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ORIGINAL ARTICLE

How technological change affects regional voting patterns

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Abstract
Does technological change fuel political disruption? Drawing on fine-grained labor market data from Germany, this paper examines how technological change affects regional electorates. We first show that the well-known decline in manufacturing and routine jobs in regions with higher robot adoption or investment in information and communication technology (ICT) was more than compensated by parallel employment growth in the service sector and cognitive non-routine occupations. This change in the regional composition of the workforce has important political implications: Workers trained for these new sectors typically hold progressive political values and support progressive pro-system parties. Overall, this composition effect dominates the politically perilous direct effect of automation-induced substitution. As a result, technology-adopting regions are unlikely to turn into populist-authoritarian strongholds.

Keywords: Automation; occupational determinants of political preferences; political preferences; robots; technological change; voters

2020 *Mathematics Subject Classification*: P16; D72; O33; J31

1. Introduction

The widespread use of new technology at the workplace has raised fears about wage pressure and employment loss. Influential work in labor economics shows that capital in the form of industrial robots or specialized software directly replaces certain routine tasks previously done by human labor in both white- and blue-collar occupations (Autor *et al.*, 2003; Acemoglu and Restrepo, 2019). These findings have sparked a vivid debate about the political and societal consequences of such an uncertain future of work (Gallego and Kurer, 2022). A growing literature in political science has gathered evidence that workers directly threatened by a transforming employment structure seek for ways to express their discontent and disproportionately support anti-establishment parties (Frey *et al.*, 2018; Im and others, 2019; Kurer, 2020; Anelli *et al.*, 2021; Milner, 2021).

However, there is another side of the same coin that has attracted less attention in this literature. Labor economists also agree that new technologies increase productivity and contribute to rising demand for labor in non-automatable tasks, which may well result in aggregate welfare gains. It is widely accepted that this productivity growth leads to job creation, yet of a very different type of jobs. Far away from the conveyer belt, new jobs tend to pertain to more high-skilled, cognitive, and interactive occupations oftentimes requiring tertiary education (e.g., Michaels *et al.*, 2014; Graetz and Michaels, 2018; Dauth *et al.*, 2021). In contrast to the emblematic manufacturing worker, individuals in those growing occupations tend to hold more cosmopolitan and progressive values through their experience of higher education and the exposure to a profoundly different work logic (Kitschelt, 1994; Oesch, 2006; Kitschelt and Rehm, 2014). In this sense, technological change may also lay the foundation for a socially progressive society, a possibility that is widely appreciated in the influential literature on the rise of the "knowledge economy" (e.g., Iversen and Soskice, 2019).

This paper explicitly recognizes that technological innovation affects regional voting outcomes in two ways. On the one hand, there is a *direct effect* on workers who are threatened by technology and may well become more supportive of radical right and populist forces. On the other hand, technological innovation also affects regional voting through a *compositional effect*. Over time, more and more workers belong to occupations which are associated with more progressive values. The direction of the net effect of technological innovation on regional voting outcomes is theoretically ambiguous. We advance the existing literature by an empirical analysis of the relative importance of the direct and compositional effect in West Germany. This case is relevant because West Germany (a) is both one of the largest information and communication technology (ICT) markets in the world and home to the overwhelming majority of industrial robots currently installed in Europe, (b) still has the largest manufacturing share of employment compared to other advanced economies, and (c) has recently seen the rapid rise of a radical right party.

Fine-grained labor market data with high levels of geographical disaggregation from the German Institute for Employment Research (IAB) allow for a more detailed regional analysis than most existing accounts. We combine these detailed labor market data with two distinct empirical measures of technological change. First, we use data from the International Federation of Robotics (IFR) to measure county-level exposure to robotization and how it has changed over time. This indicator mainly captures automation in the manufacturing sector. Second, we measure county-level exposure to digitalization in the form of ICT by relying on EU-KLEMS data, which constitutes a distinct form of technological change that also affects the service sector. Following pioneering work in the field (Acemoglu and Restrepo, 2020), identification stems from a shift-share approach, where we use pre-sample-period local employment composition to estimate the exposure to new technologies in a time-varying fashion. We employ a panel model with region and time-fixed effects to control for unobserved factors.

Unlike most existing work, our approach allows us to document technology-induced changes in the labor market that are typically invoked to explain political reactions. This is important as all studies on the topic—more or less explicitly—argue that technological change affects political outcomes through material changes at the workplace. In line with previous work in labor economics, our approach reveals that robot adoption and ICT investment shift employment from manufacturing and routine jobs to the service sector. Regions with faster growing technological innovation experience stronger labor market polarization. Robots primarily displace manual routine jobs, whereas ICT investment more powerfully substitutes for cognitive routine jobs. However, importantly, overall employment does not decrease in West German counties with higher exposure to technological change. To the contrary, we find weakly positive net employment effects.[1]

Our analysis of political outcomes shows that, on average, regions more strongly affected by technological innovation shift their political support toward socially progressive parties. The *regional* vote shares of center-right and right-authoritarian parties *decline* as a result of the labor market transitions caused by robot adoption and ICT investment. We provide evidence that these results are indeed the consequence of changing local labor market composition. In

[1]This finding helps correct a common misperception. Investment in new technologies is actually a sign of a relatively healthy, future-oriented local economy. While it could be imagined that the alternative to robot adoption were thriving manufacturing plants relying on human work, recent research suggests that the more realistic counterfactual scenario is substantial job loss and closed factories as companies without robots fall behind in global competition (Koch *et al.*, 2019).

line with the literature on occupational preference formation, we demonstrate that a lower number of regional manufacturing jobs is associated with less support for right-authoritarian parties whereas a larger interpersonal service sector is associated with more support for progressive left parties.

By highlighting that new technologies not only replace human work (the replacement effect) but also create new jobs (the productivity effect), we challenge rather gloomy perspectives on the political repercussions of technological change. Concerning the important case of West Germany, we show that compositional effects of technology adoption on local labor markets can outweigh the political resentment among workers directly affected by the adverse consequences of technological change. Hence, our results suggest that technological innovation need not result in local political disruption. While we acknowledge that automation contributes to the emergence of anti-establishment forces through electoral support from the segment of society directly exposed to the negative consequences of this process, our results show that, overall, technology adopting regions do not necessarily turn into right-authoritarian strongholds.

2. Labor market implications of technological change

The seminal work by Autor *et al.* (2003) argues that new technologies substitute for routine tasks that follow clearly defined rules. Such rules make routine jobs "codifiable" and hence replaceable by computers or robots. This *substitution effect* mainly hits workers located at the middle of the income and skill distribution and in particular those in the manufacturing sector. At the same time, technology also has a *reinstatement effect* (Acemoglu and Restrepo, 2019). New technologies raise productivity which leads to an increased demand for workers whose skills are complementary to automation. Newly created jobs pertain either to the growing group of white-collar professionals with college education focusing on cognitive and interpersonal tasks (management, education, and cultural and health sector) or to low-skilled manual services (retail, restaurants, and hospitality). Most of them benefit from automation indirectly through lower prices of goods and new demands for their products and services.

While scholars agree that these are the main forces at work, it is still hotly debated whether the substitution or productivity effect dominates. With respect to robotization, an influential paper on the US found that the substitution effect dominates as regions adopting more robots experienced weaker employment growth (Acemoglu and Restrepo, 2020). However, studies focusing on Europe and on Germany in particular found null or slightly positive employment effects (Klenert *et al.*, 2020; Dauth *et al.*, 2021). With regard to ICT, existing work appears slightly less controversial and tends to show that investment in technology has not led to a decline in employment (Biagi and Falk, 2017) but shifted jobs from mid-skill to high-skilled sectors, consistent with ICT-based employment polarization (Michaels *et al.*, 2014). Our own original analysis points in the same direction: although we do find that mid-skilled routine jobs in general, and manufacturing employment in particular, are negatively affected by technological innovation, this decline is more than offset by an increase in work in other sectors.

