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

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Abstract

We investigate the impact of automation on electoral outcomes in 15 Western European countries, between 1993 and 2016. In particular, we focus on the structural change induced by the adoption of industrial robots across industries and regions. We employ both official election results at the district level and individual-level voting data from the European Social Survey, combined with party ideology scores from the Manifesto Project. We measure the 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, both at the regional and individual level.

Keywords: Automation; Nationalism; Radical Right.

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1 Introduction

Nationalist and radical-right parties and candidates have been increasingly successful in Western democracies over the past three decades. A growing stream of research relates such political developments to the distributional consequences of structural changes in the economy. In particular, a number of studies shows how globalization, and more specifically the economic distress driven by the China shock, has had an anti-incumbent and polarizing effect on politics in the US (Margalit 2011; Autor et al. 2016; Che et al. 2016; Jensen et al. 2016), and has led to higher support for nationalist, isolationist, and radical-right parties in Western Europe (Colantone and Stanig 2018a, 2018b; Malgouyres 2014; Dippel et al. 2016; Guiso et al. 2017).

In this paper, we set out to study the political consequences of automation. Specifically, we focus on the shock driven by the adoption of industrial robots between the early 1990s and 2016. Similarly to globalization, this wave of automation has led to productivity and welfare gains, but it has also produced substantial distributional effects. These have penalized in particular those regions that were ex-ante more vulnerable to the adoption of robots, due to their historical industry specialization, and those individuals whose skills were more substituted than complemented by the new technologies, especially workers with less than college education and blue-collar workers employed in routine manual tasks and assembling. Evidence along these lines has been provided by Acemoglu and Restrepo (2018) for the US, Dauth et al. (2018) for Germany, Chiacchio et al. (2018) across six European countries, and Graetz and Michaels (2018) on a larger set of 17 countries. Our aim is investigating the political implications of this phenomenon.

We focus on fifteen Western European countries, between 1993 and 2016. We rely on two alternative and complementary identification strategies to estimate the causal impact of automation on voting behavior. The first strategy exploits regional variation in exposure to robot adoption. In particular, we adopt the measurement approach developed by Acemoglu and Restrepo (2018), which attributes stronger automation shocks to regions historically specialized in industries where more robots have been adopted over the sample period. We then use this regional exposure to automation as the main regressor in specifications that have as dependent variables different measures of the ideological leaning of electoral districts in each election. Specifically, we focus on three electoral outcome variables: (1) the nationalism score of the party voted by the median voter in each district; (2) the average nationalism score of the parties voted in each district, weighted by the parties' vote shares; and (3) the vote share for radical-right parties in each district. The nationalism scores are computed based on the manifesto of each party in each election, as coded by the Manifesto Project (Volkens et al., 2018). We address the endogeneity concerns as in Acemoglu and Restrepo (2018). Specifically, we instrument the adoption of robots in each country and industry using the adoption of robots in the same industry but in different countries. This instrumental variable approach is designed to capture the role of industry-specific technological shifts that are plausibly exogenous to country-specific political developments.

The second strategy leverages individual-level data from the European Social Survey (ESS) to capture within-region variation across individuals. We introduce a new measure of individual exposure to robot adoption. This measure is computed by interacting the overall rate of robot adoption in each country with a measure of individual vulnerability to robots. Such vulnerability is in turn obtained by combining individual estimates of the probability to be employed in each occupation, with an automatability index of each occupation. Crucially, the individual probabilities are estimated using individual characteristics and historical information on the composition of employment in each region. In particular, we compute them by combining the ESS data with pre-sample data from the European Labor Force Survey (EU-LFS). Intuitively, our methodology assigns higher vulnerability scores to individuals whose educational profile, age, gender, and region of residence would have made them more likely to work in occupations whose estimated automatability is higher. As an index of automatability, we use either the one made available by Frey and Osborne (2017), or our own estimates based on individual data from the International Social Survey Program (ISSP).

Our empirical approach builds upon the idea that automation not only affects workers initially employed in specific industries, but might also reduce job opportunities for prospective workers with certain characteristics in a given region. For instance, we can capture the fact that, due to automation, some workers who might have obtained a well-paid routine job in the automotive industry find themselves employed in low-wage service occupations. This empirical strategy constitutes an original contribution to the literature studying the effects of automation and has multiple advantages. First, it allows to capture potential heterogeneous effects across individuals, even within the same region. Second, it makes it possible to control in the econometric analysis for region-specific trends, which absorb unobserved long-term political dynamics at the regional level that might be confounded with the increase in robot adoption. 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 as compared to the regional indicator.

Our results show that automation shocks have political effects that are detectable in 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. The individual-level findings are consistent with the district-level results, showing that individuals that are more exposed to automation are substantially more likely to vote for radical-right parties and parties with higher nationalism scores. Exposure to automation has instead a negative effect on support for liberal-right parties, and pro-trade left parties. Our results are robust to using different measures of vulnerability, including the one based on the routine task-intensity index by Autor and Dorn (2013). Moreover, we perform a large number of additional robustness checks in which: (1) we control for different sets of fixed effects and region-specific trends; (2) we control for other economic shocks, including trade and ICT; (3) we change the set of countries used to construct the instrument; and (4) we restrict our analysis to older individuals, who are unlikely to have endogenously changed their level or type of education in response to the automation shock.

2 Technology and the labor market

Technological progress and innovation are primary determinants of economic growth and improvements in living standards. Yet, shifts in technology determine distributional consequences in society by affecting labor market dynamics. Intuitively, every technological innovation opens new opportunities for workers endowed with skills that are complementary to the new technologies, but at the same time there is a range of workers who lose out as they are more substitutable by machines. In simple words, technology produces winners and losers, at least in relative terms.

The groups of winners and losers may vary depending on the nature of technological changes and other conditions. To provide some historical perspective, in the nineteenth century the introduction of machines in manufacturing benefited large numbers of low-skill workers while penalizing specialized high-skill artisans (Goldin and Katz 1998). Indeed, the breakdown of production activities in simple machine-assisted tasks at factories allowed low-skill workers to engage in the production of goods that would previously require specific expertise in artisanal shops. Physical capital thus complemented low-skill labor, while substituting high-skill labor. This pattern turned around in the early twentieth century, when technological advances started to favor more skilled workers. According to Goldin and Katz (1998), this shift was first driven by the electrification of factories and by the spread of continuous-process and batch production methods. These advancements reduced the need for large numbers of unskilled manual workers while raising the demand for relatively skilled blue-collar workers and high-skill white-collars.

The complementarity between technology and skills was reinforced in the second half of the twentieth century by the computer revolution, with the widespread adoption of IT and computer-based technologies. In particular, during the 1980s and 1990s there was a sharp increase in computer power, and computing costs dropped on average by 64% per year (Nordhaus 2007). At the same time, these years marked a surge in wage inequality and educational premia both in the US and in Europe. A large body of economic literature points to technological change as a main reason behind these labor market dynamics, which have fostered social cleavages in Western democracies (Acemoglu and Autor 2011).

