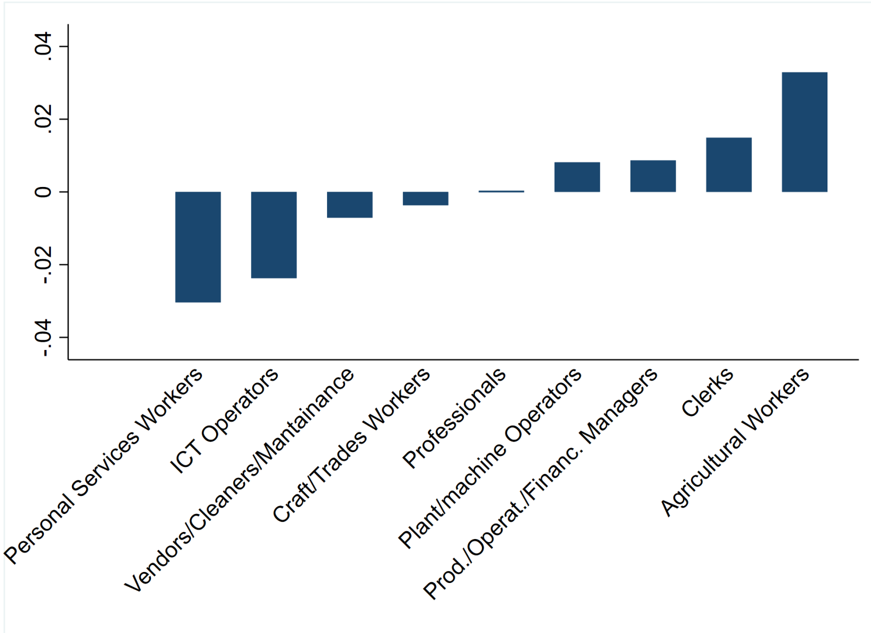
In practice, we exploit historical data from the early 1990s, sourced from the European Labor Force Survey (EU-LFS), to estimate multinomial logit models of occupational choice. These models have the set of occupations as outcome variable, while the predictors are age, gender, educational attainment, and regional effects. Occupations are defined at the 2-digit level of the International Standard Classification of Occupations (ISCO). We estimate the occupational choice models separately for each country.[3] We then use the parameter estimates to predict $\widehat{Pr}(o_i = j|\text{age}, \text{gender}, \text{edu}, r)$ out of sample, for each individual in the first seven waves of the European Social Survey, spanning the period 1999-2015. Figure 1 shows the difference between the predicted share of employees in each aggregated 1-digit occupational group, based on historical data, and the actual share observed in the subsequent ESS data. Intuitively, we under-predict the proportion of, e.g., personal service workers, ICT operators, and cleaners, while we over-predict the share of agricultural employees, clerks, machine operators and assemblers. These patterns are in line with the transformation of the European labor market discussed earlier, and suggest that we are indeed assessing the individual vulnerability to automation based on occupational trends that are not contaminated by the same phenomenon.

The θ_j component of individual exposure to automation is an occupation-specific score of automation threat. We adopt two main strategies to assess this threat. In the first strategy, θ_j is the probability of computerization for each 2-digit occupation, as estimated by Frey and Osborne (2017) based on a combination of expert data and detailed task content. These estimates capture the automatability of both routine and non-routine tasks, taking into account the recent developments in mobile robotics and machine learning.

The second strategy relies on an item in the 1997 wave of the ISSP "Work Orientations" module (International Social Survey Program Research Group 1999), asking re-

[3]We employ EU-LFS data from the first available year including information on occupational codes. This is 1992 for most countries. The pseudo R^2 of the country-specific multinomial logit models ranges between 11 and 22%, with an average of 16%.

Figure 1: Predicted vs. actual occupation shares



spondents about the perceived effect of new technologies on the number of jobs. Using all available data from advanced industrial democracies, we estimate the occupation-specific perceived automation threat via a model with random intercepts for occupations, of the form: $y_i = \alpha + \beta_{k(i)} + \epsilon_i$ with $\beta \sim N(0, \sigma_\beta)$, where y_i is the perceived automation threat for respondent i and β_k is the random intercept for occupation k. Our approach is analogous to the one used by van Hoorn (2018), who calculates the average threat by occupation.[4]

Our measure of individual exposure to automation has multiple advantages. First, it can capture potential heterogeneous effects across voters, even within regions. Second,

[4]The random-intercept model shrinks the occupation-specific averages towards the grand mean when they are imprecisely estimated, e.g., when there are few respondents in an occupation cell.

it allows to control in the analysis for region-specific trends, which absorb potential unobserved, long-term political and economic dynamics that might be confounded with the increase in the adoption of industrial robots. Third, it is based on occupational categories rather than industries, and therefore it captures a different, and complementary, source of variation in terms of automation exposure compared to the regional measure.