3. Political implications of technological innovation

These distributive implications of technological innovation give rise to two distinct and most likely countervailing political implications. On the one hand, studies that focus on the *direct* effect are interested in the individual-level response to imminent automation exposure. On the other hand, studies on the consequences of economic modernization and occupational change at the aggregate level emphasize the changing *composition* of postindustrial societies. It should not come as a surprise that these two perspectives offer starkly different views on the prospect of democracy in the age of automation. While the first is often motivated by a concern about the potential substitution of human labor and resulting political disruption, the second provides a much more optimistic outlook, emphasizing economic opportunity and mobility in the rising knowledge economy. Interestingly, the net impact of the two effects remains unclear. It appears that the relative importance of winners and losers is at the root of much of the ongoing debate about the political implications of technological change.

3.1. Direct effect

Existing papers studying what we call the direct effect of automation focus on individual-level responses regarding political preferences and voting behavior. Despite the fact that technological change creates both winners and losers, it is safe to say that most existing work investigates the political reactions of workers who stand to lose from technological change. Alluding to historical examples of machine breaking during the Industrial Revolution, pundits and academics alike have raised concerns that the left-behind would turn against the system. In short, it is argued that losers of technological change become more attracted to anti-establishment forces due to their economic decline (Kurer and Palier, 2019; Im *et al.*, 2019). Specifically looking at the impact of robots, Frey *et al.* (2018) showed an association between robot adoption and anti-incumbent voting in the US and Anelli *et al.* (2021) and Milner (2021) provide evidence for a link between local robot penetration and support for right-authoritarian parties across Western Europe.

The political reactions of winners of technological change have received considerably less attention in individual-level research. Gallego *et al.* (2020) examine political preferences of "ordinary winners" of digitalization in the UK. They show that a majority of the population, but especially high-skilled workers, benefit from ICT capital investment and that these economic benefits translate into more support for moderate incumbent parties, hence creating a stabilizing pro-system force.

Summing up, workers imminently threatened by automation tend to become more supportive of radical parties challenging the political status quo. The direct effect of automation seems to primarily benefit authoritarian-right parties. Voters who benefit at least moderately from the "digital revolution," in contrast, tend to vote for more centrist ideological positions and support incumbent parties. Technological change hence potentially creates political divergence between winners and losers and can contribute to increasing political polarization.

3.2. Compositional effect

While research on individuals' susceptibility to automation has concentrated on the downsides of the technological revolution, its upside is at the heart of a different body of work that describes the transition of modern society into "knowledge economies." Starting back in the late 1970s, technological progress has facilitated a transition in advanced capitalist democracies from a manufacturing-based to a more services dominated economy, with an ever greater reliance on intellectual capabilities (Powell and Snellman, 2004). Influential recent accounts highlight the relevance of a broad (upper) middle class enjoying economic growth, wealth, and opportunity (Iversen and Soskice, 2019).

The emergence of the knowledge economy is intimately linked to the distributional implications of technological change discussed above. Non-routine and service sector jobs, especially higher skilled ones, have expanded at the expense of mid-skilled routine jobs. A changing composition of local labor markets is politically highly relevant because occupations are known as important sites of preference formation (Kitschelt, 1994; Oesch, 2006; Kitschelt and Rehm, 2014). Occupations shape political preferences through both a market logic reflecting vertical divisions in marketable skills and economic self-interest, and an important additional horizontal differentiation in terms of work logic. The literature differentiates between a technical, organizational/bureaucratic and interpersonal work logic depending on the education level required, setting of the work process, the relation to authority, the primary type of client relation, and the kind of skills applied. At the risk of simplification, the theory of occupational preference formation thus posits that lower education levels, strict hierarchies, and dealing with objects and files (rather than people) are associated with more authoritarian views. Occupations that require university educations, which are based on cooperation (rather than hierarchies), which focus on social interactions and culture hold more cosmopolitan and progressive values.

Translating this into actual occupational groups and milieus means that mid-skilled, routine occupations in the manufacturing sector are characterized by disproportionate support for authoritarian-right parties. Much in contrast, the growing number of highly educated workers engaging in more analytical and interactive work tend to belong to a milieu which is more left-leaning and cosmopolitan. This transformation of the employment structure has resulted in a decline of traditional class voting: contemporary progressive left parties draw substantial electoral support from among an expanding highly educated middle class (Gingrich and Häusermann, 2015; Oesch and Rennwald, 2018).

It is important to note that the underlying forces changing the regional composition of the labor force go beyond a narrow individual-level mechanism. Of course, workers can retrain and change occupations in response to technology adoption and declining demand for their incumbent jobs. Existing research on intragenerational mobility and political attitudes indeed provides evidence that the theory of occupational preference formation has some traction even within an individual. Changing occupational environments and work logics have been shown to shift political participation (Lahtinen *et al.*, 2017), policy preferences (Ares, 2019), or economic ideology (Langsaether *et al.*, 2022), where the resulting political behavior typically comes to lie between the class of origin and the class of destination. This "strong theory" of occupational preference formation (Kitschelt and Rehm, 2014) is thus one possible channel contributing to changes in the composition of the local labor force resulting in a more progressive regional electorate. However, we do not believe that it is the *main* channel. Although considerable levels of incremental retraining and adjustment to new technologies happen within firms, the main driver behind the consistent decline in routine work in the aggregate is not individual occupational re-orientation. Individual-level (between-firm) transitions into (better or worse paying) jobs are relatively rare. Instead, routine workers exit into retirement and new labor market entrants find work in different (non-routine) jobs (Cortes, 2016; Kurer and Gallego, 2019). Dauth *et al.* (2021) show that the largest burden of the reduction in manufacturing employment as a consequence of robotization falls on young labor market entrants rather than on incumbent workers. Importantly, and very much in the spirit of our basic argument, they also show that displacement in manufacturing is overcompensated by offsetting gains in services. An observable implication of this narrative is the rising average age among workers in "declining jobs" (Autor and Dorn, 2009; Kurer and Gallego, 2019) while the average age should be lower in technology-adopting regions because of local labor supply.

A second likely explanation of a changing composition of the local electorate is internal migration. The evident sectoral shift in technology-adopting regions likely attracts a different type of worker with a distinct skill profile and work logic, which contributes to a changing composition of the local labor force that manifests itself also in the electoral arena. Again, Dauth *et al.* (2021) provide important evidence on the basis of high-quality administrative panel data. The productivity effects of robotization spill over into the service sector and pull in workers into this expanding sector from other regions (but see Faber *et al.* (2022) for the US case, which operates under opposite signs). Below we will provide some original evidence tracing observable implications of different plausible channels contributing to the observed transformation of the labor market composition. Our analysis supports the presence of all three channels but also confirms that an intergenerational transformation of the employment structure appears as a key source of change.

3.3. Net effect

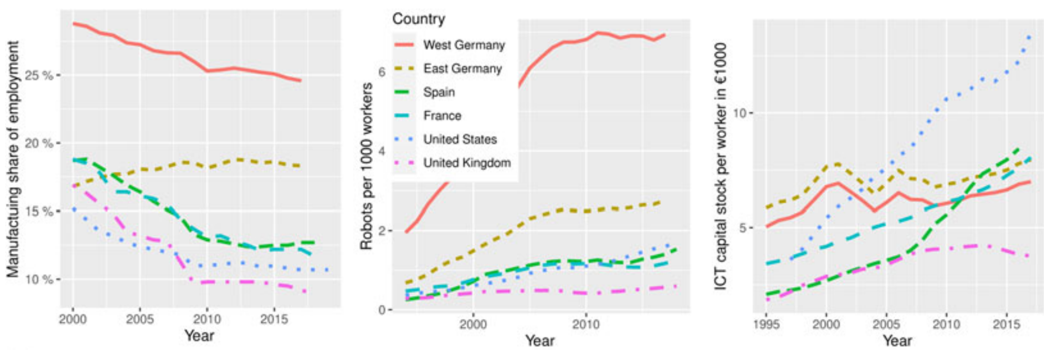
The political space in Germany and many other postindustrial democracies is composed of an economic and a cultural dimension. The lion's share of voters as well as the relevant political actors tend to cluster along the diagonal, which is characterized by a progressive, economically left-leaning pole and an authoritarian, economically right-leaning pole with progressive left parties and authoritarian-right parties representing "polar normative ideals" (Bornschier, 2010). In the online Appendix, we provide a descriptive overview of the contemporary German partisan landscape. From a theoretical perspective, the direct and the compositional effects of automation work as opposing forces. While the direct effect of automation risk and substitution may fuel individual support for the authoritarian right, the accompanying shift in the composition of the labor force fuels party support for more progressive, cosmopolitan left parties. Hence, *a priori*, technological innovation could affect regional party support in either way. We treat the question of which factor dominates as an empirical issue and strive to provide an answer, at least for the German case, in below analysis.

