The Political Economy of Artificial Intelligence: Evidence from Western Europe*

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August 11, 2025

Abstract

While advances in artificial intelligence (AI) are feared to bring about widespread job losses, workers who are highly exposed to the technology tend to anticipate productivity-driven improvements in their earnings and employment prospects. I argue that this paradox has important political economy implications: if wage gains from labor complementarities are expected to exceed losses from substitution effects, exposure to AI is more likely to weaken than strengthen support for redistributive policies and their political advocates. I test this argument using a combination of observational and experimental data from Western Europe, finding that occupational exposure to AI is negatively associated with support for redistribution, the left, and the (increasingly pro-welfare) populist right but positively associated with support for the mainstream right. The results enhance our understanding of the political economy of digitalization, suggesting a discrepancy between the perceived distributional consequences of AI and earlier automation technologies that have primarily displaced labor.

Keywords: artificial intelligence, AI, technological change, redistribution preferences, voting behavior, automation, political economy

*For valuable feedback on previous drafts, I am grateful to Daron Acemoglu, James Alt, Ben Ansell, Jeal-Paul Carvalho, Paola Conconi, Jeffry Frieden, Aina Gallego, Farsan Ghassim, Jane Gingrich, Jane Green, Benjamin Harack, Torben Iversen, Julian Jacobs, Alexander Kuo, Thomas Kurer, Walter Mattli, Manav Raj, David Rueda, Duncan Snidal, and audiences at the London School of Economics, the University of California, San Diego, the University of Oxford, the Annual Meeting of the American Political Science Association, and the Annual Conference of the European Political Science Association.

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Introduction

The development and growing adoption of artificial intelligence (AI) — technology that enables machines to perform functions usually associated with human intelligence — are expected to transform labor markets in industrialized economies, reshaping how productive assets, market power, and income are distributed. It is surprising, therefore, that AI's implications for core distributional questions of political economy — most notably how much redistribution individuals desire, a key theoretical determinant of their policy attitudes and voting behavior — have not received more attention.[1] Analyses of the impact of digital technologies on redistribution and political preferences have focused primarily on the adoption of robots, computers, and other mechanized devices designed to automate routine occupational tasks. A central finding is that workers who are more exposed to routine-biased automation typically express stronger support for redistribution (Thewissen and Rueda 2019; Dermont and Weisstanner 2020; Busemeyer and Sahm 2022; Kurer and Häusermann 2022), a pattern consistent with "insurance" models of social policy emphasizing the desire for public protection against the risk of income loss (e.g., Moene and Wallerstein 2001; Iversen and Soskice 2001).[2] Extending this line of analysis to voting behavior, Gingrich (2019) shows that automation exposure is also associated with support for parties on the left side of the ideological spectrum, which are defined in large part by their commitment to promoting equality and social justice through redistribution.

This study proposes and tests a simple framework for analyzing the distributive politics of AI that predicts a *negative* relationship between exposure to the technology and support for redistribution and left-wing politics. My argument accepts a key premise of insurance models, namely, that individuals form redistribution preferences based not only on their current labor

[1] As Rueda and Stegmueller (2019, 7) remark, "The (often implicit) model behind much of comparative politics and political economy starts with redistribution preferences as given."

[2] This finding is not undisputed, however, with some studies identifying no link between automation risk and redistribution preferences (Jeffrey 2021; Gallego and Kurer 2022; Bicchi, Kuo, and Gallego 2024).

market situation but also on their expected position in future income distributions. Building on an influential theory of how opportunities for upward mobility shape attitudes toward redistribution (Benabou and Ok 2001; Alesina and La Ferrara 2005), however, I emphasize that insurance motives need not dominate incentives to maximize post-tax income among forward-looking individuals exposed to an emerging technology. If wage gains from technology-enabled improvements in labor productivity are expected to exceed losses from substitution effects, exposed workers should anticipate higher rather than lower relative earnings in the future, dampening their support for redistribution. Mapping redistribution preferences onto the traditional ideological spectrum, exposure should, in turn, strengthen support for the political right — with the likely exception of populist parties, which have adopted an increasingly pro-welfare stance on social policy issues (Harteveld 2016; Afonso and Rennwald 2018; Chueri 2022; Rathgeb and Busemeyer 2022) — and weaken support for the left.

A striking paradox of the emerging era of AI is that, while public discourse has centered on the threat of widespread job losses, workers with higher exposure to the technology tend to be more optimistic about its labor market consequences. This puzzle arises because exposure is not the same as displacement risk; rather, it captures a technology's potential to alter the means by which occupational tasks are performed and thus to *complement* as well as substitute for labor. Survey evidence indicates that workers whose functions are heavily impacted by AI generally expect complementarities to exceed substitution effects, with gains in productivity and the creation of new tasks spurring improvements in their future earnings and employment prospects (e.g., Lane, Williams, and Broecke 2023; Pew Research Center 2023; Jitterbit 2024; PwC 2024; Stack Overflow 2024).[3] These expectations are consistent with a growing body of research linking the adoption of AI to increases in worker performance (Briggs and Kodnani 2023; Noy and Zhang 2023; Peng et al. 2023), firm output (Alderucci et al. 2020; Damioli, Van Roy, and Vertesy

[3]As one recent headline about software programmers summarizes, "Developers aren't worried about AI taking their jobs — but excited about productivity gains." https://www.techradar.com/pro/developers-arent-worried-about-ai-taking-their-jobs-but-excited-about-productivity-gains.

2021; Fossen and Sorgner 2022), and wage growth (Felten, Raj, and Seamans 2019; Stephany and Teutloff 2024; PwC 2025), while detecting few signs of job displacement thus far (Acemoglu et al. 2022; Shen and Zhang 2024; The Economist 2025; Humlum and Vestergaard 2025). Incorporating this evidence into my framework yields the prediction that occupational exposure to AI will be associated with weaker support for redistribution, the left, and the populist right but stronger support for the mainstream right. Importantly, though, I only expect these relationships to materialize after around 2010, when demand for AI skills began to rise rapidly in advanced labor markets (Alekseeva et al. 2021; Squicciarini and Nachtigall 2021; Acemoglu et al. 2022).

I test these expectations using three complementary sources of individual-level survey data from Western Europe, where attitudes toward redistribution are well developed and levels of AI adoption are comparatively high (IBM 2023). I begin by combining three widely used measures of occupational exposure to AI with European Social Survey (ESS) data on redistribution preferences and voting behavior in 12 countries over the period 2002-2021. Controlling for country and survey wave fixed effects as well as standard socioeconomic controls, I find that AI exposure became negatively associated with support for redistribution, the left, and the populist right after 2010 yet positively associated with support for the mainstream right. These relationships hold across a variety of robustness checks, including controlling for susceptibility to automation and other types of occupational risks posed by digital technologies, exploiting variation within (broad and narrow) occupational categories, and instrumenting AI exposure with parental occupational characteristics.

A limitation of the ESS is that each survey wave draws a new sample of respondents, preventing us from controlling for fixed individual characteristics — a key threat to causal inference in observational survey research. While there are no sources of longitudinal data on Western European attitudes toward redistribution during the period of interest (to my knowledge), the Socio-Economic Panel (SOEP) has tracked the political preferences of a large, representative sample of German households over recent decades using the most granular and up-to-date international occupational classification system.[4] In the second stage of my empirical investigation, therefore, I conduct a within-individual analysis of the relationship between AI exposure and party support in Germany between 2000 and 2021. The results again comport with expectations: post-2010, respondents with higher exposure became less likely to support left-wing and right-wing populist parties but more inclined to back mainstream right-wing parties.

Finally, to probe the hypothesized causal mechanism and further substantiate a causal interpretation of the previous findings, I present a preregistered survey experiment involving the random assignment of informational vignettes highlighting AI's labor-complementing or labor-substituting effects to working-age residents of the United Kingdom. In line with my argument, respondents receiving the complementarity frame reported more positive expectations about AI's impact on their productivity and future earnings, expressed weaker support for redistribution, and were more likely to vote for the mainstream right-wing Conservative Party. Respondents receiving the substitution frame, on the other hand, were less confident that AI would improve their livelihoods, more supportive of redistribution, and more likely to vote for the left-wing Labour Party and the right-wing populist Reform UK. Furthermore, I find that both sets of treatment effects are stronger for respondents with greater occupational exposure to AI (measured both objectively and subjectively), for whom the "stakes" of the information presented are higher.

Taken as a whole, the findings point to the importance of distinguishing between different digital technologies — and their perceived distributional implications for individuals with varying exposure to them — for understanding the evolving political economy of technological change (Gallego and Kurer 2022). Although often grouped together with "pure" automation techniques, AI carries the potential to enhance and expand human skills in ways that shore up

[4] The SOEP and the UK Household Longitudinal Survey (UKHLS) include a question capturing support for government intervention in the market to provide jobs, a somewhat indirect proxy for redistribution preferences. Even this item, however, is included only in a handful of (mostly pre-2010) survey waves.

demand for labor — a distinction with critical consequences for how exposed workers will be impacted by redistributive policies in the future. The political implications are significant: if exposure to AI tends to diminish preferences for redistribution, as my results suggest, a relatively skilled and prosperous segment of the workforce may come to oppose demands for social protection arising from the spread of routine-biased automation. Similarly, gains in support for the left and the populist right associated with such demands may be offset by movement toward the mainstream right among AI-exposed workers, potentially increasing polarization within the electorate. It is important to stress, however, that these implications are not set in stone; rather, as discussed in the concluding section, they reflect contemporary expectations about AI's capabilities and labor market consequences that may change as the technology spreads and becomes more mature.

Technological Change, Redistribution, and Political Preferences

Technological innovation presents opportunities as well as risks for workers. Different methods, tools, and systems of production can affect the returns to labor both by influencing its efficiency in performing existing occupational tasks and by creating new functions in which it has a comparative advantage (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018). The winners and losers of technological change are thus determined by how gains in productivity are distributed across factors of production and tasks. In the early stages of a technology's adoption, the nature of this distribution is often uncertain and debated — AI representing a clear case in point.

The canonical model of how individuals' economic position influences their redistribution preferences sheds little light on processes of ongoing technological change. In this framework, the size of government — proxied by the share of income redistributed — is determined by the choice of the median voter, who seeks to maximize current post-tax income (Meltzer and Richard 1981). The economic consequences of emerging technologies, however, may take years or even decades to play out. Assuming that individuals are rational and forward-looking, therefore, their redistribution preferences should also reflect how such innovations impact their expected *future* income (Rueda and Stegmueller 2019). As Alesina and Giuliano (2011, 94) note, "Economists traditionally assume that individuals have preferences defined over their lifetime consumption (income)...[P]references for redistribution depend not only on where people are today in the income ladder but also on where they think they will be in the future if redistributive policies are long-lasting."

Two approaches to understanding the relationship between expected future income and redistribution preferences have been particularly influential. According to the first, a key source of demand for redistribution is the risk-averse desire for social insurance against employment and wage loss (Iversen and Soskice 2001; Moene and Wallerstein 2001). The second perspective highlights how the prospect of upward mobility (POUM) can discourage relatively poor and risk-tolerant individuals from supporting extensive redistribution (Benabou and Ok 2001; Alesina and La Ferrara 2005). While neither perspective directly addresses the issue of technological change, the former has recently been extended to analyze the consequences of routine-biased automation, the central implication being that individuals facing a greater threat of displacement will favor higher levels of social protection and hence redistribution (Thewissen and Rueda 2019; Dermont and Weisstanner 2020; Busemeyer and Sahm 2022; Kurer and Häusermann 2022).

The more general theoretical proposition suggested by the insurance approach is that support for redistribution will strengthen with exposure to technologies that are expected to reduce relative future earnings. As the POUM conjecture implies, however, the desire for social protection need not dominate redistribution motives among rational, forward-looking individuals. New technologies may generate sufficiently sizable gains in worker productivity that they raise demand for labor in exposed occupations, overcoming any downward pressures stemming from substitution effects. In this scenario, more exposed workers should anticipate a higher — not lower — position in future income distributions and accordingly favor more extensive redistribution.

More formally, consider a two-period setting in which individual i seeks to maximize the utility function $u(c_{it}, c_{i,t+1})$, where c_{it} depends on y_{it}, i's pretax income in period t, and $c_{i,t+1}$ depends on $y_{i,t+1}$, i's pretax income in period $t+1$.[5] Let τ denote a fixed linear tax rate determined at the start of t, which finances a lump-sum redistribution with a distortionary cost of $d\tau^2$ per person. Assuming that t and $t+1$ are close enough that discounting is negligible, i's total expected consumption over the two periods can be written as:

$$c_{it} + c_{i,t+1} = \overbrace{(1-\tau)(y_{it} - \mathbb{E}(y_{i,t+1}))}^{\text{after-tax labor income}} + \overbrace{\tau\overline{y}_t + \tau\mathbb{E}(\overline{y}_{t+1})}^{\text{government transfer}} - \overbrace{2d\tau^2}^{\text{distortion}} \tag{1}$$

where $\overline{y}$ is the average income in i's country and $\mathbb{E}()$ stands for expected value. Differentiating with respect to τ and rearranging yields the optimal tax rate:

$$\tau^*_{it} = \frac{1}{4d}(\overline{y}_t + \mathbb{E}(\overline{y}_{t+1}) - y_{it} - \mathbb{E}(y_{i,t+1})). \tag{2}$$

The amount of redistribution preferred by i is thus an increasing function of the average current and expected future income but a decreasing function of i's own current and expected future income.

The impact of a technological innovation can be modeled as a change in the equilibrium wage for the set of occupational tasks performed by i. Assume that these N tasks produce a unique final good, markets are competitive, and the only factors of production are capital and labor. Building on task-based models of labor markets (Acemoglu and Autor 2011; Acemoglu

[5] I assume risk neutrality for the purposes of this exposition.

and Restrepo 2018; Acemoglu 2024), i's earnings in t can be expressed as:

$$y_{it} = \overbrace{\left(\frac{X}{L}\right)^{\frac{1}{\sigma}}}^{\substack{\text{intrinsic}\\ \text{productivity}}} \overbrace{(B(N)A_L)^{\frac{\sigma-1}{\sigma}}}^{\substack{\text{technological}\\ \text{augmentation}}} \overbrace{\left(\int_I^N \gamma_L(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}}^{\text{task allocation}} \tag{3}$$

where X is the output produced by tasks $[0, N]$, L is the supply of labor for these tasks, σ is the elasticity of substitution between tasks, B is a general productivity multiplier for technology-enabled tasks, A_L is a productivity multiplier for labor-augmenting technology specifically, $\gamma_L(z)$ is labor's productivity in performing task $z \in [0, N]$, and I is some task threshold above which it is cost-minimizing to employ labor rather than capital.[6] Thus, the first term in Equation 3 represents labor's intrinsic productivity, while the second and third terms capture its marginal productivity from complementary technologies and task allocation, respectively.

Comparative statics reveal the wage effects of technological change:

$$d\ln y_i = \frac{1}{\sigma}d\ln\left(\frac{X}{L}\right)^{\frac{1}{\sigma}} + \frac{\sigma-1}{\sigma}(d\ln B(N) + d\ln A_L) + \frac{1}{\sigma}d\ln\left(\int_I^N \gamma_L(z)^{\sigma-1}dz\right). \tag{4}$$

This expression implies that a new technology can influence i's earnings through several parameters of the production process, most notably i's (intrinsic and task-specific) productivity, i's number of tasks, and the allocation of labor and capital to tasks. The anticipated net effect of changes in these parameters determines whether i expects pretax income to rise or decline in $t+1$:

$$\mathbb{E}(y_{i,t+1}) \begin{cases} > y_{it} & \text{if } \mathbb{E}(d\ln y_{it}) > 0 \\ < y_{it} & \text{if } \mathbb{E}(d\ln y_{it}) < 0. \end{cases} \tag{5}$$

In sum, a technological innovation that, in expectation, raises i's position in future income distributions by expanding i's productivity and range of occupational tasks is likely to weaken

[6] Online Appendix A.1 provides a more detailed discussion of this setup. I assume that $0 \leq \sigma \leq 1$, so that tasks are gross complements.

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i's support for redistribution today. Conversely, an innovation that reduces i's relative future income by curtailing i's output and task range should strengthen i's redistribution preferences.

From Redistribution to Political Preferences

Given the centrality of redistributive issues to the left-right axis of political competition (e.g., Iversen and Soskice 2006; Rehm, Hacker, and Schlesinger 2012; Gallego, Kurer, and Schöll 2022), this framework also carries implications for voting behavior. In the words of Alesina and La Ferrara (2005, 94–95), "[T]he question of whether or not a government should redistribute from the rich to the poor and how much is probably the most important dividing line between the political left and the political right, at least on economic issues." Indeed, several studies show that individuals who prefer higher levels of redistribution are more likely to favor and vote for left-wing parties (e.g., Rueda 2018; Rueda and Stegmueller 2019; Quinlan and Okolikj 2020; Abou-Chadi and Hix 2021). This pattern suggests a straightforward extension to the framework: exposure to technologies that are expected to depress relative future income will be associated with support for the left, while exposure to technologies that are expected to boost relative future income will be associated with support for the right.[7]

A likely exception to this logic lies at the populist end of the political right, where policy positions on redistributive issues have evolved significantly in recent decades. While right-wing populism traditionally combined neoliberalism on the economic dimension with authoritarianism on the cultural dimension, the early 2000s saw populist challengers frequently "blurring" their positions on established issues to broaden their appeal (Rovny 2013). As populist parties have emerged as a major political force over the past 15 years, however, they have predominantly embraced a pro-welfare stance on social policy (albeit one that tends to emphasize assistance for "deserving" recipients) (Harteveld 2016; Afonso and Rennwald 2018; Chueri 2022; Rathgeb

[7] Consistent with this proposition, Gallego, Kurer, and Schöll (2022) document increased support for the United Kingdom's Conservative Party among skilled workers, who have derived greater economic benefits from workplace digitalization.

and Busemeyer 2022). As Chueri (2022, 383) summarizes, "Populist radical right-wing parties in Western Europe have, in recent years, almost without exception changed their position on welfare state from pushing for a minimal state to supporting strong welfare." As a result, the relationship between redistribution preferences and support for the populist right is liable to vary over time, with a positive association highly plausible during the past 15 years.

