How Technological Change Affects Regional Electorates

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Abstract

This paper challenges the common perception that automation and digitalization generally reduce employment and primarily result in political discontent. Drawing on fine-grained labor market data from West Germany and shift-share instruments combined with two-way fixed-effect panel models, we study how technological change affects regional electorates. We show that the expected decline in manufacturing and routine jobs in regions with higher robot adoption or higher investment in information and communication technology (ICT) was in fact more than compensated by parallel employment growth in the service sector and cognitive non-routine occupations. This change in the regional composition of the electorate has important political implications as workers trained for these new sectors typically hold progressive political values. Consequentially, local advances in technology are associated with higher vote shares for progressive parties. This finding adds important nuance to the popular narrative that technological change fuels radical right voting.

JEL: P16, D72, O33, J31

Keywords: Technological Change, Automation, Robots, Political Preferences, Voters, Occupational Determinants of Political Preferences

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1 Introduction

The widespread use of new technology at the workplace – ranging from self-learning software to increasingly sophisticated industrial robots – has raised fears about wage pressure and employment loss. A vivid debate has evolved about the political and societal consequences of an uncertain future of work. Those who lose out in this process are likely to voice their dissatisfaction and seek for ways to express their discontent. Not surprisingly, observers have thus been quick to relate the recent surge of xenophobic forces and populist anti-establishment movements in many post-industrial democracies to technology-induced changes in the employment structure. While bold journalistic accounts claiming that "robots have helped elect Trump" (Edsall, 2018) seem exaggerated, a growing literature in political science suggests that direct susceptibility to automation and robotization is related to support for anti-incumbent and anti-establishment forces (Frey, Berger and Chen, 2018; Im et al., 2019; Anelli, Colantone and Stanig, 2019; Kurer, 2020; Milner, 2021).

This growing literature in political science builds its causal chain on research from labor economics showing that technological change has a displacement effect for certain tasks and occupations (Acemoglu and Restrepo, 2019). Capital in the form of industrial robots or specialized software takes over routine tasks previously done by human labor in both white- and blue-collar occupations. The existing literature in political science then moves on to show that manufacturing and routine workers –who are directly threatened by this process– become more supportive of authoritarian-right parties (Frey, Berger and Chen, 2018; Im et al., 2019; Anelli, Colantone and Stanig, 2019; Kurer, 2020; Milner, 2021).

However, and this is mostly ignored by existing work in political science, labor economists also agree that new technologies increase productivity and contribute to rising demand for labor in non-automatable tasks. It is widely accepted that this productivity growth leads to the creation of new jobs, yet of a very different type. Far away from the conveyer belt, new jobs tend to pertain to more high-skilled, cognitive and interactive occupations oftentimes requiring tertiary education (Michaels, Natraj and Van Reenen, 2014; Dauth et al., 2021; Graetz and Michaels, 2018; Koch, Manuylov and Smolka, 2019; de Vries et al., 2020). Through the widespread experience of attending university and a distinct work culture and work logic, workers in those occupations tend to hold more cosmopolitan and progressive values (Kitschelt, 1994; Oesch, 2006*a*; 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 arguably 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 thus theoretically ambiguous and it requires an empirical analysis to determine which effect dominates.

We advance the existing literature empirically by studying the political implications of technological change in West Germany. The West German case is highly relevant because (a) West Germany 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) West Germany has still the largest manufacturing share of employment compared to other advanced economies and (c) has recently seen the rapid rise of the party "Alternative für Deutschland" (AfD), which puts an end to the historic taboo of supporting right-authoritarian parties.

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 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 (Jaeger, 2016). This constitutes a distinct form of technological change which (in contrast to robotization) 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 (generalized diff-in-diff) to control for unobserved factors.

Unlike most existing work studying the political implications of the most recent wave of technological change, our approach allows 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 the labor market. 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. Furthermore, regions with faster growing technological innovation experience stronger labor market polarization: Semi-skilled and routine occupations decline at the expense of non-routine work at both ends of the skill spectrum. 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 at the regional level does not support the narrative that new technology at the workplace first and foremost results in right-authoritarian success. Instead, we find that, on average, regions more strongly affected by technological innovation shift their political support towards socially progressive parties. The regional vote shares of center-right and right-authoritarian parties, including the AfD, 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 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.

Our study of a European frontrunner in terms of technology adoption adds to a burgeoning literature on the political and societal consequences of technological change (Frey, Berger and Chen, 2018; Im et al., 2019; Anelli, Colantone and Stanig, 2019; Gallego, Kurer and Schöll, 2020; Kurer, 2020). Importantly, our analysis systematically examines the entire causal chain from technology exposure to election results including the intermediary distributive implications on local labor markets based on geographically fine-grained labor market data. By highlighting that new technologies not only replace human work (the replacement effect) but also create new jobs

[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 seems to be substantial job loss and closed factories as companies without robots fall behind in global competition (Koch, Manuylov and Smolka, 2019).

(the productivity effect), we challenge rather gloomy perspectives on the political repercussions of technological change. In the conclusion of the paper, we provide an extensive discussion of the relative importance of the direct individual-level effect of automation risk that could create support for radical-right parties vis-à-vis the aggregate-level effects of economic modernization that may work in the opposite direction by changing the composition of local labor markets away from manufacturing towards more high-skilled non-routine jobs. 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

In their seminal work on routine biased technological change (RBTC), Autor, Levy and Murnane (2003) argue that new technologies primarily substitute for routine tasks that follow clearly defined rules, which makes jobs that heavily rely on such tasks "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 workers in the manufacturing sector.

On the other hand, new technologies raise productivity which leads to an increased demand for workers whose skills are complementary to automation. Newly created jobs tend to 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 a rather precarious group of 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. This was dubbed the *productivity* or *reinstatement effect* (Acemoglu and Restrepo, 2018, 2019).

While there seems to be a general consensus among scholars 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). On the other hand, studies focusing on Europe and on Germany in particular found null or slightly positive employment effects (Dauth, Findeisen and Suedekum, 2019; Klenert, Fernandez-Macias and Antón, 2020). 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, Natraj and Van Reenen, 2014).[2]

Our own original analysis points in the same direction: although we do find that mid-skilled routine jobs generally 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. While no single analysis will be able conclusively answer the question of whether technology adoption tilts the balance towards more or less employment, for our purpose the distributive implications of robotization and ICT investment and how they transform the composition of local labor markets are particularly relevant. Parts of society, namely manufacturing and routine workers, stand to lose from this process whereas non-routine occupations requiring cognitive and social skills (and oftentimes a university education) are growing in numbers.

3 Political Implications of Technological Innovation

The distributive implications of technological innovation as described in the previous section 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 consequences of direct exposure to automation. On the other hand, a different strand of literature has studied the consequences of economic modernization and occupational change at the aggregate level and emphasizes the changing *composition* of postindustrial societies, i.e. general upskilling and the emergence of modern "knowledge economies". These two perspectives have most often been studied in isolation and it should not come as a surprise that they come to fundamentally different conclusions about the prospects for advanced capitalist democracy exposed to automation. While the first is often motivated by a concern about the potential substitution of human labor

[2]It should be noted, however, that it remains unclear to what extent the findings on traditional ICT investment can be applied to the most recent and, especially, future developments in the domain of software development and artificial intelligence (Graetz, 2020; Frank et al., 2019).

and resulting political disruption, the second provides a much more optimistic outlook emphasizing economic opportunity and mobility through widespread higher education. Interestingly, the net impact of the two effects remains unclear and the relative importance of winners and losers is at the root of much of the debate about the political implications of technological change.

3.1 Direct Effect

Existing papers that according to our grouping study the direct effect of automation risk focus on individual-level effects on political preferences and voting behavior. Despite the fact that technological change creates both winners and losers, it seems safe to say that most existing work investigates the political reactions of workers who stand to lose from technological change. Alluding to the historical examples of Luddites destroying machines 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 become more attracted to anti-establishment forces due to their economic decline (Frey, Berger and Chen, 2018; Anelli, Colantone and Stanig, 2019; Kurer and Palier, 2019; Im et al., 2019). Specifically looking at the impact of robots, Frey, Berger and Chen (2018) showed an association between robot adoption and anti-incumbent voting in the U.S. and Anelli, Colantone and Stanig (2019) 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, Kurer and Schöll (2020) examine political preferences of "ordinary winners" of digitalization in the United Kingdom. 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, in particular those from the center right. The intragenerational experience of growing economic prosperity as a consequence of technological innovation hence creates a stabilizing pro-system force. A recent working paper suggests that governments' investment in higher education, which demonstrably mitigates negative labor market consequences of technological change, might represent one important mechanism explaining such a pro-government shift in partisan voting (Lastra-Anadon, Scheve and Stasavage, 2020). The more specific literature on political consequences of robotization has so far exclusively focused on the downsides of this process. We are not aware of scholarly work analyzing how robotization affected the political attitudes of those who benefited from this process.

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 rather than on physical inputs or natural resources (Powell and Snellman, 2004). Although the inclusiveness of contemporary knowledge economies remains somewhat disputed (Unger, 2019), influential recent accounts highlight the value of the educational expansion (Boix, 2019) and 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. Importantly, this change in the composition of local labor markets has important political implications since occupations are known as important sites of preference formation (Kitschelt, 1994; Oesch, 2006*b*; 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. Key contributions to the literature differentiate 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 (Oesch, 2006*a*,*b*). 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 authoritarian views. Occupations that require university educations, which are based on cooperation (rather than hierarchies), which focus on social interactions and culture tend to entertain more cosmopolitan and progressive values (Kitschelt, 1994).[3] 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 (see, e.g. Oesch, 2008*b*). Much in contrast, the growing number of highly educated workers engaging in more analytical and interactive work ("socio-cultural professionals") tend to belong to a milieu which is more left-leaning and cosmopolitan. Gingrich and Häusermann (2015) show how 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.[4]

Going back to the expected distributional implications of automation, it becomes clear that the compositional effect shifts political support to progressive left parties. The manufacturing sector and in particular semi-skilled routine work is shrinking through the substitution effect. At the same time, occupations with higher educational requirements and a more client-interactive work logic are growing due to the productivity effect of automation.[5]

3.3 Net Effect

The political space in Germany and many other postindustrial democracies is composed of an economic and a cultural dimension (see, e.g., Kitschelt, 1994). 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). Appendix Figure A.1 provides a descriptive overview of the contemporary German partisan landscape. From a theoretical perspective, the direct and the compositional effect 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

[3] Kitschelt and Rehm (2014) provide an extensive discussion on whether these correlations may result from a selection into occupations ("weak theory") or from socialization within occupations ("strong theory").

[4] Section 5.2 provides additional micro-level evidence from household panel data bolstering this conjecture.

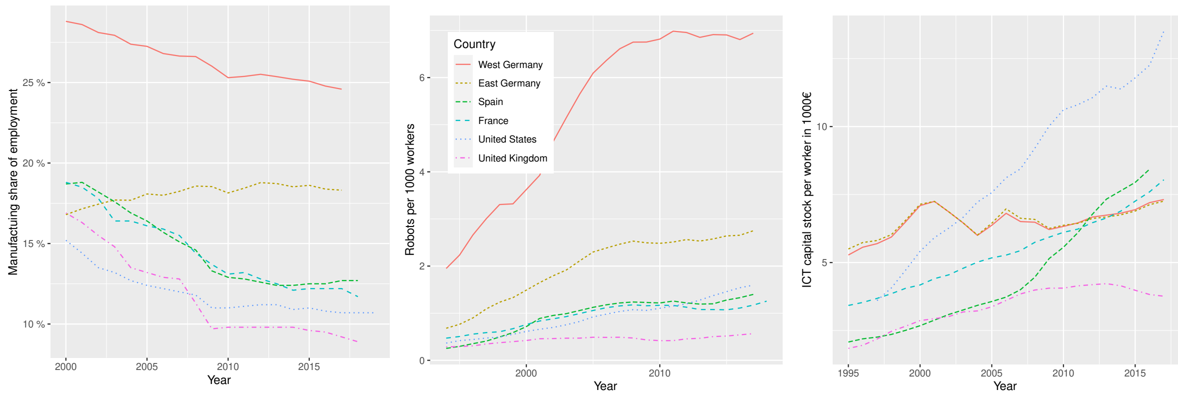
[5] Note that the regional labor force composition can change through different mechanisms: (a) workers can retrain and change occupations as demand for their original occupation declines, (b) the region can attract migrant workers from elsewhere if they have the education and skills now required and (c) new generations will choose a different educational path and take up occupations that are now in high demand.

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 the important case of West Germany. The number of voters potentially affected by technological change is larger than in other advanced economies as West Germany still has a large manufacturing sector and at the same time has deployed the largest number of robots anywhere outside Asia (see Figure 1). Furthermore, West Germany also experienced large investments in ICT over the years.[6]

Figure 1: Evolution of manufacturing share, robot penetration and ICT



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

We apply a regional approach similar in spirit to previous studies in economics and political science (Acemoglu and Restrepo, 2020; Dauth et al., 2021; Anelli, Colantone and Stanig, 2019; Frey, Berger and Chen, 2018). We chose counties, *Landkreise und kreisefreie Städte*, to be the regional unit of analysis (n = 324, NUTS-3).[7] In the following, we describe how we constructed

[6] We do not consider regions of the former GDR for their quite distinct economic and political trajectory. The structure of the manufacturing sector differs quite fundamentally, with technology penetration being much slower in the East. In addition, while East German manufacturing has imploded right after the fall of the iron curtain in 1989, resulting in a much lower but eventually slightly growing manufacturing share (19% in 2017, up from 17% in 1994), West German manufacturing has seen a more steady decline (25% in 2017, down from 32% in 1994). Finally, with respect to the political arena, existing research shows that support for radical right parties has historically been stronger in the East. In light of the time period under consideration, we think that a focus on West German counties is reasonable in that it provides a cleaner, more homogeneous sample to study the questions at hand.

[7] In the early nineties there were still almost 400 counties in West Germany which were then merged and reshaped in various rounds of regional reforms. Election results and other control variables are according to those

a yearly panel of economic and political variables on county level for the time period 1994 to 2017.

4.1 Robot exposure

To calculate how a county's exposure to robots is changing over time, we use data on robot adoption from the International Federation of Robotics (IFR). A robot is defined as an "automatically controlled, re-programmable, and multipurpose machine". As explained in more detail in IFR (2016), this means that robots are "fully autonomous machines that do not need a human operator and that can be programmed to perform several manual tasks such as welding, painting, assembling, handling materials, or packaging". The yearly data differentiates between 25 industries, mostly in manufacturing.

To measure robot exposure at a time-varying county level, we follow Acemoglu and Restrepo's (2020) approach to exploit information on pre-sample regional employment composition. The idea is to distribute the robots of a given sector to regions based on the the number of employees in the region working in the sector relative to the nation-wide employment in the sector. Since we are interested in the robot intensity of a region, 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 demonstrates that our results do not hinge on this transformation of the explanatory variable.)

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

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 particular, we use employment records from a 2% sample randomly drawn from the universe of German employees subject to social security (Antoni et al., 2019). For those, we have information on employment status, employer and occupation for any given day for the entire sampling period. An adjacent firm data set includes

historic definitions of counties. To create a consistent panel based on the current shape of counties, we employ population weights which we obtained from the Federal Statistics Office.