Voting behavior data and models

The empirical analysis consists of two parts. First we work with district-level election results, which are regressed on the regional exposure to automation. Then, we move to the analysis of individual data from the ESS, with variation in voting outcomes explained by both regional and individual exposure to automation.

District-level data and specification

The district-level analysis uses legislative election results for 83 elections in fourteen Western European countries, between the early 1990s and 2016. Data are assembled from various sources: CLEA (Kollman et al. 2017), the Global Election Database (Brancati 2016), and national sources. For all parties that are coded in the Manifesto Project (MPD, Volkens et al. 2018), we match vote data with information on ideological stances based on party manifestos.

Our main focus is the nationalism score of parties, computed following Lowe et al. (2011). Specifically, for party ℓ, in country c and year (election) t, we define:

$$\text{Nationalism Score}_{\ell ct} = \log(.5 + z^{+}_{\ell ct}) - \log(.5 + z^{-}_{\ell ct}), \tag{4}$$

where $z^{+}_{\ell ct}$ is the number of claims in the manifesto that are oriented in a nationalist direction, i.e., supporting "the national way of life", traditional morality, law and order, and opposing multiculturalism, while $z^-_{\ell ct}$ is the number of claims in the opposite direction.[5] This indicator is analogous to the measure of the cosmopolitan-traditional dimension used by Hall and Evans (2019).

Combining the party ideology scores, which are party-election specific, and the district-level election returns, we calculate two summaries of the ideological leaning of each district in each election: the center of gravity (COG) and the median voter score. The nationalism center of gravity is the average of the nationalism scores of the competing parties, weighted by their vote shares in the district. Formally, for district d at election t, it is defined as:

$$\text{Nationalism COG}_{dt} = \frac{\sum_{\ell=1}^{n} p_{\ell dt} \text{Nationalism Score}_{\ell t}}{\sum_{\ell=1}^{n} p_{\ell dt}},$$

where $\text{Nationalism Score}_{\ell t}$ is the nationalism score of party ℓ at election t, and $p_{\ell dt}$ is the vote share for party ℓ in district d and election t.

The center of gravity is sensitive to the ideological position also of the most extreme parties, while the (weighted) median voter score captures the location of a "centrist" voter in the district. In substantive terms, this is the sincere median voter choice in a proximity voting model, unidimensional in nationalism vs. cosmopolitanism. In a pure two-party system, like the US, the median voter score would be equivalent to the score of the district winner.

As a third summary of the ideological positioning of districts, we compute the vote

[5]Specifically, $z^+_{\ell ct}$ contains the number of claims coded by MPD in categories 601, 603, 605, and 608, while $z^-_{\ell ct}$ refers to codes 602, 604, and 607.

share for radical-right parties in each district and election. These parties are identified based on the conventional wisdom in the literature.[6]

At the district level, the specification we estimate has the general form:

$$\text{Electoral Outcome}_{cdt} = \alpha_{ct} + \beta_1 \text{Regional Exposure}_{cr(d)t} + \varepsilon_{cdt}, \tag{5}$$

where c indexes countries, d districts, t years (elections), and ε_{cdt} is an error term.

$\text{Electoral Outcome}_{cdt}$ is one of the three district-level summaries defined above. The function $r()$ maps district d to its NUTS-2 region r. The terms α_{ct} are country-year (i.e., election) fixed effects. $\text{Regional Exposure}_{\text{cr(d)t}}$ is the exposure to robot adoption as defined in Equation (1), computed over two years prior to the election. Each observation is a district in a given election, while the regional exposure to automation is measured at the level of NUTS-2 regions, which contain multiple districts in some cases. Standard errors are clustered at the region-year level, which is how the treatment variable is assigned. The country-year fixed effects account for any factors (e.g., incumbent government, political climate in the country, national economic performance) that affect all the districts within a country in a given election: this implies that we identify the effect of automation exposure only out of variation across regions within the same country and year.

Individual-level data and specification

For the individual-level analysis, we rely on the first seven waves of the European Social Survey. Elections span the period 1999-2015. Our main focus is on two dependent variables: (1) the nationalism score of the party voted by the individual; and (2) a dummy

[6]Full list in the Online Appendix.

equal to one if the chosen party is categorized as a radical-right party.