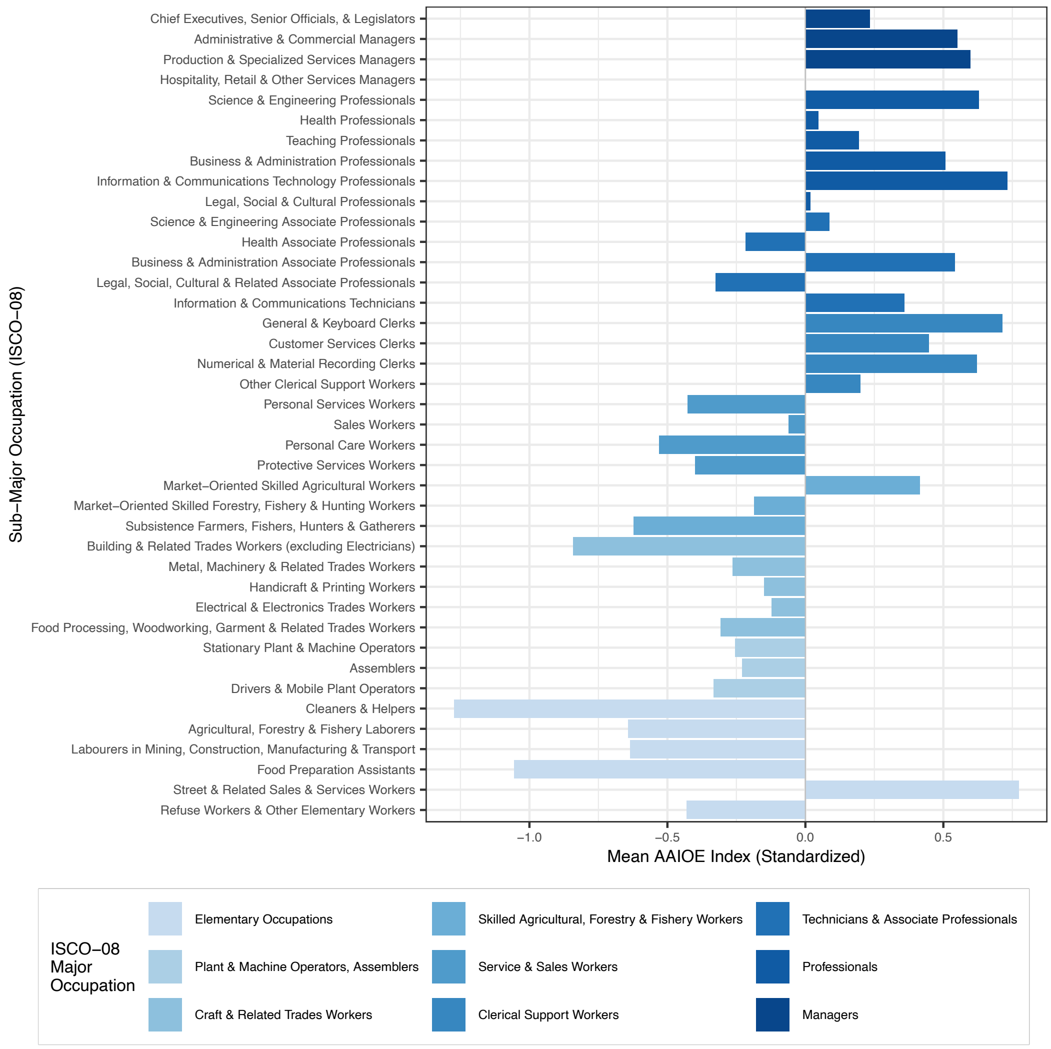
Application to Artificial Intelligence

According to the framework set out in the previous section, the consequences of an emerging technology for redistribution and voting preferences are a function of (1) occupational exposure to this innovation and (2) expectations about its impact on relative future income. This section discusses each component in the context of AI, allowing us to develop testable hypotheses about the technology's influence on such preferences.

Occupational Exposure

Which jobs are most impacted by AI? To answer this question, economists have developed granular occupation-level indices of exposure to the technology, three of which have gained particular prominence: (1) Felten, Raj, and Seamans' (2021) AI Occupational Exposure (AIOE) index, which draws on the Electronic Frontier Foundation's AI Progress Measurement project, an open-source database gauging AI's ability to perform basic human functions; (2) Brynjolfsson, Mitchell, and Rock's (2018) Suitability for Machine Learning (SML) index, which is based on crowdsourced expert assessments of the potential for work activities to be codified in an algorithmic program; and (3) Webb's (2020) AI exposure index, which is constructed from the text of AI patents filed around the world. As Acemoglu et al. (2022) point out, these indices are methodologically and substantively complementary: in addition to drawing on different sources of information and expertise, they capture AI's existing as well as potential future capabilities. I

FIGURE 1. Exposure to Artificial Intelligence by Occupation



Notes: Mean value of the AAIOE — an average of three standardized indices of occupational exposure to AI developed by Felten, Raj, and Seamans (2021), Brynjolfsson, Mitchell, and Rock (2018), and Webb (2020) — for sub-major (2-digit) ISCO-08 occupations, with shades representing major (1-digit) occupations.

thus make use of all three measures in my empirical investigation, averaging their standardized scores to construct an Aggregate AI Occupational Exposure (AAIOE) index.

Figure 1 provides an overview of occupational exposure to AI based on the AAIOE, displaying its mean score for "sub-major" (2-digit) categories of the latest International Standard Classification of Occupations (ISCO-08), which are grouped by shade into "major" (1-digit) categories.[8] Among the latter, professionals and managers exhibit the highest average exposure to AI, while elementary workers and crafts and related trades workers register the lowest. At the sub-major level, the five most exposed occupations are information and communication technology (ICT) professionals (0.7SD above the mean AAIOE score), sales and services workers (+0.6SD), general and keyboard clerks (+0.5SD), science and engineering professionals (+0.4SD), and business and administration professionals (+0.3SD). The five least exposed occupations are cleaners and helpers (−1.4SD), food preparation assistants (−1.2SD), building and related trades workers (−1.1SD), agricultural, forestry, and fishery laborers (-0.8SD), and subsistence farmers, fishers, hunters, and gatherers (−0.8SD).[9] In short, AI exposure is concentrated in relatively skilled jobs involving the application of technical expertise or specialized knowledge, particularly in the areas of ICT and professional services.

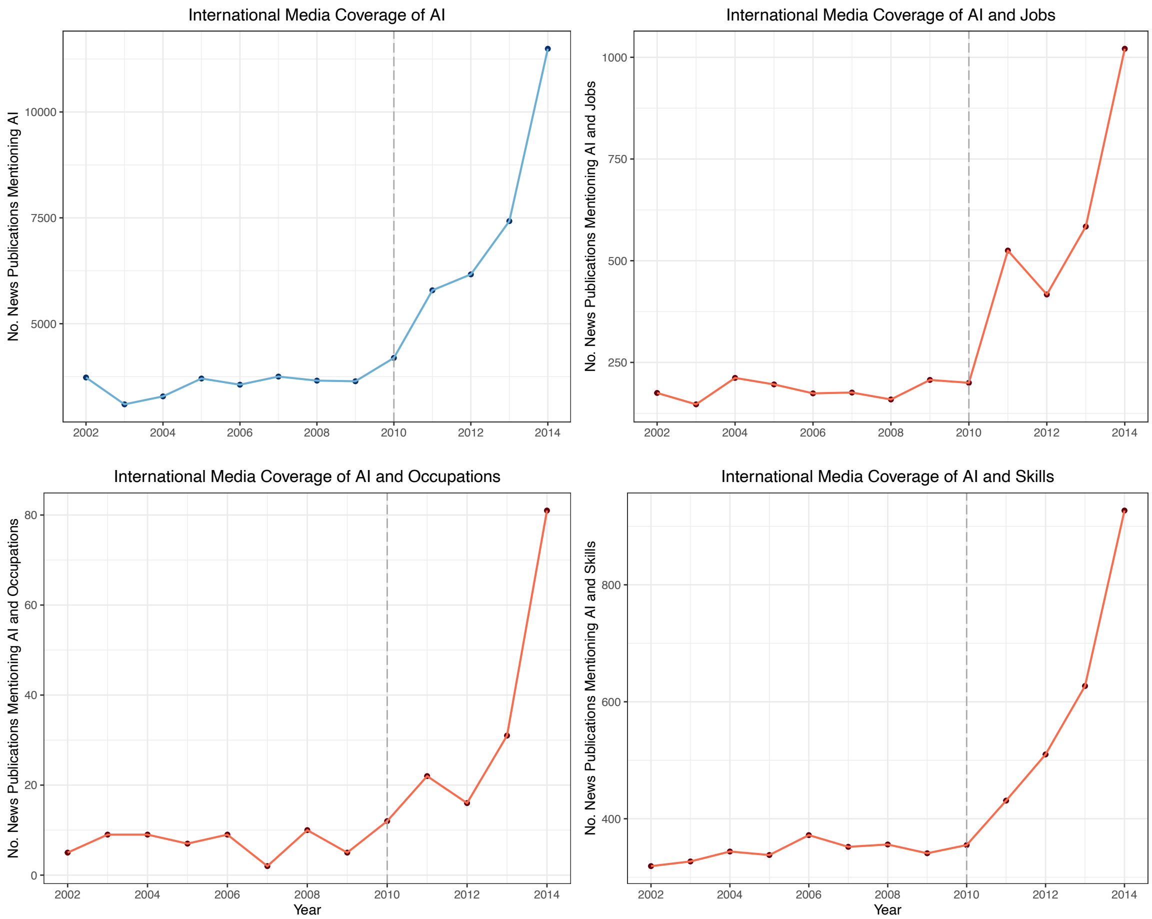
A crucial caveat to these patterns is that they primarily reflect progress in AI achieved during the past 15 years. While many of the concepts underpinning contemporary AI were developed several decades ago, the 2010s witnessed a fundamental transformation in the technology fueled by improvements in computing power, data storage, and algorithmic design, which laid the foundations for a "resurgence of neural networks through deep learning. . .leading to dramatic advances in the application of AI to many fields of science and other areas of human endeavor" (Dean 2022, 58).[10] These developments, job postings indicate, spurred a sharp rise in demand for AI skills across advanced labor markets — demand that was essentially non-existent during the 2000s (Alekseeva et al. 2021; Squicciarini and Nachtigall 2021; Acemoglu et al. 2022). As illustrated in Figure 2, they also prompted a surge in international media coverage of AI (upper

[8]The three component indices of the AAIOE are converted from the 2010 Standard Occupational Classification (SOC2010) — the classification system used in the United States — to ISCO-08. Figure A1 in Online Appendix B disaggregates Figure 1 by AAIOE component, revealing a reasonably strong correlation between the indices.

[9]Table A1 in Online Appendix B enumerates the 25 most and least exposed occupations at the most granular (4-digit) ISCO-08 level.

[10]Key AI breakthroughs in the early 2010s include the use of NVIDIA graphics processing units to efficiently train deep learning models; the victory of AlexNet — a convolutional neural network — in the ImageNet visual recognition competition; and the introduction of real-time virtual assistants based on natural language processing and speech recognition, such as Apple's Siri and IBM's Watson.

FIGURE 2. International Media Coverage of Artificial Intelligence Before and After 2010



Notes: This figure plots the number of English-language (print and online) media publications that contain the term "artificial intelligence" (upper left panel) plus "jobs" (upper right), "occupations" (lower left), and "skills" (lower right) between 2002 and 2014. Source: Dow Jones Factiva global news database.

left panel) and its implications for work (upper right and lower panels). Prior to approximately 2010, therefore, exposure to AI is unlikely to have been high enough in *any* occupation to have meaningfully influenced redistribution and voting preferences.

Expectations about Future Income

The nature of AI's impact on highly exposed occupations is also the subject of a growing number of studies and policy reports, many of which point to improvements in productivity, expectations of wage growth, and relatively low levels of concern about job displacement.

AI-driven improvements in labor productivity have been documented at the level of specific tasks as well as whole firms, occupations, and industries. With the aid of AI tools, workers have been found to perform a variety of tasks more efficiently — and often to a higher standard — including computer programming (Peng et al. 2023), professional writing (Noy and Zhang 2023), customer support (Brynjolfsson, Li, and Raymond 2023), and management consulting (Dell'Acqua et al. 2023). Firms embracing AI, meanwhile, have enjoyed increases in annual output per worker of 2-7 percentage points, accelerating revenue and employment growth (Alderucci et al. 2020; Damioli, Van Roy, and Vertesy 2021; Fossen and Sorgner 2022; Rammer, Fernández, and Czarnitzki 2022).[11] Similarly, occupations and industries that are more exposed to the technology have experienced consistently faster productivity and wage growth, with AI skills typically commanding a salary premium in excess of 20% (Felten, Raj, and Seamans 2019; Alekseeva et al. 2021; Stephany and Teutloff 2024; PwC 2025). Notably, these gains do not appear to have come at the expense of jobs (Felten, Raj, and Seamans 2019; Acemoglu et al. 2022; Humlum and Vestergaard 2025), with some analyses finding evidence of *increased* hiring in AI-exposed occupations (Babina et al. 2024; Shen and Zhang 2024; PwC 2025).

Consistent with this research, surveys indicate that workers with greater exposure to AI harbor more positive expectations about the technology's labor market consequences. According to a recent Pew analysis of AI's impact on the American labor market, "many U.S. workers in more exposed industries do not feel their jobs are at risk — they are more likely to say AI will help more than hurt them personally" (Pew Research Center 2023, 6). For example, only 11% of ICT professionals believe that AI will hurt more than help them, compared to almost a quarter of retail trade workers. In a similar vein, OECD surveys reveal that AI programmers in the finance and manufacturing sectors are, on average, more than twice as likely to expect their wages to

[11] Based on these estimates, the International Monetary Fund (Cazzaniga et al. 2024) and Goldman Sachs (Briggs and Kodnani 2023) forecast an annual rise in average labor productivity of approximately 1.5 percentage points following the widespread adoption of AI — a major positive shock equivalent to tripling the European Union's recent growth rate.

rise over the next decade as they are to anticipate a decline (Lane, Williams, and Broecke 2023, 49). In PwC's 2024 *Global Workforce Hopes and Fears Survey*, the largest cross-national survey on the future of work, around 80% of daily AI users expect the technology to boost their salary and job security over the next 12 months (PwC 2024). Limited concern about job displacement also emerges from a host of more specialized surveys, such as Jitterbit's 2024 *AI Attitudes Report*, in which only 19% of office workers in the United Kingdom and the United States report concerns that AI could make their role redundant (Jitterbit 2024, 15), and Stack Overflow's 2024 *Developer Survey*, in which just 12% of computer programmers worldwide consider the technology a threat to their job (Stack Overflow 2024).[12]

Some of the above-mentioned surveys also shed light on the anticipated drivers of wage growth in exposed occupations, painting a more detailed picture of AI's expected impact. In the OECD surveys of finance and manufacturing workers, four-fifths of respondents report that AI has improved their job performance, three-quarters that it has increased the speed at which they perform tasks, and 82% that it has helped them make superior decisions (Lane, Williams, and Broecke 2023, 52). Furthermore, around half of AI-adopting employers credit the technology with introducing tasks not previously undertaken by their workforce. This echoes the findings of an earlier OECD survey of trade union confederations, in which almost two-thirds of respondents cited the creation of "new tasks and jobs" as a key benefit of AI adoption (Kramer and Cazes 2022, 23). Improvements in efficiency and opportunities to expand skill sets and occupational responsibilities were also highlighted as advantages of AI usage by a high proportion of participants in the *Global Workforce Hopes and Fears Survey*, the *AI Attitudes Report*, and the *Developer Survey*.

[12]For context, in a recent survey of 38,000 workers in 34 countries spanning every world region, 31% of respondents express fears that AI could replace their job (ADP Research 2025).

Hypotheses

Bringing the framework's two components together, available evidence suggests that the relatively skilled and specialized workers who are more exposed to AI tend to anticipate higher rather than lower earnings in the future: $\mathbb{E}(d\ln y_i) > 0$, with the upshot that $\mathbb{E}(y_{i,t+1}) > y_{it}$. In particular, wage growth is expected to result both from an increase in workers' productivity in performing existing tasks ($dA_L > 0$) and from the emergence of new tasks that make intensive use of their skills ($dN > 0$). The combination of these labor-complementing effects is assumed to overcome downward pressures on wages stemming from AI-based automation, raising the expected future income of exposed workers relative to that of insulated workers:

$$\mathbb{E}\Big(\overbrace{\frac{d\ln y_i}{dA_L}}^{\substack{\text{factor}\\ \text{augmentation}}} + \overbrace{\frac{d\ln y_i}{dN}}^{\substack{\text{new}\\ \text{tasks}}} + \overbrace{\frac{d\ln y_i}{dI}}^{\text{automation}}\Big) > 0.\text{[13]} \tag{6}$$

In light of these considerations, two principal hypotheses can be derived from the framework:

H1 *In the era of rising AI adoption that began around 2010, occupational exposure to the technology is negatively associated with support for redistribution.*

Linking redistribution preferences to the left-right ideological spectrum in the manner proposed by the framework generates an additional three-part hypothesis on political preferences:

H2 *During the same period, occupational exposure to AI is negatively associated with support for (i) the left and (ii) the populist right but positively associated with support for (iii) the mainstream right.*

[13] Online Appendix A.2 provides a more detailed explanation of each term.