In order to understand the labor market implications of computer-based technologies, economists have started by reflecting on what computers can and cannot do. In particular, computers and computer-based machines are good at performing routine, codifiable tasks, both of the cognitive and manual type. On the contrary, they are much less capable of performing non-routine tasks involving abstract thinking, creativity, social interaction, and the manual ability to work in irregular environments. Accordingly, as computer-based technologies became ubiquitous, the most penalized workers have been those performing routine tasks, while jobs involving mostly non-routine tasks have been complemented by the shift in technology. Since routine jobs –both manual and cognitive– were mostly middle-income and middle-skill jobs, the outcome has been a so-called "polarization" of the labor market, which has been documented both in the US and in Europe (Autor and Dorn 2013; Goos et al. 2014).

By polarization we mean a relative increase in the number of people employed at the two tails of the wage and skill distribution, along with a shrinkage of the traditional middle class. For instance, computers have destroyed many decently paid clerical jobs for white collars, while the computer-based automation of production processes has reduced job opportunities for relatively skilled blue collars. These workers (both actual and prospective) 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, to provide some paradigmatic examples).

In terms of wage gains, the main computerization winners have been the high-skill (college-educated) workers in cognitive occupations, who have been strongly complemented by the new technologies. 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 only to a lesser extent compared to 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 has been a continuous expansion of the capabilities of computer-based technologies. In particular, in a widely cited paper, Frey and Osborne (2017) have identified two major developments: machine learning and mobile robotics. Both of them are taking computerization to the next level by allowing for the automation of non-routine tasks. Specifically, machine learning allows for the computerization of non-routine cognitive tasks in data mining, machine vision, computational statistics and other forms of artificial intelligence. This technology has path-breaking applications in multiple fields, from medical diagnostics to financial and legal services, as well as marketing and education. Mobile robotics allows for the automation of an expanding array of non-routine manual tasks. These involve not only assembly line operations in factories, but also domains such as demolition and construction, maintenance of industrial plants, logistic services, transportation, and mining activities.

The wide and unprecedented reach of these new technologies has revamped people's fears and a huge public debate on technological unemployment. Several assessments of the potential job displacement have been made. For instance, Frey and Osborne (2017) estimate that 47% of US workers are employed in occupations at high risk of automation over the coming two decades.[1] Their estimate is based on a detailed study on the probability of computerization of each occupation, depending 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; (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. In their study, Frey and Osborne show that the occupations that are more threatened by the new wave of automation are those characterized by lower wages and a less educated workforce. Hence, once again, the main winners of the technological shift seem to be the high-skill, high-wage individuals. This is consistent with the observation that wage inequality has kept increasing over the past two decades (Autor 2015).

Besides studies such as Frey and Osborne (2017), which attempt to forecast the potential displacement of automation in the coming years, a few recent papers have started to investigate the actual economic effects of the most recent automation wave, from the mid-1990s onwards. Specifically, these studies exploit detailed data on the adoption of industrial robots within several countries at the industry level, as made available by the International Federation of Robotics (IFR). According to these data, the stock of operational robots in advanced economies has in-

[1] Similar figures have been obtained by McKinsey (45%) and by the World Bank focusing on OECD countries (57%).

creased substantially 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, thus contributing to the increase in wage inequality. These findings are broadly consistent with the analysis by Frey and Osborne (2017) on the characteristics of the most vulnerable occupations, and square with the results obtained by Graetz and Michaels (2018) on a larger sample of countries. In particular, using industry-level data, they find that robot adoption has a positive effect on productivity, but a negative impact on the share of hours worked by low-skill workers.

In a recent working paper, Chiacchio et al. (2018) perform a similar analysis as in Acemoglu and Restrepo (2018), but focusing on six European countries. They also find a negative effect of robot adoption on employment at the level of local labor markets, but do not detect robust negative effects on wages. Dauth et al. (2018) investigate the impact of industrial robots using matched employer-employee data for Germany. They find that the adoption of robots leads to job losses in manufacturing. However, these losses are compensated by employment gains elsewhere, mostly in the business service sector. Hence, overall they do not detect negative employment effects at the local labor market level, although less manufacturing jobs become available for the young new entrants in the labor market. Using individual data, they find that affected workers mostly stay with the same employer, but change their occupation and incur wage losses. Overall, automation increases wage inequality. Indeed, it benefits managers and high-skill workers performing abstract tasks, while there are negative earnings effects for low- and medium-skill workers, and 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

We investigate the political consequences of the most recent automation wave, focusing specifically on the adoption of industrial robots. In order to understand the theoretical link between automation and voting, we need to start by reckoning that technological progress in general, and automation in particular, 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 machines, but also sizable segments of the traditional middle class. Automation has indeed reduced those mid-level, relatively well-paid, and also quite secure job opportunities that had been the backbone of manufacturing employment in the golden decades of Western European welfare states.

The literature on the political implications of structural economic changes has so far mostly focused on the effects of globalization, especially in terms of rising import competition from China and other low-wage emerging economies. Globalization-induced economic distress has been singled out as one of the factors behind the growing appeal of nationalist, authoritarian, and anti-cosmopolitan platforms (Bornschier 2005; Kriesi et al. 2006; Swank and Betz 2003; Zaslove 2008), and therefore as one of the structural drivers of the so-called "Populist Zeitgeist" (Mudde 2004). In particular, import competition in advanced countries has been shown to shift voter support towards nationalist options and radical-right parties and candidates (Autor et al. 2016; Che et al. 2016; Colantone and Stanig 2018a, 2018b; Dippel et al. 2016; Guiso et al. 2017;

Jensen et al. 2016; Malgouyres 2014; Margalit 2011).

The economic effects of automation are very similar to those of globalization. These two phenomena constitute two facets of structural change that have profound distributional consequences. They open cleavages within national societies by raising inequality both across geographic areas and across groups of individuals. In what follows, we outline the theoretical reasons why automation, similarly to globalization, might increase support for nationalist and radical-right parties.

A theoretical framework that has been fruitfully employed in order to explain the recent political backlash is the "crisis of embedded liberalism" (Colantone and Stanig 2018a; Hays 2009). That is, the crisis of the socio-political equilibrium that has characterized Western democracies for many decades after World War II. This equilibrium was characterized, especially in Western Europe, by a fortunate combination of liberal economic policies and generous welfare states, thereby sustained economic growth led to widespread improvements in living standard and to the creation of a large and wealthy middle class. Welfare provisions provided a buffer for economic shocks induced by globalization and innovation (Cameron 1978, Rodrik 1998). Strong trade unions and progressive taxation reduced income inequality and provided financial resources for the system to work effectively. Political support for this European social market economy model was channeled through support for mainstream parties, chiefly social-democratic and Christian-democratic parties.

This model has entered a crisis from the 1990s onwards, as first discussed by Rodrik (1997). The liberalization of capital flows made it increasingly difficult for governments to raise sufficient tax revenues from multinationals and top individual earners. At the same time, workers were exposed to stronger structural shocks like rising imports from China and automation. The system was not effective at managing the adjustment costs of these shocks and preventing inequalities from rising. The whole embedded liberalism model started to lose credibility, and the traditional mainstream parties that backed it started to lose support. The recent financial crisis, and the sovereign-debt crisis the has plagued Western Europe for many years, have made the crisis of embedded liberalism even more evident. Losers of globalization and automation do not perceive the promise of compensation coming from mainstream parties as being credible anymore, and turn to anti-establishment forces of the nationalist and radical-right type.