4. Data

Our empirical analysis focuses on West Germany, a highly relevant case characterized by a large manufacturing sector, the largest number of robots anywhere outside Asia, and large investments in ICT over the past decades (see Figure 1). East-German regions of the former German Democratic Republic (GDR) are dropped due to their profoundly distinct economic and political trajectories. We apply a regional approach similar in spirit to previous studies in economics (Acemoglu and Restrepo, 2020; Dauth *et al.*, 2021), choosing West German counties (*Landkreise und kreisefreie Städte*) as the regional unit of analysis (n = 324, NUTS-3). We employ population weights from the Federal Statistics Office to take care of mergers and create a consistent panel based on the current shape of counties.

4.1. Robot exposure

To calculate regional robot exposure over time, we use data from the IFR (IFR, 2016). A robot is defined as an "automatically controlled, re-programmable, and multipurpose machine." The



(a) Manufacturing share of employment (b) Robots (c) ICT

Figure 1. Evolution of manufacturing share, robot penetration, and ICT.
Note: The graph shows (a) the share of employees working in the manufacturing sector, (b) the number of robots per thousand employees, and (c) the ICT capital stock per worker in 1000. Compared to other advanced economies, West Germany still has a large manufacturing sector, while robots are already playing an important role. Digitalization also plays an important role in West Germany. Sources: IFR, ILO, EUKLEMS, own calculations.

yearly data differentiate between 25 industries, mostly in manufacturing. We follow Acemoglu and Restrepo's (2020) approach to exploit information on pre-sample regional employment composition. Robots of a given sector are distributed to regions based on the number of employees in the region working in the sector relative to the nation-wide employment in the sector. To capture robot intensity, i.e., the number of robots per workers, we normalize by the region's total employment in thousands. Finally, to account for the heavily skewed distribution of robots across regions, we apply a logarithmic scale. (The robustness section shows results without this transformation.)

$$\text{Robot intensity}_{r,t} = log\left(\frac{1}{E_r}\sum_j \frac{Robots_{j,t} * E_{j,r}}{E_j/1000}\right) \tag{1}$$

where E_r is the employment in region r, $E_{j,r}$ is the employment in industry j in region r, $Robots_{j,t}$ is the number of robots in industry j in year t, and E_j is the total employment in industry j across all regions.

Information on local employment composition is derived from administrative data of the Institute for Employment Research (IAB). In constructing the measure, we rely on employment records from a 2 percent sample randomly drawn from the universe of German employees subject to social security (Antoni *et al.*, 2019). To further increase the effective sample size, we also take advantage of the fact that the IAB provides information on the number of co-workers for every randomly selected employee. For every respondent, we have information on employment status, employer, and occupation for any given day for the entire sampling period. An adjacent firm dataset includes information on the firm's industry classification, its number of employees, and geographic information. We aggregate information on all firms in a 10-year window prior to our sample period by region and industry to approximate local employment composition. Employment data are used from pre-sample period, as later sectorial employment composition might be endogenous to the adoption of robots. In addition, IAB data also provide regional employment shares along various dimensions (e.g., by sector, main task, or skill requirements). These time-varying, disaggregated employment shares allow us to carefully trace distributional implications on the regional level. The measure constitutes a typical Bartik-style shift-share variable where an industry-level shock is apportioned across regions (Bartik and Doeringer, 1993).

4.2. ICT investment

We use changes in ICT capital stock by industry to measure digitalization, drawing on the 2019 release of the EU-KLEMS dataset (Stehrer *et al.*, 2019), which contains yearly measures of output, input, and productivity for 40 industries in a wide range of countries, including Germany, and covers the period 1995–2017. The data are compiled using information from the national statistical offices and then harmonized to ensure comparability. Most importantly for our purposes, the database provides a breakdown of capital into ICT and non-ICT assets. We define the industry-level ICT capital stock as the capital stock in information technologies, communication technology, and software and databases. Based on this, we create a time-varying, industry-specific measure of digitalization using a shift-share approach analog to our robot intensity measure. More specifically, we calculate the ICT capital stock per 1000 in region r in year t as

$$\text{ICT}_{r,t} = \frac{1}{E_r}\sum_j \frac{\text{ICT}_{j,t} * E_{j,r}}{E_j} \tag{2}$$

where E_r is the employment in region r in the base year, $E_{j,r}$ is the employment in industry j in region r in the base year, $ICT_{j,t}$ is the industry ICT capital stock in 1000 in industry j in year t, and E_j is the total employment in industry j across all regions.

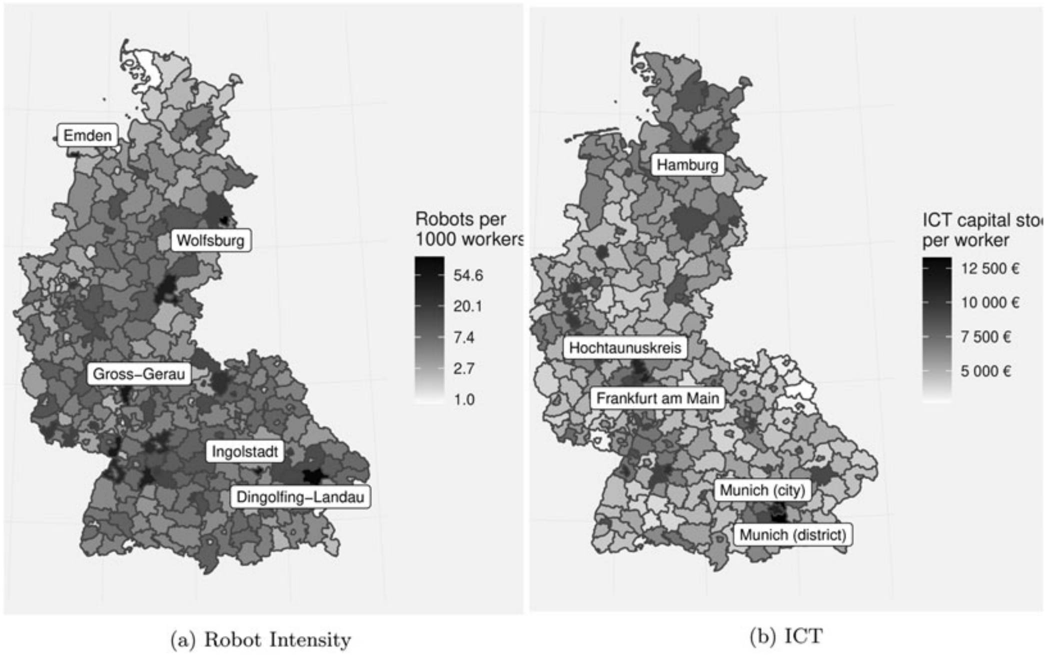


Figure 2. Regional distribution of new technologies.
Note: The graph shows (a) the estimated number of robots per thousand workers and (b) the ICT capital stock per worker for 324 West-German regions (*Kreise und kreisfreie Städte*) in 2017. Top 5 cities are labeled. Analogous to our measure of robot intensity in the main analysis, the color scale is in logs.

