I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 12485

We Were the Robots: Automation and Voting Behavior in Western Europe

Massimo Anelli
Italo Colantone
Piero Stanig

JULY 2019

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 12485

We Were the Robots: Automation and Voting Behavior in Western Europe

Massimo Anelli
Bocconi University and IZA

Italo Colantone
Bocconi University

Piero Stanig
Bocconi University

JULY 2019

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

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

We investigate the impact of robot adoption on electoral outcomes in 14 Western European countries, between 1993 and 2016. We employ both official election results at the district level and individual-level voting data, combined with party ideology scores from the Manifesto Project. We measure exposure to automation both at the regional level, based on the ex-ante industry specialization of each region, and at the individual level, based on individual characteristics and pre-sample employment patterns in the region of residence. We instrument robot adoption in each country using the pace of robot adoption in other countries. Higher exposure to robot adoption is found to increase support for nationalist and radical-right parties. 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.

JEL Classification: D72, J23, J24, O33
Keywords: automation, nationalism, radical right

Corresponding author:
Massimo Anelli
Department of Social and Political Sciences and Dondena Research Centre
Bocconi University
Via Roentgen 1
20136, Milano
Italy
E-mail: massimo.anelli@unibocconi.it

* We thank Andrea Fracasso, Peter Hall, Dominik Hangartner, Thomas Kurer, Arlo Poletti, seminar participants at Bocconi University, Cornell University, Erasmus University Rotterdam, ETH Zurich, Harvard University, Hebrew University of Jerusalem, LMU Munich, NYU, SciencesPo, Southern Methodist University, the 2018 Workshop on Populism of the Scuola Normale di Pisa, the Anti-Globalization Backlash Conference in Florence, the 2018 APSA Annual Meeting and the 2019 MPSA Annual Meeting. The authors acknowledge funding from the European Union Horizon 2020 research and innovation programme under grant agreement no. 822390 (MICROPROD).

1 Introduction

Nationalist and radical-right parties and candidates have become increasingly successful in Western democracies over the past three decades. A growing body of research relates such political developments to structural changes in the economy. In this paper, we contribute to this literature by studying the political consequences of automation. We focus on the effects of industrial robot adoption in fourteen Western European countries, between the early 1990s and 2016. This wave of automation has 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). Robot adoption in each country is instrumented using the pace of robot adoption in other countries. Detailed data on robots by country and industry are sourced from the International Federation of Robotics.

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.

2 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.

As discussed by Goldin and Katz (1998), in the nineteenth century the introduction of machines in manufacturing allowed low-skill workers to engage in the production of goods that previously required specific expertise in artisanal shops. Technology thus complemented low-skill labor, substituting high-skill labor. This pattern turned around in the early twentieth century, when technological advances started to favor more skilled workers. Trends such as the electrification of factories reduced the need for large numbers of unskilled manual workers, raising the demand for relatively skilled blue-collar and high-skill white-collar workers. In the second half of the twentieth century, and chiefly during the 1980s and 1990s, the computer revolution, with the widespread adoption of IT and computer-based technologies, reinforced the complementarity between technology and skills. At the same time, these years marked a surge in wage inequality and educational premia both in the US and in Europe. Technological change has been isolated as a main driver of these labor market dynamics, which have fostered social cleavages in Western democracies (Acemoglu and Autor 2011).

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 (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, there have been two major developments in computer-based technologies: machine learning and mobile robotics. As discussed by Frey and Osborne (2017) in their seminal paper, both developments are taking computerization to the next level by allowing for the automation of non-routine tasks. Of particular interest for us, mobile robotics allows for 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 has started to investigate 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.

Graetz and Michaels (2018), using industry-level data from seventeen countries, find that robot adoption has a positive effect on productivity, but a negative impact on the share of hours worked by low-skill workers. 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.

Taking stock of the available evidence, the diffusion of robots seems to have generated important distributional consequences, favoring mostly high-skill individuals vis-à-vis others. The main difference compared to the earlier wave of automation seems to be the absence of job polarization, since the number of jobs for low-skill workers is strongly negatively affected. If anything, this makes the position of losers even worse than before, as the reduction in available jobs compounds the rising gap in wages. In this paper, we investigate the political implications of this phenomenon.