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 is used from pre-sample period as later sectorial employment composition might be endogenous to the adoption of robots.[8]

The measure constitutes a typical Bartik-style shift-share variable where an industry-level shock is apportioned across regions (Bartik and Doeringer, 1993).[9]

4.2 ICT investment

To measure digitalization, we follow Michaels, Natraj and Van Reenen (2014), who use yearly changes in ICT capital stocks within industries(see also Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). We use 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 to 2017. The data is 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 (O'Mahony and Timmer, 2009). 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 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

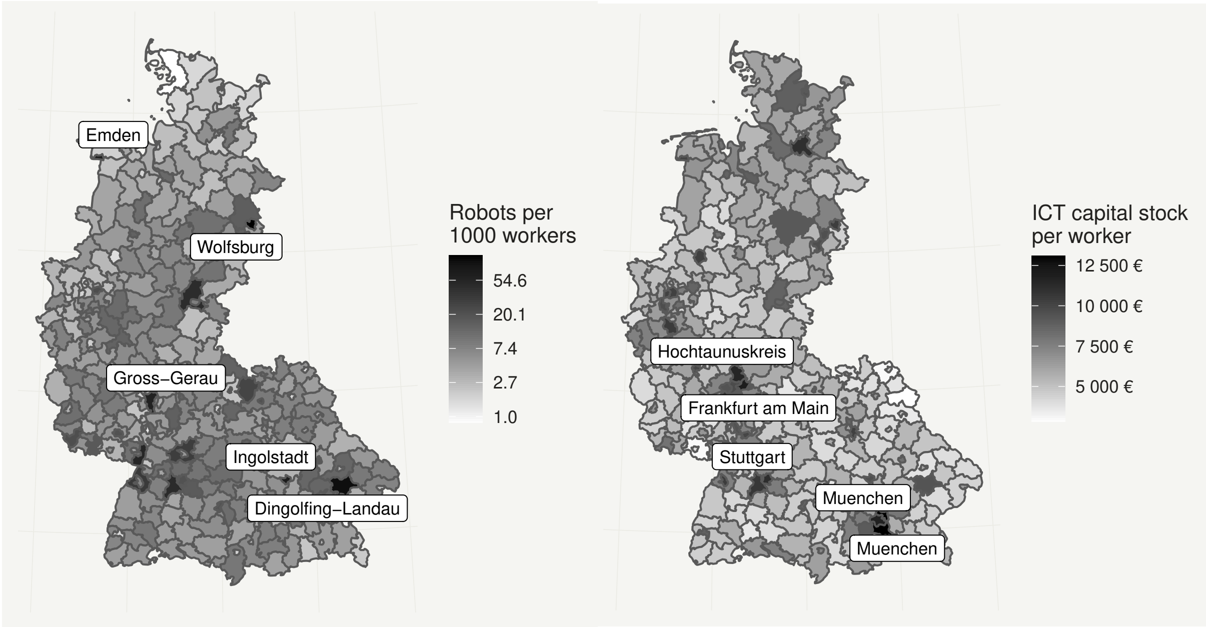
$$\mathrm{ICT}_{r,t} = \frac{1}{E_r} \sum_j \frac{\mathrm{ICT}_{j,t} * E_{j,r}}{E_j} \tag{2}$$

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

[8]In the construction of the measure of robot intensity, we closely follow Dauth et al. (2021) who study the labor market effects of robot adoption in Germany using the same data sources. Unlike them, we do not have access to the universe of German employees but only to a (still very large) 2% sample of all employees provided to external researchers by the IAB. To get closer to the universe of employees, we take advantage of the fact that the IAB provides information on number of coworkers for all of the sampled workers. By counting all employees of their respective workplaces we increase the effective sample size drastically. Furthermore, we considered information from all years between 1984 and 1994 to get a clear estimate of regional employment composition. In Section A.5 of the appendix, we confirm that – despite the lack of access to the full employee sample – our proposed approach can successfully replicate the main results of Dauth et al. (2021).

[9]Even though popular in the literature, this approach has also received criticism in recent years (for discussions see Goldsmith-Pinkham, Sorkin and Swift, 2020; Jaeger, Ruist and Stuhler, 2018)

Figure 2: Regional distribution of new technologies



(a) Robot Intensity

(b) ICT

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.

year t and E_j is the total employment in industry j across all regions.

This allows for the creation of time-varying, industry-specific indicators of digitalization based on ICT stocks.

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. Hence, face validity of our measure is high: All regions standing out due to their exceptionally high exposure to robotization can be clearly associated to (car) manufacturing hot-spots. The right panel shows that ICT is concentrated in the major service-sector business hubs of Munich, Frankfurt and Stuttgart. This shows that we capture two distinct forms of technological change. In fact, the correlation between the two measures is 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 election 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 AfD (right-authoritarian). Since the AfD was only founded in 2013, we pool it with other right-authoritarian parties (NPD, DVU, Republikaner). Previous research shows that the AFD grew strongly in regions that have been strongholds of other right-authoritarian parties before (Cantoni et al., 2019).

4.4 Other data sources

From the IAB data, we can additionally derive regional and time-varying employment shares along other dimensions that allow us to carefully trace distributional implications on the regional level. For our purposes, we distinguish between manufacturing and non-manufacturing employment, employment shares by main task, employment shares by skill requirements and employment shares by education attainment of the region's workforce.

Employment shares by main task are derived from occupation descriptions filled out by the employer which can matched to task profiles (Dengler, Matthes and Paulus, 2014). Employment shares by skill and education are also derived from information provided by the employer. Occupational skill requirements range from low-skilled (*Helfertätigkeit*) over mid-skilled (*Fachliche Tätigkeit* to high-skilled (*komplexe Spezialistentätigkeit, hochkomplexe Expertentätigkeit*).Education is classified by thee level of school leaving certificates ranging from school drop outs, over high school diploma (*Hauptschule*, *Realschule*) to A-levels (*Abitur*) which enables students to pursue a university education. [10]

In addition, we will control for increasing trade with eastern Europe and China as they are potentially correlated with the adoption of new technology and have been shown to affect voting behavior of affected workers (Dippel, Gold and Heblich, 2015; Colantone and Stanig, 2018). We obtained data from the UN Comtrade database on industry level net-exports to construct another shift-share variable. To calculate net exports of goods, we first compute German net exports vis-a-vis China and Eastern European for every product category from UN Comtrade data. Using an official transition matrix provided by the UN, we calculate industry level net

[10] For a detailed description of the classifications see Antoni et al. (2019).

exports. If a product group is associated with multiple industries, we weight by industry-level employment shares and normalize by the initial number of employees in the sector to account for industry size. To calculate regional exposures, we then employ shift-share instruments where regional employment composition was calculated analogously to the robots data. Finally, we obtained information about regional GDP per capita from the federal statistics office.

4.5 Empirical Approach

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

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

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 also 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.

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 modelling the direct relationship between regional technological adoption and regional election outcomes.[11] Figure 3 plots estimated marginal effect of regional robot intensity (see Panel 3a) and ICT investment (see Panel 3b) on regional electoral vote shares of all major German parties. The reported coefficients each stem from a separate regression. We first run a specification where only include one of the technological change measures (blue triangles) and secondly a specification including both measures of technological change simultaneously (red circles). Both specifications include a region and an election fixed effect.[12]

[11] We call this "reduced form" as it is not the technological innovation itself which affects election results. Instead, our imagined causal chain is that technological innovation affects the fate of workers, who react to the change through altered voting pattern.

[12] See column (1) and (3) of Tables A.1-A.12 in the Appendix. Further note that election fixed effects differ from year fixed effects in the case of multiple state elections held in the same year.

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. The social-democratic SPD has positive but imprecisely estimated positive 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 hence provide evidence that the compositional effect of digitalization (measured as ICT investment) favoring progressive left parties dominates at the regional level.

For robotization, the picture is less clear. When considering the effect of robotization in isolation, we find a similar gradient across the political spectrum: progressive-left parties gain whereas conservative and authoritarian-right parties tend to receive less votes when a region adopts robots. However, only the effect of the progressive-left party *Die Grünen* is statistically significant. Moreover, when controlling for the parallel influence of ICT, the marginal effects of robotization hover around zero and none of them is significant. We interpret this as evidence that for robotization, the direct effect favoring authoritarian-right parties and the compositional effect favoring progressive left parties are on balance. Nevertheless, we consider this an important result as it contrasts with previous work claiming that robotization leads to an unambiguous shift towards the right of the political spectrum.

In terms of effect magnitude, our baseline models predict that a one standard deviation increase in the log number of robots per thousand workers (+30% more robots) is associated with an increase of the *Grünen* vote share of 0.15 percentage points. Taken as such, we interpret this as modest effects. However, considering that the average region increased its number of robots by 270% between 1994 and 2017, the accumulated effect for *Die Grünen* is an estimated increase of the vote share by 0.71 percentage points, which is important for a party which usually attracted a vote share of less than 10%.[13] A one standard deviation increase of within-region robot exposure (+30% more robots) decreases support for right-authoritarian parties by 0.06

[13] Using the formula

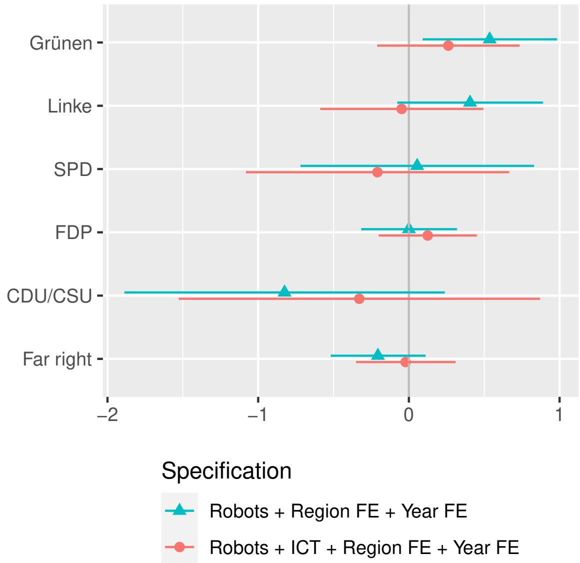
$$\Delta\text{vote share} = \hat{\beta} * log(\frac{\text{robots growth in } \% + 100}{100})$$

implies the overall increase in robot exposure over our sample period (on average +270% between 1994 and 2017) predicts an increase of *Die Linke* vote share of $0.54 * log(\frac{270+100}{100}) = 0.71$ percentage points.

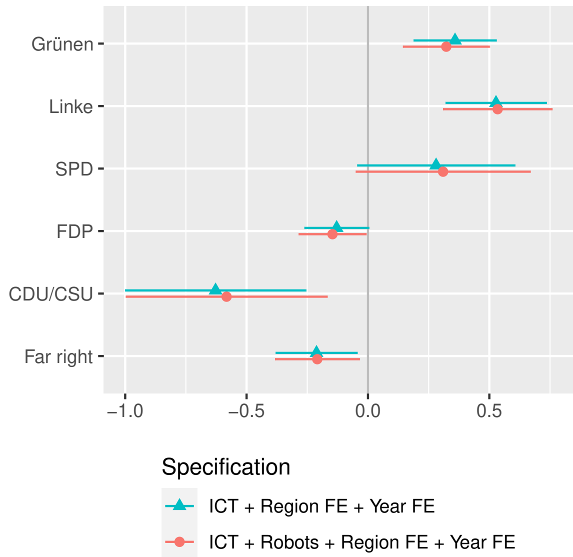
Note, however, that this back-of-the-envelope calculation should be interpreted with a large grain of salt as it ignores equilibrium effects such as the endogenous responses of parties to changing electorates.

percentage points (not statically significant) or 0.27 percentage points considering the estimated effect of the average increase in robot intensity over the entire sample period.

Figure 3: Region-level exposure to technological change and Party Vote Shares



(a) Marginal Effect of Robot Intensity



(b) Marginal Effect of ICT

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). The sample consists of all federal, state and European elections between 1994 and 2017 measured on a county level (324 *Kreise und kreisfreie Städte*, NUTS-3) . AfD, DVU, Republikaner and NPD are coded as right-authoritarian parties.
Standard errors clustered at the county level. Bars represent 95% confidence intervals.

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 and a decrease of the right-authoritarian vote share by -0.11 percentage points.

We resist the temptation to compare the magnitude of effects sizes of the two technologies for two reasons. First, 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. Secondly, the comparison would implicitly assume that we measure both concepts equally well. However, we have to be clear that both measures are only an approximation of the underlying concept and both suffer from measurement bias to some extent, which attenuates effect sizes.

Next, we run a series of robustness checks to increase confidence in our results (see Appendix A.2 for details). First, additional to the two-way fixed effects, we control for the trade exposure vis-à-vis China and Eastern Europe as an additional economic shock 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 digitalization (ICT), effects are marginally attenuated when controlling for net exports or GDP growth. The IV results for ICT are in fact stronger than the OLS results: The progressive parties *Die Grünen* and *Die Linke* have larger positive coefficients whereas the socially-conservative and authoritarian-right end of the party spectrum has stronger negative effects. We conclude that the ICT results are very robust.

Considering the automation in the form of robots, all results turn statistically insignificant when controlling for GDP or when considering the IV results. This again highlights that robotization may not have clear-cut political implications at the regional level. In additional robustness checks for the analysis on robots, we use an alternative specification of our main explanatory variable using the number of robots per thousand workers in levels rather than in logs. Using this alternative specification, the effects change substantially and in fact reverse to some extent, i.e. we find negative coefficients for progressive-left parties and weakly positive coefficients for the authoritarian-right AfD. However, the bottom panel of Tables A.1-A.6 in the Appendix show that the effect of the non-logged specification is driven by a few regions with extreme robot concentration. When excluding the top 10 region in terms of robotization, the estimated gradient between the progressive-left and the authoritarian-right reverts back to what we found in the main results. It seems that different specification implying different relative weights of each region can be enough to change the interpretation of the results. The fact that results are quite unstable may be a further indication that direct and compositional effect are broadly on par.

5.2 Understanding Compositional Effects and Underlying Mechanisms

Our findings conflict with more gloomy projections put forward in the media and the public debate but also in important scholarly work, in which automation has been unambiguously related to the rise of populism and the success of right-authoritarian parties not only on the individual but also on the regional level (Anelli, Colantone and Stanig, 2019; Milner, 2021).

The remainder of the empirical exercise makes use of our fine-grained labor market data to demonstrate that the adoption of new technologies affects the composition of local labor force towards 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. We build on both regional-level and individual-level data to bolster our arguments. 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.