The first specification we estimate has the general form:

$$\text{Vote Choice}_{icrt} = \alpha_{ct} + \beta_1 \text{Regional Exposure}_{cr(i)t} + \mathbf{Z}_{it}\gamma' + \varepsilon_{icrt}, \tag{6}$$

where i indexes individuals, c countries, r regions, t election years, and ε_{icrt} is an error term. The function $r()$ maps each individual i to her NUTS-2 region of residence r; this allows us to assign to each respondent the regional exposure to automation in the election year: $\text{Regional Exposure}_{cr(i)t}$. $\mathbf{Z}_{it}$ is a vector of individual-level controls: the age of the respondent, a dummy equal to one for females, and a set of dummies indicating different levels of educational attainment. To account for additional variables that might affect vote choice of all respondents in a given election, we include election fixed effects. This means that the coefficients are estimated based on variation across regions in a given country and election year.

The second specification relies on the individual-level exposure to automation, and has the form:

$$\text{Vote Choice}_{icrt} = \alpha_{ct} + \beta_1 \text{Individual Exposure}_{it} + \varepsilon_{icrt}, \tag{7}$$

where $\text{Individual Exposure}_{\text{it}}$ is computed as outlined in Equation (3), over two years prior to the election. In all the individual specifications standard errors are clustered at the NUTS2-year level. Given that the individual-level robot exposure is obtained based on information regarding age, education, and gender of the respondents, it would be redundant to include these variables as controls in the regressions. At the same time, given that robot exposure varies across individuals within a given region and year, we can identify the effect of automation while accounting for additional region-level effects. In particular, in the robustness section, we discuss the estimates of specifications of the form $\text{Vote Choice}_{icrt} = \alpha_r + \delta_r t + \beta_1 \text{Individual Exposure}_{it} + \varepsilon_{icrt}$, with region-specific intercepts (α_r) and linear time trends ($\delta_r t$), that account for persistent differences across regions and unobserved regional long-term political and economic dynamics.

Results

This section presents the empirical results, first at the district level, then at the individual level.

District-level results

Table 1 reports the baseline estimates of the district-level specification of Equation (5). We consider three different dependent variables: the median voter and the center of gravity scores of nationalism, and the cumulative vote share for radical-right parties in each district. For each outcome variable, we report both OLS and instrumental variable results. The regional exposure to robots is computed as in Equation (1), based on robot adoption over two years prior to each election. In the IV regressions, the instrument for each country exploits the adoption of robots in other European countries, as detailed in Equation (2).

The estimated coefficient on robot exposure is positive and precisely estimated across the board, pointing to a positive link between automation and support for nationalist and radical-right parties at the district level. In the IV regressions, the first-stage coefficient on the instrument is positive and highly statistically significant. The F-statistic is well above 10, suggesting that we do not face a problem of instrument weakness. The instrumental variable estimates are somewhat larger than the OLS estimates, consistent with the procyclicality of robot adoption.

How large are the effects of robot exposure? This can be grasped most easily from the

IV regression of column 6, where the dependent variable is the vote share for radical-right parties. The estimated coefficient implies that a one standard deviation increase in robot exposure (0.217) leads to an increase by 1.8 percentage points in support for the radical right. This is far from negligible, considering that the average vote share for radical-right parties is 5.7%, with a standard deviation of 7.7%.

Table 1: District-Level Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	**Nationalism**				**Radical Right**	
	Median		COG		Share	
Robots Regional Exposure	0.452*** [0.127]	0.650*** [0.167]	0.276*** [0.056]	0.396*** [0.090]	0.039** [0.017]	0.083** [0.037]
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
Country-Year Effects	yes	yes	yes	yes	yes	yes
Obs.	8,906	8,906	8,906	8,906	8,983	8,983
R2	0.57	0.57	0.84	0.84	0.64	0.64
First-stage results						
Robots other countries	- -	0.798*** [0.071]	- -	0.798*** [0.071]	- -	0.798*** [0.071]
Kleibergen-Paap F-Statistic	-	127.4	-	127.4	-	127.6

Standard errors clustered by region-year. *** p$<$0.01, ** p$<$0.05

To gauge the magnitude of the effects in terms of nationalism, we shall start by considering that the median voter score ranges between -4.2 and 3.4, with a standard deviation of 0.89, while the center of gravity score ranges between -4.2 and 2.7, with a standard deviation 0.69. Then, a one standard deviation increase in robot exposure leads to an increase in the median voter score by 16% of its standard deviation (column 2), and to an increase in the center of gravity score by 12% of its standard deviation (column 4).

Overall, the results of this section show that automation has effects that are detectable in aggregate election returns, leading to a tilt in favor of parties promoting an anti-cosmopolitan agenda, and towards radical-right parties. In order to better understand how these aggregate results emerge from individual voting behavior, we now turn to individual-level data.