3 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, the economic nationalist platform places a strong emphasis on the protection of workers. Such protection is articulated in broad terms, encompassing both protectionism in international trade and proposals to fight job losses due to automation by directly taxing companies adopting robots. Thus far, the growing appeal of nationalist 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; Che 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 support for government intervention in favor of declining industries is higher among respondents more exposed to automation risk. These automation-induced preferences for more redistribution and government intervention should orient voters towards parties of the left. 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 has 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 has 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, the role of labor unions has been weakened by globalization and technological change. In particular, automation in manufacturing disrupts the established patterns of shop-floor organization, making it more difficult for unions to retain their central role. 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; Cerrato et al. 2018; 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, 2018) 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 pointed out by Frieden (2018). The same structural changes are accompanied by a cultural shift: less social value is assigned to "hard work", which is a source of status for low- and middle-skill workers, and more value is assigned to knowledge and entrepreneurial spirit. 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 preferences and 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 are found to become more likely to vote Conservative and less likely to vote Labour. Gallego et al. (2018) also find that losers are more likely to support the UKIP. Yet, due to data limitations, they refrain from making more general claims about the radical-right turn of the losers in the British setting. 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 is robustly correlated with support for the Sweden Democrats in local elections.

This paper aims at furthering our understanding of the political implications of technological change. We provide cross-country causal evidence on the effects of automation, using detailed information on robot adoption at the industry level, and employing an identification strategy that exploits plausibly exogenous technological trends. The way we measure individual exposure to automation, based on a counter-factual exercise rather than on the potentially endogenous current occupation exploited in earlier work, is in itself a novel methodological contribution to the literature.

4 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.

4.1 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 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 procyclical: 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

[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.

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). That is, 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.

4.2 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 who is 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:

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

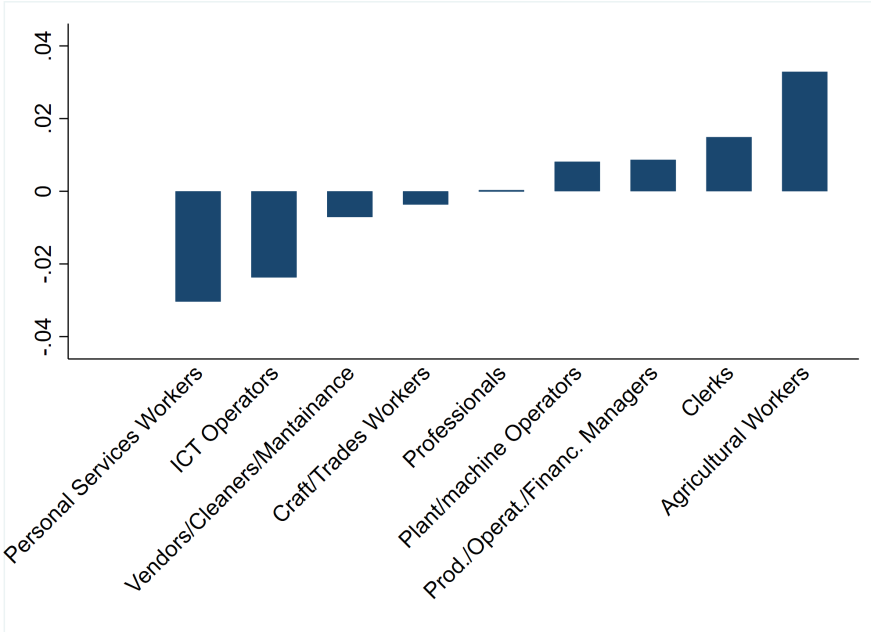
where ΔR_{ct} is the national percentage change in total operational robots between year $t-1$ and $t-n$, in the country c where individual i resides, i.e., $\frac{R_{c(i)}^{t-1} - R_{c(i)}^{t-n}}{R_{c(i)}^{t-n}}$.