Figure 2 shows the spatial distribution of both measures of technological change per county for 2017. The left panel shows that most robots can be found in regions dominated by the automotive industry: For example, Volkswagen has its headquarters in Wolfsburg, Audi in Ingoldstadt, Opel in Gross-Gerau, and Dingolfing-Landau and Emden are major production sites of BMW and Volkswagen respectively. The right panel shows that ICT is concentrated in the major service-sector business hubs of Munich, Frankfurt, and Stuttgart. This pattern suggests that we capture two distinct forms of technological change. The correlation between the two measures is indeed low (0.12).

4.3. Elections

For each county we gathered official election results for all Federal, State, and European elections between 1994 and 2017 which yields 7 federal, 40 state elections, and 5 European elections. If multiple elections were held in the same year, we only consider one of them, preferring federal election over state election over EU election (order of voter turnout) which gives a total of 4277 county–election pairs. We consider all parties currently represented in national parliament: Grünen (greens), Linke (leftist), SPD (social democrats), FDP (pro market), CDU-CSU (christian democrats), and the Alternative für Deutschland (AfD, right-authoritarian). Since the AfD was only founded in 2013, we pool it with other right-authoritarian parties (NPD, DVU, Republikaner).

According to expert judgements (see online Appendix Figure A.1), the Greens, the SPD, and the Left party all fall into the camp of what we broadly call progressive-left parties, which we expect to benefit from local technology adoption. Assessments based on party manifestos provide a very similar overall picture (see, e.g., Burst *et al.*, 2021). Despite such "objective" mappings, one might query an uncritical classification of the Left party within this group. Some would rather classify the Left party as a populist or radical left party that arguably attracts groups of angry voters that do not resemble the successful, skilled workers in the growing cognitive professions. We will come back to this question in the empirical analysis.

4.4. Empirical approach

We employ a two-way fixed effect panel model to capture the effect of new technologies, measured as robotization or ICT investment, respectively, on economic and political outcomes:

$$Y_{r,t} = \beta_1 Technology_{r,t} + \mu_t + \eta_r + \epsilon_{r,t} \quad (3)$$

The dependent variable $Y_{r,t}$ is a party vote share or an employment outcome in region r in year t which is regressed on $Technology_{r,t}$ measured as (a) the number of log robots per 1000 workers or (b) the ICT capital stock per worker in 1000. The model includes region fixed effects η_r and year fixed effects μ_t. As robustness checks, we will further add a vector of control variables in later specifications. These specifications have sometimes been presented as "generalized" versions of the canonical diff-in-diff with two time periods and two groups, but recent research has highlighted that one has to be careful with a causal interpretation of the aggregated parameters (e.g., Callaway and Sant'Anna, 2021). The two-way fixed-effects estimator has been shown to equal a weighted average of all possible two-group/two-period diff-in-diff estimators in the data (de Chaisemartin and D'Haultfoeuille, 2020; Goodman-Bacon, 2021). A causal interpretation hence rests on the assumptions of parallel trends and constant treatment effects over time.

5. Results

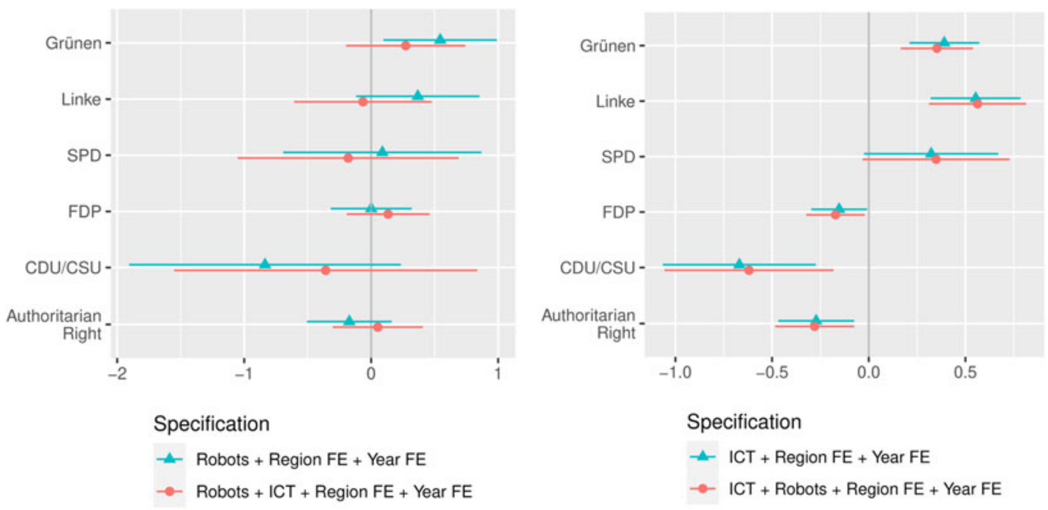
5.1. Political outcomes

In line with our theoretical point of departure, we first turn our attention to political outcomes and look at "reduced-form" specifications modeling the direct relationship between regional technological adoption and regional election outcomes. Figure 3 plots estimated marginal effect of regional robot intensity and ICT investment, respectively, on regional electoral vote shares of all major German parties. The reported coefficients each stem from a separate regression. The first specification only includes one of the technological change measures (blue triangles) and the second includes both measures simultaneously (red circles). Both specifications include a region and an election fixed effect.[2]

The results show that regions exposed to more intense technology adoption generally shifted their electoral support to the progressive-left of the political spectrum. For ICT, the patterns are consistent and robust. We find that the green party *Die Grünen* and leftist party *Die Linke* were the parties that gained most votes in digitalizing regions. For the social-democratic SPD, we find a positive but imprecisely estimated effect. On the other hand, the center-right CDU/CSU and the authoritarian-right party AfD received less support. The estimated effect for the pro-market party FDP is marginally negative. These findings are not affected when controlling for the effect of regional robotization. These reduced form models focusing on ICT investment hence provide evidence that the compositional effect, which favors progressive-left parties, seems to dominate the direct substitution effect at the regional level.

For robotization, the overall pattern is similar but much more noisy. When considering the effect of robotization in isolation, we find the same gradient across the political spectrum: progressive-left parties gain, whereas conservative and authoritarian-right parties tend to receive

[2]See column (1) and (3) of Tables A.1–A.12 in the online Appendix. Election fixed effects differ from year fixed effects in the case of multiple state elections held in the same year.



(a) Marginal Effect of Robot Intensity

(b) Marginal Effect of ICT

Figure 3. Region-level exposure to technological change and party vote shares.
Note: The graph shows estimated marginal effect of the (a) regional log number of robots per thousand workers and (b) the regional ICT capital stock per worker in 1000 on regional party vote shares in percentage points (see column (1) and (3) of Tables A.1–A.12). Standard errors clustered at the county level. Bars represent 95 percent confidence intervals.

fewer votes when a region adopts robots. However, only the effect of the progressive-left party *Die Grünen* is statistically significant. When controlling for the parallel influence of ICT, the marginal effects of robotization hover around zero. One might interpret this as evidence that, with regards to robotization, the direct effect favoring authoritarian-right parties and the compositional effect favoring progressive-left parties are on balance. This contrasts with previous work claiming that robotization leads to an unambiguous shift toward the right of the political spectrum. However, given the large confidence intervals, we do not want to over-interpret potentially countervailing effects, which might simply reflect a noisy estimation process.