Cross-National Evidence from the European Social Survey

The first stage of my empirical investigation draws on biennial ESS data from 2002 to 2021, focusing first on redistribution preferences and then on voting behavior. I restrict the sample to the 12 Western European countries that participated in every ESS wave: Belgium, Finland, France, Germany, Great Britain, Ireland, the Netherlands, Norway, Portugal, Spain, Sweden, and Switzerland. Each wave comprises between 20,000 and 30,000 (newly recruited) respondents, the vast majority of whom (91% on average) were employed at the time of fieldwork and can thus be included in the analysis.

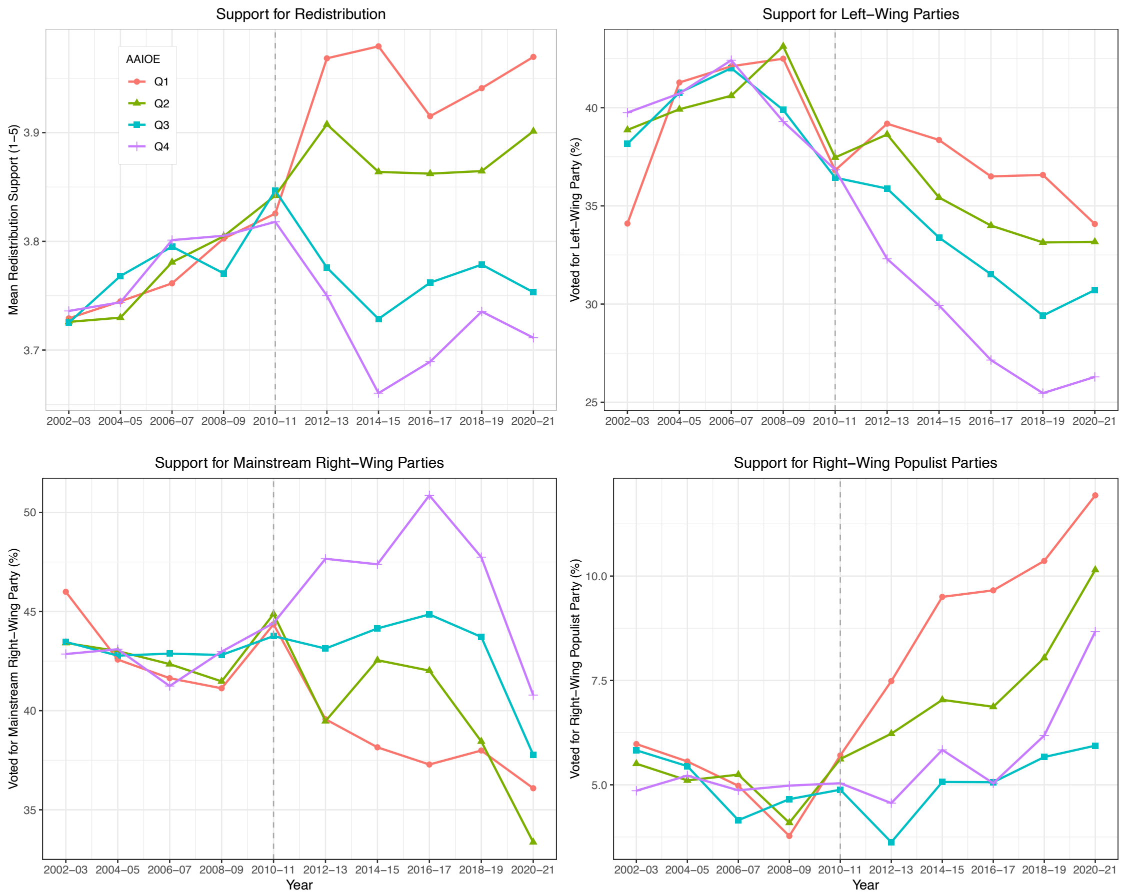
Redistribution Preferences

Data and Specification Following an extensive literature (e.g., Rehm 2009; Burgoon 2014; Rueda and Stegmueller 2019; Thewissen and Rueda 2019), I measure redistribution preferences using a question on the extent to which respondents agree with the statement: "The government should take redistributive measures to reduce differences in income levels." Responses are recorded on a 5-point Likert scale, which I reverse such that 1 = "disagree strongly" and 5 = "agree strongly."[14] My main measure of occupational exposure to AI is the AAIOE index described earlier, which I assign to respondents via a pretreatment item on occupation scaled at the most granular ISCO-08 level, namely, 4-digit "unit groups" (436 categories).

Suggestively, the upper left panel of Figure 3 shows that support for redistribution is lower among respondents who are more exposed to AI, albeit only following the 2010–2011 wave. The mean value of the redistribution support scale varies little across quartiles of the AAIOE between 2002 and 2011 but declines with each quartile thereafter. Averaging over the post-2011 period, the scale mean is 3.96 for respondents in the bottom quartile versus 3.71 for respondents

[14]As shown in Figure A2 of Online Appendix C.1, support for redistribution remained relatively high across Western Europe throughout the sample period, with between 61% and 91% of respondents in every country agreeing that the government should reduce income differences (the mean is 71%).

FIGURE 3. Redistribution Support and Vote Choice by Exposure to Artificial Intelligence



Notes: In the upper left panel, the y-axis measures average agreement among ESS respondents that the government should reduce differences in income. In upper right, lower left, and lower right panels, it measures the proportion of such respondents who voted for the left, the mainstream right, and the populist right, respectively, in the last national election.

in the top quartile, a difference that is highly statistically significant ($t = 28.36$, $p = 0.000$).

To more rigorously assess the relationship between exposure to AI and support for redistribution, I estimate two sets of OLS regression models that control for fixed country and survey period characteristics in addition to a battery of individual-level attributes. My baseline specification compares average support for redistribution before and after the 2010-2011 wave across individuals with varying AI exposure:

$$R_{it} = \alpha \text{AAIOE}_{it} + \beta \text{AAIOE}_{it} \times \text{Post-2011}_t + \gamma \mathbf{X}'_{it} + \phi_{c(i)} + \psi_t + \epsilon_{it} \tag{7}$$

where R_{it} is respondent i's level of support for reducing income differences in wave t; $AAIOE_{it}$ is i's AAIOE score in t; $Post\text{-}2011_t$ is an indicator for whether t is after 2011; $\mathbf{X}'_{it}$ is a vector of socioeconomic controls common in the redistribution preferences literature, namely, i's age, gender (indicator), years of education, degree of religiosity (1–10 integer scale), past or present union membership (indicator), and residence in an urban area (indicator) in t; $\phi_{c(i)}$ denotes fixed effects for i's country of residence (c); and ψ_t denotes wave fixed effects.[15]

The second specification replaces $Post\text{-}2011_t$ with ψ_t in Equation 7, allowing us to examine how the relationship of interest evolves over time. Building on the "one-before-treatment" normalization strategy widely used in event study designs (Miller 2023), I set the 2008–2009 wave as the reference period. In both specifications, heteroskedasticity-robust standard errors are clustered at the country level.

Results The key estimates from Equation 7 are reported in column 1 of Table 1. In line with **H1**, there is a negative and highly significant relationship between exposure to AI and support for redistribution after the 2010–2011 wave. A 1-standard-deviation increase in a respondent's AAIOE score during this period is associated with a decline in the redistribution support scale of 0.1, which also represents 0.1 standard deviations. As indicated by the lower-order coefficient on $AAIOE_{it}$, the two variables are essentially unrelated before 2012.

The results of the dynamic specification, plotted in the upper panel of Figure 4, tell a similar story. From 2002 to 2011, exposure to AI does not predict differential support for redistribution: every coefficient on $AAIOE_{it} \times \psi_t$ is statistically indistinguishable from 0, implying that redistribution preferences among individuals with varying exposure followed roughly parallel trends before the era of rapid AI expansion. Throughout the latter period, AI exposure is negatively and significantly associated with redistribution support.

[15] Summary statistics are provided in Table A3, Online Appendix C.1.

TABLE 1. Cross-National Analysis: AI Exposure, Redistribution Support, and Voting Behavior

Outcome:	Redistribution Support	Vote Choice: Left	Vote Choice: Mainstream Right	Vote Choice: Populist Right
Panel A: Baseline Specification	(1)	(2)	(3)	(4)
AAIOE	0.001	0.002	0.000	0.000
	(0.004)	(0.002)	(0.002)	(0.000)
AAIOE $\times$ Post-2011	-0.067***	-0.028***	0.038***	-0.014***
	(0.009)	(0.005)	(0.005)	(0.004)
N	208,546	129,708	129,708	129,708
Mean Outcome	3.801	0.366	0.426	0.060
Panel B: Automation Risk Control	(5)	(6)	(7)	(8)
AAIOE	0.001	0.002	0.000	0.000
	(0.004)	(0.002)	(0.002)	(0.000)
AAIOE $\times$ Post-2011	-0.065***	-0.027***	0.036***	-0.015***
	(0.009)	(0.005)	(0.005)	(0.004)
Goos et al. RTI Index	0.015***	0.007**	-0.007**	0.001
	(0.003)	(0.003)	(0.003)	(0.001)
N	187,900	116,014	116,014	116,014
Mean Outcome	3.801	0.368	0.423	0.062
Socioeconomic Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓

Notes: Standardized OLS estimates with robust standard errors, clustered by country, in parentheses. Socioeconomic controls: age, years of education, gender, union membership, religiosity, and urban residence. Full results are reported in Table A4, Online Appendix C.2. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

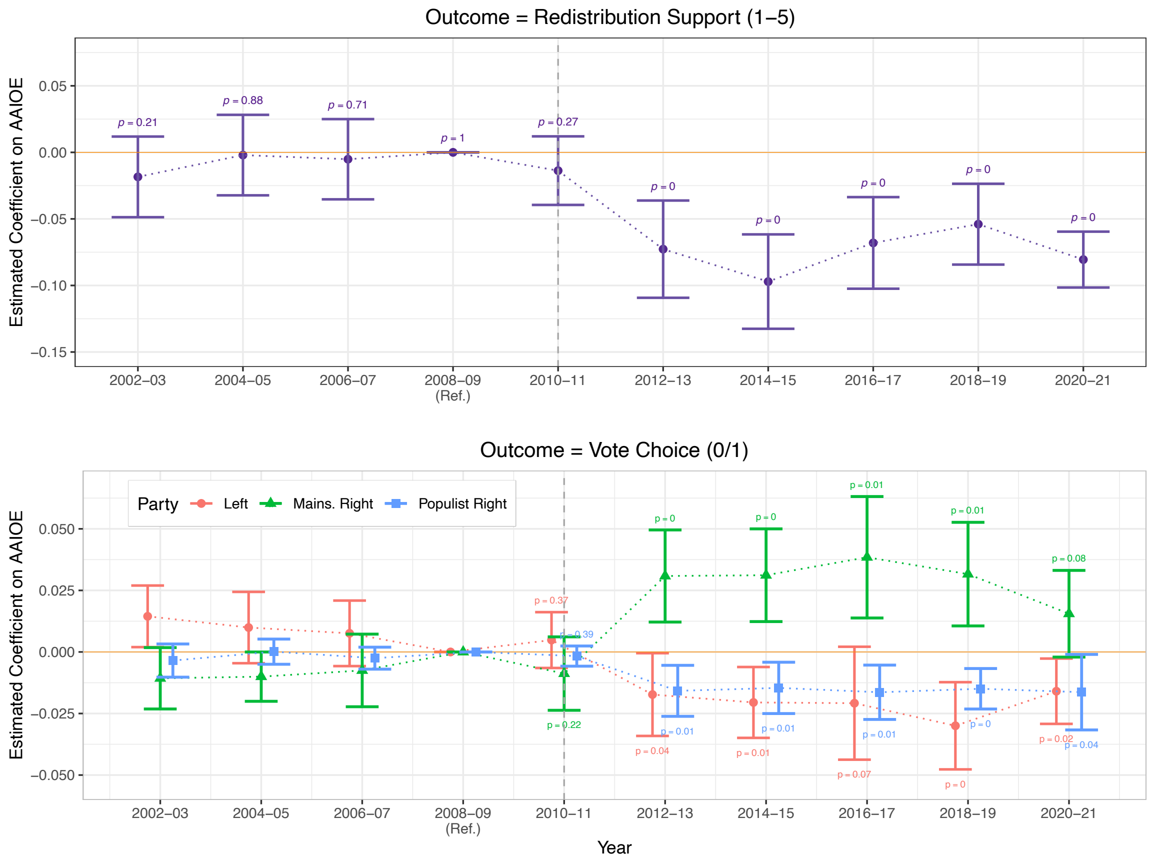
Voting Behavior

Data and Model Turning to **H2**, I replace the outcome variable in Equation 7 with V_{itp}, an indicator for whether respondent i voted for party family p (left, mainstream right, or populist right) in the previous national election as of wave t.[16] I follow Rovny and Rovny's (2017) classification of party families, filling in gaps with the aid of the ParlGov database (Döring, Huber, and Manow 2022).[17] To ensure meaningful vote choice comparisons, abstainers are omitted from the sample (Rueda and Stegmueller 2019). Similarly to before, the dynamic version of the

[16]For consistency with the previous analysis and ease of interpretation, I estimate a linear probability model rather than a logistic regression. Nevertheless, the latter yields similar results.

[17]For a list of parties by family, see Table A2 in Online Appendix C.1. Regional and single-issue parties are excluded from consideration.

FIGURE 4. Results of Dynamic Cross-National Analysis



Notes: Standardized OLS estimates with 95% confidence intervals based on robust standard errors clustered by country; *p*-values are reported above or below. The reference period is 2008-2009. All models control for age, years of education, gender, union membership, religiosity, and urban residence and include country and survey wave fixed effects. For full results, see Table A4, Online Appendix C.2.

specification interacts $AAIOE_{it}$ with ψ_t instead of $Post\text{-}2011_t$.

As illustrated in Figure 3, descriptive evidence accords with **H2**. There is little difference in voting behavior across AAIOE quartiles between 2002 and 2011, after which respondents in higher quartiles are consistently less supportive of the left (upper right panel) and the populist right (lower right panel) but more supportive of the mainstream right (lower left panel). On average over the 2012-2021 period, 37%, 10%, and 38% of bottom-quartile respondents voted for left-wing, right-wing populist, and mainstream right-wing parties in the last national election, respectively, versus 28%, 6%, and 47% of top-quartile respondents.

Results The regression results, presented in columns 2-4 of Table 1, offer more systematic evidence for **H2**. The coefficient on $AAIOE_{it} \times Post\text{-}2011_t$ is negative and significant when the outcome is an indicator for left-wing (column 2) and right-wing populist (column 4) voting versus positive and significant when it is an indicator for mainstream right-wing voting (column 3). With each standard deviation increase in a respondent's AAIOE score, the probability of voting for the left and the populist right declines by 2.8 percentage points and 1.4 percentage points, respectively, while the probability of voting for the mainstream right rises by 3.8 percentage points. Once again, the lower-order coefficient on $AAIOE_{it}$ is small and far from significant in every model, indicating a weak relationship between AI exposure and voting behavior prior to 2012.

The lower panel of Figure 4 displays estimates from the dynamic specification. Over the first nine years of the sample, all three models yield null results, implying comparable "pretrends" in voting behavior among respondents with differing AI exposure. In the AI expansion era, as expected, AAIOE scores become negatively and significantly associated with voting for the left and the populist right yet positively and significantly associated with voting for the mainstream right.

Robustness and Extensions

I now extend the baseline analyses in a variety of directions, probing the robustness of the main findings as well as exploring further issues of interest. Unless otherwise indicated, the results are reported in Online Appendix C.3.

Additional Controls and Fixed Effects I begin by incorporating an array of additional controls into the analyses. Perhaps most importantly, I include the standard measure of automation risk at the occupation level, Goos, Manning, and Salomons' (2014) routine task intensity (RTI) index. As reported in panel B of Table 1 (columns 5-8), the baseline estimates are not materially altered, with the coefficient on the RTI index pointing in the opposite direction and mostly reaching significance (in keeping with Gingrich 2019; Thewissen and Rueda 2019; Dermont and Weisstanner 2020; Busemeyer and Sahm 2022). Table A6 documents similar results when controlling for other occupational risks entailed by digital technologies: susceptibility to computerization, as measured by Frey and Osborne (2017); the potential for offshoring, coded by Blinder and Krueger (2013); skill specificity, as per Cusack, Iversen, and Rehm (2006); and labor market "outsiderness" (Rueda 2005), which I capture using an ESS-based indicator for employment on a fixed-term contract (following Thewissen and Rueda 2019). The table also demonstrates robustness to the inclusion of Hughes et al.'s (2024) survey-based ratings of occupational prestige, a proxy for status concerns (Gingrich 2019).

Second, I control for four additional socioeconomic characteristics measured by the ESS that could plausibly predict AI exposure, redistribution preferences, and voting behavior: (1) household net income (1-10 decile scale); (2) employment in the public sector (indicator); (3) ethnic minority status (indicator); and (4) left-right ideological position (0-10 integer scale).[18] The findings remain intact (Table A7).

Third, I follow several analyses of redistribution preferences (e.g., Burgoon, Koster, and Van Egmond 2012; Burgoon 2014; Rueda 2018; Thewissen and Rueda 2019) in controlling for three country-level variables, all of which are lagged by one year: (1) social spending as a percentage of GDP; (2) the unemployment rate; and (3) foreign-born residents as a percentage of total population.[19] Again, the results are effectively unchanged (Table A8).