$\widehat{Pr}(o_i = j|\text{age}, \text{gender}, \text{edu}, r)$ 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 by multiplying this individual vulnerability times 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

Figure 1: Predicted vs. actual occupation shares



ISCO (International Standard Classification of Occupations) classification. 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

[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%.

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.[4] The automation threat of each occupation depends on the presence of what they call “engineering bottlenecks” to automation. These can be of three types: (1) perception and manipulation, which includes manual and finger dexterity, as well as the ability to work in a cramped workspace and in awkward positions; (2) creative intelligence, needed for original intellectual work and fine arts; and (3) social intelligence, including perceptiveness, negotiation and persuasion activities, as well as assisting and caring for others. The higher the relevance of these bottlenecks for a given occupation, the lower the probability that workers employed in that occupation will be substituted by machines. These estimates capture the automatability of both routine and non-routine tasks, taking into account the recent developments in both mobile robotics and machine learning.

The second strategy relies on information from the 1997 wave of the ISSP “Work Orientations” module (International Social Survey Program Research Group 1999). This contains an item asking respondents about the perceived effect of new technologies on the number of jobs, with responses on a five-point scale from “greatly increase” to “greatly decrease”. We use these answers to estimate a measure of perceived automation threat by occupation. In practice, using data from all advanced industrial democracies included in the ISSP sample, we estimate the occupation-specific perceived automation threat via a model with random intercepts for occupations. The model has the following 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, β_k is the random intercept for occupation k, the function $k(i)$ maps respondent i to her occupation k, and ϵ_i is an idiosyncratic shock for individual respondents. Our approach is, in substance, equivalent to calculating the average perceived threat by occupation, which is the method adopted by van Hoorn (2018) to estimate a similar summary on the same data.[5]

Our measure of individual exposure to automation has multiple advantages. First, it can

[4]Frey and Osborne (2017) focus on US Census Standard Occupational Codes (SOC); we use the SOC-ISCO crosswalk provided by the US Bureau of Labor Statistics to obtain automatability indexes for the 2-digit ISCO codes used in our analysis.

[5]The main advantage of using a random-intercept model is that the occupation-specific averages are shrunk towards the grand mean when they are imprecisely estimated, for instance when there are fewer respondents in a given occupation cell.

capture potential heterogeneous effects across voters, even within regions. Second, 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.

5 Voting behavior data and models

The empirical analysis is divided in 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.

5.1 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), from which we get the majority of data, 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 on the nationalism score of parties. This is computed using the methodology by 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 party 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.[6] 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 in a district is the average of the nationalism scores of the competing parties, weighted by their vote shares in the district. Formally, for district d at time (election) t, it is defined as:

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

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

While the center of gravity takes into account the positions of all parties voted in the district (and is thus sensitive to the ideological position also of the most extreme parties), the median voter score captures the location of a "centrist" voter in the district. To compute it, parties in each election are sorted from least to most nationalist, and the cumulative vote share in each district is calculated (in the usual fashion, as the sum of the vote shares of a given party and of all parties to its left in the distribution). The median voter score is then obtained as the nationalism score of the party at which the cumulative vote share reaches 50%. 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.

Finally, as a third summary of the ideological positioning of districts, we employ the vote share for radical-right parties in each district and election. These parties are identified based on the conventional wisdom in the literature.[7]

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

[7] Full list in the Online Appendix.

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 fixed effects, which are equivalent to 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 refers to 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 always clustered at the region-year level, which is how the treatment variable is assigned. The country-year fixed effects are meant to control for any factors that affect all the districts within a country at the time of a given election, such as the orientation of the incumbent government, the overall political climate in the country, and the national economic performance. The inclusion of country-year fixed effects implies that we identify the effect of automation exposure only out of variation across regions within the same country and year.