Individual-level results

As a transition from the district-level to the individual-level analysis, we start by regressing individual vote choices on regional exposure to robots, based on the region of residence of each respondent. Specifically, Table 2 reports the baseline estimates of Equation (6). The empirical set-up is analogous to the one adopted in the district-level analysis. Robot exposure in each region is computed over two years prior to each election, and the instrument exploits robot adoption in other European countries. We employ two outcome variables: the nationalism score of the party voted, and a dummy variable indicating whether the respondent voted for a radical-right party. For each variable we report both OLS and instrumental variable results.

The individual-level results of Table 2 are fully in line with the district-level findings presented in Table 1. Voters residing in regions that are more exposed to robot adoption tend to support more nationalist parties, and are more likely to vote for the radical right. In the IV regressions, the first-stage coefficient on the instrumental variable is always positive and statistically significant, with an F-statistic that remains well above the critical threshold of 10, pointing to the strength of the instrument. Also in this case, the IV estimates are somewhat higher than the OLS ones. The magnitude of the effects is in line with the district-level findings. For instance, according to the IV estimate of column 4, a one standard deviation increase in regional robot exposure increases the probability of voting for a radical-right party by about 1.4 percentage points. The results on the individual controls are in line with earlier literature. In particular, we find that women support on average less nationalist parties, and are less likely to vote for the radical right.

The main empirical contribution of our paper consists of studying the role of individual exposure to automation. This is computed as per Equation (3), multiplying the

Table 2: Individual-Level Estimates - Regional Exposure

	(1)	(2)	(3)	(4)
Dep. Var.:	**Nationalism Score**		**Radical Right**	
Robots Regional Exposure	0.236***	0.381***	0.019**	0.063***
	[0.088]	[0.126]	[0.010]	[0.022]
Female	-0.073***	-0.073***	-0.017***	-0.017***
	[0.010]	[0.010]	[0.002]	[0.002]
Age	0.004***	0.004***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Estimator	OLS	2SLS	OLS	2SLS
Education Dummies	yes	yes	yes	yes
Country-Year Effects	yes	yes	yes	yes
Obs.	95,822	95,822	97,981	97,981
R2	0.23	0.23	0.10	0.10
First-stage results				
Robots other countries	-	1.217***	-	1.211***
	-	[0.102]	-	[0.102]
Kleibergen-Paap F-Statistic	-	141.9	-	142.2

Standard errors clustered by region-year. *** $p<0.01$, ** $p<0.05$

overall pace of robot adoption in each country by a measure of individual vulnerability to automation. Before analyzing the impact of individual robot exposure on voting, in Table 3 we provide some preliminary evidence of its effects on individual economic conditions and perceptions, as well as on meta-political attitudes. In details, we estimate the specification of Equation (7) using ten different dependent variables, as specified in each row. Individual exposure to robots is evaluated over two years, and instrumented using a variable that combines individual vulnerability with the average pace of robot adoption in other European countries. We show estimates based on both the Frey and Osborne (2017) and the ISSP-based automatability scores, in columns 1 and 2, respectively.

Higher robot exposure at the individual level leads to: lower likelihood of having a permanent contract, poorer perceived economic conditions and well-being, lower satisfaction with the government and democracy, and a reduction in perceived political self-efficacy. The contribution of these findings is twofold. First, they provide an important validation of our novel measure of individual exposure to automation, which emerges as being causally related to gloomier conditions and perceptions along several dimensions, ranging from the personal to the public sphere. Second, these outcomes suggest a number of possible transmission channels from the economic shock to voting, consistent with our theoretical discussion.

Table 3: Individual Exposure to Automation - Preliminary Evidence

	(1)	(2)
Individual exposure based on:	Frey and Osborne (2017)	ISSP
Dep. Var. Specified in each row		
1) Dummy for having a permanent contract	-2.581***	-1.383***
	[0.332]	[0.204]
2) Perceiving pay as inappropriate	0.542***	0.379***
	[0.195]	[0.114]
3) Perceiving household income as not sufficient	1.010***	0.761***
	[0.161]	[0.102]
4) Perceived likelihood of unemployment in 12 months	2.306***	0.979***
	[0.367]	[0.189]
5) Suffering more often from anxiety	0.316**	0.146**
	[0.128]	[0.064]
6) Satisfaction with life as a whole	-0.117**	-0.147***
	[0.049]	[0.030]
7) Satisfaction with state of the economy in country	-0.219***	-0.199***
	[0.056]	[0.037]
8) Satisfaction with national government	-0.159***	-0.128***
	[0.048]	[0.029]
9) Satisfaction with the way democracy works in country	-0.246***	-0.234***
	[0.066]	[0.043]
10) Perceived own political efficacy	-10.523***	-6.508***
	[1.962]	[1.280]