Fourth, I add fixed effects for ISCO-08 major groups (1 digit), sub-major groups (2 digits), and minor groups (3 digits), thereby exploiting variation in AI exposure *within* occupations. Robustness to these more econometrically demanding specifications would imply that, on average,

[18]As suggested by the theoretical discussion, political ideology is hard to distinguish from redistribution and voting preferences. Nevertheless, some studies treat it as a determinant rather than a component of social policy attitudes (Margalit 2013).

[19]Accessed from the OECD Data Explorer at: `https://data-explorer.oecd.org/?lc=en`.

the hypothesized relationships obtain even among workers in highly exposed occupations (e.g., software and applications developers) and highly sheltered ones (e.g., mining, manufacturing, and construction supervisors) — whether these roles are defined narrowly or broadly.[20] In addition, I include 2-digit Nomenclature of Economic Activities (NACE) fixed effects, which hold constant a respondent's industry (e.g., financial services, textile manufacturing, fishing and aquaculture); and country $\times$ wave fixed effects, which capture country-specific temporal trends. In all specifications, **H1** and **H2** continue to receive support (Table A9).

Instrumental Variables Analysis In the absence of longitudinal data, a popular strategy for identifying the causal effect of occupational attributes is to instrument them with related characteristics of an individual's parents. Building on Fletcher and Sindelar (2009) and Kelly et al. (2014), I instrument $AAIOE_{it}$ with the equivalent score of respondent i's father when i was 14 years old, which I compute using an ESS item on paternal occupation. I implement the analysis using a two-stage least squares estimator, supplementing the baseline controls with i's net household income and left-right ideological position. The rationale for these additional covariates is that once we account for the known direct pathways through which paternal occupation can influence political preferences — most notably education, ideology, and income — the instrument is unlikely to affect the outcome variables *except* via occupation.[21] The second-stage estimates, reported in Table A10, are consistent with the main findings.[22]

Alternative Samples The results are also robust to four modifications of the baseline ESS sample (Table A12). First, I integrate the four Western European countries that did not participate in every ESS wave (Austria, Denmark, Greece, and Italy). Second, I restrict the sample to in-

[20]Relatedly, clustering standard errors by ISCO-08 user group (4 digits) rather than by country does not alter significance levels.

[21]Hoogerheide, Block, and Thurik (2012) show that under plausible assumptions about the size of exclusion restriction violations, the potential bias generated by family background instruments for educational variables is typically small.

[22]First-stage F-statistics, also conveyed in Table A10, indicate a strong association between paternal and respondent AAIOE scores.

dividuals from households whose main source of income is market earnings (wages, salaries, income from self-employment, and capital income) as opposed to social assistance. Third, I attach the survey's recommended design weights to respondents, correcting for differences in the probability of recruitment due to country-specific sampling design. Fourth, in the 2010-2011 wave of the voting analysis sample, I exclude respondents from countries whose last national election took place before this biennium.

Different Party Categorizations Table A11 confirms that the relationship between exposure to AI and left-wing voting remains negative when we restrict the analysis to the principal left-wing party in a given country as well as to far left parties. Analogously, the relationship between such exposure and mainstream right-wing voting stays positive when we focus on the principal right-wing party in each country.[23]

Disaggregating Artificial Intelligence Table A13 shows that the results remain similar when $AAIOE_{it}$ is disaggregated into its three constituent indices, albeit with a modest decline in coefficient size. The same is true when the AAIOE is replaced by Pizzinelli et al.'s (2024) Complementarity-Adjusted AI Occupational Exposure (C-AIOE) index, which modifies the AIOE to account more explicitly for potential labor complementarities.[24] Finally, given that AI is not a single technique but a diverse collection of models and algorithms, one might wonder whether the findings vary across applications of the technology. Usefully for this purpose, the AIOE aggregates measures of the compatibility between occupational abilities and 10 distinct AI applications ranging from image recognition to language modeling. When $AAIOE_{it}$ is replaced by these 10 measures in the baseline specifications, all coefficients on the interaction term with $Post\text{-}2011_t$ maintain their sign and significance level, though are slightly larger for the image

[23] See Table A2 in Online Appendix C.1 for party categorizations.

[24] Other recent measures of occupational AI exposure, such as those developed by Gmyrek, Berg, and Bescond (2023) and Schendstok and Wertz (2024), focus on generative forms of the technology (exemplified by ChatGPT) and thus do not match the substantive and temporal scope of the analysis.

generation, visual interpretation, and abstract strategy games applications (Table A14).

Longitudinal Evidence on Political Preferences in Germany

Despite the assortment of robustness checks undertaken in the previous section, the pooled cross-sectional nature of the ESS creates a perennial threat of confounding by fixed individual characteristics. For example, respondents with personality or genetic traits associated with conservative political attitudes may have self-selected into occupations with greater exposure to AI after 2010. Alternatively, respondents with a predisposition to progressive attitudes may have been more likely to leave or lose high-exposure jobs during this period (while retaining their political attitudes).

Drawing on the German SOEP, I seek to address such possibilities by conducting a longitudinal analysis of political preferences that exploits within-individual variation over time. While the SOEP is not the only national socioeconomic panel survey in Western Europe — the UK Household Longitudinal Study (UKHLS) and the Swiss Household Panel (SHP) are relatively close comparators — it is unique in classifying occupations according to the ISCO-08 scheme (rather than an earlier, less granular typology). Furthermore, its annual panel is substantially larger than that of either the UKHLS (by an average of almost 50% per wave since 2000) and the SHP (by more than twofold).

Data and Specification

As in the cross-national analysis, I group Germany's federal parties into three families: (1) left-wing parties, comprising *Sozialdemokratische Partei Deutschlands* (SPD) and *Die Linke*; (2) mainstream right-wing parties, comprising *Christlich Demokratische Union Deutschlands* (CDU) and *Christlich-Soziale Union in Bayern* (CSU); and (3) right-wing populist parties, comprising *Alter-*

native für Deutschland (AfD) and *Die Heimat* (DH).[25]

Based on responses to a SOEP question on party support ("Which party do you lean toward?"), Figure A3 in Online Appendix D.1 replicates the descriptive evidence on AI exposure and political preferences presented in Figure 3. For left-wing and mainstream right-wing parties, the expected patterns only emerge consistently after around 2010: support for the former declines with quartiles of the AAIOE, whereas support for the latter grows. In the case of the populist right, a negative association obtains throughout the sample but becomes more pronounced after the AfD's establishment in 2013. Between 2011 and 2021, the average difference in support between the highest and lowest AAIOE quartiles is -8.2 percentage points for left-wing parties, 3.3 percentage points for mainstream right-wing parties, and -5.1 percentage points for right-wing populist parties.

To analyze the impact of AI exposure on support for each party family, I employ a difference-in-differences-style design that modifies the approach taken in the cross-national analysis in two ways. First, I replace country fixed effects with respondent and federal state (*Bundesland*) fixed effects, thereby leveraging variation within individuals and within regions across survey waves. Second, to prevent any bias from endogenous occupational changes during the sample period, I fix AAIOE scores at the wave respondent i enters the panel (f_i). My baseline specification hence takes the form:

$$\mathrm{S}_{itp} = \alpha \mathrm{AAIOE}_{if_i} + \beta \mathrm{AAIOE}_{if_i} \times \text{Post-2010}_t + \gamma \mathbf{X}'_{it} + \theta_i + \phi_t + \eta_b + \epsilon_{iptb} \tag{8}$$

where S_{itp} is an indicator for whether i supports a member of party family p in wave t; $AAIOE_{if_i}$ is i's AAIOE score in wave f_i; and $\mathbf{X}'_{it}$ is a vector of controls for i's age, years of education, frequency of religious activity (1-5 ordinal scale), gender (indicator), and current union membership (indicator) in wave t; and θ_i, ϕ_t, and η_b denote respondent, wave, and federal state fixed

[25] *Bündnis 90/Die Grünen*, a green party, and *Freie Demokratische Partei*, a liberal party, do not clearly fit into these three families and are thus excluded from the analysis.

effects, respectively.[26] I cluster robust standard errors by respondent.

The key identifying assumption in Equation 8 is that in the absence of AI, support for each party family would have followed the same trajectory across individuals with varying exposure to the technology. Similarly to before, I assess the plausibility of this (untestable) assumption by estimating a dynamic version of Equation 8 in which $\textit{Post-2010}_t$ is replaced by a sequence of temporal indicators. As there are not enough observations in the SOEP to include a separate indicator for each year or biennium, I define indicators for the intervals 2000–2002, 2007–2010, 2011–2013, 2015–2018, and 2019–2021, setting 2003–2006 as the reference category (following the one-before-treatment normalization strategy). Once more, null coefficients on the interaction terms between $AAIOE_{if_i}$ and indicators for pre-2011 intervals would provide evidence for the parallel trends assumption. The results are presented in the next section.

Results

Panel A of Table 2 reports the main estimates from Equation 8. In accordance with **H2**, the coefficient on $AAIOE_{if_i} \times \textit{Post-2010}_t$ is negative and significant when the outcome variable is support for the left (column 1) and the populist right (column 3) but positive and significant when it is support for the mainstream right (column 2). With each standard deviation increment in AI exposure, respondents become 1.7 percentage points and 0.6 percentage points less likely to favor the left and the populist right, respectively, and 1.6 percentage points more likely to back the mainstream right.

Figure 5 plots the results of the dynamic specification. During the 2000s, AAIOE scores do not predict differential support for any party family, implying approximately parallel trends in each outcome among respondents with diverse AI exposure. From 2011 onward, these scores are negatively and significantly associated with support for the left versus positively and signif-

[26] The SOEP contains no equivalent of the ESS item on urban residence, though the federal state fixed effects capture much of the same heterogeneity.

TABLE 2. Longitudinal Results: AI Exposure and German Political Preferences

Outcome: Support for...	Left	Mainstream Right	Populist Right
Panel A: Baseline Specification	(1)	(2)	(3)
AAIOE$_f$	-0.727	3.083	0.024
	(1,721.885)	(1,242.078)	(792.598)
AAIOE$_f$ × Post-2010	-0.017***	0.016***	-0.006**
	(0.004)	(0.004)	(0.003)
N	39,209	39,209	39,209
Mean Outcome	0.377	0.367	0.030
Panel B: Automation Risk Control	(4)	(5)	(6)
AAIOE$_f$	-0.822	0.555	-0.160
	(1,221.782)	(692.273)	(626.875)
AAIOE$_f$ × Post-2010	-0.016***	0.017***	-0.010***
	(0.006)	(0.005)	(0.004)
Goos et al. RTI Index	-0.008**	0.003	0.001
	(0.004)	(0.003)	(0.001)
N	27,595	27,595	27,595
Mean Outcome	0.372	0.374	0.032
Socioeconomic Controls	✓	✓	✓
Respondent FEs	✓	✓	✓
Year FEs	✓	✓	✓
Federal State FEs	✓	✓	✓

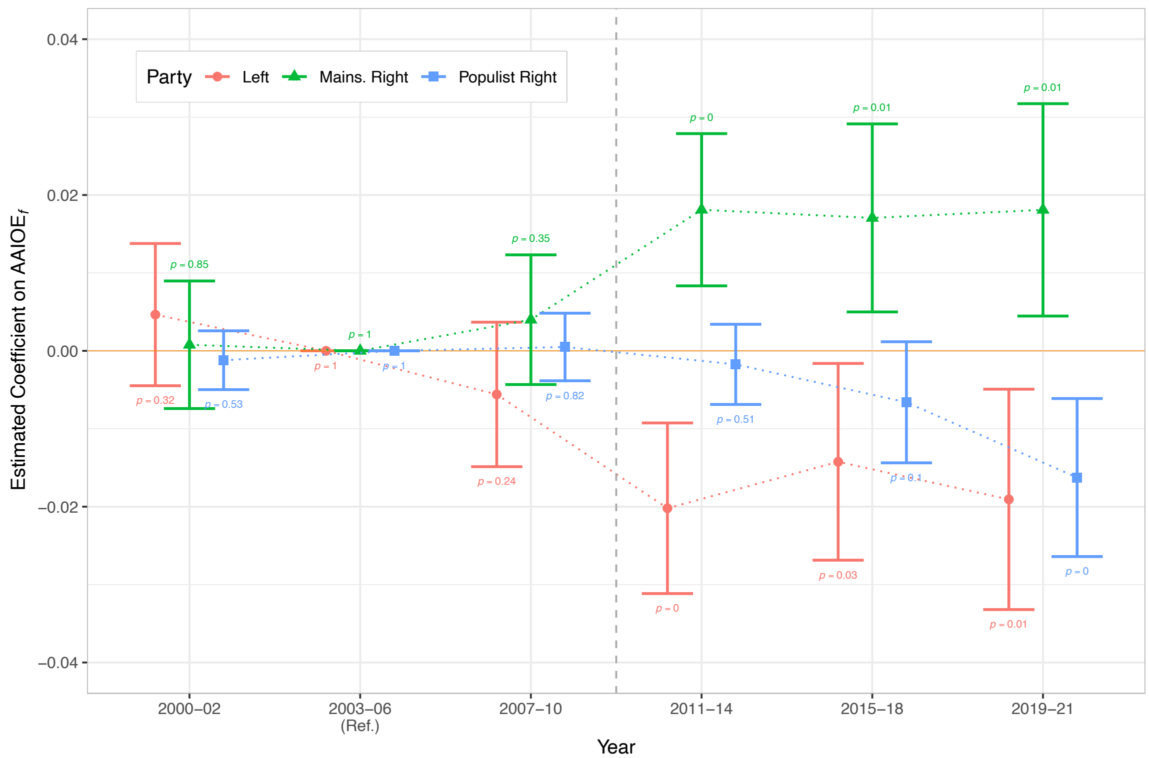
Notes: Standardized OLS estimates from Equation 8 with robust standard errors, clustered by respondent, in parentheses. Socioeconomic controls: age, years of education, gender, union membership, and frequency of religious activity. For full results, see Table A15, Online Appendix D.2. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

icantly associated with support for the mainstream right. In the case of the populist right, the coefficient on $AAIOE_{if_i} \times \phi_t$ steadily declines during this period but only attains significance in the 2019–2021 interval. This pattern mirrors the AfD's growing embrace of social assistance and redistributive economic policies following its establishment, which saw it devote "more attention to welfare expansion in every general election from 2013 to 2021" (Irion 2023, 10).

Robustness and Extensions

The findings withstand a variety of alternative specifications, including the key robustness checks from the cross-national examination. The results are summarized in this section and, unless

FIGURE 5. Results of Dynamic Longitudinal Analysis of German Political Preferences



Notes: Standardized OLS estimates from a modified version of Equation 8 in which *Post-2010*$_t$ is replaced by indicators for the five intervals displayed on the x-axis; the reference period is 2003–2006. Bars represent 95% confidence intervals based on robust standard errors clustered by respondent; p-values are reported above or below. All models control for age, gender, years of education, union membership, and frequency of religious activity and include respondent, survey wave, and federal state fixed effects. For full results, see Table A16, Online Appendix D.2.

noted otherwise, reported in full in Online Appendix D.3.

I start by introducing a selection of additional controls and fixed effects into the baseline specification. First, I include the proxies for automation risk, susceptibility to computerization, offshorability, skill specificity, labor market outsiderness, and occupational prestige described earlier. As shown in panel B of Table 2 (for the RTI index) and Table A17 (for the remaining proxies), the estimates of interest are substantively unaltered. Unlike before, the RTI index has a negative relationship with support for the left and a weak positive relationship with support for the right, suggesting that the earlier results either do not extend to the German context or were confounded by unobserved individual-specific heterogeneity.

https://doi.org/10.33774/apsa-2025-4n31w **ORCID:** https://orcid.org/0000-0003-1455-3506 Content not peer-reviewed by APSA. **License:** CC BY 4.0

Second, turning to other socioeconomic characteristics, I add SOEP-based measures of gross labor income (in euros), possession of a migrant background (indicator), employment in the civil service (indicator), and left-right ideology (0–10 integer scale). The findings continue to hold (Table A18).

Third, the findings also survive the inclusion of 1-digit, 2-digit, and 3-digit ISCO-08 fixed effects as well as 2-digit industry and interactive federal state $\times$ year fixed effects (Table A19).

Fourth, building on Acemoglu et al.'s (2022) analysis of AI's impact on the American labor market, I employ a single-difference estimator that avoids the need for respondent fixed effects:

$$\Delta \mathrm{S}_{i,t_1-t_0,p} = \beta \mathrm{AAIOE}_{it_0} + \gamma \mathbf{X}'_{it_0} + \eta_b + \epsilon_{i,t_1-t_0} \tag{9}$$

where $\Delta S_{i,t_1-t_0,p}$ denotes the difference in respondent i's support for party family p between periods t_0 and t_1. With each respondent now representing a single observation, I cluster robust standard errors by federal state. The results, presented in Table A20 for a variety of temporal windows, are in keeping with the main findings.[27]

Fifth, I demonstrate robustness to three adjustments to the baseline sample (Table A21): (1) fixing the control variables at year f_i, which mitigates the possibility of posttreatment bias; (2) excluding respondents from households that derive the majority of their income from non-market sources; and (3) applying the SOEP's recommended weighting factor to respondents to compensate for differential sampling probabilities and panel attrition.

Lastly, I disaggregate the outcome variable into indicators of support for individual parties. While broadly consistent with the main findings, the results are stronger for the more popular of the two parties within each family, that is, the SPD, the CDU, and the AfD (Table A22). This should not be surprising: voters are likely to be better acquainted with the social policy platforms of more prominent parties, in addition to the fact that statistical relationships are easier to detect

[27] To smooth out annual fluctuations in political preferences and maximize the sample size, I designate t_0 and t_1 not as individual years but as intervals of several years (averaging each variable over these periods).

in larger samples.