5.2 Individual-level data and specification

For the individual-level analysis, we rely on the first seven waves of the European Social Survey. In total, we use data on about 100,000 individuals, for whom information on the party voted in the last election before the interview is available. 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 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. This includes the age of the respondent, a dummy equal to one for females, and a set of dummies indicating different levels of educational attainment. In order to account for additional variables that might affect vote choice of all respondents in a given election, also in the individual-level models we include country-year (in practice, 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. 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 we have variation in robot exposure across individuals within a given region and year, we have enough information to 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 $\text{Vote Choice}_{icrt} = \alpha_r + \delta_r t + \beta_1 \text{Individual Exposure}_{it} + \varepsilon_{icrt}$, thus with region-specific intercepts (α_r) and linear time trends ($\delta_r t$). These account for persistent differences across regions in terms of political culture and economic conditions, and for any unobserved, long-term political and economic dynamics that might be confounded with the increase in the adoption of industrial robots. In all the individual specifications, like in the district-level analysis, standard errors are clustered at the NUTS2-year level.

6 Results

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

6.1 District-level results

Table 1 reports the baseline estimates of the district-level specification outlined in 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%.

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

Table 1: District-Level Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	**Nationalism**				**Radical Right**	
	Median		COG		Share	
Robots Regional Exposure	0.452***	0.650***	0.276***	0.396***	0.039**	0.083**
	[0.127]	[0.167]	[0.056]	[0.090]	[0.017]	[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***	-	0.798***	-	0.798***
	-	[0.071]	-	[0.071]	-	[0.071]
Kleibergen-Paap F-Statistic	-	127.4	-	127.4	-	127.6

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

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.

6.2 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.

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

The main empirical contribution of our paper consists of studying the role of individual exposure to automation. This is computed as explained in Equation (3), by multiplying the overall pace of robot adoption in each country, times 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 outlined in Equation (7) using ten different dependent variables, as specified in each row. Consistent with the district-level analysis, 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 are suggestive of 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: 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. *** $p<0.01$, ** $p<0.05$

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 Osrborne (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, the main message emerging from this set of results is that the individual exposure to robot adoption, based on our counter-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.

6.3 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. Such probabilities are estimated based on, among others, the educational attainment of each individual. 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.

First, we include the categorical variable Augmented Oesch, encompassing the original occupational classes in Oesch (2006), plus separate categories for the unemployed and individuals out of the labor force. This variable captures differences across respondents who belong to different occupational classes, that might in turn be associated with systematically different value orientations, as documented by Kitschelt and Rehm (2014). Second, we rely on a battery of twenty-one ESS questions about aspects of life that are important to the respondent (from "thinking new ideas and being creative" to "following traditions and customs"). These are meant to capture very basic orientations about individual and social life. We include as controls the first two factors from a factor analysis on these items.[8] Finally, we also consider attitudes towards the cosmopolitan agenda that are non-economic in nature. In particular, we focus on the ESS survey question about agreement with the statement that gays and lesbians should be free to live life as they wish. While very domain-specific, this item is related to one of the main components of the

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

"cosmopolitan values" package.

Importantly, the variables that we include in these augmented specifications are, possibly, post-treatment. For instance, 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 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. The evidence, then, points to the fact that, even if we compare two individuals that belong to the same Oesch (2006) social class and have the same value orientations, those more exposed to automation due to their background characteristics are more supportive of nationalist options and radical-right parties.[9]

To characterize in a more comprehensive way 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

[9]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

–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 instead 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 side of the political spectrum.

Table 7 presents a series of additional robustness checks for the individual-level regressions. All the reported coefficients refer to individual robot exposure. Each coefficient is obtained from a separately estimated IV specification. In the first row, instead of using our counter-factual measure of individual exposure to automation, we compute a measure that exploits the current occupation of each respondent. As discussed earlier, this is sub-optimal since current occupation is likely to be endogenous to automation. Moreover, we are forced to exclude from the analysis respondents who are unemployed or not in the labor force. Nevertheless, results are in line with our baseline evidence. This suggests that, to an extent, the threat of automation also affects workers who have not been displaced and are still employed in occupations at high risk of automation.

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
R2	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

One could be concerned that education might be endogenous to automation dynamics. For instance, some individuals might choose to receive more education fearing "competition with robots". To address this concern, in the second row of Table 7 we restrict the analysis to respondents born before 1980, whose educational choices are arguably less affected by the latest wave of automation. The coefficients on individual robot exposure are positive and highly statistically significant. They are also somewhat larger in magnitude compared to the baseline estimates (albeit not statistically significantly so), suggesting that automation might have been more consequential for older individuals. In the third row, we exclude all workers employed in the automotive industry, which is the most automation-intensive according to the robot data. Reassuringly, results are fully in line with the baseline evidence, suggesting that our general findings are not purely driven by workers in this industry.