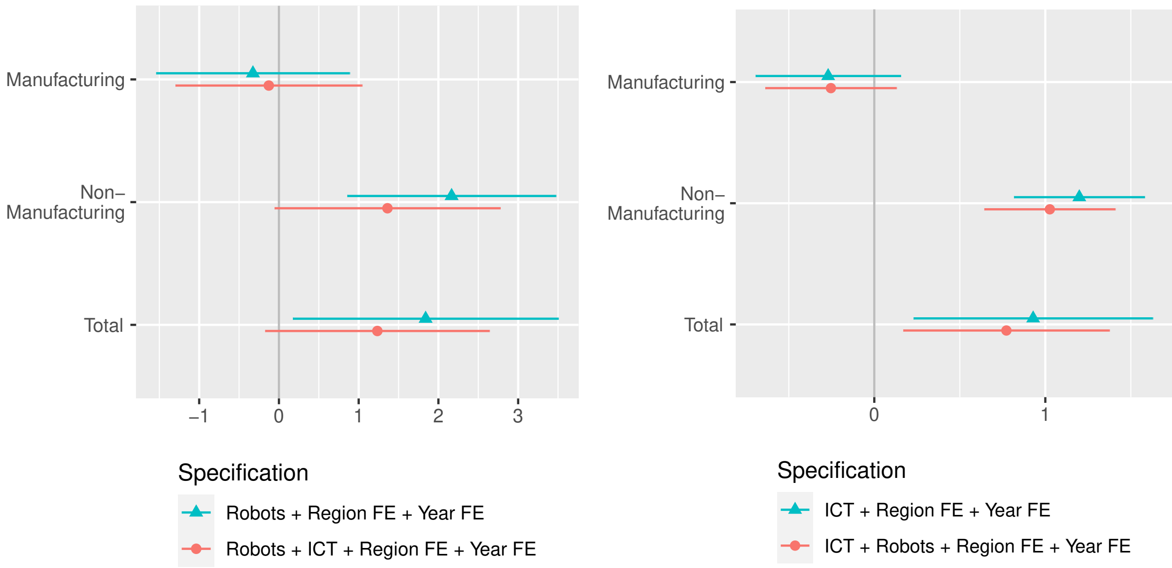
Regional-Level Economic Outcomes

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 (Michaels, Natraj and Van Reenen, 2014; Biagi and Falk, 2017; Dauth et al., 2021; Graetz and Michaels, 2018; Klenert, Fernandez-Macias and Antón, 2020; de Vries et al., 2020), 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 decreases 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. This hold considering each technology on its own or both jointly (see Figure 4 and Tables A.13-A.18).

The point estimates imply that focusing on the within-region variation, a one standard deviation increase in robot exposure (+30% more robots) is associated with a decrease of the manufacturing employment to population ratio of -0.09 percentage points (not statistically significantly different from zero) and a statistically significant increase of the non-manufacturing employment to total population ratio of +0.65 percentage points. On the other hand, an increase of the ICT capital stock of one within-region standard deviation (+520€) is associated with a decrease of the manufacturing employment to population ratio of -0.14 percentage points (not statistically significantly different from zero) and a statistically significant increase of the non-manufacturing employment to total population ratio by +0.60 percentage points. When considering the effect of both technologies jointly, effect sizes are somewhat attenuated. Again, we want to emphasize that we believe that these figures to not lend themselves for a horse race to determine which technology has a larger impact.

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). Our results align well with this explanation. When looking at labor shares of task groups instead of sectors, we find that technology adoption increases non-routine cognitive jobs

Figure 4: Region-level exposure to robots and employment effects



(a) Robot Intensity

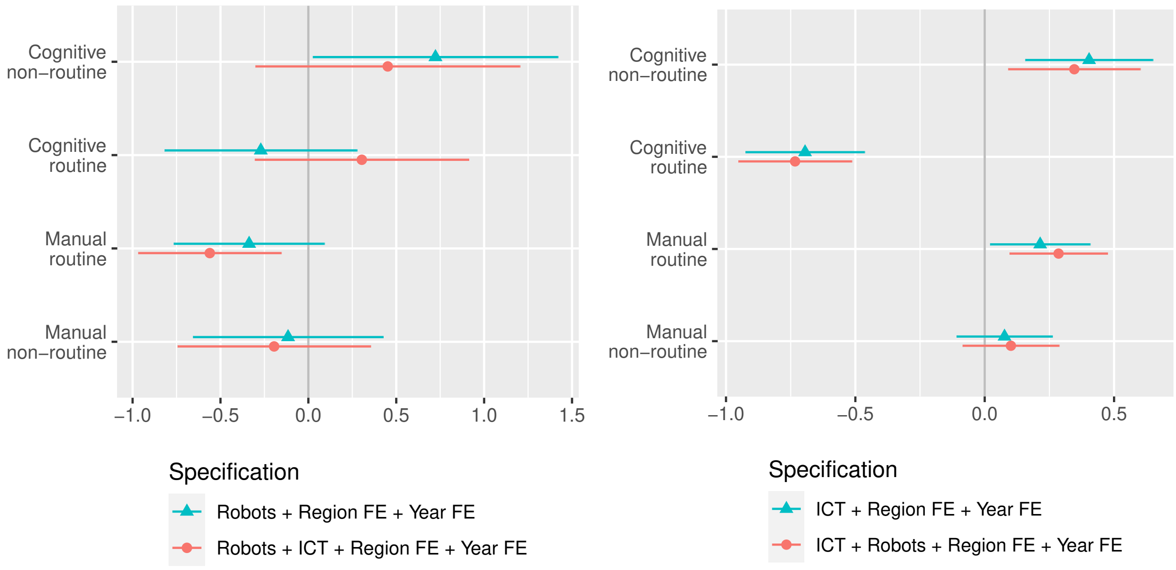
(b) ICT

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

at the cost of routine jobs (see Figure 5). In 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, which one might call "polarized upgrading" (Oesch and Rodriguez-Menes, 2010), 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). ICT investment in particular seems to foster upskilling. We also find evidence that education requirements are changing in a region more exposed to technology. Investment in robots or ICT increases the share of workers with at least a university entrance degree (Abitur) but decreases the share of workers with only High school degrees. Interestingly, with respect to education requirements, we find some evidence of polarizing labor markets in the sense that technology adoption does not reduce the the share of workers who did not finish secondary school. These workers presumably find jobs in low-skilled services which are created due to positive spillover effects of technology adoption (see Figure 7). The described are generally robust to controlling for the other type of technology adapted. Only the effect of robotization on the education composition of the labor force changes markedly. When additionally controlling for ICT, the effect of robotization turn statistically

Figure 5: Technological change and Regional Task Composition



(a) Robot Intensity

(b) ICT

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

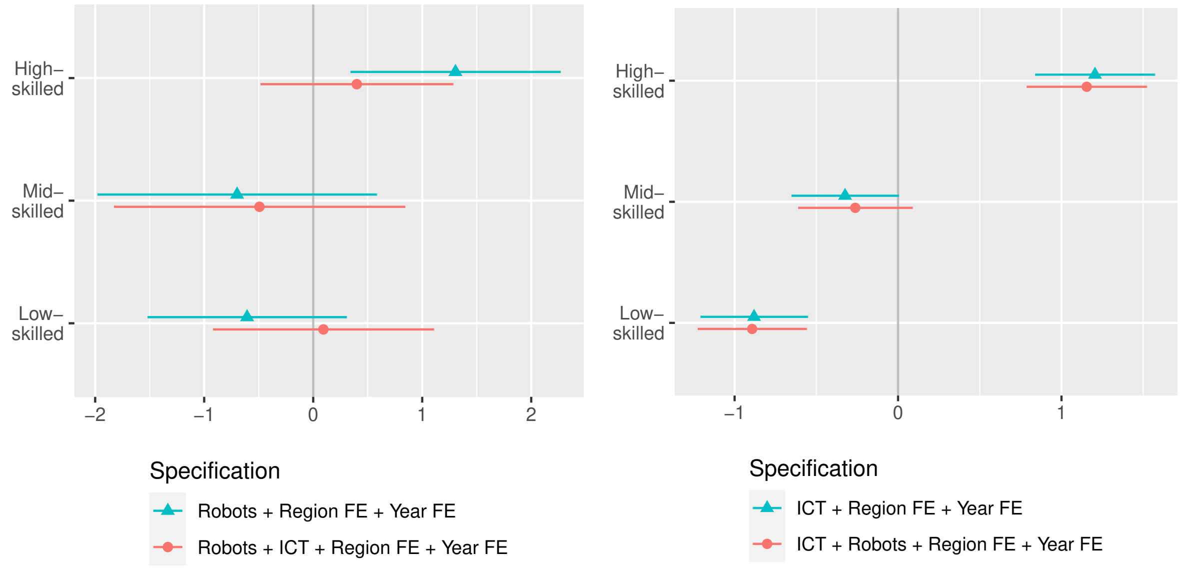
insignificant and changes signs. This again supports the conjecture that ICT has a stronger impact on the overall labor force than robotization, a finding that makes sense in light of the strong concentration of robots in a few highly-exposed sectors.

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. These findings are not in itself ground-breaking as they are largely in line with previous papers studying 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.

Regional-Level Relationship between Occupation and Vote Choice

To understand why technological change may shift the regional electoral landscape to the progressive left, it is important to analyze how the local labor force composition affects voting outcomes. As we showed before, increased exposure to technology is associated with a shift from manufacturing to services, from (manual) routine occupations to non-routine (cognitive) occupations, from low- and mid-skilled jobs to high-skilled jobs and towards a more educated local workforce. According to the theory of occupational preference formation, all these changes

Figure 6: Technological change and Regional Skill Requirements

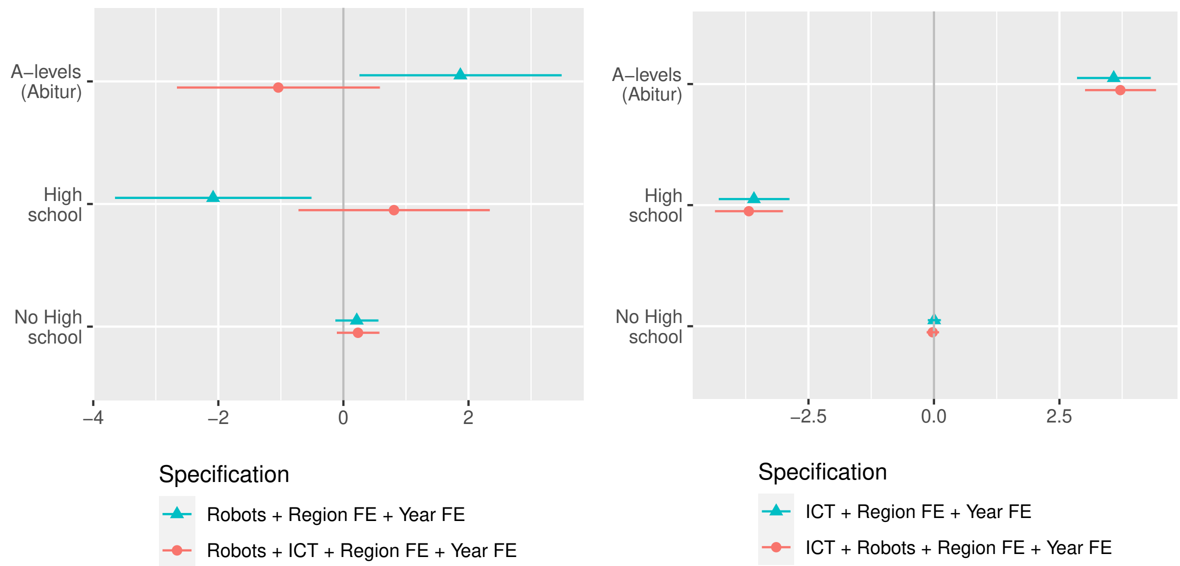


(a) Robot Intensity

(b) ICT

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

Figure 7: Technological change and Regional Education Levels



(a) Robot Intensity

(b) ICT

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

in the labor market composition should shift political support more towards 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.[14] For each party p - employment share s (manufacturing share, routine worker share, etc.) pair we run a separate regression of the following kind:

$$VoteShare_r^p = \beta * EmploymentShare_r^s + \epsilon_r \tag{4}$$

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.

The results presented in Figure 8 shows 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. On the other hand, conservatives and right-authoritarian parties perform particularly well where the manufacturing employment to population ratio is high (see Panel 8a).

Similarly, regional labor market characterised by a high share of cognitive non-routine occupations display more support for cosmopolitan-left parties 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 support of the progressive left parties and more supportive of authoritarian right parties (see Panel 8b).

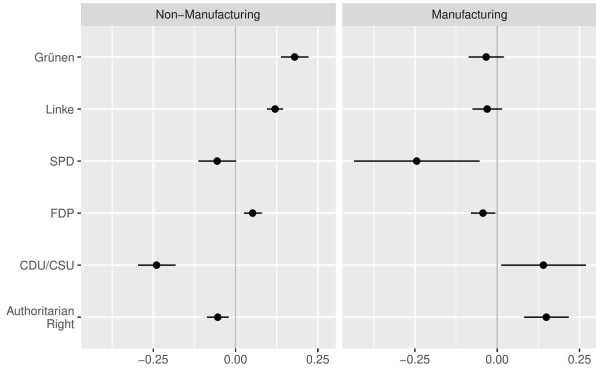
Furthermore, we find evidence that a high number of high-skilled workers is associated with more support for progressive left parties and less support for center-right and right-authoritarian parties. Conversely, it is mostly regions harboring more low-skilled and mid-skilled workers that are less supportive of progressive-left parties and more supportive of right-authoritarian parties. (see Panel 8c).

Finally, a higher share of highly educated workers is associated with more support for progressive workers and a lower support for conservative workers. The opposite is true looking at the share of workers with only intermediate levels of education. The share of High School

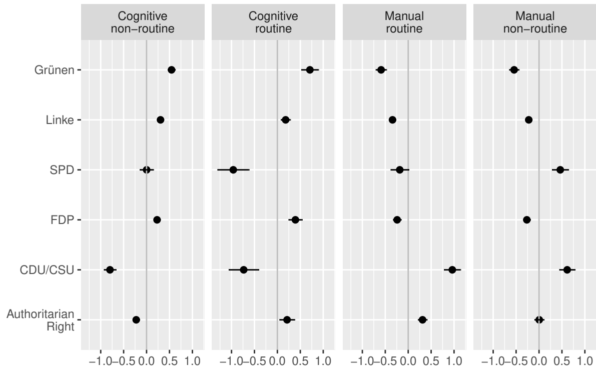
[14] Using previous election years leads to similar results.

drop-outs is weakly correlated with more support for authoritarian-right parties. However, the effects are imprecisely estimated (see Panel 8d).

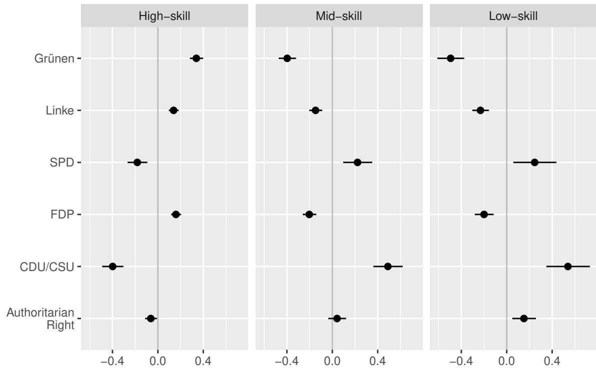
Figure 8: Cross-sectional correlations of regional employment shares and party vote shares in 2017 Federal Elections



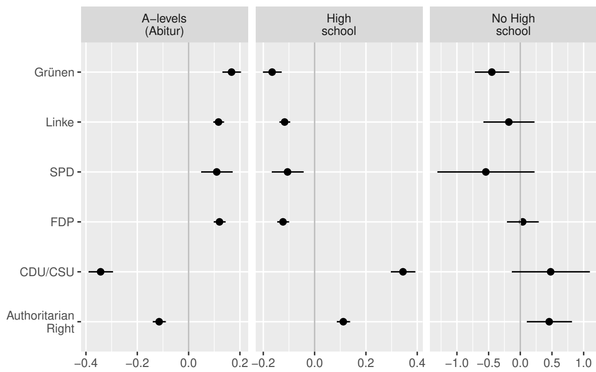
(a) Sector



(b) Main task



(c) Skill



(d) Education

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% confidence intervals.