In terms of effect magnitude, our baseline models predict that a one standard deviation increase in the log number of robots per thousand workers (+35% more robots) is associated with an increase of the *Grünen* vote share of 0.15 percentage points. In itself, this is a relatively modest effect but considering that the average region increased its number of robots by 270 percent between 1994 and 2017, the accumulated effect for *Die Grünen* is an estimated increase of the vote share by 0.71 percentage points. This is significant for a party that typically attracted less than 10 percent of the vote. Similarly, an increase of the ICT capital stock by one within-region standard deviation (+520 per worker) is associated with an increase of the vote for *Die Grünen* by 0.19 percentage points.[3]

We run a series of robustness checks (see online Appendix section A.2 for details). First, additional to the two-way fixed effects, we control for trade exposure and GDP growth. Furthermore, we use an instrumental variable (IV) approach, where we instrument technology adoption in Germany with values from other European countries. Considering ICT investments, effects are

[3]We cannot directly compare the absolute change in robot intensity and ICT capital stocks as the former is measured in counts whereas the latter is measured in monetary terms. Moreover, a direct comparison would assume that we measure both concepts equally well, which is unlikely as both measures are proxies of the underlying concept prone to some measurement error.

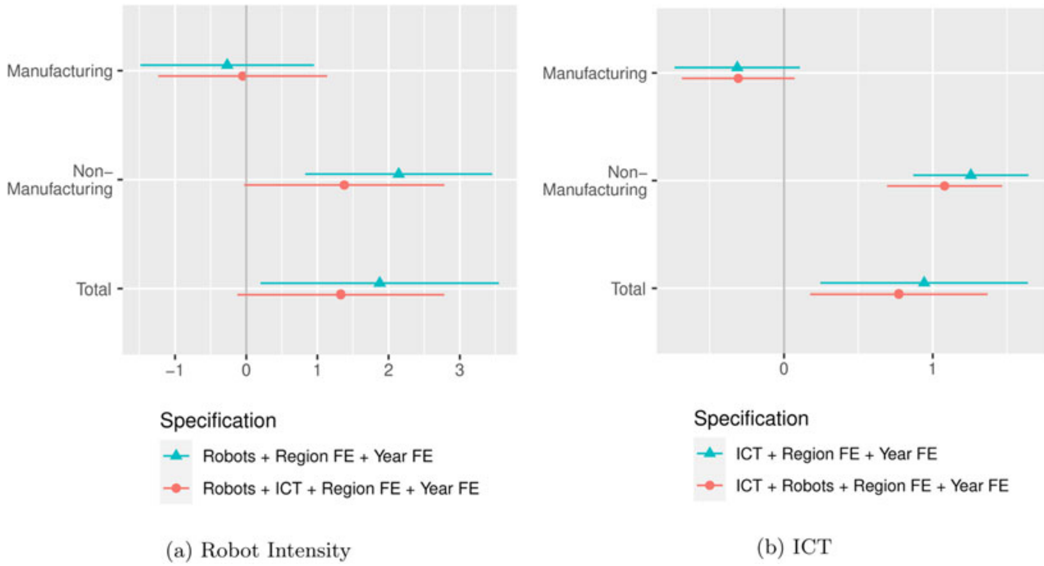


Figure 4. Region-level exposure to robots and employment effects.
Note: Estimated coefficients of effect of log number of robots per thousand workers on employment to population ratios (in percent) after controlling for region and year fixed effects. See column (1) of Tables A.13–A.15. Black bars represent 95 percent confidence intervals.

stable or even stronger in the case of IV results. Again, the robotization findings are not very stable, which is why the above results should be interpreted with caution.

5.2. Understanding compositional effects and underlying mechanisms

The remainder of the empirical exercise makes use of fine-grained individual and regional labor market data to trace underlying distributive implications of regional technology adoption. We first empirically confirm that the regional employment composition indeed shifts toward higher skilled and less routine occupations. Second, we show that the disappearing jobs are associated with conservative and authoritarian-right vote, whereas the newly appearing jobs are associated with voting for more progressive parties. In sum, the analysis of intermediary distributive mechanisms on labor markets supports our conjecture that technological change results in a relative growth of occupations that are generally more supportive of progressive left parties.

5.2. Regional-level economic outcomes

We first turn our attention to the economic effects of technology adoption by simply switching the dependent variable from voting results to labor market indicators. In line with much of the existing literature in labor economics, we find that robot adoption and ICT investment affect the composition of the labor force but do not result in net employment loss. Both forms of technological innovation (if anything) marginally decrease manufacturing employment. Importantly, this decline in manufacturing is more than offset by an increase in the non-manufacturing (service) sector employment. The sum of both coefficients represents the effect of robot exposure on total employment relative to population (see Figure 4).

The main reason for an increase in aggregate employment is that the fall of routine jobs is often accompanied by disproportionate job growth in non-routine occupations (de Vries *et al.*, 2020). Indeed, when looking at labor shares of task groups instead of sectors, we find that technology adoption increases non-routine cognitive jobs at the cost of routine jobs (see Figure 5). In

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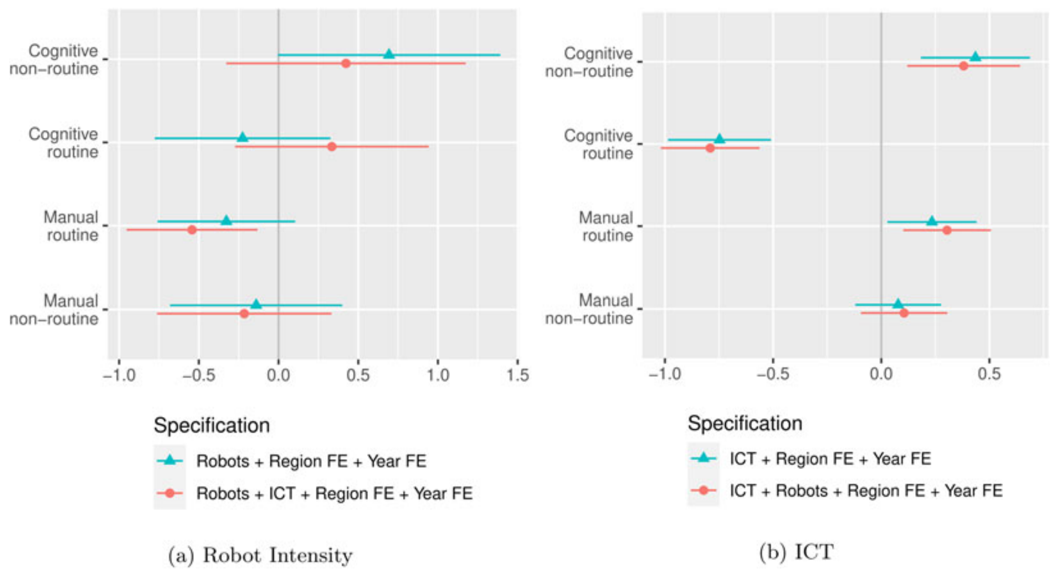

Figure 5. Technological change and regional task composition.
Note: All variables are expressed as changes in regional employment shares in percentage points such that coefficients sum up to zero. Bars represent 95 percent confidence intervals where standard errors are clustered at the commuting zone-year level.

line with our intuition, robots have a stronger replacement effect with respect to routine manual jobs, whereas ICT investment substitutes in particular for routine cognitive occupations. The share of low-skilled manual non-routine jobs is not significantly affected by technology adoption in Germany. This pattern is largely confirmed when looking at labor shares by skill group. Technology-adopting regions experience a strong increase in the share of high-skilled jobs and stagnation or even decline in mid- and low-skill jobs (see Figure 6).

Summing up, we show that regions with stronger exposure to technology adoption experience a polarized upgrading of labor markets. While overall employment is not negatively affected, the share (and numbers) of jobs in the semi-skilled and manufacturing domain decreases markedly. The observed pattern in which technology adoption shifts the sectoral and task-specific composition of the local labor force could be a result of at least three distinct mechanisms: (1) The incumbent labor force can retrain and change occupations and sectors, (2) young workers may enter different jobs than those exiting the local labor market or (3) a changing labor demand may attract workers from other regions. While it is beyond the scope of this study to offer a definite explanation of these different channels, we collected additional regional-level indicators to trace observable implications of each possible mechanism (see Appendix A.4.2 and Figure A.3 for details). Based on these auxiliary analyses, we conclude that the narrow individual-level mechanism is certainly not the only channel contributing to a changing labor market composition. Both intergenerational occupational upgrading and migration play a role, too. The results suggest that ICT investment in particular seems to attract (young, skilled) workers from other regions, whereas robotization is more strongly related to intergenerational transitions into other sectors with a more stable population size and local skill mix. These findings are not in itself groundbreaking, but align with previous work on the labor market effects of automation. Nevertheless, they provide a vital first piece of evidence to strengthen our argumentation that compositional effects play an important role to understand how automation affects political preferences at a regional level.