Why are these parties appealing to automation losers? There are multiple reasons. A first, and relatively obvious one, is that they are perceived as new and different compared to the traditional mainstream parties. Even though some radical-right parties, like the National Front in France, have a relatively long history, most of them have never really been in government positions. Hence, to the extent that economic distress leads to generalized anti-incumbent sentiments, these parties provide an appealing option for voters who are dissatisfied not only with a specific incumbent government, but also with the system at large.

Moving beyond the simple anti-incumbent motivation, it is important to focus on the political platforms of nationalist and radical-right forces. Earlier work has identified "economic nationalism" as a fundamental trait of these parties (Colantone and Stanig 2018a). Besides a common nationalist rhetoric, the economic nationalism platform entails two main elements from the economic policy point of view: protection of workers and lower taxes. The protection of workers is cast in different ways, encompassing both nationalist protectionism in international trade, and proposals to fight job losses due to automation by directly taxing companies adopting robots. As a matter of fact, globalization and automation are clearly intertwined economic phenomena, which companies and workers face at the same time, and whose economic effects are difficult to tease out from each other even for researchers, let alone for voters. Nationalist and radical-right parties offer a generalized promise of protection, conveyed to voters through a rhetoric that involves not only the idea of taking-back-control of the country from global impersonal forces, but also the defense of a traditional way of life that supposedly characterized the nation before computers and robots had a disruptive impact on society. This approach typically involves the defense of the traditional family, with a strong role for the male head of household empowered by a well-paid and stable job.

Coming to the second element of economic nationalism, promises of tax reductions are always particularly appealing to the middle class. This becomes even more the case when the middle class has witnessed an erosion of job opportunities, relative income, and status due to automation. All these factors explain why exposure to the robot shock might tilt voters in a nationalist and radical-right direction.

Having described the crisis of embedded liberalism as driven by a failure of redistribution, 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. This question is particularly relevant in light of the findings of two recent studies that show how workers employed in occupations that are more at risk of automation report preferences for more redistribution (Thewissen and Rueda 2019; van Hoorn 2018). These findings resonate with those of an established literature showing how exposure to economic distress, including 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 who are more exposed to automation risk. These automation-induced preferences for redistribution and government intervention would be expected to orient voters towards parties of the left. Whether this happens or not is ultimately an empirical question, which we address in our econometric analysis. 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. There are several theoretical explanations for this. We review them in what follows.

A first possible explanation involves labor unions, whose role 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. Moreover, by reducing employment in manufacturing and tilting it towards the service sector, automation also reduces the number of workers that are unionized or easily reached by unions. Since labor unions have historically been an important link between left parties and their blue-collar constituencies, as suggested by Kitschelt (2012), their reduced importance might be a reason why automation losers have turned more towards nationalist and radical-right forces rather than left parties.

A second possible explanation is that promises of redistribution and compensation of losers have become less appealing and credible over time, due to the above mentioned fiscal constraints faced by governments, especially since the financial crisis. In a parallel process, significant convergence between mainstream left and mainstream right in terms of redistribution and welfare state policies took place, weakening the link between working class constituencies and social democratic parties (Oskarson and Demker 2015; Spies and Frantzmann 2011). This convergence can arguably be attributed in large part to structural determinants. In particular, the centrist move of mainstream left parties (e.g., the Third Way) might have been dictated by these fiscal constraints. Moderating the economic platforms helped the mainstream left capture more economically centrist voters, especially the so-called socio-cultural (semi-)professionals, who were attracted to left parties mostly because of their stances in terms of cosmopolitan values (Keman 2011; Kitschelt 2012; Kriesi 1998). At the same time, this process led to the defection from social-democratic parties of their traditional target constituencies of low- and medium-skill manufacturing workers, which became increasingly important in the electorate of the radical right (Betz and Meret 2012).

Yet, radical-right parties tend to propose platforms that are not particularly redistributive, as initially understood by Kitschelt and McGann (1997), and more recently shown by Colantone and Stanig (2018a). A recent move of these parties towards the center in terms of economic policies has been documented (Ivaldi 2015; de Lange 2007; Schumaker Van Kerseberger 2016). But even then, the support of radical-right parties for the welfare state is always qualified, involving access restricted to natives as per "Welfare Chauvinism" (de Koster et al. 2013; Schumaker Van Kerseberger 2016; Van der Waal et al 2010). According to what was dubbed the "winning formula" by Kitschelt and McGann (1997), 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. Hence, due to strategic placement considerations, radical-right parties might run the risk of alienating their petty bourgeois and white-collar constituencies if they were to further move leftwards in terms of redistribution platforms.

The intuition by Kitschelt and McGann (1997) suggests that automation losers might be pushed towards the radical right notwithstanding its economic conservatism, for reasons that have more to do with nativism and authoritarianism. This leads to the third possible reason why the left has not benefited from the automation shock, a reason that is related to low-level psychological phenomena leading to a change in people's attitudes. 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; Colantone and Stanig 2018c). This type of reaction would naturally push voters towards nationalist and radical-right parties, and away from left parties that have a reputation of proletarian international solidarity (Betz and Meret 2012, Kriesi et al. 2012). Not by chance, opposition to immigration 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; Ivarsflaten 2008; Lucassen and Lubbers 2012).

In addition, other studies show that economic insecurity is associated with less trust in political institutions (Algan et al. 2017; Guiso et al. 2017). All this evidence points to an interaction between economic and cultural factors in explaining the political backlash. Gidron and Hall (2017) provide the most complete line of argumentation in this direction, claiming that the effects of economic, as well as culturalhanges are channeled by social status. The process that matters the most in our context is the following. First, 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. In addition, 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). Third, 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 higher skills 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 across countries compared to previous generations. In turn, self-reported social status is found to be significantly associated with support for the radical right.

All the processes we have discussed lead to an opposition to the cosmopolitan agenda that encompasses lifestyle choices, individual freedoms, immigration, technological progress and globalization. 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 (Hooghe and Marks 2018; Margalit 2012). Indeed, Euroscepticism 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 three contributions that, like ours, directly link recent technological developments to voting behavior. All of them are single-country studies. Gallego et al. (2018), using data from the UK, show that one facet of the IT revolution, namely computerization, has detectable political implications. The 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 radical-right option, namely the UKIP. Yet, due to limited data to answer this type of question, 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. (2017) 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 which, in many of its facets, resembled those of the European radical right, both in economic and identitarian terms. Finally, Finan et al. (2018) study patterns of support for the Sweden Democrats in local elections. They show that the share of automation-vulnerable workers in a municipality is robustly correlated with support for the radical-right option.