Individual-Level Relationship between Occupation and Vote Choice

To increase confidence in these patterns, we analyze the aggregate party preferences of different occupation groups using individual-level data from the German Socio-Economic Panel (SOEP). This allows us to test more directly how local labor market composition affects election results. Our aim here was to recreate the sectorial and occupational groups from the previous analysis as closely as possible to ensure comparability. Therefore, we considered all respondents between 18 and 65 for the years 1994 to 2018 (n=323000) and classified them into manufacturing and non-manufacturing, by main task (see Section 4 for details) and created three education groups ranging from low (High school drop-outs and basic secondary education, *Hauptschule*) over middle (intermediate secondary education, *Realschule*) to high (A-levels, *Abitur*). Figure 9 plots the party support of different occupational groups over time. To facilitate the visualization we grouped responses in 5-year intervals.

The findings confirm a few common priors of the relevant literature (e.g. 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 conservative and authoritarian-right parties over the last years (see panel 9a). Secondly, 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) (see panel 9b). 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 (see Panel 9c). This further corroborates the 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.[15]

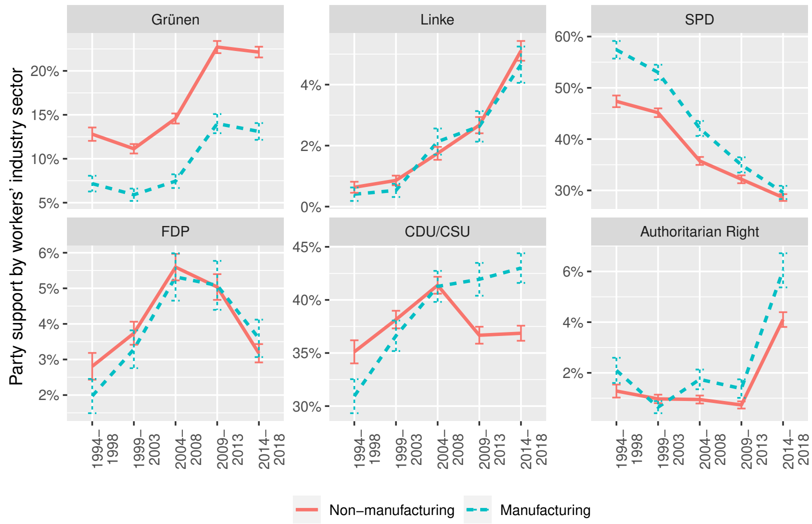
In sum, a theory of occupational preference formation in tandem with a gradually changing composition of local labor markets provides a reasonable explanation of why technological innovation can shift the regional electoral landscape to the progressive left. This is what we dubbed the "compositional effect". Perhaps somewhat counter-intuitively, the deployment of

[15] To be sure, the results also show that over the last years, authoritarian-right parties gained disproportionately within those occupation groups that stand to lose from technological change, i.e, manufacturing workers, the lower educated and manual workers.

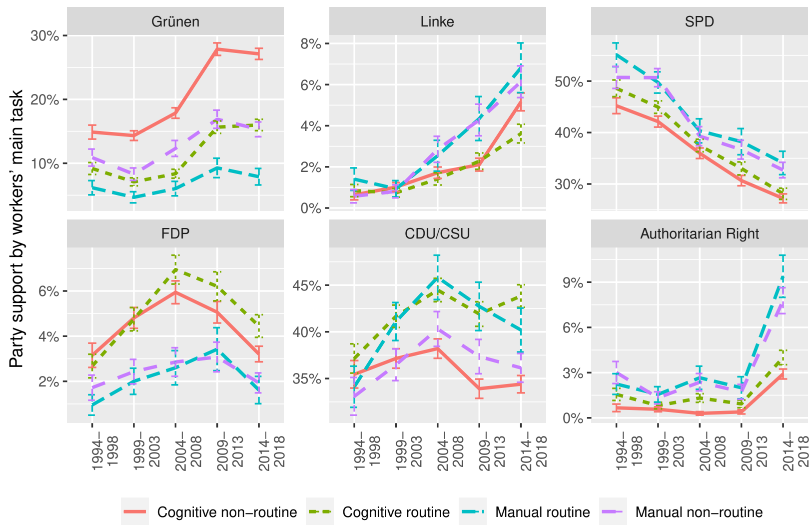
new technologies in a region fosters the creation of employment far away from the conveyor belt in service-oriented human-interaction occupations. Workers in these occupations often belong to the expanding "new middle class" and are generally open to the ideas of cosmopolitan-left parties as their education, their organizational structure and their work environment is more conducive to inclusive views on society (Kitschelt, 1994; Kriesi, 1998; Oesch, 2008*a*; Gingrich and Häusermann, 2015).

Figure 9: Party support of different segments of the workforce over time

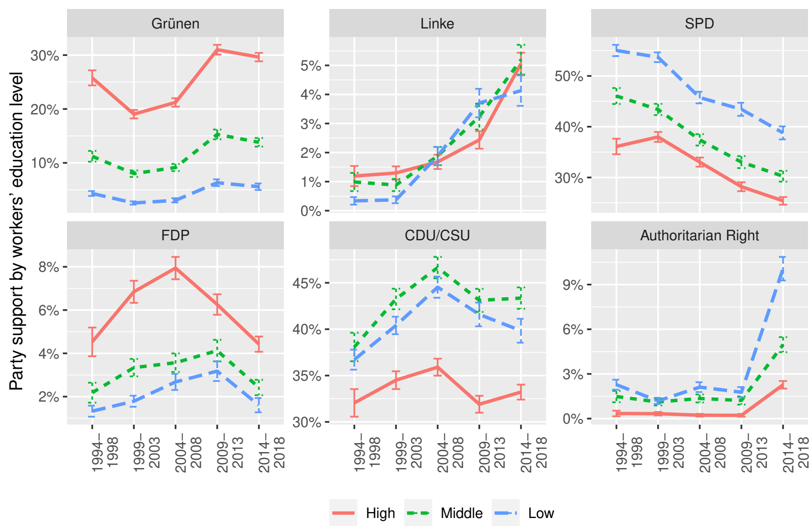
(a) Sector



(b) Main Task



(c) Education



Note: Graphs show self-reported party support of different occupation groups over time (clustered into 5-year intervals). Bars represent 95% confidence intervals.

6 Reconciling Conflicting Evidence

Our findings conflict with more gloomy projections put forward in the media and the public debate but also in important scholarly work, in which especially robotization has been related to the rise of populism and the success of right-authoritarian parties (Frey, Berger and Chen, 2018; Im et al., 2019; Anelli, Colantone and Stanig, 2019; Kurer, 2020; Milner, 2021).

We argued before that the differences partially stem from different level of analysis. Studies with individual level data focus on what we dubbed the *direct effect*: those threatened by technological innovation (normally measured through robotization) become more supportive of authoritarian right parties.

However, some studies also use regional data which includes the *compositional effect* and still find a shift towards authoritarian right parties. This is at odds with our theory and empirical findings and in the following, we will try to determine why this is the case.

For this, we replicate the work of Anelli, Colantone and Stanig (2019) (henceforth ACS) which also inspired the work of Milner (2021). Their regional analysis is the study most similar to our setting. ACS find that Western European regions with increasing robot exposure became more supportive of right-authoritarian parties. They argue that displaced or economically threatened manufacturing workers turned to right-authoritarian parties as they felt left behind.

We present the details of our replication exercise in Appendix A.4. In short, we demonstrate that the conflicting evidence is a consequence of different modelling approaches. In our understanding, the reason for diverging results lies in the difference between levels and changes. What the ACS approach captures is that new robots are installed where the *level* of manufacturing employment is high. This is intuitive as industrial robots are most needed in manufacturing hot-spots. As we showed before, manufacturing workers (who are also concentrated in manufacturing hot-spots) feel attracted by right-authoritarian parties and hence there is a positive correlation between the change in robot exposure, the level of the manufacturing share and the level of right-authoritarian support. Yet, this does not prove that regional growth in robot exposure leads to positive *change* in regional right-authoritarian support. Our approach using fixed effects instead captures how the *change* in robot exposure affects the *change* in partisan support. To be sure, regions initially specialized in manufacturing adopted more robots and were generally more supportive of right-authoritarian parties. Yet, their support of right-authoritarian parties grew slower than in regions without robots due to the compositional effect: robots increased the local share of, for example, socio-cultural professionals in sectors with a strong emphasis on interpersonal interactions, which in turn limited the appeal of right-authoritarian parties.[16]

7 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 less votes in affected regions. The increased prevalence of robots and ICT changes the local labor market 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 towards 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 who showed evidence in favor of the populism 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. It is entirely plausible that robotization increases right-authoritarian support among individuals or occupational groups that are imminently affected – or threatened – by automation. 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.

[16] Our rich data set allows to provide further empirical support for this line of argumentation by studying intermediary economic outcomes of robotization relying on ACS' empirical strategy. This empirical exercise shows why the mix of changes in the independent variable and levels in the dependent variables might be problematic. In fact, strictly applying ACS's modelling approach suggests that robotization leads to *more* manufacturing, routine and mid-skilled jobs (see Appendix A.4). Hence, there seems to be a mismatch between the theoretically hypothesized mechanism (robots threaten the jobs of manufacturing and routine workers) and the empirical reality resulting from the applied modelling approach (robots increase manufacturing and routine employment).

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. Our approach inherently bundles winners and losers within the unit of analysis. Depending on the workers' skills and occupation, the adoption of robots 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. 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 shows that technological change mostly shapes employment composition through generational turnover rather than directly displacing affected workers (Cortes, 2016; Dauth et al., 2021; Kurer and Gallego, 2019). Hence, in the long term, the compositional effect may be considered more important and more consequential in political terms.[17]

Finally, we want to reflect about why ICT produces clearer effect on voting patterns compared to robotization. One reason might be that the two technologies are different in scope. Digitalization in the shape of computers can be seen as a general purpose technology and as such, is complementary to workers as it increases their productivity. This is predominantly true for what we previously introduced as "socio-cultural professionals". Their interactive and cognitive work logic is clearly complementary to computer technology, some occupations in this domain were even only made possible by the introduction of computers. In general, direct replacement effects of computers seem relatively rare. Robots on the other hand were specifically developed

[17]Reflecting on the value of regional shift-share approaches more generally, we have to realize that, by construction, the measure of robot exposure needs to be interpreted as an *intention to treat* (ITT) variable. We do not know if a county actually invested in robots or ICT. Instead, it is inferred from the pre-sample local industry structure combined with industry-level data on robot adoption. Hence, this approach necessarily includes some regions that *should have* adopted robots but in fact did not. Therefore, we cannot distinguish if a worker's position is threatened due to innovation (robots taking over workers' jobs) or the lack thereof (jobs are endangered to due decreasing competitiveness of the firm). Yet, this distinction is crucial if we believe that job loss due to automation has a distinct effect on the workers' attitudes beyond the "normal" effect of job loss.

to replace certain tasks in manufacturing. This might be perceived as more of a threat by some segments of the labor force and hence, a direct negative effects is more important in this context. Our results suggest that at the regional level, the direct effect resulting from a fear of being replaced is on par with the compositional effect (and heavily dependent on model specification). While previous studies interested in the political ramification of technological change almost exclusively focused on a replacement narrative motivated by robotization, this paper suggests that extending the perspective to digitalization and incorporating compositional effects leads to a quite different outlook on the link between new technologies and voting behavior.

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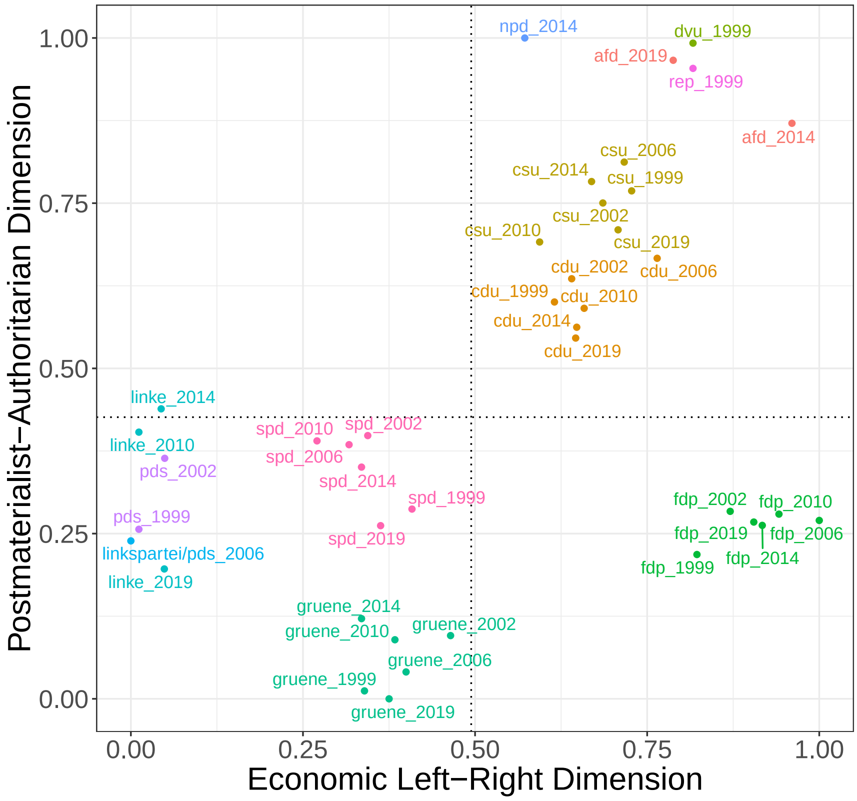
A Appendix

Contents

A.1 The Political Space in Germany

Figure A.1 shows that party positions in Germany are broadly aligned along one one dimension. They span from progressive-left (*Die Linke*) to authoritarian-right (*AFD* and other right-authoritarian parities). Notable exception is the pro-business party *FDP* which combines economic conservatism with social progressiveness. However, they do not play a central role in our analysis as their electoral support does not seem to be affected by robots adoption.

Figure A.1: Political Parties in the Two-Dimensional Space



Note: Party positions based on Chapel Hill Expert Survey data between 1994 and 2019 (Bakker et al., 2012, 2020). Both lrecon and galtan dimensions are standardized between 0 and 1. The dotted lines show average values pooled over time weighted by party-seat share.

A.2 Robustness Checks

In this section we report in more detail on the robustness checks we briefly described in Section 5.1. We report one regression table for each economic and political outcome, once for robot adoption and once for ICT investment in the section that follows. In the first column of each table we present our baseline model which relies on county and year fixed effects.[18] Note that the two-way fixed effect specification is already quite demanding as it holds constant all factors that are either constant over time within a region (for example if a region belonged to the former GDR, an important factor to explain electoral differences in Germany) or common shocks to all regions in a given year (for example changing party platforms or external events that affect the general success of parties).