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

Another possible threat to our identification arises from the fact that different regions might have persistent differences in political orientations that are correlated with historical industry specialization. In that case, rather than detecting an effect of automation shocks on political orientations, our estimates could be picking up differences in voting behavior across regions that are spuriously related to stronger or weaker automation exposure. To account for that, we estimate models with fixed effects for NUTS-2 regions, and models where we add region-specific linear time trends, in rows 4 and 5, respectively. The results are robust to these additional controls, corroborating a causal interpretation of our main findings on automation. Finally, results are robust to instrumenting individual robot exposure using robot adoption in North America, and in all the advanced non-European countries for which data are available (i.e., countries of North America, plus Japan and South Korea). Results are presented in rows 6 and 7, respectively.

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 that is 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, and Graetz and

Michaels, 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, which exploit either the Frey and Osborne (2017) or the ISSP-based automation threats; however, it is based on an alternative automatability score: the occupation-specific routine-task intensity index introduced by 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

7 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.

References

Acemoglu, Daron, and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics* 4, Elsevier, 1043-1171.

Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review* 108(6): 1488-1542.

Akkerman, Tjitske. 2015. "Gender and the Radical Right in Western Europe: A Comparative Analysis of Policy Agendas." *Patterns of Prejudice* 49(1-2): 37-60.

Algan, Yann, Sergei Guriev, Elias Papaioannou, and Evgenia Passari. 2017. "The European Trust Crisis and the Rise of Populism." *Brookings Papers on Economic Activity* 2017(2): 309-400.

Arzheimer, Kai. 2009. "Contextual Factors and the Extreme Right Vote in Western Europe, 1980-2002." *American Journal of Political Science* 53(2): 259-275.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103(5): 1553-97.

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103(6): 2121-2168.

Autor, David H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives* 29(3): 3-30.

Autor, David H., David Dorn, Gordon H. Hanson, and Kaveh Majlesi. 2016. "Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure." NBER WP 22637.

Ballard-Rosa, Cameron, Mashail Malik, Stephanie Rickard, and Kenneth Scheve. 2018. "The Economic Origins of Authoritarian Values: Evidence from Local Trade Shocks in the United Kingdom." Unpublished manuscript, Department of Political Science, UNC Chapel Hill.

Ballard-Rosa, Cameron, Amalie Jensen, and Kenneth Scheve. 2019. "Economic Decline, Social Identity, and Authoritarian Values in the United States." Unpublished manuscript, Department of Political Science, UNC Chapel Hill.

Betz, Hans-Georg. 1993. "The New Politics of Resentment: Radical Right-Wing Populist Parties in Western Europe." *Comparative Politics* 25(4): 413-427.

Betz, Hans-Georg. 1994. *Radical Right-Wing Populism in Western Europe*. Springer.

Betz, Hans-Georg, and Susi Meret. 2009. "Revisiting Lepanto: The Political Mobilization against Islam in Contemporary Western Europe." *Patterns of Prejudice* 43(3-4):313-334.

Betz, Hans-Georg, and Susi Meret. 2012. "Right-Wing Populist Parties and the Working-Class Vote." In Jens Rydgren (ed.), *Class Politics and the Radical Right*, Oxford, UK: Routledge, 107-121.

Bornschier, Simon. 2005. "United against Globalization: An Analysis of Convergence in the Programs of Right-Wing Populist Parties in Europe." *Revue Internationale de Politique Comparée* 12(4): 415-432.

Bornschier, Simon and Hanspeter Kriesi. 2013. “The populist right, the working class, and the changing face of class politics.” In Jens Rydgren (ed.), *Class Politics and the Radical Right*, Oxford, UK: Routledge, 10-29.

Brancati, Dawn. 2016. *Global Elections Database* [computer file]. New York: Global Elections Database [distributor].