Experimental Evidence from the United Kingdom

Even with the inclusion of individual fixed effects, the previous analyses cannot conclusively rule out the possibility of unmeasured confounding. In the third stage of my empirical investigation, therefore, I conduct a survey experiment involving the random assignment of informational vignettes about AI's labor market consequences to respondents. An additional advantage of this strategy is that it allows us to probe the hypothesized causal mechanism by studying how treatment assignment influences respondents' expectations about their future productivity, earnings, and employment prospects.

Using a combination of the Amazon Mechanical Turk crowdsourcing platform and advertising on social media, I administered the survey to almost 800 adults based in the United Kingdom — one of the world's leaders in AI development and adoption — in late 2024 and early 2025. As discussed in Online Appendix E.1, this sample is reasonably representative of the British population, exhibiting only a small bias toward younger, male, and more educated individuals. Specifically, respondents were either presented with one of two textual prompts or assigned to the control condition. The first prompt presents a "complementarity" perspective that emphasizes AI's benefits for labor productivity, earnings, and demand:

> *AI technologies are revolutionising the possibilities for work. With the aid of AI tools, workers have been found to perform a variety of tasks more efficiently and to a higher standard, from computer programming and customer support to professional writing and management consulting. In addition, firms embracing AI technologies are already enjoying large increases in output per worker. Economists from the International Monetary Fund and Goldman Sachs forecast a rise in average annual labour productivity of approximately 1.5 percentage points following the widespread adoption of AI technologies by businesses. Some experts believe that workers with AI skills could see a boost in earnings of up to 30%.*

The second prompt advances a "substitution" viewpoint that highlights AI's disruption to labor markets and potential to increase unemployment and inequality:

> *AI technologies threaten to fundamentally disrupt labour markets, leading to a "jobless future" in which the vast majority of occupations are performed by advanced algorithms. In addition to routine work, such as secretarial support and customer service, AI has the potential to undertake high-skilled tasks, such as creating databases, copywriting, and graphic design, threatening lucrative as well as low-paid jobs. Goldman Sachs predicts that AI could replace 300 million jobs around the world by 2030, posing a risk of soaring unemployment and inequality. In the United Kingdom alone, the Institute for Public Policy Research warns that almost 8 million jobs could be lost to AI in a "jobs apocalypse" over the next 3-5 years.*

Respondents were then asked two sets of questions: (1) how much they agree (on a 0–100 scale) that the government should (i) take measures to reduce differences in income levels, (ii) increase spending on unemployment benefits, and (iii) increase spending on public services and social benefits; and (2) which political party they would vote for if a general election were held tomorrow. To assess my posited mechanism, respondents were also posed a series of questions about how they expect AI to impact their job performance and wages in the future.[28]

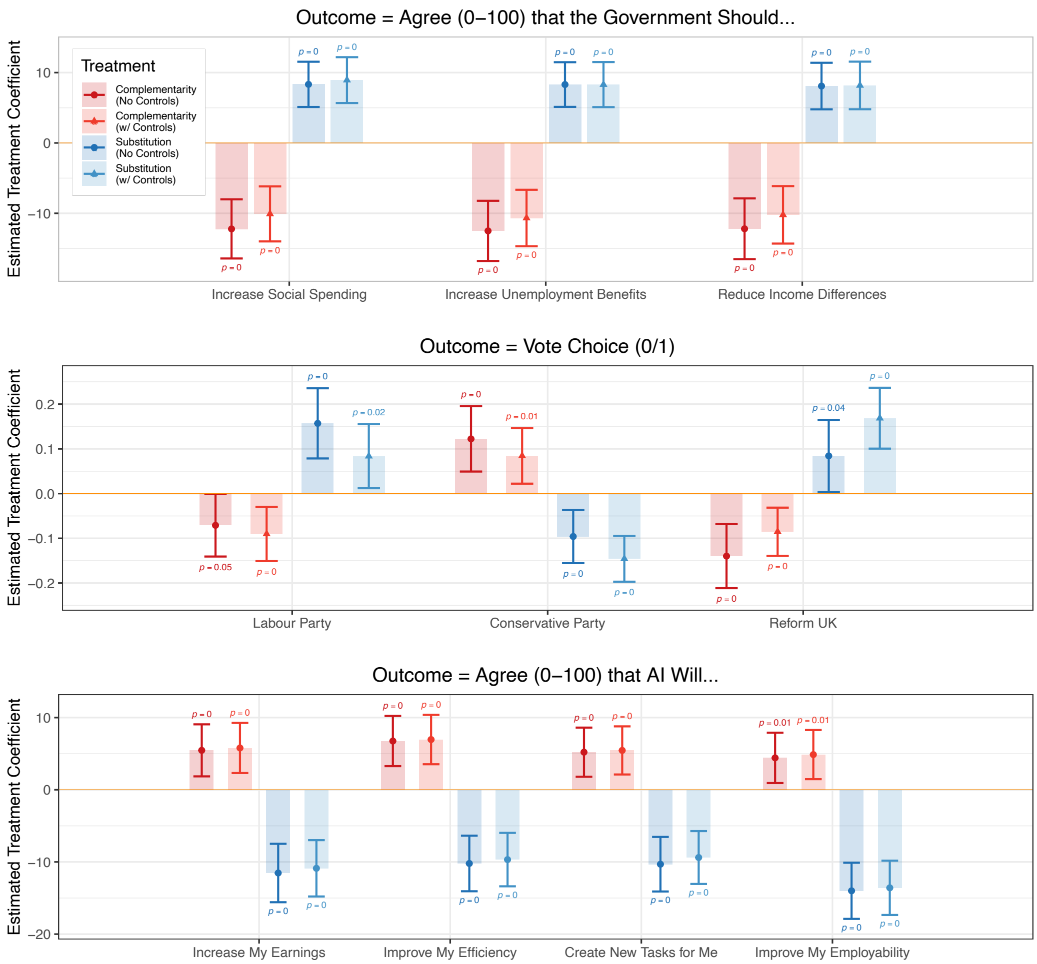
I regress responses to the previous questions on treatment status plus a battery of socioeconomic and political controls (measured prior to treatment assignment):

$$Y_i = \alpha + \beta \begin{cases} C_i \\ S_i \end{cases} + \gamma \mathbf{X}_i' + \eta \mathrm{PID}_{ip} + \epsilon_{ip} \tag{10}$$

where Y_i is respondent i's value of a given outcome; C_i and S_i are indicators for whether i is assigned the complementarity prompt and the substitution prompt, respectively; $\mathbf{X}_i'$ is a vector of controls for i's age (10 categories), gender (indicator for female), ethnicity (indicator for white), income (eight categories), and education (nine categories); and PID_{ip} is an indicator for whether

[28]The order of the three sets of posttreatment questions was randomized. The structure of the survey is described in detail in Online Appendix E.1.

FIGURE 6. Results of Survey Experiment in United Kingdom



Notes: OLS estimates from Equation 10 with 95% confidence intervals based on robust standard errors; p-values are reported above or below. All models control for age, gender, ethnicity, income, education level, and party identification. Full results are provided in Tables A26–A28, Online Appendix E.5.

i identifies with political party p (six categories).[29] Both variants of the specification exclude respondents in the alternative treatment condition, ensuring that parameters are estimated against the appropriate baseline (i.e., members of the control group).

Main Hypotheses The results are presented in Figure 6. The top panel reveals robust support for **H1**: whether the controls are included or excluded, assignment to the complementarity

[29]Table A25 in Online Appendix E.4 indicates that these covariates are well balanced between the treatment and control groups. Table A24 reports summary statistics for the full dataset.

https://doi.org/10.33774/apsa-2025-4n31w **ORCID:** https://orcid.org/0000-0003-1455-3506

treatment is negatively and significantly related to support for reducing income differences, expanding unemployment benefits, and raising social spending. In line with **H2**, it has the same association with the intention to vote for the Labour Party and Reform UK, the United Kingdom's major left-wing and right-wing populist parties, respectively, but a positive and significant association with the intention to vote for the Conservative Party, the principal party of the mainstream right (middle panel). These relationships are exactly reversed in the case of the substitution treatment.[30] Effect sizes are generally large, particularly for the complementarity treatment. Agreement that the government should reduce income differences, for instance, is 10.2 percentage points lower among individuals receiving the complementarity prompt, while the likelihood of voting for the Conservative Party is 8.4 percentage points higher.

Causal Mechanism To confirm that the previous findings reflect the hypothesized mechanism, I replace the outcome variable in Equation 10 with responses to the aforementioned questions about AI's anticipated impact on work. In line with my argument, exposure to the complementarity prompt is positively and significantly associated with the expectation that AI will increase a respondent's earnings, efficiency, range of occupational tasks, and ability to find employment (bottom panel of Figure 6). Once again, assignment to the substitution treatment has the opposite effects. As summarized in Table A29 of Online Appendix E.5, a formal mediation analysis indicates that expectations about AI's labor market consequences are a key channel through which the two treatments influence redistribution preferences. These preferences, in turn, strongly mediate the treatment effects on the three voting outcomes.

Heterogeneity Across and Within Occupations Another implication of my argument is that the treatment effects will be stronger for respondents with higher occupational exposure to AI, whose livelihoods are more likely to be impacted by the technology. To assess this proposition,

[30]This finding is consistent with the results of two survey experiments fielded in the United States by Heinrich and Witko (2025), who focus primarily on attitudes toward AI regulation.

I interact C_i and S_i with respondent i's AAIOE score, which I compute using a pretreatment survey item on occupation (scaled at the 2-digit ISCO-08 level). Figure A4 in Online Appendix E.5 shows that the marginal effects of both treatment variables on the redistribution and voting outcomes strengthen with AI exposure, only attaining significance at medium or high values of the AAIOE. Figure A5 displays comparable results when the moderator is a subjective measure of exposure constructed from a pretreatment question on the compatibility between i's occupational tasks and AI's current and likely future capabilities — a measure strongly correlated with AAIOE scores ($r = 0.88$).[31]

Finally, I take advantage of exogenous treatment assignment to test a related implication of my argument: the complementarity treatment will exert a larger effect on more skilled workers *within* each occupation, who are more likely to "have the cognitive abilities to use new technologies productively at the workplace" (Gallego, Kurer, and Schöll 2022, 419).[32] This conjecture also finds support: controlling for 2-digit ISCO-08 fixed effects, the marginal effects of C_i on the redistribution, voting, and work-related outcomes intensify with respondent i's level of education (see Figure A6).

Discussion

Advances in AI are anticipated to profoundly alter industrialized labor markets over the coming years and decades, potentially bringing about far-reaching changes in the distribution of income and wealth within societies. Surprisingly little is known, however, about how this transformation is shaping preferences over the allocation of resources among citizens, a key predictor of

[31]Based on a representative survey undertaken in Great Britain, Green et al. (2025) also report a positive correlation between subjective and objective measures of AI exposure. They observe only a modest correlation between subjective exposure and opposition to redistribution, though emphasize that their examination is descriptive rather than causal in nature.

[32]There is less reason to expect such heterogeneity in the case of the substitution treatment: skilled workers are more exposed to displacement effects generated by AI yet also better placed to adapt to structural occupational changes and to find new employment.

voting behavior and social policy outcomes in traditional models of political economy. Previous research on the distributional politics of digitalization has concentrated on routine-biased automation procedures pioneered in the 1980s and 1990s, generally finding that occupational exposure to these techniques strengthens support for redistribution and the political left. Bringing together insights from forward-looking models of redistribution preferences, I have argued that these relationships are reversed in the case of AI: rather than simply replacing humans with machines, AI has the capacity to reinforce labor demand by expanding the productivity and task range of exposed workers — complementarities that such individuals widely expect to yield economic dividends for them in the future. Analyses of observational and experimental data from Western Europe have furnished consistent evidence that occupational exposure to AI is negatively associated with support for redistribution, the left, and the (increasingly pro-welfare) populist right but positively associated with support for the mainstream right.

The findings point to a sharp discrepancy between the political consequences of AI and earlier automation technologies that have primarily substituted for labor (Acemoglu and Restrepo 2018, 2019, 2020), generating interesting implications for the future of social policy and party competition in advanced democracies. Reflecting on the negative relationship they observe between exposure to routine-biased automation and redistribution preferences, Thewissen and Rueda (2019, 194) speculate: "Although recent increases in inequality in industrialized democracies may promote more anti-redistribution attitudes from the affluent, increasing levels of automation risk could mitigate these effects." Conversely, the spread of AI could intensify this trend, weakening demand for a social safety net from the relatively skilled and affluent portion of the workforce that stands to gain most from the technology. The upshot could be a more divided electorate: as coalitions of automation-exposed workers seek protection from left-wing and right-wing populist parties advocating extensive redistribution and social insurance, coalitions of AI-exposed workers — potentially joined by employers in technology-intensive sectors — may turn toward mainstream right-wing parties favoring low taxes and a modest welfare state (Mares 2003).[33] The precise electoral ramifications of such shifts will depend on factors such as the size of each coalition, its degree of political mobilization, and the intensity of its redistribution preferences (Mares 2004; Kurer and Häusermann 2022).

These implications are subject to some important caveats. AI is evolving rapidly, and it is conceivable that future iterations of the technology are perceived as less complementary to skilled labor, taking over the full range of tasks performed by exposed workers without creating enough new activities to sustain high levels of employment. It bears emphasizing, therefore, that this study's argument and results only pertain to *recent* expectations about AI's labor market consequences. Nor, on the "supply side" of the political equation, will party strategy necessarily remain static during the AI era. While mainstream parties are unlikely to radically alter their stance on redistributive issues, they may develop packages of AI-specific policies that influence the economic fortunes of exposed workers in more direct ways (e.g., regulations on AI usage, subsidies for AI developers). Non-mainstream parties, meanwhile, may be willing and able to modify core policy positions in response to labor market — and broader societal — upheavals wrought by the AI revolution. Looking ahead, therefore, a nuanced grasp of the interplay between progress in AI technology, changes in labor market structure, and party responses to these trends is likely to be crucial for understanding the fast-moving political economy of digitalization in industrialized democracies.

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[33] Consistent with this implication, Jacobs (2024) finds that the spread of AI has been accompanied by heightened polarization on economic and cultural issues in the United States. This trend could be exacerbated by populist appeals to feelings of "status anxiety" experienced by workers excluded from the benefits of AI (Gingrich 2019).

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Online Appendices for:

The Political Economy of Artificial Intelligence: Evidence from Western Europe

August 11, 2025

Contents

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A Formal Details

A.1 Task-Based Approach to Labor Markets

The main text's formal exposition of the implications of technological change for expected future earnings is informed by the task-based approach to analyzing labor markets, which was developed in a series of articles by Daron Acemoglu and collaborators (e.g., Acemoglu and Autor 2011; Acemoglu and Restrepo 2018, 2019; Acemoglu 2024). To keep the model as simple as possible, I draw on the single-sector, static version of the task-based framework, in which a unique final good is produced by combining N tasks according to the function:

$$X = B(N) \left(\int_0^N x(z)^{\frac{\sigma-1}{\sigma}} dz \right)^{\frac{\sigma}{\sigma-1}} \tag{A1}$$

where $x(z)$ denotes the output from task $z \in [0, N]$ and the remaining notation is the same as in the main text. I assume that individual i performs all tasks $[0, N]$.

Workplace tasks are completed by either labor or capital — the supply of which is fixed — via the production function:

$$x(z) = \begin{cases} \gamma_L(z)l(z) & \text{if } z \in [I, N] \\ \gamma_L(z)l(z) + \gamma_L(z)k(z) & \text{if } z \in [0, I] \end{cases} \tag{A2}$$

where $l(z)$ and $k(z)$ are the amount of labor and capital allocated to task z, respectively. Following the modeling convention that labor has a comparative advantage in higher-indexed tasks — formally, $\gamma_L/\gamma_K(z)$ increases with z — there is some threshold I above which tasks are produced with labor only. In other words, labor is the sole input in tasks $z > I$, while capital is the sole input in tasks $z \leq I$.

A competitive equilibrium is characterized by (1) an allocation of tasks to factors of production that minimizes costs, (2) a capital production decision that maximizes net output, and (3) clearing in the markets for labor and capital. The last condition can be written as:

$$L = \int_0^N l(z)dz \qquad \text{and} \qquad K = \int_0^N k(z)dz. \tag{A3}$$

It follows that the equilibrium price of the $(N - I - 1)$ tasks performed by labor must meet the requirement:

$$p_l = B(N)^{\frac{\sigma-1}{\sigma}} A_L^{\frac{\sigma-1}{\sigma}} \gamma_L(z)^{\frac{\sigma-1}{\sigma}} l(z)^{-\frac{1}{\sigma}} X^{\frac{1}{\sigma}} \tag{A4}$$

where p_l is the price of labor (i.e., the equilibrium wage). Combining Equations A3 and A4 yields Equation 3, the expression for individual i's pretax income in period t.

A.2 Equilibrium Effects of Artificial Intelligence

In the task-based model described above, technological change can influence the equilibrium wage through a variety of channels. As discussed in the main text, existing evidence suggests that the widespread adoption of AI is expected to principally affect three parameters: the labor-augmenting productivity multiplier (A_L), the overall number of tasks (N), and the division of tasks between labor and capital (I). Drawing on Acemoglu and Restrepo (2019), this section provides a formal characterization of each effect.