This paper aims to push further our understanding of the political implications of technological change. We provide cross-country causal evidence on the effects of automation, by exploiting detailed information on robot adoption at the industry level, and employing an identification strategy that exploits plausibly exogenous cross-country technological trends. Moreover, we exploit both regional and individual measures of automation exposure. In particular, the individual measure is meant to capture the effects of automation not only for workers initially employed in specific industries, but also for prospective workers who might miss well-paid and stable job opportunities due to automation. The way we measure individual exposure to automation, based on a counter-factual exercise, is itself a novel methodological contribution to the literature.

4 Measurement of exposure to automation

We follow two complementary empirical approaches: we measure the exposure to robot adoption at the regional level, based on the historical industry specialization of each region, and the vulnerability to automation at the individual level, capturing differences across voters.

4.1 Regional exposure

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

$$\text{Reg Exp}_{crt} = \sum_j \frac{L_{crj}^{\text{pre-sample}}}{L_{cr}^{\text{pre-sample}}} \frac{R_{cj}^{t-1} - R_{cj}^{t-n}}{L_{cj}^{\text{pre-sample}}}, \tag{1}$$

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: 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, this ratio is 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.

We calculate our regional measure combining two different data sources. We retrieve employment data for 194 NUTS-2 administrative regions from national sources and Eurostat. Table A1 in the Online Appendix reports year and source for each country in our sample. Yearly data on the stocks of industrial operational robots in each NACE Rev. 1.1 industry of 15 European countries –and some advanced countries outside of Europe– are published by the International Federation of Robots.[2] The average yearly change in the stock of operational robots between 1993 and 2016 is an increase of 6.3 robots for every 100,000 workers in the region, with a standard deviation of 9.5. In some regions and years the yearly increase in the number of operational robots has been as much as 94 industrial robots for every 100,000 workers.

Our regional measure of exposure to automation can be included in regressions of district level vote summaries; however, one could be concerned with endogeneity from various sources. First, robot adoption tends to be pro-cyclical: firms install more robots during periods of economic growth. If economic cycles are associated to patterns of support for given sets of parties, the estimates of the impact of robots on voting are biased. Second, robots may be installed at higher pace in regions that have stronger labor unions. Depending on whether unions are related to political parties, the estimates could also suffer from endogeneity. Finally, more robots might be installed in regions that strengthen employment protection legislation, making 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. To address these concerns, we instrument our exposure to automation with the pace of adoption of robots, by industry, in all other European countries in the main analysis, and other advanced economies outside of Europe in the robustness checks.

We define our instruments as

$$\text{IV Reg Exp}_{crt} = \sum_{j} \frac{L_{crj}^{\text{pre-shock}}}{L_{cr}^{\text{pre-shock}}} * \frac{\bar{R}_{-c,j}^{t-1} - \bar{R}_{-c,j}^{t-n}}{L_{cj}^{\text{pre-shock}}} \tag{2}$$

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

[2]For the Netherlands, Belgium, Austria, Portugal, Switzerland, Ireland and Greece, robot data disaggregated by industry are not available for the earliest years. For these years we have allocated the total number of robots to industries based on the average share of total operational robots in that industry and country in the years for which the robot stock data are available with industry level disaggregation.

main specification, $\bar{R}^{t-1}_{-c,j} - \bar{R}^{t-n}_{-c,j}$ is the change in the average stock of operational robots in industry j of all other European countries (i.e. excluding c) between year $t-1$ and year $t-n$. The term replaces $R^{t}_{cj} - R^{t-n}_{cj}$ in the regional exposure to automation as per Equation 1. In the robustness checks, we construct $\bar{R}^{t-1}_{-c,j} - \bar{R}^{t-n}_{-c,j}$ respectively using data about robot adoption in North America, and in all the non-European advanced countries for which we have data (countries in North America, plus Japan and South Korea).

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 orthogonal to the political dynamics of each domestic region.

4.2 Individual exposure to automation

We introduce an individual-level measure of exposure to automation which builds upon the idea that automation not only affects workers employed in specific industries, but also reduces labor demand and therefore job opportunities for prospective workers. For instance, workers who might have obtained, in the absence of extensive automation, a well-paid job in a routine-type manual occupation in the automotive sector find themselves employed in low-wage service occupations. It is important, then, to have a measure of individual exposure to automation that is not contaminated by the consequences of automation itself. In particular, it might be the case that individuals that are employed at a given point in time in industries in which automation is prevalent are exactly those with complementary skills to robots. If we were to use as predictor a function of current occupation, we might pick up the voting behavior of respondents who operate in occupations at high risk of automation *in spite* of the surge in automation. Our aim, on the other hand, is to characterize the behavior of losers from automation, including those that have been expelled from high-automation occupations and those who were never able to enter a given occupation because automation reduced labor demand. Our measure captures this logic by combining estimates of individual vulnerability and patterns of robot adoption to arrive at a measure of individual exposure to automation. We formally define the individual exposure as:

$$\text{Ind Exp}_{it} = \frac{R_{c(i)}^{t-1} - R_{c(i)}^{t-n}}{R_{c(i)}^{t-n}} \sum_j \widehat{Pr}(o_i = j|\text{age}, \text{gender}, \text{edu}, r)\theta_j \tag{3}$$

where $\widehat{Pr}(o_i = j|\text{age}, \text{gender}, \text{edu}, r)$ is individual i's predicted probability of working in occupation j, predicted based on age, gender, educational attainment and region. The score θ_j is an estimate of the automation threat for occupation j. The individual vulnerability to robots of individual i (at time t) is obtained by summing the product $\widehat{Pr}(o_i = j|\text{age}, \text{gender}, \text{edu}, r)\theta_j$ over all occupations j and multiplying the resulting sum with the national percentage change in all operational robots between year $t-1$ and $t-n$.

The individual exposure is a weighted average of the threat score of each occupation multiplied by the pace of robot adoption (across all sectors) in the country, where the weights are the predicted probabilities for an individual to be in a given occupation. Intuitively, this score assigns higher values to individuals whose educational profile, age, gender, and region of residence would have made them more likely to work in an occupation whose estimated automatability is higher. The important element that allows us to avoid the issue of contamination discussed above is that we estimate the parameters of the occupation model, used for prediction, from the occupational patterns prevailing in the 1990s, before the latest spurt of automation and robot adoption.

In practice, we exploit historical data from the European Labor Force Survey (EU-LFS) to estimate multinomial logit models with the set of possible occupations as outcome variable and, as predictors, both individual characteristics (gender, age and educational attainment) and regional effects.[3]

We focus on the 2-digit occupational ISCO (International Standard Classification of Occupations) codes, and estimate the occupational choice models separately for each country.[4] We then use the estimates to predict $\widehat{Pr}(o_i = j|\text{gender}, \text{age}, \text{edu}, r)$, out of sample, for each individual in the first seven waves of the European Social Survey.

[3]Occupational codes are available in EU-LFS data starting 1992 for most countries in our data. We thus use 1992 to estimate our model. For some countries joining the European Union after 1992 we use data from the earliest available year.