Next, we add economic shocks as control variable to rule out that our results suffer from omitted variable bias. In column (2) of each table, we control for the net trade balance of each region vis-à-vis China and Eastern Europe. This is important as thriving manufacturing regions, which adopt robots at a fast pace are likely to also be more involved in international trade. At the same time, it has been shown that trade exposure affects the political preferences of voters (Dippel, Gold and Heblich, 2015; Colantone and Stanig, 2018). We find that this is not a major confounder as the unconditional correlation of net exports and robot intensity (0.04) or ICT (0.12) is low and also the estimated effect of regional robot intensity and regional ICT investment on regional election results and regional economic outcomes remain stable. Column (3) includes the other source of technological change as an additional control. Again, the concern is that it is an alternative economic shock is correlated with our technology shock.As noted before, the correlation between per worker ICT capital stocks and robot intensity is rather low (0.12). The effect of robotization on voting patterns virtually disappears after controlling for ICT. The effect of ICT on regional-level election outcomes on the other hand is not affected. As a third control, we include GDP per capita (column 4). This is important as robot adoption could be just one symptom of generally thriving regions (on the other hand, it could also be argued that GDP is a bad control as it part of the mechanism how technological change affects economic and political outcomes). Similar to controlling for the influence of the other technology, the point estimates of ICT on voting shares is not affected whereas there is no effect robotization on party support after controlling for GDP growth. Regarding the labor market consequences of technological change, it turns out that point estimates become more negative after controlling for GDP growth. This is intuitive as newly created job usually go hand in hand with economic growth.

Next, we use an instrumental variable approach where we instrument industry-level technology adoption in Germany with values from other European countries.[19] As argued before, the pace of robot

[18]To be precise, we use election fixed effects for political outcomes. These differ from year fixed effects in the case of state elections as each state has its own fixed effect.

[19]For robotization, we use data on all European countries included in the IFR database: Sweden, Denmark, Italy, Belgium, Netherlands, Austria, Slovenia, Spain, Slovakia, France Finland, Czech Republic. For ICT, we use data from all other EU member state countries (EU28 including the UK).

adoption or ICT investment might be influenced by surrounding labor market institutions. In Germany, workers councils and trade unions have been shown to affect the process how companies digitalize (Genz, Bellmann and Matthes, 2019). Simultaneously, labor unions have strong linkages to leftist and social democratic parties which could create an omitted variable bias in our OLS estimates. Using the speed of adoption in other European countries as a valid instrument implies the exclusion restriction that specific labor market and political institution in Germany do not affect industry level decision to adopt new technologies abroad. Instead, it is assumed to be driven by a technological frontier. In a second panel of each table we replicate all specifications using a 2SLS estimator. We find that labor market outcomes are comparable to the OLS estimates when considering ICT. Again, for robotization the result are less stable. Concerning the case of robots, it has been noted that despite the strong first stage, using other Western countries as an instrument might be problematic in the case of Germany as it precedes other Western countries when it comes to adopting robots. Nevertheless, we included the instrumental variable analysis to facilitate the comparison to previous research.

Finally, we use the number of robots per thousand workers in levels (not in logs) as main explanatory variable (third panel). This gives more weight to outlier region (recall that a few manufacturing hotspots attracted the bulk of new robots). The voting pattern results completely change and this analysis suggests that automation is associated with less support for progressive-left parties and more support for conservative and authoritarian-right parties. However, as is shown in the last panel of each table, this pattern reverts if we exclude the top ten regions in terms of robot intensity. The estimated labor market consequences of both specifications are similar and in line with the results described previously. This suggests that the general distributive effects are captured with either approach. However, voting results depend on the specification. We interpret this as further evidence that here, the compositional and the treatment are of similar strength.

Summing up, we find stable results for ICT with respect to voting and labor market outcomes. Regarding robotization, the labor market effects are relatively robust, the political consequences are robotization are not robust.

A.3 Regression Tables

A.3.1 Robots & Election Outcomes

Table A.1: Fixed-Effects Estimation of robot exposure on support for *Die Grünen*

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	0.536**	0.571**	0.261	0.364	0.278
	(0.227)	(0.230)	(0.240)	(0.237)	(0.248)
Net Exports		−0.036			−0.045
		(0.033)			(0.031)
ICT			0.323***		0.216**
			(0.091)		(0.101)
GDP per capita				0.038***	0.034***
				(0.012)	(0.012)
2SLS					
Robots	−0.204	−0.182	−0.270	−0.239	−0.213
	(0.327)	(0.330)	(0.321)	(0.355)	(0.353)
First-stage F-stat	252.44	124.72	153.61	146.35	78.66
Non-logged robots					
Robots	0.0004	0.001	−0.014*	−0.020***	−0.026***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Non-logged robots exclude outliers					
Robots	0.024	0.026	0.007	−0.004	−0.007
	(0.025)	(0.025)	(0.023)	(0.025)	(0.023)
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.937	0.937	0.937	0.937	0.938

Note: Fixed-effects regressions of party vote share (in %) on log number of robots per 1000 workers for federal, state and European Elections. Column (2) adds net exports per worker (in 1000 €), column (3) adds ICT capital stocks per worker (in 1000 €), column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*), once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*) and once using robots in levels but excluding 10 outlier counties (*Non-logged robots exclude outliers*). All models include region and election fixed effects. Standard errors reported in parenthesis are clustered by county. *p<0.1; **p<0.05; ***p<0.01

Table A.2: Fixed-Effects Estimation of robot exposure on support for *Die Linke*

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	0.406*	0.382	−0.048	0.258	−0.105
	(0.246)	(0.244)	(0.275)	(0.252)	(0.271)
Net Exports		0.024			0.021
		(0.022)			(0.022)
ICT			0.534***		0.561***
			(0.115)		(0.116)
GDP per capita				0.011	−0.004
				(0.008)	(0.008)
2SLS					
Robots	0.388	0.365	0.315	0.265	0.232
	(0.351)	(0.351)	(0.371)	(0.352)	(0.371)
First-stage F-stat	236.7	116.74	141.53	142.26	74.08
Non-logged robots					
Robots	0.011	0.010	−0.009	0.002	−0.012
	(0.009)	(0.009)	(0.010)	(0.012)	(0.012)
Non-logged robots exclude outliers					
Robots	0.057*	0.055*	0.035	0.042	0.028
	(0.030)	(0.029)	(0.030)	(0.028)	(0.028)
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	3,792	3,792	3,792	3,651	3,651
Adjusted R^2	0.888	0.888	0.890	0.892	0.894

Note: Fixed-effects regressions of party vote share (in %) on log number of robots per 1000 workers for federal, state and European Elections. Column (2) adds net exports per worker (in 1000 €), column (3) adds ICT capital stocks per worker (in 1000 €), column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*) and once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*). All models include region and election fixed effects. Standard errors reported in parenthesis are clustered by county. *p<0.1; **p<0.05; ***p<0.01

Table A.3: Fixed-Effects Estimation of robot exposure on support for SPD

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	0.055	0.082	−0.209	−0.261	−0.442
	(0.394)	(0.400)	(0.445)	(0.416)	(0.447)
Net Exports		−0.028			−0.026
		(0.044)			(0.044)
ICT			0.309*		0.331*
			(0.183)		(0.197)
GDP per capita				0.016	0.007
				(0.019)	(0.019)
2SLS					
Robots	−0.215	−0.193	−0.268	−0.783	−0.784
	(0.684)	(0.694)	(0.698)	(0.591)	(0.599)
First-stage F-stat	252.44	124.72	153.61	146.35	78.66
Non-logged robots					
Robots	−0.010	−0.010	−0.023	−0.033*	−0.041**
	(0.012)	(0.012)	(0.014)	(0.019)	(0.020)
Non-logged robots exclude outliers					
Robots	−0.026	−0.025	−0.041	−0.062*	−0.068*
	(0.038)	(0.038)	(0.039)	(0.037)	(0.038)
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.962	0.962	0.963	0.962	0.962

Note: Fixed-effects regressions of party vote share (in %) on log number of robots per 1000 workers for federal, state and European Elections. Column (2) adds net exports per worker (in 1000 €), column (3) adds ICT capital stocks per worker (in 1000 €), column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*) and once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*). All models include region and year fixed effects. Standard errors reported in parenthesis are clustered by county. *p<0.1; **p<0.05; ***p<0.01

Table A.4: Fixed-Effects Estimation of robot exposure on support for FDP

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	0.0002	0.038	0.125	−0.070	0.092
	(0.161)	(0.162)	(0.165)	(0.169)	(0.168)
Net Exports		−0.039**			−0.042**
		(0.019)			(0.019)
ICT			−0.146**		−0.183**
			(0.071)		(0.074)
GDP per capita				0.011	0.017**
				(0.007)	(0.006)
2SLS					
Robots	−0.060	−0.026	−0.040	−0.097	−0.038
	(0.253)	(0.255)	(0.258)	(0.250)	(0.253)
First-stage F-stat	252.44	124.72	153.61	146.35	78.66
Non-logged robots					
Robots	0.003	0.003	0.008	0.002	0.007
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Non-logged robots exclude outliers					
Robots	0.004	0.007	0.010	−0.005	0.001
	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.917	0.917	0.917	0.917	0.918

Note: Fixed-effects regressions of party vote share (in %) on log number of robots per 1000 workers for federal, state and European Elections. Column (2) adds net exports per worker (in 1000 €), column (3) adds ICT capital stocks per worker (in 1000 €), column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*) and once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*). All models include region and election fixed effects. Standard errors reported in parenthesis are clustered by county. *p<0.1; **p<0.05; ***p<0.01

Table A.5: Fixed-Effects Estimation of robot exposure on support for CDU / CSU

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	−0.825	−0.926*	−0.329	−0.035	0.022
	(0.542)	(0.543)	(0.611)	(0.586)	(0.612)
Net Exports		0.103			0.121
		(0.078)			(0.076)
ICT			−0.582***		−0.302
			(0.212)		(0.229)
GDP per capita				−0.096***	−0.091**
				(0.036)	(0.037)
2SLS					
Robots	0.073	−0.008	0.182	0.765	0.660
	(0.949)	(0.957)	(0.965)	(0.859)	(0.867)
First-stage F-stat	252.44	124.72	153.61	146.35	78.66
Non-logged robots					
Robots	−0.017	−0.018	0.006	0.036	0.042
	(0.019)	(0.019)	(0.021)	(0.027)	(0.027)
Non-logged robots exclude outliers					
Robots	−0.048	−0.053	−0.023	0.043	0.043
	(0.058)	(0.058)	(0.058)	(0.059)	(0.059)
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.924	0.924	0.924	0.926	0.926

Note: Fixed-effects regressions of party vote share (in %) on log number of robots per 1000 workers for federal, state and European Elections. Column (2) adds net exports per worker (in 1000 €), column (3) adds ICT capital stocks per worker (in 1000 €), column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*) and once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*). All models include region and election fixed effects. Standard errors reported in parenthesis are clustered by county. *p<0.1; **p<0.05; ***p<0.01

Table A.6: Fixed-Effects Estimation of robot exposure on support for right-authoritarian Parties

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	−0.205	−0.216	−0.022	−0.295	−0.118
	(0.160)	(0.163)	(0.168)	(0.180)	(0.191)
Net Exports		0.013			0.013
		(0.029)			(0.029)
ICT			−0.209**		−0.306***
			(0.089)		(0.095)
GDP per capita				0.006	0.014**
				(0.007)	(0.007)
2SLS					
Robots	−0.294	−0.304	−0.265	−0.373	−0.381
	(0.209)	(0.212)	(0.212)	(0.245)	(0.247)
First-stage F-stat	234.07	116.32	139.11	142.37	73.7
Non-logged robots					
Robots	0.008*	0.008*	0.019***	0.006	0.015**
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
Non-logged robots exclude outliers					
Robots	−0.022	−0.022	−0.009	−0.019	−0.011
	(0.014)	(0.014)	(0.013)	(0.016)	(0.014)
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	3,197	3,197	3,197	3,056	3,056
Adjusted R^2	0.925	0.925	0.926	0.924	0.925

Note: Fixed-effects regressions of party vote share (in %) on log number of robots per 1000 workers for federal, state and European Elections. Column (2) adds net exports per worker (in 1000 €), column (3) adds ICT capital stocks per worker (in 1000 €), column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*) and once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*). All models include region and election fixed effects. Standard errors reported in parenthesis are clustered by county. *p<0.1; **p<0.05; ***p<0.01

A.3.2 ICT & Election Outcomes

Table A.7: Fixed-Effects Estimation of ICT on support for *Die Grünen*

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	0.359***	0.363***	0.323***	0.240**	0.216**
	(0.087)	(0.087)	(0.091)	(0.099)	(0.101)
Net Exports		−0.032			−0.045
		(0.031)			(0.031)
Robots			0.261		0.278
			(0.240)		(0.248)
GDP per capita				0.033***	0.034***
				(0.012)	(0.012)
2SLS					
ICT	0.732***	0.734***	0.742***	0.660***	0.659***
	(0.152)	(0.152)	(0.164)	(0.169)	(0.179)
First-stage F-stat	296.46	147.08	127.71	137.83	71.04
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.937	0.937	0.937	0.937	0.938

Note: Fixed-effects regressions of county-level party vote share (in %) on ICT capital stocks per worker (in 1000 €) for federal, state and European Elections. Column (2) adds net exports per worker (in 1000 €), column (3) adds log number of robots per 1000 workers, column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and election fixed effects. Standard errors reported in parenthesis are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.8: Fixed-Effects Estimation of ICT on support for *Die Linke*

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	0.527***	0.524***	0.534***	0.552***	0.561***
	(0.106)	(0.106)	(0.115)	(0.112)	(0.116)
Net Exports		0.022			0.021
		(0.022)			(0.022)
Robots			−0.048		−0.105
			(0.275)		(0.271)
GDP per capita				−0.004	−0.004
				(0.008)	(0.008)
2SLS					
ICT	0.691***	0.689***	0.711***	0.722***	0.740***
	(0.164)	(0.164)	(0.180)	(0.171)	(0.179)
First-stage F-stat	246.95	122.56	105.71	112.41	58.55
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	3,792	3,792	3,792	3,651	3,651
Adjusted R^2	0.890	0.890	0.890	0.894	0.894

Note: Fixed-effects regressions of county-level party vote share (in %) on ICT capital stocks per worker (in 1000 €) for federal, state and European Elections. Column (2) adds net exports per worker (in 1000 €), column (3) adds log number of robots per 1000 workers, column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and election fixed effects. Standard errors reported in parenthesis are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.9: Fixed-Effects Estimation of ICT on support for SPD

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	0.281*	0.285*	0.309*	0.282	0.331*
	(0.166)	(0.166)	(0.183)	(0.191)	(0.197)
Net Exports		−0.031			−0.026
		(0.043)			(0.044)
Robots			−0.209		−0.442
			(0.445)		(0.447)
GDP per capita				0.005	0.007
				(0.019)	(0.019)
2SLS					
ICT	0.078	0.079	0.079	0.059	0.084
	(0.253)	(0.254)	(0.279)	(0.283)	(0.296)
First-stage F-stat	296.46	147.08	127.71	137.83	71.04
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.963	0.963	0.963	0.962	0.962