Burgoon, Brian. 2012. “Partisan Embedding of Liberalism: How Trade, Investment, and Immigration Affect Party Support for the Welfare State.” *Comparative Political Studies* 45(5): 606-635.

Cantoni, Davide, Felix Hagemeister, and Mark Westcott. 2019. “Persistence and Activation of Right-Wing Political Ideology.” Unpublished manuscript, Department of Economics, Ludwig-Maximilians-Universität München.

Cerrato, Andrea, Federico Maria Ferrara, and Francesco Ruggieri. 2018. “Why Does Import Competition Favor Republicans? Localized Trade Shocks, Voting Behavior, and Scapegoating in the US.” Unpublished manuscript, Department of Economics, UC Berkeley.

Che, Yi, Yi Lu, Justin R. Pierce, Peter K. Schott, and Zhigang Tao. 2016. “Does Trade liberalization with China Influence US Elections?”. NBER WP 22178.

Chiacchio, Francesco, Georgios Petropoulos, and David Pichler. 2018. “The Impact of Industrial Robots on EU Employment and Wages: A Local Labour Market Approach.” Bruegel Working Papers.

Colantone, Italo, and Piero Stanig. 2018a. “The Trade Origins of Economic Nationalism: Import Competition and Voting Behavior in Western Europe.” *American Journal of Political Science* 62: 936-953.

Colantone, Italo, and Piero Stanig. 2018b. “Global Competition and Brexit.” *American Political Science Review* 112: 201-218.

Cusack, Thomas, Torben Iversen, and Philipp Rehm. 2006. "Risks at Work: The Demand and Supply Sides of Government Redistribution." *Oxford Review of Economic Policy* 22 (3): 365-389.

Dal Bó, Ernesto, Frederico Finan, Olle Folke, Torsten Persson, and Johanna Rickne. 2018. "Economic Losers and Political Winners: Sweden's Radical Right." Unpublished manuscript, Department of Political Science, UC Berkeley.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner. 2018. "Adjusting to Robots: Worker-Level Evidence." Unpublished manuscript, Julius-Maximilians-Universität Würzburg.

De Vries, Catherine E. 2018. "The Cosmopolitan-Parochial Divide: Changing Patterns of Party and Electoral Competition in the Netherlands and Beyond." *Journal of European Public Policy* 25(11):1541-1565.

Di Tella, Rafael and Dani Rodrik. 2019. "Labor Market Shocks and the Demand for Trade Protection: Evidence from Online Surveys." NBER WP 25705.

Dippel, Christian, Robert Gold, and Stephan Heblich. 2015. "Globalization and Its (Dis-)Content: Trade Shocks and Voting Behavior." NBER WP 21812.

European Labor Force Survey. 2018. Eurostat.

European Social Survey. 2016. *European Social Survey Cumulative File, ESS 1-7. Data file edition 1.0.* NSD - Norwegian Centre for Research Data, Norway - Data Archive and distributor of ESS data for ESS ERIC.

Frey, Carl Benedikt, and Michael A. Osborne. 2017. "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Technological Forecasting and Social Change* 114:254-280.

Frey, Carl Benedikt, Thor Berger, and Chinchih Chen. 2018. "Political Machinery: Did Robots Swing the 2016 US Presidential Election?" *Oxford Review of Economic Policy* 34(3): 418-442.

Frieden, Jeffry A. 2018. "The Politics of the Globalization Backlash: Sources and Implications." Unpublished manuscript, Department of Government, Harvard University.

Gallego, Aina, Thomas Kurer, and Nikolas Schöll. 2018. "Not So Disruptive After All: How Workplace Digitalization Affects Political Preferences." Unpublished manuscript, Barcelona Institute of International Studies.

Gamez-Djokic, Monica, and Adam Waytz. 2019. "Concerns About Automation and Negative Sentiment Toward Immigration." Unpublished manuscript, Kellogg School of Management, Northwestern University.

Gennaioli, Nicola, and Guido Tabellini. 2018. "Identity, Beliefs, and Political Conflict." CEPR Discussion Paper No. DP13390.