[4]The pseudo R^2 of the multinomial logit models estimated separately for each country ranges between

The θ_j component of the individual vulnerability is an occupation-specific score of automation threat. We adopt two main strategies to assess this threat. The first strategy uses the estimates of the probability of computerization for over seven hundred occupations, based on the combination of expert data and detailed task content, from Frey and Osborne (2017). These estimates capture computerization of both routine and non-routine tasks. 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 calculate computerization probabilities for the 2-digit occupation ISCO codes used by the EU-LFS data.

The second strategy relies on information from the 1997 wave of the ISSP "Work Orientations" module, that 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 perceptions to estimate a measure of automation threat by occupation: assuming that workers in a given occupation have local knowledge about the impact of automation, we can treat respondents in a given occupation as "experts".[5] Our measure is akin to the one devised by van Hoos (2018). In order to obtain an occupation-specific measure of automation threat, at the two-digit ISCO occupation code, we restrict the analysis to advanced industrial democracies (excluding also the former Communist countries of Eastern and Central Europe). For most of the countries, the survey reports the three-digit or four-digit ISCO88 code of the respondent's occupation. For the UK, the OCC code is reported, while for Italy and Spain only the three-digit ISCO68 code is available. We recode these different classifications into the two-digit ISCO88 code using the appropriate crosswalks. The final sample of countries that enter the estimation of the occupation-specific perception of automation threat are Canada, Denmark, France, Germany, Italy, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the US, and the UK.

We then estimate the occupation-specific perceived threat via a model with random intercepts for occupation. In detail, we estimate a model of the form $y_i = \alpha + \beta_{k(i)} + \epsilon_i$ with $\beta \sim N(0, \sigma_\beta)$, where y_i is the perceived automation threat for respondent i, 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

[5] Alternatively, these can be read as the perceived threat of automation within occupational groups.

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 Hoos (2018) to estimate a similar summary on the same data. Using a random-intercept model has one main advantage: 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. This makes the measure more conservative: we discount large deviations from the grand mean for a given occupation when they are not backed by a sufficiently large number of respondents in the occupational cell. van Hoos (2018) on the other hand drops the occupational categories (two-digit ISCO) for which too few respondents are represented. For the main measure, we pool all available advanced countries.[6] We have estimates for more than thirty occupation categories, based on the perceptions of almost twenty thousand respondents in fourteen countries.

Finally, we calculate the individual exposure for ESS respondents by multiplying individual vulnerability by the pace of robot adoption at the country level. Our individual exposure has multiple advantages. First, it can capture potential heterogeneous effects across voters, even within regions. Second, it makes it possible to control for region-specific trends which absorb unobserved long-term political dynamics in each region 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 source of variation in terms of automation exposure. Moreover, the focus on occupational categories allows us to also detect the consequences of automation in sectors of the economy that are not considered by the regional exposure, such as utilities, construction and services.

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

[6]In addition, we also estimate analogous models: a) only for European countries –hence excluding the observations from Canada, New Zealand, and the US; b) pooling only the three non-European countries for which we have data ; c) excluding one country at a time.

survey data from the European Social Survey, with variation in individual-level voting behavior outcome variables explained by both regional and individual exposure to automation.

5.1 District-level election data

The starting point of the district level analysis are the results in legislative elections assembled from various sources: CLEA (Kollman et al. 2016), from which we get a majority of the elections, the Global Election Database (Brancati 2016), and in a few cases national sources. We have data on 73 elections in fifteen Western European countries, between the early 1990s and 2016. For all parties that are coded in the Manifesto Project data (Volkens et al. 2018), we assign by hand the Manifesto Project identifier code to each party in the election datasets. This makes it possible to then merge party-election level data on ideological stances (constant at the national level in a given election) with election returns, that vary by district in a given election.

We define various measures of ideology following Burgoon (2012), Colantone and Stanig (2018) and Burgoon et al. (2018). The scores are calculated from the Manifesto Project data according to the methodology recommended by Lowe et al. (2011). For the main analysis we calculate, for each party in each election, the score of *Nationalism* based on support for or opposition to "the national way of life", traditional morality, law and order, and multiculturalism. Based on the ideology scores and the district level election returns, we calculate some summaries at the district level:

- the Center of Gravity as the mean of the ideological scores weighted by the vote shares obtained by the parties in the district;
- the Median Voter Score, as the location of the median party.

Formally, the center of gravity for district d at time (election) t is defined as

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

where $\mathrm{Score}_{\ell t}$ 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 at election t.

While the Center of Gravity takes into account the positions of all parties in the district (and is sensitive to the ideological position also of the most extreme parties that received votes in the district and for which we have ideological scores), the Median Voter Score captures the location of a "centrist" voter in the district. In practice, parties are sorted from least- to most-nationalist, and the cumulative vote share is calculated (in the usual fashion, as the sum of the vote shares of a given party and all parties to its left in the distribution). The median voter score is the ideology of the party at which cumulative vote share reaches 50%: in substantive terms, the party chosen by a (sincere, proximity-driven) median voter on the nationalism dimension. In pure two-party systems like the United States, the median voter score would be equivalent to the ideological score of the district winner.

We also calculate some additional ideology scores from Manifesto data: *Nationalist Autarchy* that includes, on top of the items included in Nationalism, also stances about democracy, constitutionalism, international trade, the European Union, and international cooperation; *Economic Ideology*, on a classical left-right scale, from strong support for to strong opposition to redistribution, regulation, and Keynesian demand management; and *Net Autarky*, that captures the extent to which the platform of a party supports or opposes European integration, international trade, and internationalism (vs. isolationism). The latter two scores allow us to categorize political parties in one of four families: Pro-Trade Left, Liberal Right, Protectionist Right, and Protectionist Left. We first locate parties in the two-dimensional space defined by economic ideology and isolationist or pro-globalization stances. Parties are then classified as belonging to one side of the spectrum depending on whether their ideology score is above or below the median for that country in that given election.[7]

[7] As an additional check, we also create a party category, Protectionist Left Proper, that combines the information we compute on the quadrant in the two-dimensional policy space with qualitative information –coded by the Comparative Manifesto Project team– regarding party family. To be classified as Protectionist Left Proper, a party needs to belong to our category of protectionist and economic left parties, and in addition must be classified as socialist, communist, or green by the Manifesto dataset. This, in practice, excludes from the category of Protectionist Left economic interventionist and nationalist parties that are not, in general, part of the historical left spectrum. Examples of these parties are the Five Star Movement in Italy in the 2013 election, or the Party for the Animals in the Netherlands in several elections.

We also rely on a qualitative classification of radical right parties based on the conventional wisdom in the literature and an update of the scheme adopted in Colantone and Stanig (2018).[8]

Once we have classified parties, we combine this information with district level data to obtain further district-level summaries:

- Radical Right Share is the share obtained in a given district in a given election by parties classified as belonging to the radical right family;
- Protectionist Left Share, Protectionist Left Proper Share, Protectionist Right Share, Liberal Right Share and Pro-Trade Left Share are the vote shares obtained in a given district in a given election by parties belonging to each of the five categories.