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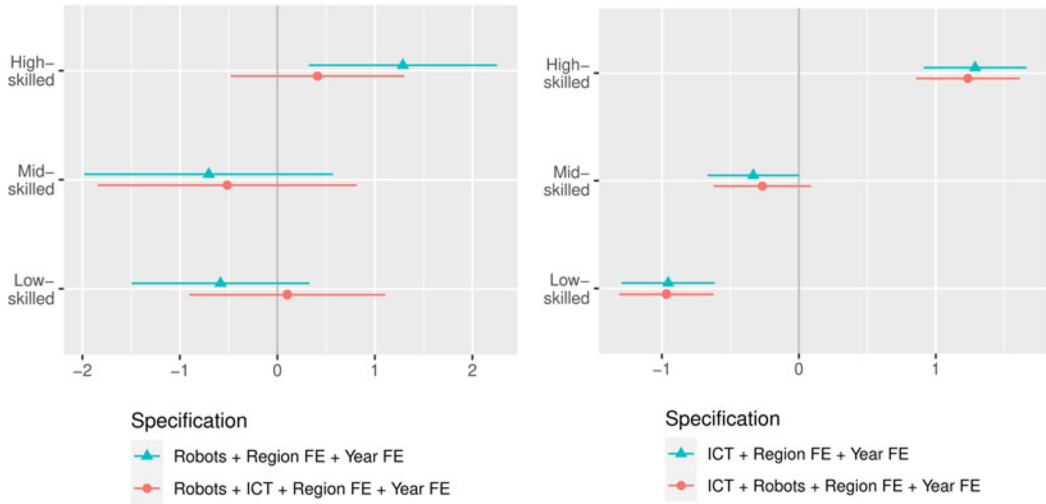

(a) Robot Intensity (b) ICT

Figure 6. Technological change and regional skill requirements.
Note: All variables are expressed as changes in regional employment shares in percentage points, such that coefficients sum up to zero. Bars represent 95 percent confidence intervals, where standard errors are clustered at the commuting zone-year level.

Both mechanisms contribute to a lower average and median age of the local labor force. This aspect of a changing composition of the local electorate may add to our finding that technology-adopting regions tend to lean toward the political left—beyond an explanation based on occupational preference formation. However, note that—in contrast to the popular narrative—young voters in Europe are not generally more "socialist" than older voters. While younger cohorts are much more socially liberal, they are, if anything, *more* economically conservative, i.e., more opposed to government spending and higher taxes (O'Grady, 2022). An explanation focusing on the impact of technology on the local age structure—in principle fully compatible with our arguments—is thus unlikely to account for much of the observed shifts in political support. Still, it is possible that parties that are particularly appealing to young, socially liberal voters benefit from this side effect of technology adoption on top of a changing occupational structure.

5.2. Regional-level relationship between occupation and vote choice

According to the theory of occupational preference formation, the shown changes in the labor market composition should shift political support more toward progressive parties. In order to corroborate these underlying expectations, the following analyses zoom in on the relationship between regional employment composition and party vote shares. For this, we focus on the results of the 2017 Federal Elections (the last year in our sample) and regress the county-level party vote share on the local employment share as of 2017. For each party p–employment share s (manufacturing share, routine worker share, etc.) pair, we run a separate regression of the following kind:

$$VoteShare_r^p = \beta * EmploymentShare_r^s + \epsilon_r \qquad (4)$$

where $VoteShare_r^p$ is the vote share of party p in region r which is regressed on the employment share of type s in region r.

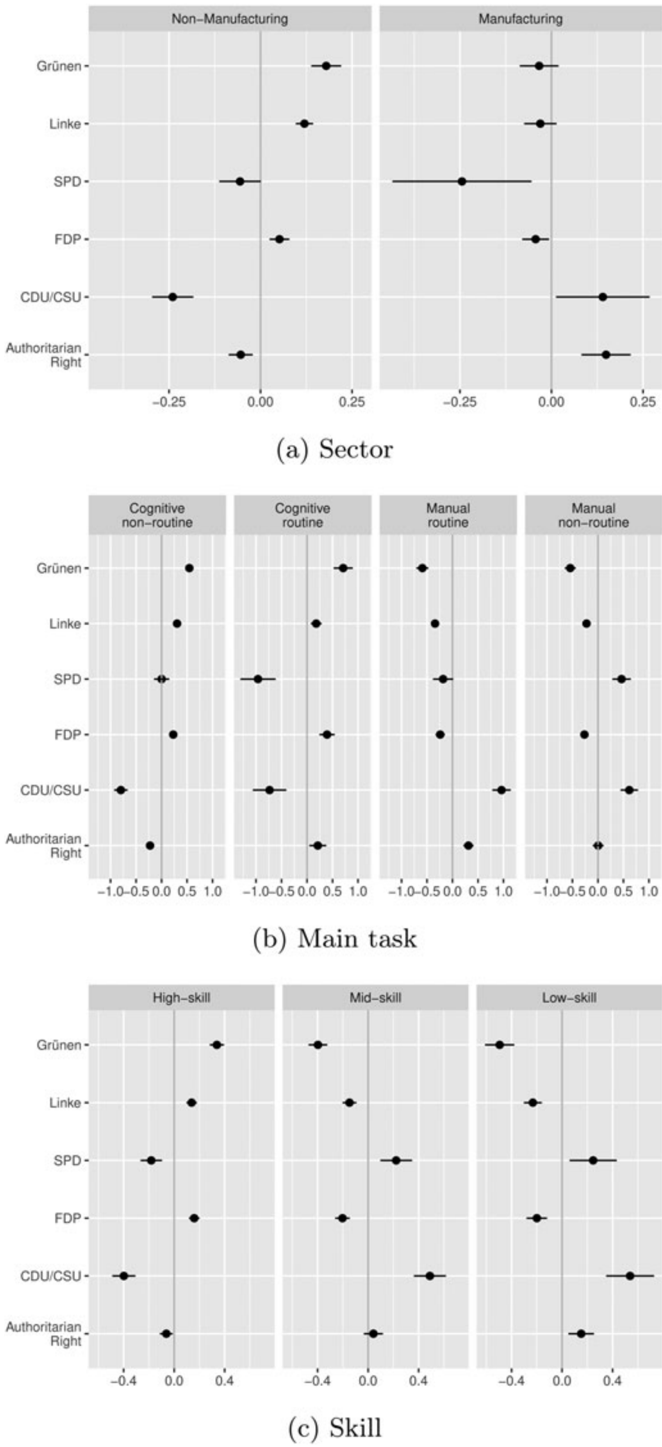

Figure 7. Cross-sectional correlations of regional employment shares and party vote shares in 2017 Federal Elections.
Note: Cross-sectional regression of regional party vote shares in 2017 federal elections on regional employment shares without controls (n=324 counties). The estimated coefficients are proportional to raw correlations. Bars represent 95 percent confidence intervals.

The results presented in Figure 7 show that a higher non-manufacturing (service) employment to population ratio is associated with more vote for progressive-left parties and a less support with conservatives and right-authoritarian parties. This closely resembles the effect of technological change on voting outcomes. Conservatives and right-authoritarian parties perform particularly well where the manufacturing employment to population ratio is high (panel 7a). Similarly, regional labor market characterized by a high share of cognitive non-routine occupations display more support for cosmopolitan-left parties and less support for conservative and authoritarian-right parties. Conversely, regions with a large share of manual workers (both routine and non-routine) tend to be less supportive of the progressive left parties and more supportive of authoritarian right parties (panel 7b). Similar patterns emerge when we look at the regional skill distribution (panel 7c).