Gest, Justin, Tyler Reny, and Jeremy Mayer. 2018. "Roots of the radical right: Nostalgic deprivation in the United States and Britain." *Comparative Political Studies* 51(13): 1694-1719.

Gidron, Noam, and Peter A. Hall. 2017. "The Politics of Social Status: Economic and Cultural Roots of the Populist Right." *British Journal of Sociology* 68: S57-S84.

Gidron, Noam, and Peter A. Hall. 2018. "Populism as a Problem of Social Integration." Unpublished manuscript, Woodrow Wilson School of Public and International Affairs, Princeton University.

Golder, Matt. 2003. "Explaining Variation in the Success of Extreme Right Parties in Western Europe." *Comparative Political Studies* 36(4): 432-466.

Goldin, Claudia and Lawrence F. Katz. 1998. "The Origins of Technology-Skill Complementarity." *Quarterly Journal of Economics* 113(3):693-732.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review* 104(8): 2509-26.

Graetz, Georg, and Guy Michaels. 2018. "Robots at Work." *Review of Economics and Statistics* 100(5): 753-768.

Guiso, Luigi, Helios Herrera, Massimo Morelli, and Tommaso Sonno. 2017. "Populism: Demand and Supply." Center for Economic Policy Research Discussion Paper 11871.

Hall, Peter A., and Georgina Evans. 2019. "Representation Gaps: Changes in Popular Preferences and the Structure of Partisan Competition in the Developed Democracies." Unpublished manuscript, Minda de Gunzburg Center for European Studies, Harvard University.

Hooghe, Liesbet, and Gary Marks. 2018. "Cleavage Theory Meets Europe's Crises: Lipset, Rokkan, and the Transnational Cleavage." *Journal of European Public Policy* 25(1): 109-135.

Im, Zhen Jie, Nonna Mayer, Bruno Palier, and Jan Rovny. 2019. "The 'Losers of Automation': A Reservoir of Votes for the Radical Right?" *Research & Politics* 6(1) : 1-7.

ISSP Research Group. 1999. *International Social Survey Programme: Work Orientations II - ISSP 1997.* GESIS Data Archive, Cologne. ZA3090 Data file Version 1.0.0, doi:10.4232/1.3090

Ivarsflaten, Elisabeth, and Rune Stubager. 2012. "Voting for the Populist Radical Right in Western Europe: The Role of Education." In Jens Rydgren (ed.), *Class Politics and the Radical Right*, Oxford, UK: Routledge, 122-137.

Jensen, Bradford J., Dennis P. Quinn, and Stephen Weymouth. 2017. "Winners and Losers in International Trade: The Effects on US Presidential Voting." *International Organization* 71(3): 423-457.

Keman, Hans. 2011. "Third Ways and Social Democracy: The Right Way to Go?" *British Journal of Political Science* 41(3): 671-680.

Kitschelt, Herbert, and Anthony J. McGann. 1997. *The Radical Right in Western Europe: A Comparative Analysis.* Ann Arbor: University of Michigan Press.

Kitschelt, Herbert. 2012. "Social Class and the Radical Right: Conceptualizing Political Preference Formation and Partisan Choice." Jens Rydgren (ed.), *Class Politics and the Radical Right*, Oxford, UK: Routledge, 242-269.

Kitschelt, Herbert, and Philipp Rehm. 2014. "Occupations as a Site of Political Preference Formation." *Comparative Political Studies* 47(12): 1670-1706.

Kollman, Ken, Allen Hicken, Daniele Caramani, David Backer, and David Lublin. 2017. *Constituency-Level Elections Archive* [data file and codebook]. Ann Arbor, MI: Center for Political Studies, University of Michigan [producer and distributor].

Kriesi, Hanspeter. 1998. "The Transformation of Cleavage Politics: The 1997 Stein Rokkan Lecture." *European Journal of Political Research* 33(2): 165-185.

Kriesi, Hanspeter, Edgar Grande, Romain Lachat, Martin Dolezal, Simon Bornschier, and Timotheos Frey. 2006. "Globalization and the Transformation of the National Political Space: Six European Countries Compared." *European Journal of Political Research* 45(6): 921-956.