At the district level, the specification of the regression analysis has the general form

$$\text{Electoral Outcome}_{cdt} = \alpha_{ct} + \beta_1 \text{Regional Exposure}_{cr(d)t} + \varepsilon_{cdt}, \tag{4}$$

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

$\text{Electoral Outcome}_{cdt}$ is one of the 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. Each observation is a district in a given election, and the main predictor of interest, the regional exposure to automation, is measured at the NUTS2 level (or at the NUTS1 level in selected cases), containing multiple districts. Standard errors are always clustered at the region-year level, which is how the treatment variable is assigned. The country fixed effects are meant to control for any factors that affect symmetrically all the districts within a country at the time of a given election. Examples of such factors are the political climate in the country, the political orientation of the incumbent government, and the general economic performance at the national level. The inclusion of country-year fixed effects imply that we identify the effect of the import shock only out of variations across regions within the same country and

[8]The following parties are classified as radical right: the FPÖ and the Team Frank Stronach in Austria; the Vlaams Blok and the Vlaams Belang in Belgium; the True Finns in Finland; the Front National in France; Golden Dawn and LAOS in Greece; the AFD, the NPD, and Die Republikaner in Germany; the League in Italy; the PVV and the List Fortuyn in the Netherlands; the Sweden Democrats in Sweden; the AN/NA, the Swiss Democrats, the SVP, and the FPS in Switzerland; and the UKIP in the United Kingdom.

year.

5.2 Individual-level analysis

For the individual-level analysis, we rely on the first seven waves of the European Social Survey. We assign to each party listed as a possible answer to the question regarding vote choice in the last election the identifier code used in the Comparative Manifesto Data, whenever available. We then assign to each respondent the ideology score of the party they voted (e.g., the nationalism score). We also assign to respondents a dummy equal to one if the chosen party is categorized as a radical right party.

To assign the scores of ideology (which are available only for election years) we reconstruct, based on the variables with the date of the interview, what was "the last election" a given respondent is asked about in the ESS. We then assign to the individual the corresponding ideology score of the party in the last election before the interview. We use these as outcome variables in the individual level regressions.

At the individual level, the first specification we use has the general form

$$\text{Vote Choice}_{icrt} = \alpha_{ct} + \beta_1 \text{Regional Exposure}_{cr(i)t} + \mathbf{Z}_{it}\gamma^{'} + \varepsilon_{icrt}, \tag{5}$$

where i indexes individuals, c countries, r regions, t years (elections), and ε_{icrt} is an error term.

The function $r()$ maps each individual i to her NUTS-2 region of residence r, while $\mathbf{Z}_{it}$ 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.

We assign to each respondent the region of residence at the time of the interview, and the automation exposure of their region in the election year they are being asked about. We include basic demographic controls for age and gender, that we can confidently consider pre-treatment, and education, which is plausibly pre-treatment.

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 at a given point in time.

The second specification we use relies on the individual-level exposure, and has the form

$$\text{Vote Choice}_{icrt} = \alpha_{ct} + \beta_1 \text{Individual Exposure}_{it} + \varepsilon_{icrt}, \tag{6}$$

Given that the individual-level robot shock is built 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 at a given point in time, we have enough information to identify the effect while accounting for additional region-level effects. In the robustness section, we discuss the estimates of specifications of the form $\text{Vote Choice}_{icrt} = \alpha_r + \delta_r t + \beta_1 \text{Individual Exposure}_{it} + \varepsilon_{icrt}$ with region-specific intercepts α_r and linear time trends $\delta_r t$.

In the individual specifications, like in the regional analysis, standard errors are clustered at the NUTS2-year level.

6 Results

6.1 District-level results

Table 1 reports the baseline estimates of the district-level specification outlined in eq. 4. We consider three different dependent variables: the median voter score and the center of gravity score for 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 eq. 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 eq. 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. This is consistent with the fact that robot adoption tends to be pro-cyclical. Indeed, to the extent that voters in good times are more likely to vote for incumbent and mainstream parties rather than nationalist and radical right parties, a downward bias in the OLS estimates can be expected.

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 (0.215) leads to an increase by 2 percentage points in support for the radical right. This is far from negligible, considering that the average vote share for radical-right parties is 5.5%, with a standard deviation of 7.7%.

Table 1: District-Level Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	**Nationalism**				**Radical Right**	
	Median		COG		Share	
Robots Regional Exposure	0.452*** [0.127]	0.671*** [0.179]	0.276*** [0.056]	0.419*** [0.097]	0.039** [0.017]	0.096** [0.041]
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
Country-Year Effects	yes	yes	yes	yes	yes	yes
Obs.	9,160	9,160	9,160	9,160	9,237	9,237
R2	0.57	0.57	0.84	0.84	0.64	0.64
First-stage results						
Robots other countries	- -	0.833*** [0.080]	- -	0.833*** [0.080]	- -	0.833*** [0.080]
Kleibergen-Paap F-Statistic	-	107.6	-	107.6	-	107.8

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

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 13% 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 in favor of 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

We start the analysis at the individual level by regressing individual vote choices over the exposure to robots in the region where the respondent lives. Specifically, Table 2 reports the baseline estimates of eq. 5. The empirical set-up is analogous to the one adopted in the district-level analysis. In particular, we employ two outcome variables: the nationalism score of the party voted by the respondent, and a dummy variable indicating whether the respondent has voted for a radical-right party. For each variable we report both OLS and instrumental variable results. The exposure to robots of each region is computed over two years prior to each election, and the instrument is computed based on robot adoption in other European countries.

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 1.5 percentage points. The results on the individual controls are in line with earlier literature. In particular, we find that women support on average less nationalist parties, and are less likely to vote for the radical right.

The main empirical contribution of our paper consists of studying the role of individual ex-

Table 2: Individual-Level Estimates - Regional Exposure

	(1)	(2)	(3)	(4)
Dep. Var.:	**Nationalism Score**		**Radical Right**	
Robots Regional Exposure	0.237***	0.392***	0.019**	0.069***
	[0.088]	[0.112]	[0.010]	[0.019]
Female	-0.066***	-0.065***	-0.016***	-0.016***
	[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.	104,124	104,124	107,057	107,057
R2	0.23	0.23	0.10	0.10
First-stage results				
Robots other countries	-	1.439***	-	1.432***
	-	[0.120]	-	[0.119]
Kleibergen-Paap F-Statistic	-	143.3	-	143.6

*** p<0.01, ** p<0.05, * p<0.10

posure to automation. This is computed as explained in eq. 3, by multiplying the overall rate of robot adoption in each country, times a measure of individual vulnerability to robots. Such vulnerability is in turn obtained by combining individual estimates of the probability to be employed in each occupation, times an automatability index for each occupation. The individual probabilities are estimated using individual characteristics and historical information on the composition of employment in each region. As an index of automatability, we use either the one made available by Frey and Osborne (2017), or our own estimates based on ISSP data.