AI's labor-augmenting effect is given by:

$$\frac{d \ln y_i}{d A_L} = \overbrace{\frac{1}{\sigma}\frac{d \ln X}{d A_L} + \frac{\sigma - 1}{A_L\, \sigma}}^{\text{productivity effect}} - \overbrace{\frac{1}{\sigma}\frac{d \ln}{d A_L}\left(\int_I^N \gamma_L(z)^{\sigma-1} dz\right)}^{\text{substitution effect}}. \tag{A5}$$

As captured by the first two terms, AI carries the potential to expand labor productivity in all existing tasks, raising the equilibrium wage in proportion. On the flip side, wage growth reduces the relative price of capital, increasing its share in production (adjusting for differences in factor productivity) and suppressing labor demand. This results in a negative substitution effect represented by the third term.

In addition, AI is expected to enhance worker productivity via the creation of new tasks in which labor has a comparative advantage:

$$\frac{d\ln y_i}{dN} = \overbrace{\frac{1}{\sigma}\frac{d\ln X}{dA_L} + \frac{\sigma-1}{\sigma}\frac{B(N)'}{B(N)}}^{\text{productivity effect}} + \overbrace{\frac{1}{\sigma}\frac{\gamma_L(N)^{\sigma-1}}{\left(\int_I^N \gamma_L(z)^{\sigma-1}dz\right)}}^{\text{reinstatement effect}}. \tag{A6}$$

In addition to boosting productivity, this process "reinstates" labor by raising the share of tasks it performs (the reverse of the substitution effect in Equation A5). Reinstatement effects will be especially large if new tasks make the entire production process more efficient (by raising B). Since the third term in Equation A6 is positive, task creation always boosts labor demand and thus the equilibrium wage.

Finally, AI involves an automation component:

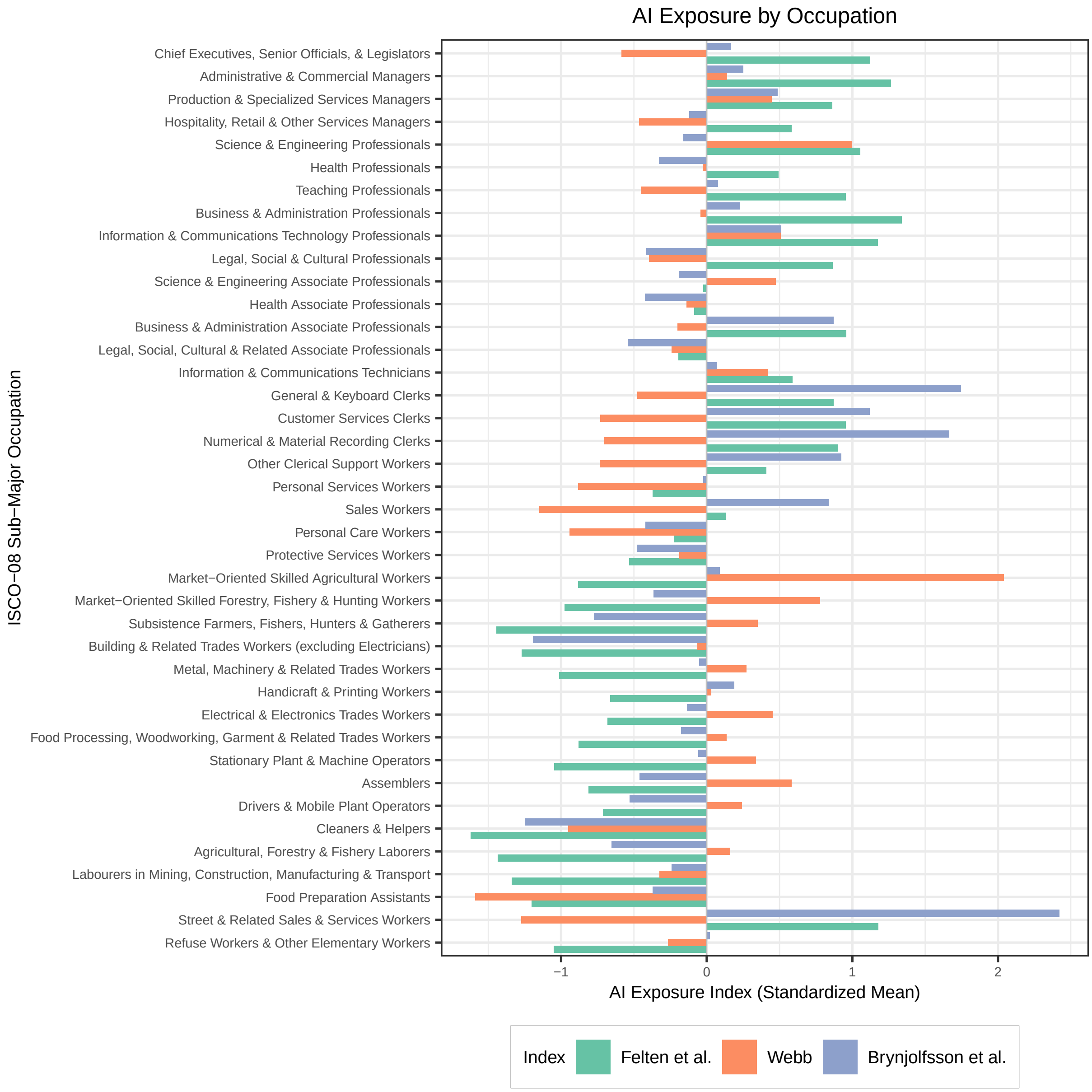
$$\frac{d\ln y_i}{dI} = \overbrace{\frac{1}{\sigma}\frac{d\ln X}{dI}}^{\text{productivity effect}} - \overbrace{\frac{1}{\sigma}\frac{\gamma_L(N)^{\sigma-1}}{\left(\int_I^N \gamma_L(z)^{\sigma-1}dz\right)}}^{\text{displacement effect}}. \tag{A7}$$

Here, the productivity effect reflects the cost savings enabled by automation as well as the rise in demand for labor in non-automated tasks. The negative displacement effect arises from the exchange of labor for capital in existing tasks, which lifts the latter's share in production. Which of these effects will predominate is unclear ex ante, depending on each factor's productivity and rental rate in automated tasks.

As captured by Equation 6, if AI is expected to raise future earnings through a combination of labor augmentation and task creation, the productivity effects in Equations A5–A7 plus the reinstatement effect in Equation A6 would have to exceed the substitution effect in Equation A5 plus the displacement effect in Equation A7.

B AI Exposure Indices

FIGURE A1. Occupational Exposure to Artificial Intelligence by Constituent Index



Notes: This figure disaggregates Figure 1 by the three component measures of the AAIOE: (1) Felten, Raj, and Seamans' (2021) AIOE index; (2) Brynjolfsson, Mitchell, and Rock's (2018) SML index; and (3) Webb's (2020) AI exposure index.

TABLE A1. Occupations Most and Least Exposed to Artificial Intelligence

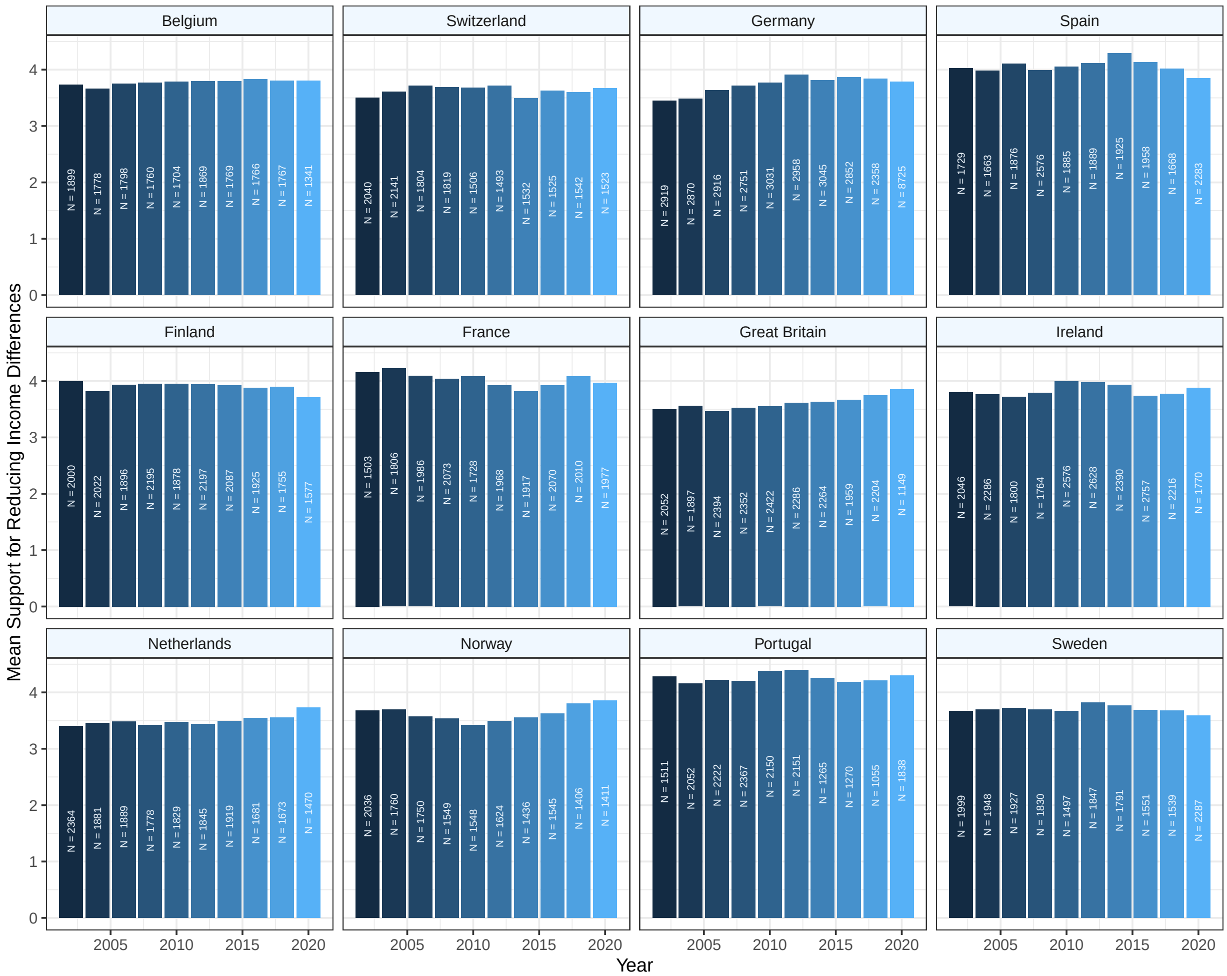
ISCO-08 Occupation (Low Exposure)	AAIOE	ISCO-08 Occupation (High Exposure)	AAIOE
Dancers and choreographers	-3.205	Optometrists and ophthalmic opticians	2.586
Stone masons, stone cutters, splitters and carvers	-2.989	Data entry clerks	2.4
Hand launderers and pressers	-2.773	Transport clerks	2.26
Concrete placers, concrete finishers and related workers	-2.622	Child care services managers	2.223
Physiotherapy technicians and assistants	-2.557	Sales and marketing managers	2.058
Bricklayers and related workers	-2.487	Graphic and multimedia designers	2.036
Athletes and sports players	-2.455	Chemical engineers	1.973
Plasterers	-2.422	Regulatory government associate professionals not elsewhere classified	1.926
Painters and related workers	-2.224	Applications programmers	1.92
Domestic cleaners and helpers	-2.217	Pre-press technicians	1.905
Vehicle cleaners	-2.009	Buyers	1.862
Clears and helpers in offices, hotels and other establishments	-1.989	Coding, proof-reading and related clerks	1.749
Building construction laborers	-1.866	Computer network professionals	1.669
Underwater divers	-1.857	Computer network and systems technicians	1.668
Water and firewood collectors	-1.799	Physicists and astronomers	1.651
Kitchen helpers	-1.776	Statistical, mathematical and related associate professionals	1.637
Butchers, fishmongers and related food preparers	-1.759	Advertising and marketing professionals	1.636
Building caretakers	-1.742	Industrial and production engineers	1.628
Window cleaners	-1.742	Electronics engineers	1.585
Floor layers and tile setters	-1.741	Telecommunications engineers	1.539
Civil engineering laborers	-1.713	Medical and pathology laboratory technicians	1.516
Plumbers and pipe fitters	-1.638	Psychologists	1.508
Fast food preparers	-1.594	Meteorologists	1.501
Actors	-1.557	Software and applications developers and analysts not elsewhere classified	1.482
Roofers	-1.533	Contact center information clerks	1.474

Notes: This table enumerates the 25 ISCO-08 unit groups — that is, 4-digit occupations — with the lowest (left column) and highest (right column) exposure to AI according to the AAIOE, a standardized average of Felten, Raj, and Seamans' (2021) AIOE index, Brynjolfsson, Mitchell, and Rock's (2018) SML index, and Webb's (2020) AI exposure index.

C Cross-National Analysis

C.1 Descriptive Data

FIGURE A2. Support for Redistribution in 12 Western European Countries, 2002–2021



Notes: The y-axis measures average agreement among ESS respondents with the statement: "The government should take measures to reduce differences in income levels" (1 = "disagree strongly," 5 = "agree strongly"). The number of observations per country-year is reported within bars.

TABLE A2. List of Political Parties by Country and Ideological Family

Party	Acronym	Country	Family	Type
Open Vlaamse Liberalen en Democraten	Open Vld	Belgium	Right	Major
Mouvement Réformateur	MR	Belgium	Right	Major
Christen-Democratisch en Vlaams/Christelijke Volkspartij	CD&V/CVP	Belgium	Right	Main
Nieuw-Vlaamse Alliantie	N-VA	Belgium	Right	Major
Socialistische Partij Anders	SP.A	Belgium	Left	Main
Parti Socialiste	PS	Belgium	Left	Main
Partij Van De Arbeid van België/Parti du Travail de Belgique	PVDA/PTB	Belgium	Far Left	Minor
Front National	FN	Belgium	Populist Right	Minor
Vlaams Belang	VB	Belgium	Populist Right	Major
Lijst Dedecker	LDD	Belgium	Populist Right	Minor
Centre Démocrate Humaniste	CDH	Belgium	Right	Major
Parti Populaire	PP	Belgium	Populist Right	Minor
Vivant	V	Belgium	Left	Minor
Parti Réformateur Libéral	PRL-FDF	Belgium	Right	Minor
Christlichdemokratische Volkspartei der Schweiz/Parti Pémocrate-Chrétien Suisse	CVP/PDC	Switzerland	Right	Main
Freisinnig-Demokratische Partei/Parti Radical-Démocratique Suisse	FDP/PRD	Switzerland	Right	Major
Sozialdemokratische Partei der Schweiz/Parti Socialiste Suisse	SP/PS	Switzerland	Left	Main
Schweizerische Volkspartei/Union démocratique du Centre	SVP/UDC	Switzerland	Populist Right	Major
Partei der Arbeit der Schweiz/Parti Suisse du Travail	PdA/PST	Switzerland	Far Left	Minor
Liberale Partei der Schweiz/Parti Libéral Suisse	LPS/PLS	Switzerland	Right	Minor
Christlich-Soziale Partei/Parti Chrétien-Social	CSP/PCS	Switzerland	Left	Minor
Schweizer Demokraten/Démocrates Suisses	SD/DS	Switzerland	Populist Right	Minor
Eidgenössisch-Demokratische Union/Union Démocratique Fédérale	EDU/UDF	Switzerland	Populist Right	Minor
Alternative Linke/La Gauche	AL	Switzerland	Far Left	Minor
Bürgerlich-Demokratische Partei Schweiz	BDP	Switzerland	Right	Minor
Freiheits-Partei der Schweiz	FPS	Switzerland	Populist Right	Minor
Partido Socialista Obrero Español	PSOE	Spain	Left	Main
Partido Popular	PP	Spain	Right	Main
Izquierda Unida	IU	Spain	Far Left	Minor
Vox	V	Spain	Populist Right	Minor
Podemos	P	Spain	Left	Minor
Unión, Progreso y Democracia	UPyD	Spain	Left	Minor
Ciudadanos	CS	Spain	Right	Minor
Partido Animalista Con el Medio Ambiente	PACMA	Spain	Left	Minor
Suomen Keskusta	KESK	Finland	Right	Major
Kansallinen Kokoomus	KOK	Finland	Right	Main
Sosialidemokraatit	SD/SDP	Finland	Left	Main
Perussuomalaiset	PS	Finland	Populist Right	Major
Suomen Kommunistinen Puolue	SKP	Finland	Far Left	Minor