Kriesi, Hanspeter, Edgar Grande, Martin Dolezal, Marc Helbling, Dominic Höglinger, Swen Hutter, and Bruno Wüest. 2012. *Political Conflict in Western Europe.* New York: Cambridge University Press.

Lowe, Will, Kenneth Benoit, Slava Mikhaylov, and Michael Laver. 2011. "Scaling Policy Preferences from Coded Political Texts." *Legislative Studies Quarterly* 36(1): 123-155.

Malgouyres, Clement. 2014. "The Impact of Exposure to Low-Wage Country Competition on Votes for the Far-Right: Evidence from French Presidential Elections." Unpublished manuscript, Department of Economics, European University Institute. https://goo.gl/wLbZRJ.

Margalit, Yotam. 2011. "Costly Jobs: Trade-Related Layoffs, Government Compensation, and Voting in US Elections." *American Political Science Review* 105(1): 166-188.

Margalit, Yotam. 2012. "Lost in Globalization: International Economic Integration and the Sources of Popular Discontent." *International Studies Quarterly* 56(3): 484-500.

Margalit, Yotam. 2013. "Explaining Social Policy Preferences: Evidence from the Great Recession." *American Political Science Review* 107(1):80-103.

Margalit, Yotam. 2019. "Political Responses to Economic Shocks." *Annual Review of Political Science* 22.

Oesch, Daniel. 2006. *Redrawing the Class Map: Stratification and Institutions in Britain, Germany, Sweden and Switzerland*. Springer.

Oskarson, Maria, and Marie Demker. 2015. "Room for Realignment: The Working-Class Sympathy for Sweden Democrats." *Government and Opposition* 50(4): 629-651.

Rehm, Philipp. 2009. "Risks and Redistribution: An Individual-Level Analysis." *Comparative Political Studies* 42(7): 855-881.

Spierings, Niels, and Andrej Zaslove. 2015. "Gendering the Vote for Populist Radical-Right Parties." *Patterns of Prejudice* 49(1-2): 135-162.

Spies, Dennis, and Simon T. Franzmann. 2011. "A Two-Dimensional Approach to the Political Opportunity Structure of Extreme Right Parties in Western Europe." *West European Politics* 34(5): 1044-1069.

Steenvoorden, Eefje and Eelco Harteveld. 2018. "The appeal of nostalgia: the influence of societal pessimism on support for populist radical right parties." *West European Politics* 41(1): 28-52.

Stubager, Rune. 2008. "Education Effects on Authoritarian-Libertarian Values: A Question of Socialization." *British Journal of Sociology* 59(2): 327-350.

Swank, Duane, and Hans-Georg Betz. 2003. "Globalization, the Welfare State and Right-Wing Populism in Western Europe." *Socio-Economic Review* 1(2): 215-245.

Thewissen, Stefan, and David Rueda. 2019. "Automation and the Welfare State: Technological Change as a Determinant of Redistribution Preferences." *Comparative Political Studies* 52(2): 171-208.

van Hoorn, Andre. 2018. "The Political Economy of Automation: Occupational Automatability and Preferences for Redistribution." Unpublished manuscript, Institute for Management

Research, Radboud University.

Volkens, Andrea, Pola Lehmann, Theres Matthiess, Nicolas Merz, Sven Regel, and Bernhard Wessels. 2018. *The Manifesto Data Collection. Manifesto Project (MRG/CMP/MARPOR). Version 2018a.* Berlin: WZB. https://doi.org/10.25522/manifesto.mpds.2018a

Zaslove, Andrej. 2008. "Exclusion, Community, and a Populist Political Economy: The Radical Right as an Anti-Globalization Movement." *Comparative European Politics* 6(2): 169-189.

A 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

B 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

C 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^+_{lct} contains the number of claims coded in categories 401, 402, 414 and 505, while z^-_{lct} refers to codes 403, 404, 405, 409, 412, 413, and 504.

For the computation of the *Net Autarky* score, z^+_{lct} contains the number of claims coded in categories 406, 109, and 110, while z^-_{lct} 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.