Table 3 reports the baseline estimates of eq. 6. In the first four columns, we employ the measure of individual exposure based on Frey and Osborne (2017), while in the next four columns we use the one based on ISSP. The dependent variables are the same as in Table 2: the nationalism score of the voted party, and a dummy for supporting a radical-right party. Both OLS and IV results are presented in all cases. The estimated coefficient on individual exposure to robots is always positive, and highly significant in all the IV regressions. The first-stage coefficients on the instrumental variables are always positve and significant, and the F-statistics are comfortably high. Overall, the main message emerging from this set of results is that the individual exposure

Table 3: 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	0.086*	0.944***	0.020*	0.312***	0.100**	0.787***	0.016**	0.199***
	[0.045]	[0.278]	[0.010]	[0.075]	[0.039]	[0.170]	[0.007]	[0.044]
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Country-Year Effects	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	104,448	104,448	107,395	107,395	104,448	104,448	107,395	107,395
R2	0.22	0.22	0.09	0.07	0.22	0.22	0.09	0.07
First-stage results								
Robots other countries	-	0.423***	-	0.426***	-	0.404***	-	0.409***
	-	[0.052]	-	[0.053]	-	[0.038]	-	[0.039]
Kleibergen-Paap F-Statistic	-	65.7	-	65.7	-	114.7	-	110.1

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

to the robot shock, 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 0.242, leads to an increase in the nationalism score by 0.23, i.e., 20% of its standard deviation, and to a 7.6% increase in the probability of supporting a radical-right party. Somewhat smaller effects are obtained when using the ISSP-based measures of automation threat. In particular, according to the IV estimates of columns 6 and 8, a one standard deviation increase in individual exposure (0.138) leads to higher nationalism by 0.11, and to an increase in the probability of supporting a radical-right party by 2.7%. Even according to these more conservative estimates, the impact of automation still looms substantial.

6.3 Robustness and extension

Our main models rely on counterfactual occupation patterns predicted by, among others, education. One might be concerned that education itself –and thus the predicted probabilities of being in a given occupation– captures omitted personality traits and basic orientations that are directly linked to vote choice. In fact, education influences an individual's exposure to automation, but also affects orientations and attitudes that are related to authoritarianism and opposition to the cosmopolitan agenda, and therefore are linked to support for nationalist and radical right parties (Ivarsflaten and Stubager 2012; Stubager 2008). To account for this fact, we estimate models that condition on measures of these orientations and attitudes. We rely on a large set of items that are available in all the waves of the ESS in our sample: a battery of twenty-one questions about aspects of life that are important to the respondent (from the importance of "thinking new ideas and being creative" to the importance of "following traditions and customs.") These are meant to capture very basic orientations about individual and social life. We use factor analysis to estimate two factors that explain variation in these orientations, and include the scores as individual controls. Tables A2 and A3 in the Appendix show respectively summary statistics for the two factors and the factor loadings.

We also consider attitudes towards 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 "cosmopolitan values" package. Furthermore, we include the categorical variable Augmented Oesch which captures differences across respondents who belong to different occupational classes that might in turn be associated to systematically different value orientations –not driven by vulnerability to automation– as documented for instance by Kitschelt and Rehm (2014).

Importantly, the orientations and attitudes that we include in this specification are, possibly, post-treatment: some evidence discussed in the theoretical discussion 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 is not spuriously picking up variation in political behavior that is driven by basic value orientation. Table 4 presents the estimated effects of robots individual exposure on the main outcomes, controlling for the Augmented Oesch occupational classes, attitudes about gay rights and the two factors aggregating orientations about individual and social life.[9] Reassuringly, the coefficient on the individual exposure to automation is always positive and highly statistical significant. As it is reasonable to expect, the effects are somewhat smaller in magnitude once we include 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, have the same overall value orientations and the same attitudes about gay rights, those who are more exposed to automation due to their background characteristics are more supportive of nationalist options and of radical right parties.[10]

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

[10]Unsurprisingly, the estimates replicate the conventional wisdom results that more conservative orientations on non-economic matters are associated with more support for nationalist and radical right parties.

Table 4: 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	0.609**	0.222***	0.449***	0.131***
	[0.240]	[0.067]	[0.141]	[0.040]
Small business owners	0.094***	0.021***	0.089***	0.020***
	[0.034]	[0.006]	[0.034]	[0.006]
Technical professionals	-0.044	0.010*	-0.045	0.009*
	[0.033]	[0.005]	[0.033]	[0.005]
Production workers	0.000	0.058***	-0.005	0.057***
	[0.041]	[0.008]	[0.041]	[0.008]
Managers	-0.004	-0.003	-0.006	-0.003
	[0.031]	[0.004]	[0.031]	[0.004]
Clerks	-0.018	0.013**	-0.022	0.013**
	[0.034]	[0.005]	[0.034]	[0.005]
Socio-cultural workers	-0.237***	-0.015***	-0.239***	-0.016***
	[0.034]	[0.005]	[0.034]	[0.005]
Service workers	-0.023	0.032***	-0.026	0.032***
	[0.035]	[0.006]	[0.035]	[0.006]
Unemployed	-0.141***	0.028***	-0.143***	0.028***
	[0.042]	[0.006]	[0.042]	[0.006]
Not in labor force	-0.011	0.011**	-0.015	0.010**
	[0.032]	[0.005]	[0.032]	[0.005]
Gay rights: agree	0.238***	0.012***	0.238***	0.012***
	[0.016]	[0.002]	[0.016]	[0.002]
Gay rights: neutral	0.366***	0.024***	0.365***	0.023***
	[0.027]	[0.004]	[0.027]	[0.004]
Gay rights: disagree	0.464***	0.029***	0.462***	0.029***
	[0.030]	[0.005]	[0.030]	[0.005]
Gay rights: strongly disagree	0.471***	0.026***	0.471***	0.026***
	[0.037]	[0.005]	[0.037]	[0.005]
Orientations - factor 1	-0.038***	-0.003***	-0.038***	-0.003***
	[0.005]	[0.001]	[0.005]	[0.001]
Orientations - factor 2	-0.048***	0.003***	-0.047***	0.003***
	[0.007]	[0.001]	[0.007]	[0.001]
Estimator	2SLS	2SLS	2SLS	2SLS
Country-Year Effects	yes	yes	yes	yes
Obs.	95,044	97,769	95,044	97,769
R2	0.24	0.09	0.24	0.09
Kleibergen-Paap F-Statistic	75.15	74.78	114.6	109.8

*** p<0.01, ** p<0.05, * p<0.10

Table 5: 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	0.096	-0.210**	-0.211**	0.325***	0.049	-0.106**	-0.149**	0.206***
	[0.087]	[0.084]	[0.100]	[0.103]	[0.050]	[0.051]	[0.066]	[0.062]
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Country-Year Effects	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	104,448	104,448	104,448	104,448	104,448	104,448	104,448	104,448
R2	0.14	0.2	0.22	0.16	0.14	0.2	0.22	0.16
Kleibergen-Paap F-Statistic	65.7	65.7	65.7	65.7	114.7	114.7	114.7	114.7

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

While our results with ideological scores make the best use of the information that can be extracted from the Manifesto Project data, we can also use voting for more traditionally-defined party families as alternative outcome.[11] As we explain in the methods section, we first locate parties in the two-dimensional space defined by economic ideology and isolationist/pro-globalization stances. Parties are then classified as belonging to one side of the spectrum depending on whether their ideology score is above or below the median for that country in that given election. The resulting four party families are: Pro-Trade Left, Liberal Right, Protectionist Right, and Protectionist Left. In Table 5, we report results of this extended individual-level analysis. Each column refers to a different party family. Results for our main IV specification are presented for both the Frey and Osborne (2017 - left panel) or the ISSP-based (right panel) vulnerability scores. The coefficient for the protectionist right is positive and statistically significant while it is negative and significant for both the liberal (i.e., mainstream) right and for the pro-trade mainstream left. There is instead a small positive, but not statistically significant effect on 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 of both the left and the right side of the political spectrum.