Note: Fixed-effects regressions of county-level party vote share (in %) on ICT capital stocks per worker (in 1000 €) for federal, state and European Elections. Column (2) adds net exports per worker (in 1000 €), column (3) adds log number of robots per 1000 workers, column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and election fixed effects. Standard errors reported in parenthesis are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.10: Fixed-Effects Estimation of ICT on support for FDP

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	−0.129*	−0.124*	−0.146**	−0.177**	−0.183**
	(0.068)	(0.068)	(0.071)	(0.073)	(0.074)
Net Exports		−0.036**			−0.042**
		(0.018)			(0.019)
Robots			0.125		0.092
			(0.165)		(0.168)
GDP per capita				0.016**	0.017**
				(0.007)	(0.006)
2SLS					
ICT	−0.051	−0.049	−0.056	−0.091	−0.094
	(0.115)	(0.115)	(0.125)	(0.126)	(0.131)
First-stage F-stat	296.46	147.08	127.71	137.83	71.04
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.917	0.917	0.917	0.918	0.918

Note: Fixed-effects regressions of county-level party vote share (in %) on ICT capital stocks per worker (in 1000 €) for federal, state and European Elections. Column (2) adds net exports per worker (in 1000 €), column (3) adds log number of robots per 1000 workers, column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and election fixed effects. Standard errors reported in parenthesis are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.11: Fixed-Effects Estimation of ICT on support for CDU / CSU

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	−0.628***	−0.642***	−0.582***	−0.288	−0.302
	(0.190)	(0.193)	(0.212)	(0.221)	(0.229)
Net Exports		0.097			0.121
		(0.076)			(0.076)
Robots			−0.329		0.022
			(0.611)		(0.612)
GDP per capita				−0.087**	−0.091**
				(0.037)	(0.037)
2SLS					
ICT	−0.835**	−0.840**	−0.822**	−0.528	−0.542
	(0.324)	(0.327)	(0.345)	(0.378)	(0.391)
First-stage F-stat	296.46	147.08	127.71	137.83	71.04
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.924	0.925	0.924	0.926	0.926

Note: Fixed-effects regressions of county-level party vote share (in %) on ICT capital stocks per worker (in 1000 €) for federal, state and European Elections. Column (2) adds net exports per worker (in 1000 €), column (3) adds log number of robots per 1000 workers, column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and election fixed effects. Standard errors reported in parenthesis are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.12: Fixed-Effects Estimation of ICT on support for right-authoritarian Parties

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	−0.212**	−0.214**	−0.209**	−0.317***	−0.306***
	(0.086)	(0.086)	(0.089)	(0.093)	(0.095)
Net Exports		0.013			0.013
		(0.028)			(0.029)
Robots			−0.022		−0.118
			(0.168)		(0.191)
GDP per capita				0.014*	0.014**
				(0.007)	(0.007)
2SLS					
ICT	−0.382***	−0.384***	−0.398***	−0.475***	−0.475***
	(0.122)	(0.123)	(0.131)	(0.138)	(0.142)
First-stage F-stat	210.8	104.69	88.26	93.46	48.56
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	3,197	3,197	3,197	3,056	3,056
Adjusted R^2	0.926	0.926	0.926	0.925	0.925

Note: Fixed-effects regressions of county-level party vote share (in %) on ICT capital stocks per worker (in 1000 €) for federal, state and European Elections. Column (2) adds net exports per worker (in 1000 €), column (3) adds log number of robots per 1000 workers, column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and election fixed effects. Standard errors reported in parenthesis are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

A.3.3 Robots & Labor Market Composition

Table A.13: Fixed-Effects Estimation of robot exposure on total employment

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	1.840**	1.811**	1.234*	−0.264	−0.192
	(0.849)	(0.849)	(0.717)	(0.471)	(0.454)
Net Exports		0.029			0.013
		(0.063)			(0.053)
ICT			0.772**		−0.165
			(0.307)		(0.196)
GDP per capita				0.238***	0.242***
				(0.023)	(0.025)
2SLS					
Robots	0.991	0.947	0.946	0.291	0.268
	(0.832)	(0.833)	(0.802)	(0.578)	(0.585)
First-stage F-stat	202.29	98.9	121.66	141.65	76.81
Non-logged robots					
Robots	0.138***	0.138***	0.127**	0.003	0.006
	(0.049)	(0.049)	(0.049)	(0.018)	(0.017)
Non-logged robots exclude outliers					
Robots	0.155**	0.152**	0.143**	0.030	0.034
	(0.067)	(0.066)	(0.067)	(0.046)	(0.044)
Region FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	7,774	7,774	7,774	7,492	7,492
Adjusted R^2	0.978	0.978	0.978	0.985	0.985

Note: Fixed-effects regressions of total employment to population ratio (in %) on log number of robots per 1000 workers. Column (2) adds net exports per worker (in 1000 €), column (3) adds ICT capital stocks per worker (in 1000 €), column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*), once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*) and once using robots in levels but excluding 10 outlier counties (*Non-logged robots exclude outliers*). All models include region and year fixed effects. Standard errors reported in parenthesis are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.14: Fixed-Effects Estimation of robot exposure on manufacturing employment

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	−0.326	−0.339	−0.127	−1.219**	−0.867
	(0.619)	(0.623)	(0.597)	(0.559)	(0.628)
Net Exports		0.013			0.009
		(0.062)			(0.065)
ICT			−0.254		−0.684***
			(0.196)		(0.172)
GDP per capita				0.081***	0.099***
				(0.020)	(0.021)
2SLS					
Robots	0.026	0.019	0.042	−0.292	−0.347
	(0.596)	(0.603)	(0.599)	(0.660)	(0.684)
First-stage F-stat	202.29	98.9	121.66	141.65	76.81
Non-logged robots					
Robots	0.045	0.045	0.061**	−0.009	0.005
	(0.029)	(0.030)	(0.029)	(0.020)	(0.018)
Non-logged robots exclude outliers					
Robots	0.010	0.009	0.028	−0.017	−0.007
	(0.057)	(0.058)	(0.056)	(0.053)	(0.050)
Region FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	7,774	7,774	7,774	7,492	7,492
Adjusted R^2	0.958	0.958	0.959	0.965	0.966

Note: Fixed-effects regressions of manufacturing employment to population ratio (in %) on log number of robots per 1000 workers. Column (2) adds net exports per worker (in 1000 €), column (3) adds ICT capital stocks per worker (in 1000 €), column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*), once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*) and once using robots in levels but excluding 10 outlier counties (*Non-logged robots exclude outliers*). All models include region and year fixed effects. Standard errors reported in parenthesis are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.15: Fixed-Effects Estimation of robot exposure on non-manufacturing employment

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	2.166***	2.149***	1.361*	0.955*	0.675
	(0.667)	(0.673)	(0.722)	(0.515)	(0.587)
Net Exports		0.016			0.004
		(0.041)			(0.038)
ICT			1.026***		0.519***
			(0.195)		(0.164)
GDP per capita				0.157***	0.143***
				(0.027)	(0.027)
2SLS					
Robots	0.964	0.928	0.904	0.583	0.615
	(0.745)	(0.755)	(0.724)	(0.599)	(0.623)
First-stage F-stat	202.29	98.9	121.66	141.65	76.81
Non-logged robots					
Robots	0.093***	0.092***	0.065***	0.012	0.001
	(0.023)	(0.023)	(0.024)	(0.014)	(0.014)
Non-logged robots exclude outliers					
Robots	0.145***	0.142***	0.115***	0.048	0.041
	(0.045)	(0.045)	(0.044)	(0.036)	(0.036)
Region FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	7,774	7,774	7,774	7,492	7,492
Adjusted R^2	0.979	0.979	0.980	0.984	0.984

Note: Fixed-effects regressions of non-manufacturing employment to population ratio (in %) on log number of robots per 1000 workers. Column (2) adds net exports per worker (in 1000 €), column (3) adds ICT capital stocks per worker (in 1000 €), column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*), once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*) and once using robots in levels but excluding 10 outlier counties (*Non-logged robots exclude outliers*). All models include region and year fixed effects. Standard errors reported in parenthesis are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

A.3.4 ICT & Labor Market Composition

Table A.16: Fixed-Effects Estimation of ICT on total employment

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	0.929***	0.922**	0.772**	−0.179	−0.165
	(0.357)	(0.357)	(0.307)	(0.202)	(0.196)
Net Exports		0.042			0.013
		(0.060)			(0.053)
Robots			1.234*		−0.192
			(0.717)		(0.454)
GDP per capita				0.242***	0.242***
				(0.024)	(0.025)
2SLS					
ICT	0.034	0.031	−0.175	−0.746***	−0.756***
	(0.323)	(0.322)	(0.361)	(0.284)	(0.287)
First-stage F-stat	217.32	108.13	96.27	97.68	52.87
Region FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	7,774	7,774	7,774	7,492	7,492
Adjusted R^2	0.978	0.978	0.978	0.985	0.985

Note: Fixed-effects regressions of total employment to population ratio (in %) on log number of robots per 1000 workers. Column (2) adds net exports per worker (in 1000 €), column (3) adds log number of robots per thousand workers, column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest using the same specification as above while instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and year fixed effects. Standard errors reported in parenthesis are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.17: Fixed-Effects Estimation of ICT on manufacturing employment

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	−0.270	−0.272	−0.254	−0.759***	−0.684***
	(0.216)	(0.218)	(0.196)	(0.161)	(0.172)
Net Exports		0.011			0.009
		(0.063)			(0.065)
Robots			−0.127		−0.867
			(0.597)		(0.628)
GDP per capita				0.095***	0.099***
				(0.023)	(0.021)
2SLS					
ICT	−1.067***	−1.068***	−1.125***	−1.445***	−1.402***
	(0.263)	(0.263)	(0.275)	(0.318)	(0.281)
First-stage F-stat	217.32	108.13	96.27	97.68	52.87
Region FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	7,774	7,774	7,774	7,492	7,492
Adjusted R^2	0.959	0.959	0.959	0.966	0.966

Note: Fixed-effects regressions of total employment to population ratio (in %) on log number of robots per 1000 workers. Column (2) adds net exports per worker (in 1000 €), column (3) adds log number of robots per thousand workers, column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest using the same specification as above while instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and year fixed effects. Standard errors reported in parenthesis are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.18: Fixed-Effects Estimation of ICT on non-manufacturing employment

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	1.199***	1.194***	1.026***	0.580***	0.519***
	(0.195)	(0.195)	(0.195)	(0.150)	(0.164)
Net Exports		0.031			0.004
		(0.041)			(0.038)
Robots			1.361*		0.675
			(0.722)		(0.587)
GDP per capita				0.147***	0.143***
				(0.028)	(0.027)
2SLS					
ICT	1.101***	1.099***	0.950***	0.700**	0.646**
	(0.377)	(0.376)	(0.331)	(0.313)	(0.287)
First-stage F-stat	217.32	108.13	96.27	97.68	52.87
Region FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	7,774	7,774	7,774	7,492	7,492
Adjusted R^2	0.980	0.980	0.980	0.984	0.984

Note: Fixed-effects regressions of total employment to population ratio (in %) on log number of robots per 1000 workers. Column (2) adds net exports per worker (in 1000 €), column (3) adds log number of robots per thousand workers, column (4) adds GDP per capita (in 1000 €). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest using the same specification as above while instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and year fixed effects. Standard errors reported in parenthesis are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

A.4 Replication of Anelli, Colantone and Stanig (2019)

In this section we replicate parts of Anelli, Colantone and Stanig (2019) (henceforth ACS). The aim is to compare their regional approach to ours to determine where conflicting results stem from. We consider three potential explanations. First, it could be that West Germany is a special case, which deviates from the general patterns across Western European democracies presented in ACS. Recall the exceptional importance of robots in West German manufacturing or the fact that, at least partly for historical reasons, no right-authoritarian party was represented in German national parliament until 2017. Second, the competing results could arise from differences in how the data set is constructed. Our studies differ in the level of regional disaggregation, the sample period, and which election types are used. In particular, we have much more fine-grained levels of regional disaggregation (NUTS-3) than the data ACS use to analyze the German case (NUTS-1). Third, it could be that distinct modelling approaches make the difference. While we employ a fixed effect panel model, ACS rely on a repeated short difference specification.

A.4.1 ACS's model

ACS regress party vote shares of right-authoritarian parties (in levels) on robot exposure (in changes) as a repeated cross section. They define regional robot exposure as the change of regional robot intensity (robots per thousand workers) in the two years prior to the elections (short-difference approach). Since they do not dispose over the data on employment composition at the county level (NUTS-3), they calculate robot exposure at the broader state level (NUTS-1 for Germany). Election results are measured at the more fine-grained county level. The estimated model is:

$$Y_{r,s,t} = \beta_1 (Robots_{s,t-1} - Robots_{s,t-n}) + \mu_{election} + \epsilon_{r,s,t} \tag{5}$$

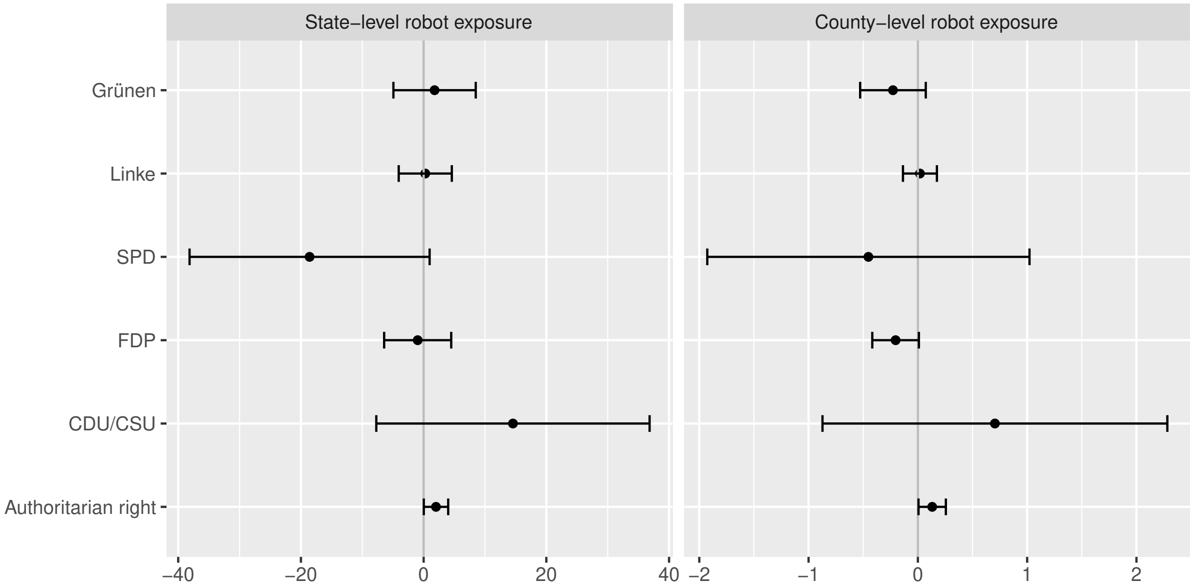
where $Y_{r,s,t}$ is the electoral outcome in region r located in state s in year t. The difference between $Robots_{s,t-1}$ and $Robots_{s,t-n}$ (number or robots per 1000 employees on state level) expresses their measure of robot exposure. $\mu_{election}$ is an election specific fixed effect. Contrary to our model, no geographic fixed effects are used.