5.2. Individual-level relationship between occupation and vote choice

As a final step, we analyze party preferences of different occupational groups using individual-level data from the German Socio-Economic Panel (SOEP). This allows us to test more directly how local labor market composition relates to election results. To do so, we recreate the sectoral and occupational groups from the previous analysis as closely as possible. Therefore, we considered all respondents between 18 and 65 for the years 1994–2018 (n=323000) and classified them into manufacturing and non-manufacturing, by main task and created three education groups. Figure 8 plots the party support of different occupational groups over time. We control for the age of individual respondents to take into account the above-discussed side effect with respect to the regional age structure in technology-adopting regions. To facilitate the visualization, we grouped responses in 5-year intervals.

The findings confirm a few common priors of the relevant literature (e.g., Oesch, 2008; Kitschelt and Rehm, 2014). First, we find that the progressive-left party *Die Grünen* is mainly supported by non-manufacturing (service sector) workers, whereas manufacturing workers became more and more supportive of conservative and authoritarian-right parties over the last years (panel 8a). Second, we observe the cognitive non-routine workers disproportionately support the progressive-left party *Die Grünen* whereas conservative parties are mainly supported by routine workers and authoritarian-right parties draw most support from manual occupations (both routine and non-routine) (panel 8b). Finally, we find a strong education gradient. Highly educated workers are the core constituents of the green party (and the pro-market FDP) whereas conservative and far-right parties find most support among middle and low educated workers (panel 8c). This further corroborates the idea that those occupational groups which expand due to technological change are more supportive of progressive-left parties, whereas conservative and authoritarian-right parties find the size of occupational groups that mainly supported them to be in decline.[4] A theory of occupational preference formation in tandem with a gradually changing composition of local labor markets hence provides a reasonable explanation of why technological innovation can shift the regional electoral landscape to the progressive left.

6. Discussion

In this paper, we demonstrate that, on average, technological innovation increased the *regional* vote shares of cosmopolitan left parties whereas right-authoritarian parties receive fewer votes in affected regions. The increased prevalence of robots and ICT changes the local labor market

[4]To be sure, we would expect that the electorate of the Left party differs from those of the Greens. Although the presented micro-level evidence demonstrates that those differences might be smaller than often assumed, the Left has been shown to find disproportionate support among low-income voters that have little in common with our winners of technological change. This discrepancy suggests a more nuanced reading of our results, which is in line with our evidence of a growing non-routine sector but highlights yet another potential aspect of job growth amid routine-biased technological change: not all of the new jobs are high-skill, high-pay jobs. Some of the job growth also happens in the weakly protected and lowly paid service sector. We do not believe that this is the core driver behind our results, because employment polarization in Germany is not particularly pronounced. But our regional-level analysis cannot rule out the possibility that some of the support for the Left party may still come from this part of the labor force.

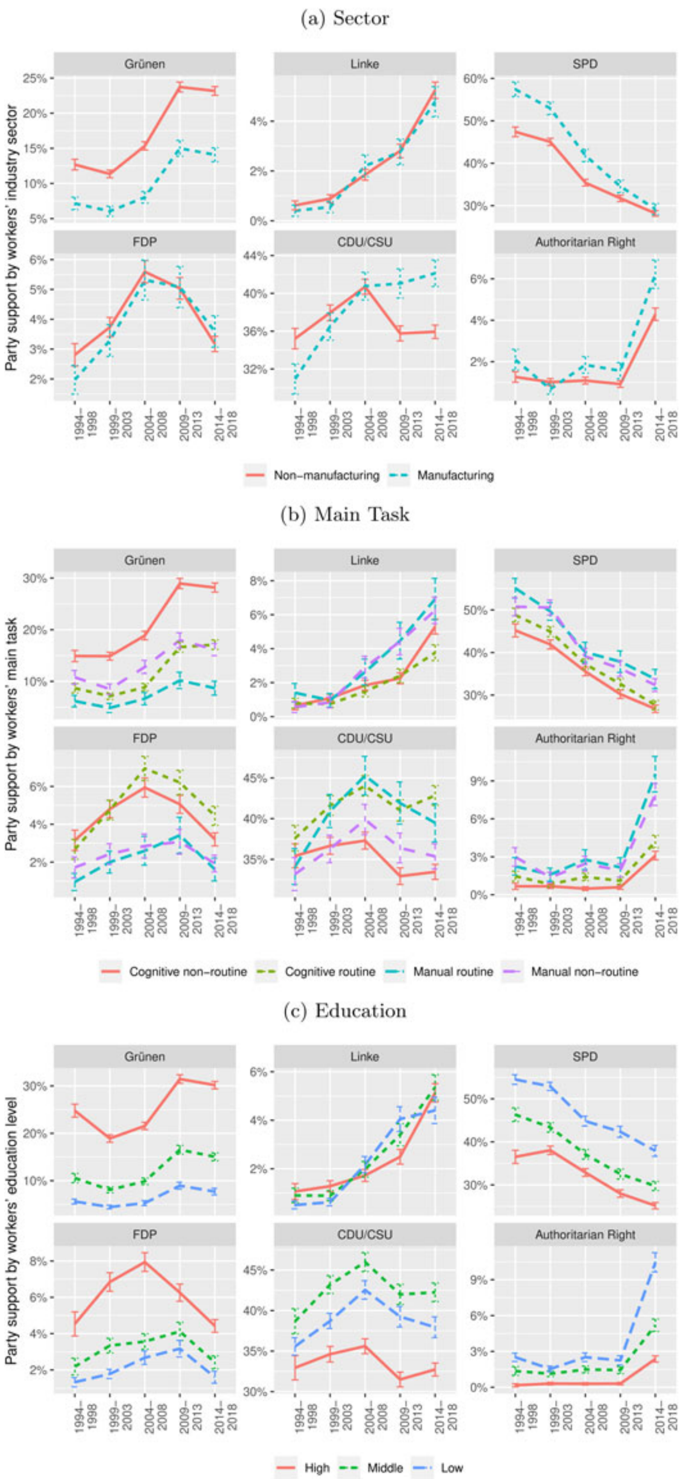

Figure 8. Party support of different segments of the workforce over time.
Note: Graphs show self-reported party support of different occupation groups over time accounting for the age of respondents (clustered into 5-year intervals). Bars represent 95 percent confidence intervals.

composition and shifts the employment structure from routine to non-routine jobs. This shift has important indirect consequences in that it opens more jobs for highly-educated, high skilled workers who often work on cognitive interactive tasks. Such "children of digitalization" gravitate toward the cosmopolitan left whereas routine workers in manufacturing whose jobs were, as we show, partly replaced by robots, often feel attracted by the promises of right-wing populism. Hence, the common narrative that technological change and robotization will first and foremost result in political disruption may provide an incomplete perspective.

How can we reconcile our findings with previous work that showed evidence in favor of the disruption narrative? Our study finds that *regions* exposed to robotization and digitalization tend to shift employment away from manufacturing and routine jobs, which in turn leads to less support for right-authoritarian parties. Hence, we would not expect that right-authoritarian parties make the strongest inroads in strongly technology-adopting regions. Here, the composition of local labor markets changes more substantially than in regions less exposed to technological change and economic modernization. And yet, it is important to repeat that we do *not* claim that technological innovation is unrelated to the recent surge in right-authoritarian and populist voting in Germany and elsewhere. The mounting evidence that automation increases right-authoritarian support among *individuals* or occupational *groups* that are imminently affected—or threatened—by automation is entirely plausible and convincing. However, we wish to highlight that the broader compositional changes in local labor markets work in the opposite direction and may well dominate the political response by those disaffected voters who lose out in the process of economic modernization.