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Vasemmistoliitto	VAS	Finland	Far Left	Minor
Kristillisdemokraatit	KD	Finland	Right	Minor
Köyhien Asialla	KA	Finland	Left	Minor
Kommunistinen Työväenpuolue	KTP	Finland	Far Left	Minor
Suomen Työväenpuolue	STP	Finland	Far Left	Minor
Seitsemän Tähden Liike	STL	Finland	Right	Minor
Korjausliike	Korj	Finland	Right	Minor
Suomen Kansa Ensin	SKE	Finland	Populist Right	Minor
Liberaalipuolue – Vapaus Valita	Lib	Finland	Right	Minor
Kansalaisliitto	KaL	Finland	Right	Minor
Union pour Un Mouvement Populaire/Les Républicains	UMP/LR	France	Right	Main
Front National	FN	France	Populist Right	Major
Mouvement pour la France	MPF	France	Populist Right	Minor
Lutte Ouvrière	LO	France	Far Left	Minor
Parti Communiste Français,	PCF	France	Far Left	Minor
Parti Socialiste	PS	France	Left	Main
Les Centristes	LC	France	Right	Minor
Parti Radical de Gauche	PRG	France	Left	Minor
Mouvement Démocrate	MoDem	France	Right	Minor
Nouveau Parti Anticapitaliste	NPA	France	Far Left	Minor
Debout la France	DlF	France	Populist Right	Minor
Ligue Communiste Révolutionnaire	LCR	France	Far Left	Minor
Mouvement Républicain et Citoyen	MRC	France	Left	Minor
Mouvement National Républicain	MNR	France	Populist Right	Minor
Conservative Party	C	UK	Right	Main
Labour Party	L	UK	Left	Main
UK Independence Party	UKIP	UK	Populist Right	Minor
Liberal Democrats	Lib Dems	UK	Left	Minor
People Before Profit	PBP	UK	Left	Minor
Brexit Party	BP	UK	Populist Right	Minor
British National Party	BNP	UK	Populist Right	Minor
Fianna Fáil	FF	Ireland	Right	Major
Fine Gael	FG	Ireland	Right	Main
Labour Party	L	Ireland	Left	Minor
People Before Profit	PBP	Ireland	Far Left	Minor
Social Democrats	SocDems	Ireland	Far Left	Minor
United Left Alliance	ULA	Ireland	Far Left	Minor
Independent Ireland	II	Ireland	Right	Minor
Centre Party of Ireland / Renua	CP	Ireland	Populist Right	Minor
Independents 4 Change	I4C	Ireland	Right	Minor
The Workers' Party	TWP	Ireland	Right	Minor
Progressive Democrats	PD	Ireland	Right	Minor
Christen-Democratisch Appèl	CDA	Netherlands	Right	Minor
Volkspartij voor Vrijheid en Democratie	VVD	Netherlands	Right	Main
Partij van de Arbeid	PvdA	Netherlands	Left	Main
Partij voor de Vrijheid	PVV	Netherlands	Populist Right	Minor
Socialistische Partij	SP	Netherlands	Far Left	Minor
Trots op Nederland	TON	Netherlands	Populist Right	Minor
Staatkundig Gereformeerde Partij	SGP	Netherlands	Right	Minor
Denk	Denk	Netherlands	Left	Minor
Forum voor Democratie	FvD	Netherlands	Populist Right	Minor
Article 1	BIJ1	Netherlands	Far Left	Minor
Volt	Volt	Netherlands	Left	Minor

JA21	JA21	Netherlands	Populist Right	Minor
BoerBurgerBeweging	BBB	Netherlands	Populist Right	Major
Lijst Pim Fortuyn	LPF	Netherlands	Populist Right	Minor
Høyre	H	Norway	Right	Main
Arbeiderpartiet	Labour	Norway	Left	Main
Fremskrittspartiet	FrP	Norway	Populist Right	Minor
Rødt	R	Norway	Far Left	Minor
Sosialistisk Venstreparti	SV	Norway	Far Left	Minor
Kristelig Folkeparti	KrF	Norway	Right	Minor
Partido Social Democrata	PSD	Portugal	Right	Main
Partido Socialista	PS	Portugal	Left	Main
Bloco de Esquerda	BE	Portugal	Far Left	Main
Coligação Democrática Unitária	CDU	Portugal	Far Left	Minor
Partido Comunista dos Trabalhadores Portugueses/Movimento Reorganizativo do Partido do Proletariado	PCTP/MRPP	Portugal	Far Left	Minor
CDS – Partido Popular	CDS	Portugal	Right	Minor
Partido da Nova Democracia	PND	Portugal	Populist Right	Minor
Partido Nacional Renovador	PNR	Portugal	Populist Right	Minor
Partido Operário de Unidade Socialista	POUS	Portugal	Far Left	Minor
Partido Trabalhista Português	PTP	Portugal	Left	Minor
Movimento Alternativa Socialista	MAS	Portugal	Left	Minor
LIVRE/Tempo de Avançar	L/TDA	Portugal	Left	Minor
Nós, Cidadãos!	NC	Portugal	Right	Minor
Cidadania e Democracia Cristã	PPV/CDC	Portugal	Right	Minor
Partido Democrático Republicano/Alternativa Democrática Nacional	PDR/ADN	Portugal	Populist Right	Minor
Partido Popular Monárquico	PPM	Portugal	Right	Minor
Aliança	A	Portugal	Right	Minor
Chega	CHEGA	Portugal	Populist Right	Major
Iniciativa Liberal	IL	Portugal	Right	Minor
Juntos pelo Povo	JPP	Portugal	Left	Minor
Coligação Democrática Unitária	CDU	Portugal	Far Left	Minor
Moderata Samlingspartiet	M	Sweden	Right	Main
Socialdemokratiska Arbetarpartiet	SAP	Sweden	Left	Main
Sverigedemokraterna	SD	Sweden	Populist Right	Major
Vänsterpartiet	V	Sweden	Far Left	Minor
Centerpartiet	C	Sweden	Right	Minor
Liberalerna	L	Sweden	Right	Minor
Kristdemokraterna	KD	Sweden	Right	Minor
Sverigedemokraterna	SD	Sweden	Populist Right	Minor
Christlich Demokratische Union Deutschlands/Christlich-Soziale Union in Bayern	CDU/CSU	Germany	Right	Main
Sozialdemokratische Partei Deutschlands	SPD	Germany	Left	Minor
Die Republikaner	REP	Germany	Populist Right	Minor
Nationaldemokratische Partei Deutschlands	NPD	Germany	Populist Right	Minor
Die Linke	LINKE	Germany	Left	Minor
Alternative für Deutschland	AfD	Germany	Populist Right	Minor
Freie Demokratische Partei	FDP	Germany	Right	Minor

Notes: This table lists all political parties in 12 Western European countries that are included as options in a vote choice question in the ESS, Rounds 1-10 (2002-2021). Regional and single-issue parties are excluded from consideration. The "family" and "type" classifications are based on Rovny and Rovny (2017), supplemented with the ParlGov database (Döring, Huber, and Manow 2022).

TABLE A3. Summary Statistics for Cross-National Analysis

	N	Mean	St. Dev.	Min	Max
Panel A: Full Sample					
Redistribution Support	236,962	3.801	1.019	1	5
AAIOE	219,160	0.000	1.000	−3.203	2.660
Age	239,125	48.914	18.680	14	123
Female	240,023	0.522	0.499	0	1
Years of Education	237,159	12.694	4.380	0.000	76.000
Degree of Religiosity	239,133	4.439	3.014	0	10
Urban Resident	239,848	0.616	0.486	0	1
Union Member	237,130	0.215	0.411	0	1
Panel B: Voting Analysis Only					
Vote Choice: Left	145,232	0.367	0.482	0	1
Vote Choice: Mainstream Right	145,232	0.426	0.495	0	1
Vote Choice: Radical Right	145,232	0.059	0.236	0	1

Notes: The sample comprises 12 Western European countries: Belgium, Finland, France, Germany, Great Britain, Ireland, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland. Source: ESS, Rounds 1-10 (2002-2021).

C.2 Full Baseline Results

TABLE A4. Full Results of Baseline Cross-National Analysis (Table 1)

Panel A: Baseline Specification				
Outcome =	Redistribution Support (1)	Vote Choice: Left (2)	Vote Choice: Mainstream Right (3)	Vote Choice: Populist Right (4)
AAIOE (Std.)	0.001	0.002	0.000	0.000
	(0.004)	(0.002)	(0.002)	(0.000)
AAIOE (Std.) × Post-2011	-0.067***	-0.028***	0.038***	-0.014***
	(0.009)	(0.005)	(0.005)	(0.004)
Age	0.003***	0.000	0.002***	-0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Female	0.162***	0.035***	-0.040***	-0.024***
	(0.015)	(0.009)	(0.006)	(0.006)
Years of Education	-0.020***	-0.008***	0.006**	-0.005***
	(0.003)	(0.002)	(0.002)	(0.001)
Degree of Religiosity	-0.013**	-0.020***	0.026***	-0.002**
	(0.005)	(0.003)	(0.003)	(0.001)
Urban Resident	0.002	0.074***	-0.070***	-0.010*
	(0.019)	(0.009)	(0.017)	(0.006)
Union Member	0.150***	0.112***	-0.102***	-0.009
	(0.019)	(0.015)	(0.010)	(0.009)
N	208,546	129,708	129,708	129,708
Mean Outcome	3.801	0.366	0.426	0.060
Panel B: Controlling for Automation Risk				
	(5)	(6)	(7)	(8)
AAIOE (Std.)	0.001	0.002	0.000	0.000
	(0.004)	(0.002)	(0.002)	(0.000)
AAIOE (Std.) × Post-2011	-0.065***	-0.027***	0.036***	-0.015***
	(0.009)	(0.005)	(0.005)	(0.004)
Goos et al. RTI Index (Std.)	0.015***	0.007**	-0.007**	0.001
	(0.003)	(0.003)	(0.003)	(0.001)
Age	0.003***	0.000	0.002***	-0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Female	0.165***	0.033***	-0.037***	-0.024***
	(0.016)	(0.009)	(0.006)	(0.007)
Years of Education	-0.021***	-0.008***	0.007***	-0.005***
	(0.003)	(0.002)	(0.002)	(0.001)
Degree of Religiosity	-0.012**	-0.019***	0.025***	-0.002**
	(0.005)	(0.003)	(0.003)	(0.001)
Urban Resident	0.002	0.072***	-0.069***	-0.011*
	(0.019)	(0.010)	(0.018)	(0.005)
Union Member	0.156***	0.113***	-0.102***	-0.009
	(0.019)	(0.015)	(0.011)	(0.009)
N	187,900	116,014	116,014	116,014
Mean Outcome	3.801	0.368	0.423	0.062
Individual-Level Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by country, in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A5. Full Results of Dynamic Cross-National Analysis (Figure 4)

Outcome =	Redistribution Support (1)	Vote Choice: Left-Wing (2)	Vote Choice: Mainstream Right (3)	Vote Choice: Populist Right (4)
AAIOE (Std.)	0.009	-0.005	0.007	0.001
	(0.009)	(0.004)	(0.005)	(0.001)
AAIOE (Std.) × Post-2002	-0.018	0.014**	-0.011*	-0.003
	(0.014)	(0.006)	(0.006)	(0.003)
AAIOE (Std.) × Post-2004	-0.002	0.010	-0.010**	0.000
	(0.014)	(0.007)	(0.005)	(0.002)
AAIOE (Std.) × Post-2006	-0.005	0.008	-0.008	-0.003
	(0.014)	(0.006)	(0.007)	(0.002)
AAIOE (Std.) × Post-2010	-0.014	0.005	-0.009	-0.002
	(0.012)	(0.005)	(0.007)	(0.002)
AAIOE (Std.) × Post-2012	-0.073***	-0.017**	0.031***	-0.016***
	(0.017)	(0.008)	(0.008)	(0.005)
AAIOE (Std.) × Post-2014	-0.097***	-0.021***	0.031***	-0.015**
	(0.016)	(0.007)	(0.009)	(0.005)
AAIOE (Std.) × Post-2016	-0.068***	-0.021*	0.038***	-0.016***
	(0.016)	(0.010)	(0.011)	(0.005)
AAIOE (Std.) × Post-2018	-0.054***	-0.030***	0.032***	-0.015***
	(0.014)	(0.008)	(0.010)	(0.004)
AAIOE (Std.) × Post-2020	-0.081***	-0.016**	0.016*	-0.016**
	(0.010)	(0.006)	(0.008)	(0.007)
Age	0.003***	0.000	0.002***	-0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Female	0.162***	0.035***	-0.040***	-0.024***
	(0.015)	(0.009)	(0.006)	(0.006)
Years of Education	-0.020***	-0.008***	0.006**	-0.005***
	(0.003)	(0.002)	(0.002)	(0.001)
Degree of Religiosity	-0.013**	-0.020***	0.026***	-0.002**
	(0.005)	(0.003)	(0.003)	(0.001)
Urban Resident	0.003	0.074***	-0.070***	-0.010*
	(0.019)	(0.009)	(0.017)	(0.006)
Union Member	0.151***	0.112***	-0.102***	-0.010
	(0.019)	(0.015)	(0.010)	(0.009)
N	208,546	129,708	129,708	129,708
Mean Outcome	3.801	0.366	0.426	0.060
Individual-Level Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by country, in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

C.3 Extensions and Robustness

Additional Controls and Fixed Effects

TABLE A6. Baseline Cross-National Results with Additional Occupational Controls

Outcome:	*Redistribution Support*	*Vote Choice: Left*	*Vote Choice: Mainstream Right*	*Vote Choice: Populist Right*
Panel A: Exposure to Computerization	(1)	(2)	(3)	(4)
AAIOE (Std.) × Post-2011	−0.068***	−0.029***	0.039***	−0.015***
	(0.009)	(0.005)	(0.006)	(0.004)
Frey & Osborne Exposure to Computerization Index (Std.)	0.010***	0.000	0.001	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)
N	199,298	123,774	123,774	123,774
Mean Outcome	3.802	0.366	0.425	0.061
Panel B: Offshorability	(5)	(6)	(7)	(8)
AAIOE (Std.) × Post-2011	−0.065***	−0.027***	0.036***	−0.015***
	(0.009)	(0.005)	(0.005)	(0.004)
Blinder & Krueger Offshorability Index (Std.)	−0.010**	0.000	0.001	−0.001
	(0.004)	(0.002)	(0.002)	(0.001)
N	187,900	116,014	116,014	116,014
Mean Outcome	3.801	0.368	0.423	0.062
Panel C: Skill Specificity	(9)	(10)	(11)	(12)
AAIOE (Std.) × Post-2011	−0.068***	−0.028***	0.038***	−0.014***
	(0.009)	(0.005)	(0.006)	(0.004)
Cusack, Iversen, & Rehm Skill Specificity Index (Std.)	0.015***	0.008***	−0.009***	0.002
	(0.004)	(0.002)	(0.002)	(0.001)
N	203,264	126,553	126,553	126,553
Mean Outcome	3.802	0.366	0.425	0.060
Panel D: Labor Market Outsiderness	(13)	(14)	(15)	(16)
AAIOE (Std.) × Post-2011	−0.072***	−0.027***	0.036***	−0.014***
	(0.010)	(0.005)	(0.007)	(0.004)
Fixed-Term Contract (0/1)	0.104***	0.030***	−0.053***	−0.001
	(0.019)	(0.008)	(0.009)	(0.003)
N	151,853	96,153	96,153	96,153
Mean Outcome	3.823	0.382	0.405	0.061
Panel E: Occupational Prestige	(17)	(18)	(19)	(20)
AAIOE (Std.) × Post-2011	−0.069***	−0.029***	0.039***	−0.014***
	(0.009)	(0.005)	(0.006)	(0.004)
Hughes et al. Occupational Prestige Rating (0–100)	−0.001***	0.000**	0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
N	208,376	129,615	129,615	129,615
Mean Outcome	3.801	0.366	0.426	0.060
Baseline Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by country, in parentheses. Baseline controls: age, years of education, gender, union membership, degree of religiosity, and urban residence. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A7. Baseline Cross-National Results with Additional Socioeconomic Controls

Outcome:	*Redistribution Support*	*Vote Choice: Left*	*Vote Choice: Mainstream Right*	*Vote Choice: Populist Right*
Panel A: Household Net Income	(1)	(2)	(3)	(4)
AAIOE (Std.) × Post-2011	-0.056***	-0.018**	0.026***	-0.013***
	(0.008)	(0.007)	(0.006)	(0.004)
Household Income (Decile)	-0.057***	-0.015***	0.021***	-0.002***
	(0.004)	(0.002)	(0.002)	(0.001)
N	123,614	79,135	79,135	79,135
Mean Outcome	3.819	0.348	0.421	0.066
Panel B: Public-Sector Employee	(5)	(6)	(7)	(8)
AAIOE (Std.) × Post-2011	-0.076***	-0.024***	0.035***	-0.015***
	(0.012)	(0.006)	(0.006)	(0.004)
Public-Sector Employee (0/1)	0.089***	0.062***	−0.059***	-0.020***
	(0.014)	(0.011)	(0.011)	(0.006)
N	136,598	86,170	86,170	86,170
Mean Outcome	3.820	0.350	0.423	0.064
Panel C: Ethnic Minority	(9)	(10)	(11)	(12)
AAIOE (Std.) × Post-2011	-0.063***	-0.029***	0.040***	-0.014***
	(0.010)	(0.006)	(0.006)	(0.004)
Ethnic Minority (0/1)	0.086**	0.170***	−0.148***	-0.027**
	(0.032)	(0.033)	(0.027)	(0.010)
N	184,834	121,259	121,259	110,107
Mean Outcome	3.797	0.370	0.429	0.064
Panel D: Left-Right Ideology	(13)	(14)	(15)	(16)
AAIOE (Std.) × Post-2011	-0.060***	-0.017***	0.027***	-0.016***
	(0.008)	(0.003)	(0.004)	(0.004)
Left-Right Position (0-10)	−0.117***	−0.101***	0.104***	0.018***
	(0.012)	(0.006)	(0.007)	(0.005)
N	191,792	125,131	125,131	125,131
Mean Outcome	3.787	0.366	0.426	0.061
Baseline Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by country, in parentheses. Baseline control variables: age, years of education, gender, union membership, degree of religiosity, and urban residence. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A8. Baseline Cross-National Results with Country-Level Controls