A.4.2 Political Outcomes

In general, we can replicate their result that robotization is associated with more right-authoritarian support if we use ACS's modelling approach even though they jointly analyzed several European countries and we only have data on Germany.

Similar to ACS, we find that one standard deviation increase in robot exposure (+0.25 robots / 1000 workers) is associated with a significant increase in the vote share of right-authoritarian parties by

Figure A.2: Replication ACS



Note: The graph shows the effect of state level robot exposure on county-level vote shares (left panel) and county-level robot exposure on county-level vote share (right panel. Robot exposure defined as change in the number of robots per thousand workers in a two year window prior to the election. The left panel shows a replication of the specification of ACS which measures robot exposure at the state level (NUTS-1) and includes election fixed effects. The right panel measures robot exposure at the region level (401 *Kreise und kreisfreie Städte*, NUTS-3) and adds region fixed effects. Standard errors are clustered at the state-election level (left panel) or at the commuting-zone election level (right panel). Bars represent 95% confidence intervals.

0.54 percentage points when we apply their statistical model to our data.[20] These results remain stable when using an instrumental variable approach (panel B of Table A.19). We thus conclude differences in observed results do not stem from the uniqueness of the German case.

Next we turn our attention to the question if differences in the geographic disaggregation of the robot exposure, the sample period or the types of elections considered could be explaining the different results. Recall that our approach uses county-level variation (NUTS-3) whereas ACS's approach uses state-level variation (NUTS-1 for Germany). Therefore, we now want to apply their modelling approach to county level rather than state-level variation in robot exposure:

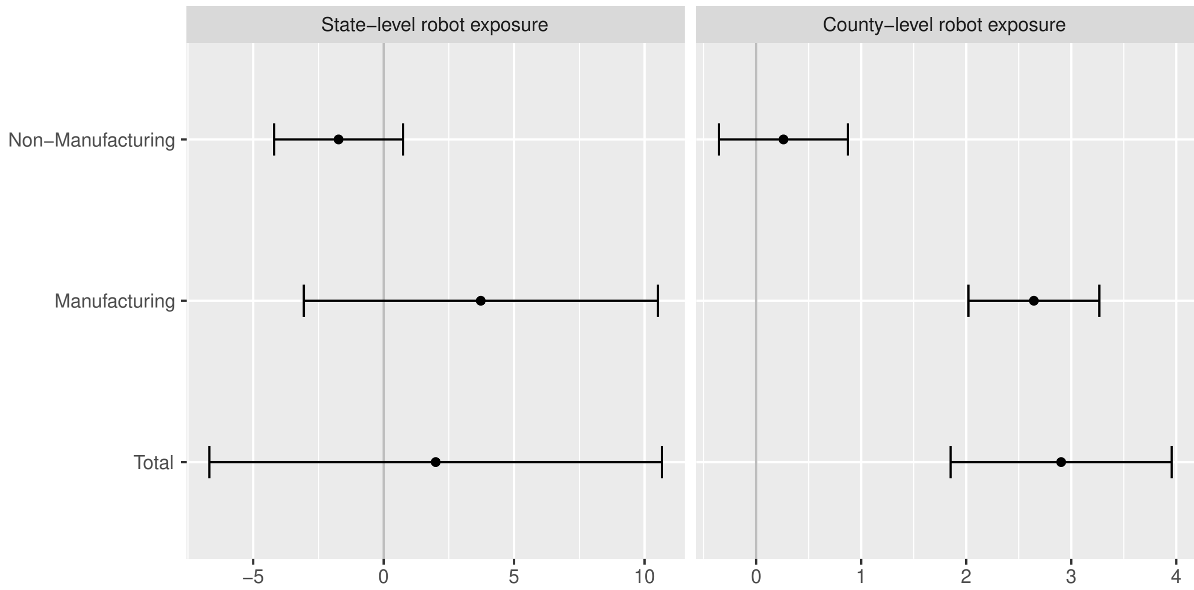
$$Y_{r,t} = \beta_1(Robots_{r,t-1} - Robots_{r,t-3}) + \mu_{election} + \epsilon_{r,t} \tag{6}$$

We now regress the electoral outcome in a region $Y_{r,t}$ directly on the regional robot exposure measured as the difference in robot intensity in the two years prior to the elections ($Robots_{r,t-1} - Robots_{r,t-n}$). Otherwise we use the same specifications as before, namely a plane OLS (see right panel of Figure A.2 and panel A of Table A.20) and a 2SLS specification (panel B). .[21]

[20] More generally, we find that increased exposure to robots shift party support to the right. Besides right-authoritarian parties, this modelling approach implies that Germany's Christian Democrats CDU has the largest point estimate, even though imprecisely estimated. On the other hand, the results show that according to this modelling approach, left and liberal parties lose support in affected areas.The only significant result is for leftist party *Die Linke* (see left panel of Figure A.2 and panel A of Table A.19).

[21] The remaining difference is that ACS's approach uses the change in number of robots in a time window two years prior to the elections as main explanatory variable. Our approach instead directly uses the log-number

Figure A.3: Robots and Employment: ACS approach



Note: The graph shows the effect of regional robot exposure on regional employment relative to population in %. Robot exposure defined as change in the number of robots per thousand workers in a two year window prior to the election. The left panel shows a replication of the specification of ACS which measures robot exposure at the state level (NUTS-1) and includes election fixed effects. The right panel measures robot exposure at the county level NUTS-3). Standard errors are clustered at the state-election level (left panel) or at the county level (right panel). Bars represent 95% confidence intervals.

The general pattern remains that increases in robot exposure are associated with a shift of political support more to the right of the political spectrum. This is remarkable as we note that point estimates are reduced dramatically if we use regional instead of state variation in the measure of robot exposure.

The positive effect of robotization on right-authoritarian support also remain stable if we restrict our sample period to the one used by ACS (they only look at the years 1999-2015), or if we remove European or state elections (both not reported).

Hence, we conclude that different results are also not driven by differences in data set construction.

A.4.3 Implied Economic Outcomes

Next, we want to ask the question if the two approaches (i.e. our two-way fixed panel model approach and ACS's short-difference repeated cross-section) indeed capture the same labor market transformation. For this, we analyze the effect of robot exposure on the same economic outcomes as used previously in Section 5.2 but now using their modelling approach. ACS do not report own labor market results but instead refer to previous literature which showed that robotization decreased manufacturing employment. It is tacitly assumed that their approach would lead to the same results.

However, Figure A.3 shows that their modelling approach suggests that increased robot adoption leads to *more* manufacturing employment. This holds using either the replication of their approach (left side) or using a model employing more fine-grained regional variation of robot exposure (right side).

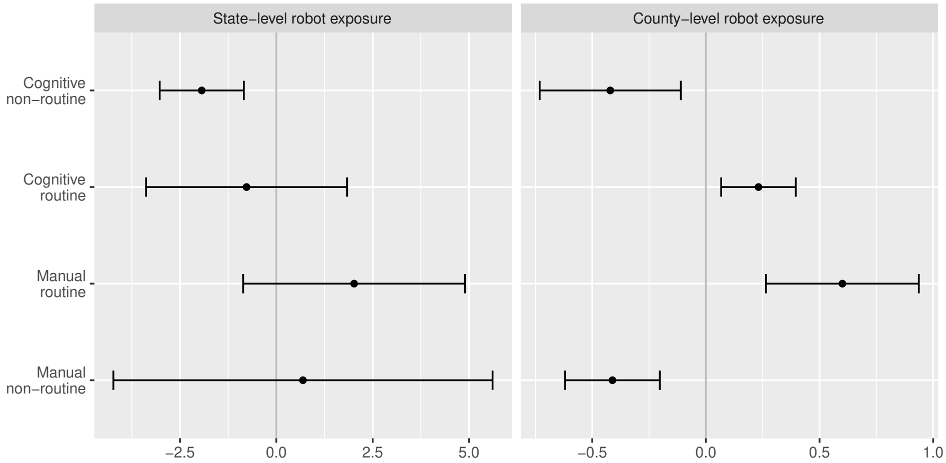
of robots per thousand workers in the year of the elections. As argued before, their approach mixes levels and changes whereas our approach uses levels for LHS and RHS variables. Note that due to the region and year fixed effect, our approach is equivalent to using a difference estimator (differences on the LHS and RHS).

Table **??** repeats the region-level analysis using a plain OLS model (panel A) and a 2SLS model (panel B). Under all specifications, the results indicate that increased exposure to robotization is associated with a larger fraction of workers being employed in the manufacturing sector. Additionally, we analyze what changing job requirements are implied by the approach of ACS. Figure A.4 shows that the repeated short-difference approach suggests that regions adopting more robots create more manual-routine jobs and using state-level variation in robot adoption, this modelling approach does not replicate well the often described 'hollowing out of the middle class'. These results stand in contrast to what we found before (see Section 5.2). Furthermore, they do not square well with the hypothesized mechanisms put forward by ACS. Rather than left behind, this approach suggests that semi-skilled routine workers in manufacturing are doing well in the face of increased robotization.

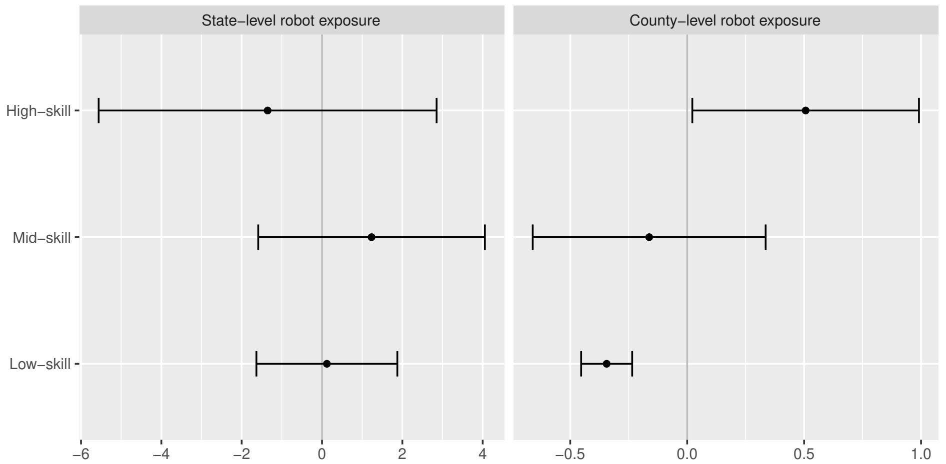
More generally, these patterns also do not align well with the RBTC paradigm. Both theoretical and empirical studies on the matter agree that semi-skill routine jobs are taken over by robots and diminish in numbers if a region is more exposed to automation (Acemoglu and Restrepo, 2020; Dauth et al., 2021). Note however, that our proposed compositional story fits the economic and political results proposed by this approach. Automation affects party support mainly through changing occupational structures and regions who still harbor a large group of semi-skilled routine workers are the ones who are most supportive of conservative and authoritarian-right parties. Since this approach predicts growing manufacturing employment with routine jobs, etc. it does not come as a surprise that this approach concludes that robotization is associated with more support for right-authoritarian parties.

As mentioned before, we believe that the results stem from mixing the *change* in robot penetration with *levels* of employment shares and party vote shares in the modelling approach (see Equation 5). However, since the number of robots grows most where there is a large manufacturing sector and routine work, this approach implicitly correlates the size of the manufacturing sector or the number of routine workers with right-authoritarian support. As we have shown in Section 5.2, larger shares of routine, mid-skilled manufacturing workers are associated with political support for right-authoritarian parties.

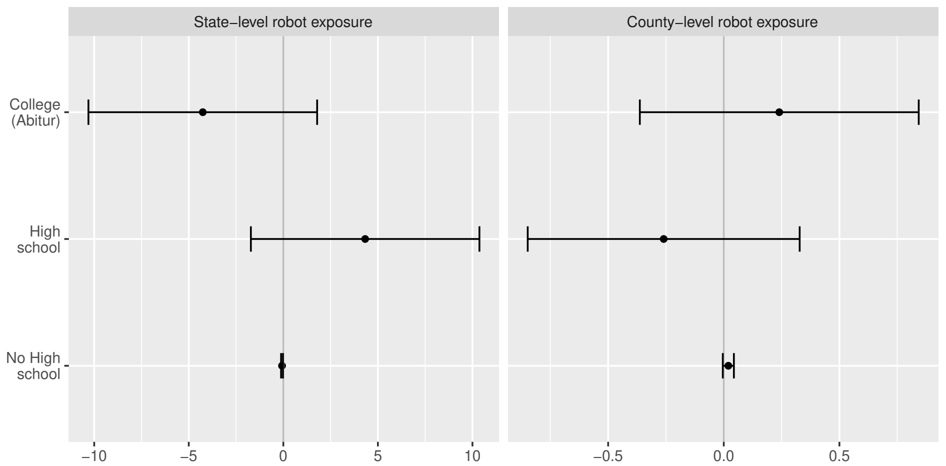
Figure A.4: Changing Job requirements: ACS approach



(a) Main task



(b) Skill



(c) Education

Note: The graph shows estimated effect of the robot exposure (change of number of robots per thousand workers over previous two years) on regional employment outcomes including year fixed effects (similar to election fixed effects used by AVS. The dependent variable in panel (a) is the main task of regional occupation composition. Panel (b) show the effect on regional jobs by skill requirement. Panel (c) shows the effect of robotization on regional employment composition by education level.).
All variables are expressed as share of regional employment in % such that coefficients sum up to zero. Black bars represent 95% confidence intervals.

A.4.4 Regression Tables

Table A.19: State-level Robot Exposure and Party Vote Shares

(A) OLS

	Dependent variable:					
	Grünen	Linke	SPD	FDP	CDU/CSU	Authoritarian right
State-Level Robot Exposure	1.784	0.267	−18.588*	−0.969	14.558	2.016**
	(3.424)	(2.207)	(9.982)	(2.790)	(11.363)	(1.015)
Election FE	X	X	X	X	X	X
Observations	1,619	1,619	1,619	1,619	1,619	1,619
R^2	0.166	0.710	0.431	0.745	0.123	0.753

(B) 2SLS

	Dependent variable:					
	Grünen	Linke	SPD	FDP	CDU/CSU	Authoritarian right
State-Level Robot Exposure	1.164	−0.578	−8.726	−1.815	7.835	1.679
	(4.770)	(2.113)	(20.367)	(3.803)	(16.756)	(1.464)
Election FE	X	X	X	X	X	X
First-stage F-stat	10.69	10.69	10.69	10.69	10.69	10.69
Observations	1,619	1,619	1,619	1,619	1,619	1,619
R^2	0.166	0.709	0.420	0.745	0.117	0.753

Note: Regressions of regional party vote share (in %) on robot exposure (change in number of robots per thousand workers over 2 years prior to the elections) measured at state level. Panel (A) shows plain OLS with election fixed effects. Panel (B) instruments robot exposure with values from other European countries. Panel (C) adds region fixed effects. Replication of Table 1 from Anelli, Colantone and Stanig (2019).
Standard errors reported in parenthesis are clustered at the state-election level. *p<0.1; **p<0.05; ***p<0.01

Table A.20: County-level Robot Exposure and Party Vote Shares

(A) OLS

	Dependent variable:					
	Grünen	Linke	SPD	FDP	CDU/CSU	Authoritarian right
Regional Robot Exposure	−0.228	0.019	−0.453	−0.204*	0.705	0.131**
	(0.153)	(0.079)	(0.752)	(0.109)	(0.805)	(0.064)
Election FE	X	X	X	X	X	X
Observations	1,619	1,619	1,619	1,619	1,619	1,619
R^2	0.164	0.710	0.393	0.745	0.097	0.741

(B) 2SLS

	Dependent variable:					
	Grünen	Linke	SPD	FDP	CDU/CSU	Authoritarian right
Regioanal Robot Exposure	−0.493*	0.012	0.342	−0.423**	0.340	0.173*
	(0.256)	(0.113)	(1.302)	(0.196)	(1.367)	(0.095)
Election FE	X	X	X	X	X	X
First-stage F-stat	35.04	35.04	35.04	35.04	35.04	35.04
Observations	1,619	1,619	1,619	1,619	1,619	1,619
R^2	0.162	0.710	0.392	0.744	0.097	0.741

Note: Regressions of regional party vote share (in %) on robot exposure (change in number of robots per thousand workers over 2 years prior to the elections) measured at region level. Panel (A) shows plain OLS with election fixed effects. Panel (B) instruments robot exposure with values from other European countries. Standard errors reported in parenthesis are clustered at the state-election level. *p<0.1; **p<0.05; ***p<0.01

A.5 Replication of Dauth, Findeisen, Südekum and Wössner (2021)

In this section, we replicate a set of basic results of Dauth et al. (2021) (henceforth DFSW) which is the study most closely related to the economic aspect of this paper. This serves mainly as a validation of our approach how to measure robot intensity. As explained in Section 4, DFSW also use IAB data to study labor market consequence of robot adoption in Germany. However, they have access to a more encompassing data set to construct their measure of robot intensity and we want to show that using our measure leads to comparable results. In contrast to our analysis, they also include Eastern Germany. We will follow their sample choice for the replication.