Standard errors clustered by region-year. *** $p<0.01$, ** $p<0.05$

Table 4 reports the baseline estimates of Equation (7). The dependent variables are the same as in Table 2: the nationalism score of the party voted, and a dummy for supporting a radical-right party. The estimated coefficients on individual exposure to robots are always positive and highly significant, both when employing the measure based on Frey and Osborne (2017) (in columns 1-4), and the one based on ISSP (in columns 5-8). The first-stage coefficients on the instrumental variables are also positive and significant, and the F-statistics are comfortably high. Overall, one main message emerges from this set of results: individual exposure to robot adoption, based on our counter-

Table 4: Individual-Level Estimates - Individual Exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Individual exposure based on:	Frey and Osborne (2017)				ISSP			
Dep. Var.:	**Nationalism Score**		**Radical Right**		**Nationalism Score**		**Radical Right**	
Robots Individual Exposure	1.510***	1.689***	0.340***	0.552***	1.127***	1.276***	0.212***	0.343***
	[0.386]	[0.408]	[0.069]	[0.109]	[0.233]	[0.249]	[0.042]	[0.066]
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Country-Year Effects	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	96,071	96,071	98,238	98,238	96,071	96,071	98,238	98,238
R2	0.22	0.22	0.09	0.09	0.22	0.22	0.09	0.09
First-stage results								
Robots other countries	-	0.907***	-	0.906***	-	0.899***	-	0.899***
	-	[0.041]	-	[0.041]	-	[0.041]	-	[0.041]
Kleibergen-Paap F-Statistic	-	488.7	-	491.7	-	485.1	-	488.8

Standard errors clustered by region-year. *** $p<0.01$, ** $p<0.05$

factual measure of vulnerability, matters for individual-level vote choices. In particular, individuals that are more exposed to automation tend to support more nationalist and radical-right parties.

In terms of magnitudes, according to the IV estimates of columns 2 and 4, a one standard deviation increase in individual exposure to robots based on Frey and Osborne (2017), which is equal to 0.051, leads to an increase in the nationalism score by 0.09, i.e., 7.4% of its standard deviation, and to a 2.8% increase in the probability of supporting a radical-right party. Somewhat smaller effects are obtained when using the ISSP-based measure of automation threat. In particular, according to the IV estimates of columns 6 and 8, a one standard deviation increase in individual exposure (0.038) leads to higher nationalism by 0.05, and to an increase in the probability of supporting a radical-right party by 1.3%. Even according to these more conservative estimates, the impact of automation still looms substantial.

Robustness and extension

The individual analysis relies on a measure of exposure to automation which is based on the predicted probabilities of employment in each occupation. A possible concern is that education, besides influencing an individual's exposure to automation, might also capture omitted personality traits and basic orientations that are directly linked to vote choice. In particular, education might affect orientations that are related to authoritarianism and opposition to the cosmopolitan agenda, and are thus linked to support for nationalist and radical-right parties (Ivarsflaten and Stubager 2012; Stubager 2008). To account for this, in Table 5 we augment the instrumental variable regressions of Table 4 with several proxies for these orientations and attitudes.

In particular, we include as controls the first two factors from a factor analysis on the twenty-one items of the Human Values Scale in the ESS.[7] Additionally, we include a control for agreement with the statement that gays and lesbians should be free to live life as they wish. While domain-specific, this item is related to one of the main non-economic components of the "cosmopolitan values" package. We also control for occupational social class following Oesch's (2006) scheme.

Importantly, these control variables are, possibly, post-treatment: evidence discussed in the theoretical section points to direct causal effects of economic vulnerability on authoritarian attitudes. In addition, these attitudinal items might even be endogenous to political choice if voters take party cues about the stance they hold –e.g., on gay rights– after deciding for other reasons –e.g., economic distress– to support a given party. Yet, if our main results survive the inclusion of these controls, we can be more confident that

[7]Tables A3 and A4 in the Online Appendix report summary statistics for the factor analysis.

the individual vulnerability to automation is not spuriously picking up variation in political behavior that is driven by basic value orientations. Reassuringly, the coefficient on the individual exposure to automation is always positive and highly significant. As it is reasonable to expect, the estimated effects are somewhat smaller in magnitude once we include all these arguably post-treatment variables. Yet, they are still clearly detectable.[8]

To characterize more broadly the impact of automation on voting, in Table 6 we re-estimate the baseline instrumental variable regressions of Table 4 using four alternative dependent variables. These are dummies denoting whether the party voted by the respondent belongs to one of the following party families: Protectionist Left, Pro-Trade Left, Liberal Right, and Protectionist Right. Parties are allocated to a family based on their position in one of the four quadrants of the two-dimensional space defined by *Economic Conservatism* –i.e., economic left-right positioning– and *Net Autarky* –i.e., stances on protectionism, Euroscepticism and isolationism vs. free trade and multilateralism (Burgoon 2012). For each ideology dimension, parties are classified as belonging to either side of the spectrum depending on whether their ideology score is above or below the median for a given country in a given election (more details in the Online Appendix). The coefficients on individual exposure to robots for the protectionist right –the family to which most radical-right parties belong– are positive and statistically significant, while they are negative and significant both for the pro-trade (i.e., mainstream) left and for the liberal right. We detect small, positive but not statistically significant effects for the protectionist left. Overall, exposure to automation seems to tilt voters in a right-wing and isolationist direction, and away from more cosmopolitan and mainstream options on both the left and the right of the political spectrum.