Hence, we can resolve the apparent conflict by a conceptual differentiation between a compositional (regional) and a direct (individual) effect. This differentiation has important implications for future research, as it highlights the pros and cons of using a regional approach versus an occupational/individual-level approach. The disadvantage of our regional analysis is its inability to isolate those workers directly threatened by technological innovation. Put differently, some disruptive political consequences of technological change "might be masked [· · ·] by the aggregate welfare gains brought about by automation" (Anelli *et al.*, 2021, p. 4). This is exactly right: Our approach inherently bundles winners and losers within the unit of analysis. Depending on the workers' skills and occupation, the adoption of technology can have either positive or negative effects, even if they live in the same region.

On the positive side, a regional approach allows us to capture the compositional effect of changing local labor markets, i.e., precisely the before-mentioned welfare *gains* in the aggregate. Recall that a focus on within-individual changes lets us focus on the direct effect but—by design—neglects the compositional effect. Positive indirect effects of technological innovation such as the creation of new jobs can only be captured by a regional approach. Also, the fact that new generations joining the labor market enter into different occupations and hold different political attitudes than previous generation is hidden when focusing on within-individual changes. The academic literature has shown that technological change mostly shapes employment composition through generational turnover, rather than directly displacing affected workers. Hence, in the long term, the compositional effect may be considered more important and more consequential in political terms.

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References

Acemoglu D and Restrepo P (2019) Automation and new tasks: how technology displaces and reinstates labor. *Journal of Economic Perspectives* **33**, 3–30.

Acemoglu D and Restrepo P (2020) Robots and jobs: evidence from US labor markets. *Journal of Political Economy* **128**, 2188–2244.

Anelli M, Colantone I and Stanig P (2021) Individual vulnerability to industrial robot adoption increases support for the radical right. page 45.

Antoni M, Schmucker A, Seth S and Berge PV (2019) *Sample of Integrated Labour Market Biographies (SIAB) 1975–2017*. Nürnberg: Institut für Arbeitsmarkt-und Berufsforschung (IAB).

Ares M (2019) Changing classes, changing preferences: how social class mobility affects economic preferences. *West European Politics* **0**, 1–27.

Autor D and Dorn D (2009) This job is "getting old": measuring changes in job opportunities using occupational age structure. *American Economic Review* **99**, 45–51.

Autor D, Levy F and Murnane RJ (2003) The skill content of recent technological change: an empirical exploration. *The Quarterly Journal of Economics* **118**, 1279–1333.

Bartik TJ and Doeringer PB (1993) Who benefits from state and local economic development policies. *Journal of Policy Analysis and Management* **12**, 411.

Biagi F and Falk M (2017) The impact of ICT and e-commerce on employment in Europe. *Journal of Policy Modeling* **39**, 1–18.

Bornschier S (2010) *Cleavage Politics and the Populist Right The New Cultural Conflict in Western Europe*. US: Temple University Press.

Burst T, Lehmann P, Regel S and Zehnter L (2021) One election, six visions for Germany: the parties' manifestos for the 2021 general election. ISBN: 9783962509736 OCLC: 1289761521.

Callaway B and Sant'Anna PHC (2021) Difference in differences with multiple time periods. *Journal of Econometrics* **225**, 200–230.

Cortes GM (2016) Where have the middle-wage workers gone? a study of polarization using panel data. *Journal of Labor Economics* **34**, 63–105.

Dauth W, Suedekum J, Findeisen S and Woessner N (2021) The adjustment of labor markets to robots. *Journal of the European Economic Association* **19**, 3104–3153.

de Chaisemartin C and D'Haultfoeuille X (2020) Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review* **110**, 2964–2996.

de Vries GJ, Gentile E, Miroudot S and Wacker KM (2020) The rise of robots and the fall of routine jobs. *Labour Economics* **66**, 101885.

Faber M, Sarto A and Tabellini M (2022) Local Shocks and Internal Migration: The disparate Effects of Robots and Chinese Imports in the US. NBER Working Paper Series no. w30048. Cambridge, Mass: National Bureau of Economic Research.

Frey CB, Berger T and Chen C (2018) Political machinery: did robots swing the 2016 US presidential election?. *Oxford Review of Economic Policy* **34**, 418–442.

Gallego A and Kurer T (2022) Automation, digitalization, and artificial intelligence in the workplace: implications for political behavior. page 22.

Gallego A, Kurer T and Schoell N (2020) Neither left behind nor superstar: ordinary winners of digitalization at the ballot box. *Journal of Politics* **84**, 418–436.

Gingrich J and Häusermann S (2015) The decline of the working-class vote, the reconfiguration of the welfare support coalition and consequences for the welfare state. *Journal of European Social Policy* **25**, 50–75.

Goodman-Bacon A (2021) Difference in differences with variation in treatment timing. *Journal of Econometrics* **225**, 254–277.

Graetz G and Michaels G (2018) Robots at work. *The Review of Economics and Statistics* **100**, 753–768.

IFR (2016) Executive summary world robotics 2016 industrial robots.

Im ZJ, Mayer N, Palier B and Rovny J (2019) The "losers of automation": a reservoir of votes for the radical right?. *Research & Politics* **6**, 2018.

Iversen T and Soskice D (2019) *Democracy and Prosperity. Reinventing Capitalism through a Turbulent Century*. Princeton, NJ: Princeton University Press.

Kitschelt H (1994) *The transformation of European Social Democracy*. Cambridge studies in comparative politics. Cambridge: Cambridge University Press.

Kitschelt H and Rehm P (2014) Occupations as a site of political preference formation. *Comparative Political Studies* **47**, 1670–1706.

Klenert D, Fernandez-Macias E and Antón J-I (2020) Do robots really destroy jobs? Evidence from Europe. Technical Report 2020/01, European Commission, Seville.

Koch M, Manuylov O and Smolka M (2019) Robots and Firms. *CESinfo Working Paper*.

Kurer T (2020) The declining middle: occupational change, social status, and the populist right. *Comparative Political Studies* **53**, 1798–1835.

Kurer T and Gallego A (2019) Distributional consequences of technological change: worker-level evidence. *Research & Politics* **6**, 2053168018822142.

Kurer T and Palier B (2019) Shrinking and shouting: the political revolt of the declining middle in times of employment polarization. *Research & Politics* **6**, 2053168019831164.

Lahtinen H, Wass H and Hiilamo H (2017) Gradient constraint in voting: the effect of intra-generational social class and income mobility on turnout. *Electoral Studies* **45**, 14–23.

Langsaether PE, Evans G and O'Grady T (2022) Explaining the relationship between class position and political preferences. *British Journal of Political Science* **52**, 958–967.

Michaels G, Natraj A and Van Reenen J (2014) Has ict polarized skill demand? Evidence from eleven countries over twenty-five years. *Review of Economics and Statistics* **96**, 60–77.

Milner HV (2021) Voting for populism in Europe: globalization, technological change, and the extreme right. *Comparative Political Studies* **54**, 001041402199717.

Oesch D (2006) *Redrawing the Class Map: Stratification and Institutions in Britain, Germany, Sweden and Switzerland.* Basingstoke [England]; New York: Palgrave Macmillan.

Oesch D (2008) Explaining workers' support for right-wing populist parties in Western Europe: evidence from Austria, Belgium, France, Norway, and Switzerland. *International Political Science Review* **29**, 349–373.

Oesch D and Rennwald L (2018) Electoral competition in Europe's new tripolar political space: class voting for the left, centre-right and radical right. *European Journal of Political Research* **57**, 783–807.

O'Grady T (2022) ls ideological polarisation by age group growing in Europe? *European Journal of Political Research.* Published Online. https://doi.org/10.1111/1475-6765.12575

Powell WW and Snellman K (2004) The knowledge economy. *Annual Review of Sociology* **30**, 199–220.

Stehrer R, Bykova A, Jäger K, Reiter O and Schwarzhappel M (2019) Industry level growth and productivity data with special focus on intangible assets. *Report on methodologies and data construction for the EU KLEMS Release 2019.*

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