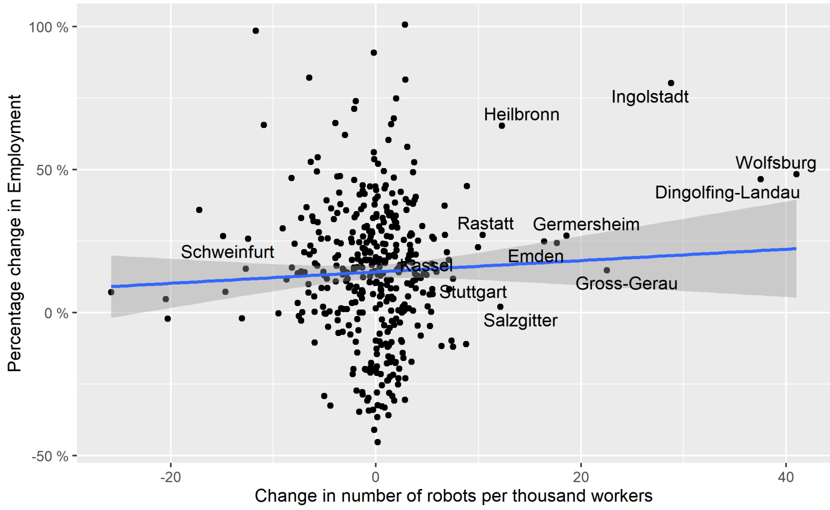
DFSW use a long difference approach where they analyze how increases in the robot exposure between 1994 and 2014 changed the labor market composition over the same time period. Their main findings are that while overall employment is not affected by the adoption of new robots, there are distributional consequences. Manufacturing jobs disappear but this is compensated by the creation of jobs in the non-manufacturing sector. Additionally leveraging on individual level data, they can show that incumbent workers are not displaced. New generations have to cope with changing labor demand by either obtaining a college education and to move into non-routine cognitive jobs or settling with rather precarious low skilled service sector jobs. Furthermore, they find evidence for skill polarization.

We replicate the part of their study focusing on regional employment effects of robotization. We successfully replicate the main figure and two main tables of the previous study using specifications as close as possible to DFSW. Figure A.5 plots the relationship between regional robot adoption and employment change. The x-axis shows that change in the number of robots per thousand workers (conditional on employment shares in broad industry groups and federal state dummies). The y-axis displays the regional employment growth. The correlation is slightly positive but not statistically significant. DFSW's graph shows similar results.

These (null-)findings are validated in a long-difference regression analysis where we regress a region's employment growth between 1994 and 2014 on changes of the region's robot exposure (see Table A.21). Again following DFSW, we additionally control for regional employment composition in the base year (employment shares of nine industry groups, share of high-, mid- and low-skilled workers, share of workers above fifty, share of female workers, share of foreign workers, 4 broad economic region dummies). Furthermore, we successively add changes in the region's trade exposure and changes in ICT capital stocks as addition controls.

Table A.21 which is an exact replication of Table 2 of DFSW shows that robots do not have an effect on total employment. The point estimate is always small and insignificant. The change of the number of robots per worker between 1994 and 2014 does not predict employment changes over the same time period. This effect holds controlling for a wide range of demographic characteristics of the region (column 2) and controlling for other economic shocks such as changes in trade exposure (column 3) and

Figure A.5: Region-level exposure to robots and employment growth.



Note: The graph plots the change in estimated number of robots per thousand workers (conditional on regional employment shares in nine broad industry groups and federal state dummies) for 401 German counties (*Kreise und kreisfreie Städte*) and the growth rate of total employment between between 1994 and 2014.

investments in ICT (column 4).[22] These results are very close to the ones DFSW find.

Table A.22 distinguishes between the manufacturing and the non-manufacturing sector. Again following DFSW, we use the same specifications as column 2-4 from Table A.21. However, the dependent variable is now either the growth of manufacturing employment or the growth of non-manufacturing manufacturing employment. While the effect of robots on manufacturing employment is slightly negative (column 2-4), the effect of robots on non-manufacturing employment is positive (column 5-7).

The coefficient we find are smaller in size (maybe due to higher measurement error) but the general pattern is close to DFSW. Note that we were not able to exactly reconstruct their ICT measure and instead use changes in the regional ICT capital stock per worker.[23]

Finally, we analyze how robots affect employment composition relative to the region's population. As Table A.23 shows, we also find a shift away from manufacturing employment towards non-manufacturing employment. However the overall trend is slightly more positive. The estimated effect of increasing robot exposure on manufacturing employment hovers around zero (column 2-4) while employment in the non-manufacturing sector is increasing (column 7-9).

What is interesting about this specification is that it allows us to calculate the effect a of single robot. We find that each robot affects manufacturing between -0.3 and +0.1 jobs depending on the specification. At the same time an additional robot is associated with the creation of between .9 and 1.5 non-manufacturing jobs. These numbers smaller than the results of DFSW who find that each robot

[22] We use the changes in the capital stock in information technology, communication technology and software and databases normalized by employment from the EUKLEMS database. Since the time series only starts in 1995 we use the difference 1995-2014 in the long-difference approach.

[23] See Gallego, Kurer and Schöll (2020) for a detailed description of the construction of our ICT measure. Note that EUKLEMS data only starts in 1995. Therefore, we use the difference between 1995-2014.

replaces between 1.6-1.8 manufacturing jobs while it creates additional 1.4-1.8 non-manufacturing jobs.[24]

[24]We calculate the absolute number effects of one additional robot similar to Acemoglu and Restrepo (2020):

$$\frac{Employment_2}{Population_2} = \frac{Employment_1}{Population_1} + \beta \frac{\Delta robots}{\frac{Employment_1}{1000}}$$

Assuming a constant population ($population_2 = population_1$), dividing the point estimate as it was in percentage points and rearranging:

$$Employment_2 - Employment_1 = \frac{\hat{\beta}}{100} \frac{\Delta robots}{\frac{Employment_1/Population_1}{1000}}$$

The average employment to population ratio across all regions in our base year ($Employment_{1994}/Population_{1994}$) is 0.301. Hence, each additional robot affects employment as:

$$\Delta Employment = 10 \frac{\hat{\beta}}{0.301} \Delta robots$$

Table A.21: Robot Exposure and Employment

	Dependent variable:			
	% change in total employment between 1994 and 2014			
	(1)	(2)	(3)	(4)
Δ robots per 1000 workers	0.132	0.023	0.050	−0.189
	(0.105)	(0.119)	(0.126)	(0.139)
% manufacturing	−0.217*			
	(0.123)			
% food products		2.575***	2.517***	2.518***
		(0.383)	(0.372)	(0.386)
% consumer goods		0.439	0.493	0.419
		(0.308)	(0.316)	(0.327)
% industrial goods		0.475**	0.412*	0.419**
		(0.207)	(0.215)	(0.212)
% capital goods		0.884***	0.825***	0.753***
		(0.248)	(0.257)	(0.257)
% construction		1.179***	1.116***	1.046***
		(0.307)	(0.317)	(0.322)
% services		0.260	0.252	−0.294
		(0.244)	(0.246)	(0.325)
% public sector		0.656***	0.635**	0.546**
		(0.250)	(0.250)	(0.255)
Δ net exports			0.588	0.422
			(0.407)	(0.446)
Δ ICT capital stock				6.050***
				(2.051)
Observations	401	401	401	401
R^2	0.469	0.556	0.558	0.567

Note: Replication of Table 2 from Dauth et al. (2021). Regressions of total employment growth (in %) on the change in robot exposure between 1994 and 2014. All specifications include a constant, broad region dummies indicating if the region is located in the north, west, south, or east of Germany and demographic control variables, measured in the base year 1994. The demographic control variables are the employment shares of female, foreign, age > 50, medium skilled (*fachliche Tätigkeit*), and high skilled (*komplexe Spezialistentätigkeit, hochkomplexe Expertentätigkein*) workers relative to total employment (reference category: *Helfertätigkeit*). In column 1, we control for the manufacturing share in total employment. In columns 2-4, we instead include broad industry shares to control better for regional industry patterns. Industry shares cover the percentage of workers in eight broad industry groups (agriculture (reference); food products; consumer goods; industrial goods; capital goods; construction; services; public sector) in the base year 1994. Columns 3 and 4 successively take into account the change in German net exports vis-à-vis China and Eastern Europe (in 1000 € per worker), and the change in ICT capital stock (in 1000 € per worker), both between 1994 and 2014.
Standard errors reported in parenthesis are clustered at the level of 50 commuting zones. *p<0.1; **p<0.05; ***p<0.01

Table A.22: Composition Effects - Employment Growth

	Dependent variable: Employment growth %						
	Total	Manufacturing	Manufacturing	Manufacturing	Non-manufacturing	Non-manufacturing	Non-manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ robots per 1000 workers	−0.189	−0.081	−0.010	−0.173	0.373**	0.389**	0.220
	(0.139)	(0.163)	(0.174)	(0.264)	(0.185)	(0.191)	(0.212)
% manufacturing	2.518***	2.016**	1.863**	1.863**	3.012***	2.978***	2.979***
	(0.386)	(0.786)	(0.777)	(0.767)	(0.426)	(0.414)	(0.426)
% food products	0.419	−0.361	−0.217	−0.268	1.032***	1.064***	1.012***
	(0.327)	(0.672)	(0.650)	(0.632)	(0.344)	(0.345)	(0.364)
% consumer goods	0.419**	−0.291	−0.456	−0.451	1.035***	0.999***	1.004***
	(0.212)	(0.765)	(0.754)	(0.751)	(0.220)	(0.241)	(0.241)
% industrial goods	0.753***	0.437	0.283	0.233	1.117***	1.083***	1.032***
	(0.257)	(0.714)	(0.702)	(0.679)	(0.268)	(0.289)	(0.299)
% capital goods	1.046***	0.371	0.204	0.157	1.318***	1.281***	1.232***
	(0.322)	(0.903)	(0.876)	(0.866)	(0.401)	(0.429)	(0.439)
% construction	−0.294	−1.045	−1.068	−1.441*	0.541***	0.536**	0.151
	(0.325)	(0.844)	(0.827)	(0.750)	(0.209)	(0.217)	(0.344)
% services	0.546**	0.084	0.031	−0.031	0.716***	0.705***	0.641**
	(0.255)	(0.697)	(0.686)	(0.668)	(0.257)	(0.260)	(0.275)
% public sector	0.422		1.555***	1.442**		0.340	0.224
	(0.446)		(0.533)	(0.565)		(0.596)	(0.631)
Δ net exports	6.050***			4.134			4.265
	(2.051)			(3.234)			(2.927)
Observations	401	401	401	401	401	401	401
R^2	0.567	0.352	0.361	0.364	0.644	0.645	0.647

Note: Replication of Table 3 Panel A from Dauth et al. (2021). Regressions of employment growth (in %) on the change in robot exposure between 1994 and 2014 for different sectors. See Table A.21 for further details.
Standard errors reported in parenthesis are clustered at the level of 50 commuting zones. *p<0.1; **p<0.05; ***p<0.01

Table A.23: Composition Effects - Employment to Population Ratio

	Dependent variable: Employment growth %						
	Total	Manufacturing	Manufacturing	Manufacturing	Non-manufacturing	Non-manufacturing	Non-manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ robots per 1000 workers	0.017	0.002	0.006	−0.010	0.044*	0.041*	0.027
	(0.056)	(0.027)	(0.026)	(0.033)	(0.023)	(0.023)	(0.034)
% manufacturing	0.202**	0.064	0.055	0.055	0.140**	0.147**	0.147**
	(0.095)	(0.047)	(0.046)	(0.046)	(0.071)	(0.070)	(0.070)
% food products	−0.053	−0.092**	−0.083**	−0.088***	0.047	0.040	0.036
	(0.083)	(0.036)	(0.035)	(0.034)	(0.056)	(0.055)	(0.057)
% consumer goods	−0.040	−0.069	−0.079*	−0.079*	0.031	0.038	0.039
	(0.083)	(0.048)	(0.047)	(0.046)	(0.051)	(0.052)	(0.053)
% industrial goods	0.077	0.039	0.030	0.025	0.049	0.056	0.052
	(0.085)	(0.044)	(0.043)	(0.041)	(0.053)	(0.054)	(0.056)
% capital goods	−0.096	−0.00002	−0.010	−0.015	−0.084	−0.077	−0.081
	(0.098)	(0.058)	(0.057)	(0.056)	(0.068)	(0.070)	(0.072)
% construction	−0.169**	−0.113**	−0.115**	−0.153***	0.015	0.016	−0.016
	(0.084)	(0.054)	(0.053)	(0.047)	(0.042)	(0.043)	(0.061)
% services	−0.003	−0.025	−0.028	−0.034	0.034	0.037	0.031
	(0.095)	(0.038)	(0.038)	(0.036)	(0.071)	(0.072)	(0.073)
% public sector	0.001		0.092	0.081		−0.070	−0.080
	(0.113)		(0.072)	(0.074)		(0.071)	(0.072)
Δ net exports	0.776			0.419			0.357
	(0.581)			(0.275)			(0.503)
Observations	401	401	401	401	401	401	401
R^2	0.499	0.383	0.386	0.389	0.653	0.653	0.654

Note: Replication of Table 3 Panel B from Dauth et al. (2021). Regressions of change in the employment to population ratio on the change in robot exposure between 1994 and 2014 for different sectors. See Table A.21 for further details.
Standard errors reported in parenthesis are clustered at the level of 50 commuting zones. *p<0.1; **p<0.05; ***p<0.01