[8]The results are robust to the inclusion of only the attitudinal variables.

Table 5: Individual-Level Estimates - Individual Controls

	(1)	(2)	(3)	(4)
Individual exposure based on:	Frey and Osborne (2017)		ISSP	
Dep. Var.:	**Nationalism Score**	**Radical Right**	**Nationalism Score**	**Radical Right**
Robots Individual Exposure	1.084***	0.420***	0.735***	0.252***
	[0.369]	[0.104]	[0.215]	[0.062]
Small business owners	0.100***	0.021***	0.096***	0.021***
	[0.036]	[0.006]	[0.036]	[0.006]
Technical professionals	-0.050	0.010*	-0.051	0.010*
	[0.034]	[0.005]	[0.034]	[0.005]
Production workers	-0.010	0.059***	-0.014	0.058***
	[0.043]	[0.008]	[0.043]	[0.008]
Managers	-0.008	-0.003	-0.009	-0.004
	[0.032]	[0.005]	[0.032]	[0.005]
Clerks	-0.024	0.013**	-0.027	0.013**
	[0.036]	[0.006]	[0.036]	[0.006]
Socio-cultural workers	-0.249***	-0.016***	-0.252***	-0.016***
	[0.035]	[0.005]	[0.035]	[0.005]
Service workers	-0.030	0.033***	-0.033	0.033***
	[0.037]	[0.006]	[0.037]	[0.006]
Unemployed	-0.166***	0.029***	-0.169***	0.029***
	[0.045]	[0.007]	[0.045]	[0.007]
Not in labor force	-0.023	0.011**	-0.027	0.010**
	[0.033]	[0.005]	[0.033]	[0.005]
Orientations - factor 1	-0.039***	-0.004***	-0.039***	-0.004***
	[0.005]	[0.001]	[0.005]	[0.001]
Orientations - factor 2	-0.051***	0.004***	-0.050***	0.004***
	[0.007]	[0.001]	[0.007]	[0.001]
Gay rights: agree	0.250***	0.013***	0.250***	0.013***
	[0.015]	[0.002]	[0.015]	[0.002]
Gay rights: neutral	0.387***	0.024***	0.385***	0.023***
	[0.026]	[0.004]	[0.026]	[0.004]
Gay rights: disagree	0.485***	0.030***	0.484***	0.030***
	[0.031]	[0.006]	[0.031]	[0.006]
Gay rights: strongly disagree	0.496***	0.024***	0.495***	0.024***
	[0.039]	[0.006]	[0.039]	[0.006]
Estimator	2SLS	2SLS	2SLS	2SLS
Country-Year Effects	yes	yes	yes	yes
Obs.	87,681	89,697	87,681	89,697
R2	0.24	0.10	0.24	0.10
Kleibergen-Paap F-Statistic	427.1	429.7	440.1	443.6

Standard errors clustered by region-year. *** p<0.01, ** p<0.05

Table 7 presents a series of additional robustness checks for the individual-level regressions. Specifically, we show that the results of the individual analysis are robust to: a different measurement of the exposure to automation, based on the current occupation of each respondent rather than the counter-factual prediction; the exclusion of individuals born after 1980, who might have adjusted their educational choices in response to fear of "competition with robots"; the exclusion of workers in the automotive industry, the most automation-intensive; the inclusion of region-specific fixed effects and time trends, to account for long-run differences in political orientations potentially correlated with historical industry specialization; and, finally, instrumenting individual exposure using robot adoption in the advanced non-European countries for which data are available (i.e., countries of North America, Japan and South Korea).