Table 6 presents a series of robustness checks for our individual-level IV regressions, using both the Frey and Osborne (2017) and the ISSP-based vulnerability scores. Each row of the Table refers to a separately estimated specification.

While our preferred way of assessing individual vulnerability to automation relies on the counter-factual employment probabilities that we introduce above, we can also straightforwardly assign to each respondent the automation threat of their current occupation. In this case we exclude from the analysis respondents who are unemployed or not in the labor force. Results for the exposure based on actual occupation presented in the first row of Table 6 are in line with those of the counter-factual based individual exposure. This implies that, to an extent, the threat of automation also affects workers still employed in occupations at high risk of automation.[12]

[11] The outcomes are dummy variables equal to one if the party chosen by the respondent belongs to a given family.

[12] Notice also that in this specification we can control for age, gender, and education levels on top of automation exposure.

There might be concerns that the level of education itself might be affected by vulnerability to automation: some individuals might choose to receive more education due to their expectation that, otherwise, they might be exposed to a tougher time on the labor market due to "competition with robots." To address this concern, we restrict the analysis to respondents born before 1980. For these respondents, arguably, educational choices are less affected by the latest wave of automation. When we restrict the analysis to this subset of respondents (second row of Table 6), the coefficients on individual exposure are positive and highly statistically significant. In addition, they are somewhat larger in magnitude (even though not statistically significantly so), pointing to the fact that to an extent some younger individuals might have been able to adjust their educational choices to avoid being vulnerable to automation once in the labor market. On the other hand, older individuals might have been caught unprepared and therefore their political response is, if anything, stronger.

Another threat to our identification arises from the fact that different regions might have persistent differences in political orientations. If that is the case, rather than detecting an effect of automation shocks on political orientations, our estimates might be picking up differences in voting behavior across areas that are spuriously correlated with stronger or weaker exposure to automation. For this reason, in row 3 and 4 of Table 6, we estimate models with fixed effects for NUTS2 regions, and models where we add region-specific linear time trends. The results for exposure to automation are robust to these additional controls, corroborating a causal interpretation of our main findings on automation.

Finally, it is worth noting that the results are robust if we instrument the individual vulnerability based, respectively, on robot adoption in the United States (row 5), and in all the advanced non-European countries (row 6) for which data are available (US, Japan, and South Korea).

In Table 7, we consider the possibility that other processes that are contemporaneous to, and possibly associated with automation, are confounding the estimates for robot exposure. In particular, there is evidence that globalization (and the rise of China as a global exporter) and adoption of information and communication technologies (ICT) in general affect voting behavior. In columns 1-4 of Table 7, we show that the results on the effects of automation are robust to the in-

Table 6: 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	0.810***	0.243***	0.859***	0.286***
	[0.273]	[0.050]	[0.362]	[0.060]
2) Excluding individuals born after 1980	1.165***	0.308***	0.842***	0.181***
	[0.293]	[0.073]	[0.170]	[0.042]
3) Including NUTS2 fixed effects	0.835***	0.292***	0.673***	0.182***
	[0.255]	[0.072]	[0.153]	[0.043]
4) Including NUTS2 fixed effects plus trends	0.854***	0.291***	0.689***	0.184***
	[0.255]	[0.072]	[0.153]	[0.043]
5) IV based on North America	0.925***	0.258***	0.763***	0.174***
	[0.263]	[0.067]	[0.162]	[0.038]
6) IV based on Non-European countries	1.406***	0.356***	1.096***	0.245***
	[0.385]	[0.092]	[0.223]	[0.050]

*** p<0.01, ** p<0.05, * p<0.10

clusion 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. This variable is instrumented as in Colantone and Stanig (2018a), using import flows from China into the US rather than in each European country. 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 (e.g., Colantone and Stanig, 2018a). In particular, our time-span encompasses the financial and sovereign debt crisis in Europe, along with the well-known "trade collapse" of 2008-2009. The short-run impact of Chinese import competition, which is captured by this measure, is then less relevant than in the earlier period analyzed in other studies.

In Columns 5-8 of Table 7 we present a similar robustness analysis that controls for the impact of ICT, built by allocating ICT investment by industry in a given time period to regions based on their initial sectoral composition. Also in these specifications, the estimates for the effects of automation remain positive and significant, consistent with other 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). The direct effect of ICT investments on voting behavior is not significant. Finally, in the last two columns of Table 7 we consider an alternative measure of individual vulnerability to automation that replicates the structure of our main individual measure of vulnerability, but is based on the routine-task intensity index of each occupation as calculated by Autor and Dorn (2013) instead of relying on the Frey and Osborne (2017) or the ISSP-based scores. Results on radical-right vote using the routine task-intensity index are consistent with our main specifications. For the nationalism score outcome, the coefficient is still positive, but not significant. This might reflect the fact that the routine-task intensity index tends to capture the vulnerability to technological shocks of a set of occupations that is not fully overlapping with the set of occupations identified as highly automatable by the two other indexes of vulnerability.

Table 7: 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	0.944***	0.312***	0.787***	0.199***	0.640***	0.208***	0.567***	0.128***		
	[0.278]	[0.075]	[0.170]	[0.044]	[0.245]	[0.065]	[0.151]	[0.038]		
China shock	0.014	0.010	0.020	0.011						
	[0.059]	[0.011]	[0.059]	[0.011]						
ICT shock					-2.840	-0.109	-2.897	-0.109		
					[3.719]	[0.261]	[3.708]	[0.261]		
Robots Indiv. Exposure based on RTI									0.038	0.067***
									[0.047]	[0.014]
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.	104,448	107,395	104,448	107,395	96,552	99,379	96,552	99,379	104,448	107,395
R2	0.22	0.07	0.22	0.07	0.23	0.04	0.23	0.04	0.22	0.07
Kleibergen-Paap F-Statistic	32.9	32.9	57.7	55.3	29.9	30.0	10.0	7.0	126.9	125.0

*** p<0.01, ** p<0.05, * p<0.10

7 Conclusion

We study the effects of automation on voting behavior, focusing on the impact of robot adoption in 15 countries of Western Europe, over the period 1993-2016. We measure exposure to robot adoption either at the regional level, based on the historical composition of employment in each region, or at the individual level, based on individual characteristics and pre-sample patterns of employment in the region of residence. We find that higher exposure to automation increases support for nationalist and radical-right parties, both at the regional and individual level.

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A Employment data sources

Table A1: Employment data

Country	Employment Data	
	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
Ireland	1995	Eurostat
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

B Factor analysis

Table A2: 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 A3: 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