Table 6: Extension: Party Families

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Individual exposure based on:	Frey and Osborne (2017)				ISSP			
Dep. Var.:	**Protectionist Left**	**Pro-trade Left**	**Liberal Right**	**Protectionist Right**	**Protectionist Left**	**Pro-trade Left**	**Liberal Right**	**Protectionist Right**
Robots Individual Exposure	0.087	-0.268**	-0.269**	0.451***	0.065	-0.142	-0.202**	0.280***
	[0.138]	[0.130]	[0.128]	[0.142]	[0.077]	[0.079]	[0.081]	[0.087]
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Country-Year Effects	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	96,071	96,071	96,071	96,071	96,071	96,071	96,071	96,071
R^2	0.14	0.19	0.22	0.16	0.14	0.19	0.22	0.16
Kleibergen-Paap F-Statistic	488.7	488.7	488.7	488.7	485.1	485.1	485.1	485.1

Standard errors clustered by region-year. *** $p<0.01$, ** $p<0.05$

Table 7: Robustness

	(1)	(2)	(3)	(4)
Individual exposure based on:	Frey and Osborne (2017)		ISSP	
Dep. Var.:	**Nationalism Score**	**Radical Right**	**Nationalism Score**	**Radical Right**
1) Real individual exposure	1.665***	0.569***	1.746***	0.654***
	[0.434]	[0.078]	[0.569]	[0.095]
2) Excluding individuals born after 1980	1.902***	0.520***	1.338***	0.315***
	[0.406]	[0.107]	[0.243]	[0.063]
3) Excluding automotive workers	1.717***	0.556***	1.290***	0.346***
	[0.408]	[0.109]	[0.248]	[0.065]
4) Including NUTS-2 fixed effects	1.433***	0.515***	1.070***	0.319***
	[0.386]	[0.106]	[0.230]	[0.065]
5) Including NUTS-2 fixed effects plus trends	1.457***	0.510***	1.094***	0.322***
	[0.383]	[0.106]	[0.232]	[0.065]
6) IV based on North America	1.965***	0.549***	1.460***	0.341***
	[0.420]	[0.099]	[0.252]	[0.059]
7) IV based on Non-European countries	3.094***	0.785***	2.110***	0.481***
	[0.530]	[0.117]	[0.319]	[0.072]

Standard errors clustered by region-year. *** $p<0.01$, ** $p<0.05$

In Table 8, we account for other phenomena that are contemporaneous to, and possibly associated with automation. First, there is evidence that globalization, especially through the rise of China as a global exporter, has had a positive effect on support for nationalist and radical-right parties. In columns 1-4 of Table 8, we show that our findings on individual exposure to automation are robust to the inclusion of a measure of the "China shock" at the regional level, following the empirical approach introduced by Autor et al. (2013). Specifically, we focus on the growth in import pressure from China over two years prior to each election, consistent with the way we measure exposure to robot adoption. Interestingly, the effect of the China shock is positive, but rather small and not significant. This is not surprising given that we consider a later period compared to previous studies. In particular, our time span encompasses the financial crisis, with the associated "trade collapse" of 2008-2009. The year-to-year impact of Chinese import competition, as captured by this measure, is then less relevant than in the earlier period analyzed by previous studies. Reassuringly, if we restrict our analysis to the pre-crisis period, as Colantone and Stanig (2018a) do, we retrieve a positive and significant effect of the China shock on nationalism and radical-right support, and the effect of robot exposure remains positive and precisely estimated.

In columns 5-8 of Table 8 we present a similar robustness analysis that controls for the impact of ICT. Specifically, we control for an ICT shock built by allocating country-industry specific ICT investments to regions based on their historical industry specialization. We consider ICT investments in the two years prior to each election, sourced from EU-KLEMS. Also in these specifications, the estimates on the effects of automation remain positive and significant. This is consistent with earlier studies showing that the impact of automation on labor market outcomes is robust to the inclusion of ICT controls (Acemoglu and Restrepo, 2018). At the same time, we detect no significant effect of ICT investments on voting.

Finally, in the last two columns of Table 8 we consider an alternative measure of individual exposure to automation. This replicates the structure of our baseline measures but is based on an alternative automatability score: the occupation-specific routine-task intensity index of Autor and Dorn (2013). Results on radical-right vote are consistent with our main specifications. For the nationalism score outcome, the coefficient is still positive, but not statistically significant. This might reflect the fact that the latest wave of automation has indeed had an impact that goes beyond the displacement of workers in routine tasks, as suggested by Frey and Osborne (2017).

Table 8: Other shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Individual exposure based on:	Frey and Osborne (2017)		ISSP		Frey and Osborne (2017)		ISSP		RTI	
Dep. Var	**Nationalism Score**	**Radical Right**	**Nationalism Score**	**Radical Right**	**Nationalism Score**	**Radical Right**	**Nationalism Score**	**Radical Right**	**Nationalism Score**	**Radical Right**
Robots Individual Exposure	1.688***	0.552***	1.275***	0.343***	1.208***	0.392***	0.933***	0.236***		
	[0.408]	[0.109]	[0.249]	[0.066]	[0.366]	[0.102]	[0.224]	[0.060]		
China shock	0.018	0.004	0.019	0.004						
	[0.020]	[0.007]	[0.020]	[0.007]						
ICT shock					-1.376	0.238	-1.393	0.233		
					[1.741]	[0.244]	[1.741]	[0.245]		
Robots Indiv. Exposure RTI									0.093	0.103***
									[0.067]	[0.020]
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Country-Year Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	96,071	98,238	96,071	98,238	88,175	90,222	88,175	90,222	96,071	98,238
R2	0.22	0.09	0.22	0.09	0.23	0.05	0.23	0.05	0.22	0.09
Kleibergen-Paap F-Statistic	488.8	491.8	485.2	489.0	435.8	438.7	436.2	439.9	566.4	570.7

Standard errors clustered by region-year. *** $p<0.01$, ** $p<0.05$

Conclusion

We study the effects of automation on voting behavior, focusing on the impact of robot adoption in fourteen countries of Western Europe, over the period 1993-2016. We find that higher exposure to automation increases support for nationalist and radical-right parties, both at the regional and at the individual level. Overall, our findings point to a strong role of automation as a driver of the surge of economic nationalism in Western Europe. By highlighting the broad implications of an important dimension of structural economic change, our paper contributes to a growing body of research that provides evidence on the material drivers behind increasing support for the radical right and the realignment witnessed by advanced Western democracies.

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Additional information on data

Table A1: Employment data

	Employment Data	
Country	**Initial Year**	**Source**
Austria	1995	Eurostat
Belgium	1995	National Bank of Belgium
Finland	1995	Statfin
France	1989	INSEE
Germany	1993	Federal Employment Agency
Greece	1988	HSA Statistics Greece
Italy	1988	ISTAT
Netherlands	1988	CBS Statistics Netherlands
Norway	1994	Statistics Norway
Portugal	1990	INE Portugal
Spain	1993	INE Spain
Sweden	1993	SCB Statistics Sweden
Switzerland	1995	SFSO Swiss Statistics
United Kingdom	1989	ONS

Table A2: 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

Factor analysis

Table A3: Factors

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.89086	1.73133	0.6021	0.6021
Factor2	2.15954	0.93786	0.3342	0.9363
Number of obs.	202,518			
Retained factors	2			
Number of parameters	41			

Table A4: Factor loadings

Variable	Factor1	Factor2	Uniqueness
ipcrtiv	0.4143	-0.2103	0.7841
imprich	0.3036	-0.3645	0.7750
ipeqopt	0.3799	0.2005	0.8155
ipshabt	0.4960	-0.2894	0.6702
impsafe	0.4246	0.3592	0.6907
impdiff	0.4997	-0.3558	0.6237
ipfrule	0.2921	0.3086	0.8195
ipudrst	0.4549	0.1789	0.7611
ipmodst	0.2599	0.4230	0.7535
ipgdtim	0.4516	-0.3661	0.6620
impfree	0.4480	-0.1215	0.7845
iphlppl	0.5156	0.2538	0.6697
ipsuces	0.5385	-0.3304	0.6008
ipstrgv	0.4702	0.3137	0.6804
ipadvnt	0.3555	-0.5586	0.5615
ipbhprp	0.4008	0.4293	0.6550
iprspot	0.4570	-0.0262	0.7904
iplylfr	0.5165	0.2030	0.6920
impenv	0.4282	0.2672	0.7452
imptrad	0.3349	0.3537	0.7628
impfun	0.4551	-0.3756	0.6518

Ideology scores and radical right parties

For the computation of the *Economic Conservatism* (left-right) score, based on the same approach as described for Nationalism in Equation (4), $z^{+}_{\ell ct}$ contains the number of claims coded in categories 401, 402, 414 and 505, while $z^{-}_{\ell ct}$ refers to codes 403, 404, 405, 409, 412, 413, and 504.

For the computation of the *Net Autarky* score, $z^{+}_{\ell ct}$ contains the number of claims coded in categories 406, 109, and 110, while $z^{-}_{\ell ct}$ refers to codes 407, 107, and 108.

The list of radical-right parties includes: FPÖ and Team Frank Stronach in Austria; Vlaams Blok and Vlaams Belang in Belgium; True Finns in Finland; Front National in France; Golden Dawn and LAOS in Greece; AFD, NPD, and Die Republikaner in Germany; (Northern) League in Italy; PVV and List Fortuyn in the Netherlands; Sweden Democrats in Sweden; AN/NA, Swiss Democrats, SVP, and FPS in Switzerland; UKIP in the United Kingdom. Some additional minor parties that could belong to the radical right family are not included, as they are too small to be recorded in the election data. If anything, this could lead us to underestimate the overall support for the radical right.