Outcome:	*Redistribution Support*	*Vote Choice: Left*	*Vote Choice: Mainstream Right*	*Vote Choice: Populist Right*
Panel A: Social Spending	(1)	(2)	(3)	(4)
AAIOE (Std.) × Post-2011	-0.067***	-0.028***	0.038***	-0.014***
	(0.009)	(0.005)	(0.006)	(0.004)
Social Spending (% of GDP), Lagged	-0.002	-0.001	0.002	0.001
	(0.012)	(0.002)	(0.003)	(0.003)
N	208,537	129,703	129,703	129,703
Mean Outcome	3.801	0.366	0.426	0.060
Panel B: Unemployment	(5)	(6)	(7)	(8)
AAIOE (Std.) × Post-2011	-0.067***	-0.028***	0.037***	-0.014***
	(0.009)	(0.005)	(0.006)	(0.004)
Unemployment Rate (% of Workforce), Lagged	0.000	0.002	-0.002	-0.002
	(0.011)	(0.004)	(0.003)	(0.001)
N	201,584	126,470	126,470	126,470
Mean Outcome	3.808	0.369	0.429	0.055
Panel C: Migration	(9)	(10)	(11)	(12)
AAIOE (Std.) × Post-2011	-0.062***	-0.029***	0.041***	-0.014***
	(0.010)	(0.006)	(0.006)	(0.004)
Foreign-Born Population (% of Total), Lagged	-0.014	0.017**	0.001	-0.007
	(0.022)	(0.006)	(0.009)	(0.005)
N	182,307	119,326	119,329	110,592
Mean Outcome	3.796	0.373	0.423	0.064
Baseline Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by country, in parentheses. Baseline control variables: age, years of education, gender, union membership, degree of religiosity, and urban residence. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A9. Baseline Cross-National Results with Additional Fixed Effects

Outcome:	*Redistribution Support*	*Vote Choice: Left*	*Vote Choice: Mainstream Right*	*Vote Choice: Populist Right*
Panel A: 1-Digit Occupation FEs	(1)	(2)	(3)	(4)
AAIOE (Std.) × Post-2011	-0.068***	-0.029***	0.038***	-0.014***
	(0.009)	(0.005)	(0.006)	(0.004)
N	208,546	129,708	129,708	129,708
Mean Outcome	3.80	0.37	0.43	0.06
1-Digit Occupation FEs	✓	✓	✓	✓
Panel B: 2-Digit Occupation FEs	(5)	(6)	(7)	(8)
AAIOE (Std.) × Post-2011	-0.066***	-0.029***	0.038***	-0.013***
	(0.008)	(0.005)	(0.005)	(0.004)
N	208,546	129,708	129,708	129,697
Mean Outcome	3.80	0.37	0.43	0.06
2-Digit Occupation FEs	✓	✓	✓	✓
Panel C: 3-Digit Occupation FEs	(9)	(10)	(11)	(12)
AAIOE (Std.) × Post-2011	-0.063***	-0.027***	0.035***	-0.012***
	(0.008)	(0.005)	(0.005)	(0.003)
N	208,546	129,704	129,708	129,672
Mean Outcome	3.80	0.37	0.43	0.06
3-Digit Occupation FEs	✓	✓	✓	✓
Panel D: 2-Digit Industry FEs	(13)	(14)	(15)	(16)
AAIOE (Std.) × Post-2011	-0.056***	-0.024***	0.033***	-0.013***
	(0.010)	(0.005)	(0.004)	(0.004)
N	189,653	122,761	122,761	122,761
Mean Outcome	3.80	0.37	0.42	0.06
2-Digit Industry FEs	✓	✓	✓	✓
Panel E: Interactive FEs	(17)	(18)	(19)	(20)
AAIOE (Std.) × Post-2011	-0.067***	-0.027***	0.038***	-0.014***
	(0.009)	(0.005)	(0.005)	(0.004)
N	208,546	129,708	129,708	98,089
Mean Outcome	3.80	0.37	0.43	0.08
Country × Year FEs	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by country, in parentheses. Baseline controls: age, years of education, gender, union membership, degree of religiosity, and urban residence. Occupations are defined according to the ISCO-08 classification, industries according to the NACE classification (Rev.1 for the period 2002-2003, Rev.1.1 for 2004-2009, Rev.2 for 2010-2021). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Instrumental Variables Analysis

TABLE A10. Cross-National Instrumental Variables Results

Outcome:	*Redistribution Support*	*Vote Choice: Left*	*Vote Choice: Mainstream Right*	*Vote Choice: Populist Right*
AAIOE (Std.) $\times$ Post-2011	-0.052***	-0.013***	0.022***	-0.014***
[Instrumented]	(0.005)	(0.003)	(0.002)	(0.003)
N	71,019	47,270	47,270	47,270
Mean Outcome	3.813	0.327	0.421	0.072
First-Stage F-Statistic	60,109,024	39,016,562	39,016,562	39,016,562
Baseline Controls	✓	✓	✓	✓
Income + Ideology Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓

Notes: Standardized 2SLS estimates with robust standard errors, clustered by country, in parentheses. The instrument is the AAIOE score of respondent i's father when i was 14 years old. Baseline controls: age, years of education, gender, union membership, degree of religiosity, and urban residence. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Difference Party Categorizations

TABLE A11. Baseline Cross-National Voting Behavior Results with Different Party Categorizations

Outcome = Vote Choice:	*Main Left* (1)	*Far Left* (2)	*Main Right* (3)
AAIOE (Std.) $\times$ Post-2011	-0.019***	-0.009***	0.027***
	(0.006)	(0.003)	(0.006)
N	129,708	129,708	129,708
Mean Outcome	0.244	0.056	0.271
Individual-Level Controls	✓	✓	✓
Country FEs	✓	✓	✓
Year FEs	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by country, in parentheses. Baseline controls: age, years of education, gender, union membership, degree of religiosity, and urban residence. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Alternative Samples

TABLE A12. Baseline Cross-National Results with Alternative Samples

Outcome:	*Redistribution Support*	*Vote Choice: Left*	*Vote Choice: Mains. Right*	*Vote Choice: Populist Right*
Panel A: All Western Europe	(1)	(2)	(3)	(4)
AAIOE (Std.) × Post-2011	-0.067***	-0.028***	0.038***	-0.014***
	(0.009)	(0.005)	(0.005)	(0.004)
N	208,546	129,708	129,708	129,708
Mean Outcome	3.801	0.366	0.426	0.060
Panel B: Market Earners Only	(5)	(6)	(7)	(8)
AAIOE (Std.) × Post-2011	-0.077***	-0.024***	0.034***	-0.015***
	(0.010)	(0.005)	(0.005)	(0.004)
N	127,158	80,472	80,472	73,600
Mean Outcome	3.720	0.355	0.417	0.069
Panel C: Design Weights	(9)	(10)	(11)	(12)
AAIOE (Std.) × Post-2011	-0.065***	-0.029***	0.039***	-0.014***
	(0.009)	(0.005)	(0.005)	(0.004)
N	208,546	129,708	129,708	129,708
Mean Outcome	3.801	0.366	0.426	0.060
Panel D: No Pre-2010 Elections in 2010-11 Wave		(13)	(14)	(15)
AAIOE (Std.) × Post-2011		-0.018***	0.030***	-0.017**
		(0.004)	(0.008)	(0.006)
N		62,842	62,842	62,842
Mean Outcome		0.394	0.374	0.078
Baseline Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by country, in parentheses. Baseline controls: age, years of education, gender, union membership, degree of religiosity, and urban residence. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A13. Baseline Cross-National Results with Individual AI Exposure Indices

Outcome:	*Redistribution Support*				*Vote Choice: Left*				*Vote Choice: Mainstream Right*				*Vote Choice: Populist Right*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
AIOE (Std.)	−0.069***				−0.025***				0.037***				−0.019***			
× Post-2011	(0.010)				(0.005)				(0.005)				(0.005)			
SML (Std.)		−0.018**				−0.014***				0.021***				−0.008***		
× Post-2011		(0.007)				(0.003)				(0.004)				(0.002)		
Webb (Std.)			−0.045***				−0.016***				0.016***				0.000	
× Post-2011			(0.005)				(0.004)				(0.005)				(0.002)	
C-AIOE (Std.)				−0.009*				−0.004*				0.009*				−0.007***
× Post-2011				(0.004)				(0.002)				(0.004)				(0.002)
N	208,546	208,546	208,546	208,546	129,708	129,708	129,708	129,708	129,708	129,708	129,708	129,708	129,708	129,708	129,708	129,708
Mean Outcome	3.801	3.801	3.801	3.801	0.366	0.366	0.366	0.366	0.426	0.426	0.426	0.426	0.060	0.060	0.060	0.060
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table shows that the results in Table 1 remain similar when we disaggregate the AAIOE into its three constituent indices (all of which are standardized): (1) Felten, Raj, and Seamans' (2021) AIOE index; (2) Brynjolfsson, Mitchell, and Rock's (2018) SML index; (3) Webb's (2020) AI exposure index; and (4) Pizzinelli et al.'s (2024) C-AIOE index. Baseline controls: age, years of education, gender, union membership, degree of religiosity, and urban residence. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A14. Baseline Cross-National Results with Different Types of AI

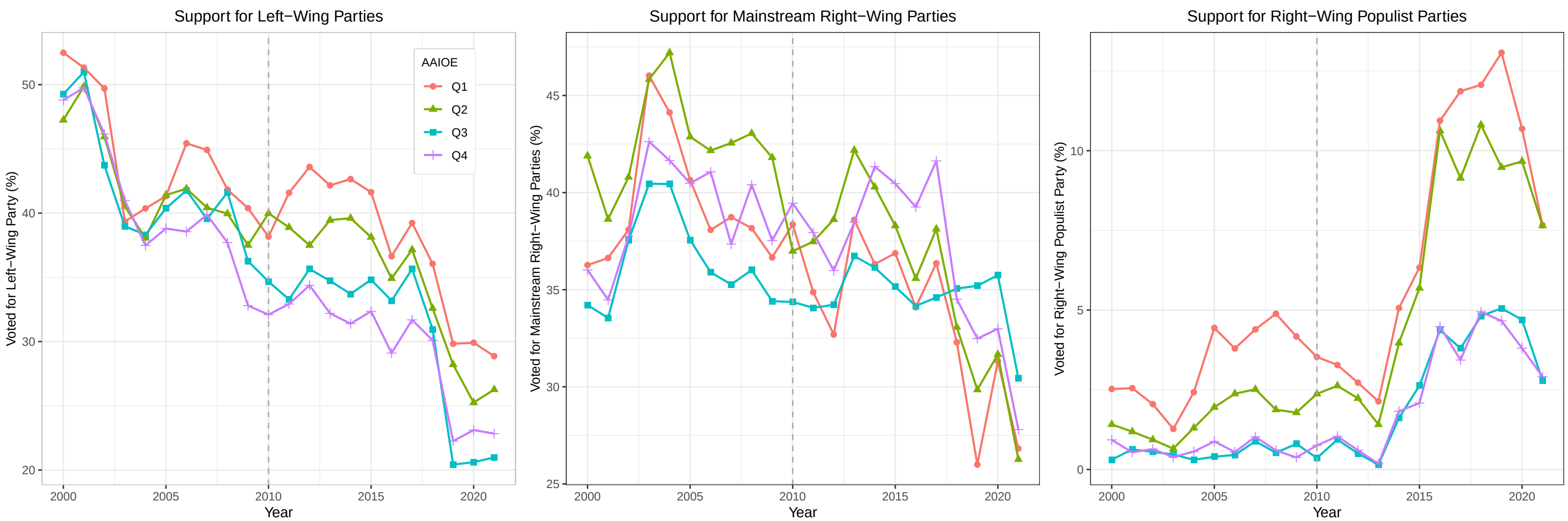
Outcome:	*Redistribution Support*	*Vote Choice: Left*	*Vote Choice: Mainstream Right*	*Vote Choice: Populist Right*
	(1)	(2)	(3)	(4)
Abstract Strategy Games (Std.) × Post-2011	−0.083*** (0.011)	−0.027*** (0.005)	0.039*** (0.005)	−0.019*** (0.005)
	(5)	(6)	(7)	(8)
Real-Time Video Games (Std.) × Post-2011	−0.076*** (0.010)	−0.028*** (0.005)	0.037*** (0.005)	−0.012*** (0.004)
	(9)	(10)	(11)	(12)
Image Recognition (Std.) × Post-2011	−0.079*** (0.009)	−0.025*** (0.005)	0.035*** (0.005)	−0.010** (0.003)
	(13)	(14)	(15)	(16)
Visual Question Answering (Std.) × Post-2011	−0.084*** (0.011)	−0.028*** (0.005)	0.040*** (0.005)	−0.015*** (0.004)
	(17)	(18)	(19)	(20)
Image Generation (Std.) × Post-2011	−0.084*** (0.010)	−0.026*** (0.006)	0.036*** (0.005)	−0.016*** (0.004)
	(21)	(22)	(23)	(24)
Reading Comprehension (Std.) × Post-2011	−0.073*** (0.011)	−0.024*** (0.005)	0.035*** (0.005)	−0.020*** (0.005)
	(25)	(26)	(27)	(28)
Language Modeling (Std.) × Post-2011	−0.066*** (0.011)	−0.022*** (0.005)	0.033*** (0.005)	−0.020*** (0.005)
	(29)	(30)	(31)	(32)
Translation (Std.) × Post-2011	−0.066*** (0.011)	−0.022*** (0.005)	0.033*** (0.005)	−0.020*** (0.005)
	(33)	(34)	(35)	(36)
Speech Recognition (Std.) × Post-2011	−0.065*** (0.011)	−0.023*** (0.005)	0.033*** (0.005)	−0.019*** (0.005)
	(37)	(38)	(39)	(40)
Instrumental Track Recognition (Std.) × Post-2011	−0.065*** (0.011)	−0.024*** (0.005)	0.034*** (0.005)	−0.018*** (0.005)
N	153,569	129,708	129,708	129,708
Mean Outcome	3.793	0.366	0.426	0.060
Baseline Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓

Notes: This table shows that the results in Table 1 remain similar when we disaggregate Felten, Raj, and Seamans' (2021) AIOE measure into its 10 sub-indices, which measure exposure to different AI applications. OLS estimates with robust standard errors, clustered by country, in parentheses. Baseline controls: age, years of education, gender, union membership, degree of religiosity, and urban residence. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D Longitudinal Analysis of German Political Preferences

D.1 Descriptive Data

FIGURE A3. Support for German Party Families by AI Exposure Quartile, 2000–2021



Notes: The *y*-axis measures the proportion of SOEP respondents who support a left-wing party (left panel), a mainstream right-wing party (middle panel), and a right-wing populist party (right panel). See the main text for a

D.2 Baseline Results

TABLE A15. Full Results of Baseline Longitudinal Analysis (Equation 8)

Outcome = Support for:	Left (1)	Mainstream Right (2)	Radical Right (3)
AAIOE_f (Std.)	-0.727	3.083	0.024
	(1,721.885)	(1,242.078)	(792.598)
AAIOE_f (Std.) $\times$ Post-2010	-0.017***	0.016***	-0.006**
	(0.004)	(0.004)	(0.003)
Female	0.074	0.694	-0.399
	(2,803.419)	(2,582.581)	(1,627.781)
Age	-0.044***	0.029***	0.000
	(0.012)	(0.009)	(0.002)
Years of Education	0.002	0.000	-0.002*
	(0.005)	(0.003)	(0.001)
Union Member	-0.004	0.001	-0.004
	(0.010)	(0.008)	(0.004)
Frequency of Religious Activity	0.005	-0.004	0.001
	(0.004)	(0.003)	(0.001)
N	39,209	39,209	39,209
Mean Outcome	0.377	0.367	0.030
Socioeconomic Controls	✓	✓	✓
Respondent FEs	✓	✓	✓
Year FEs	✓	✓	✓
Federal State FEs	✓	✓	✓

Notes: OLS estimates from Equation 8 with robust standard errors, clustered by respondent, in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A16. Full Results of Dynamic Longitudinal Specification

Outcome = Support for:	Left (1)	Mainstream Right (2)	Populist Right (3)
AAIOE$_f$ (Std.)	-0.735	3.092	0.020
	(1,721.320)	(1,242.209)	(790.338)
AAIOE$_f$ (Std.) $\times$ 2000–02	0.005	0.001	-0.001
	(0.005)	(0.004)	(0.002)
AAIOE$_f$ (Std.) $\times$ 2007–10	-0.006	0.004	0.000
	(0.005)	(0.004)	(0.002)
AAIOE$_f$ (Std.) $\times$ 2011–14	-0.020***	0.018***	-0.002
	(0.006)	(0.005)	(0.003)
AAIOE$_f$ (Std.) $\times$ 2015–18	-0.014**	0.017***	-0.007*
	(0.006)	(0.006)	(0.004)
AAIOE$_f$ (Std.) $\times$ 2019–21	-0.019***	0.018***	-0.016***
	(0.007)	(0.007)	(0.005)
Female	0.069	0.700	-0.402
	(2,803.313)	(2,582.093)	(1,626.875)
Age	-0.044***	0.029***	-0.001
	(0.012)	(0.009)	(0.002)
Years of Education	0.002	0.000	-0.002*
	(0.005)	(0.003)	(0.001)
Union Member	-0.003	0.001	-0.004
	(0.010)	(0.008)	(0.004)
Degree of Religiosity	0.005	-0.004	0.001
	(0.004)	(0.003)	(0.001)
N	39,209	39,209	39,209
Mean Outcome	0.377	0.367	0.030
Respondent FEs	✓	✓	✓
Year FEs	✓	✓	✓
Federal State FEs	✓	✓	✓

Notes: OLS estimates from a modified version of Equation 8 in which *Post-2010$_t$* is replaced by indicators for the intervals 2000–2002, 2007–2010, 2011–2014, 2015–2018, and 2019–2021; the reference period is 2003–2006. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D.3 Extensions and Robustness

Additional Controls and Fixed Effects

TABLE A17. Baseline Longitudinal Results with Additional Occupational Controls

Outcome: Support for…	*Left*	*Mainstream Right*	*Populist Right*
Panel A: Exposure to Computerization	(1)	(2)	(3)
AAIOE_f (Std.) × Post-2010	−0.019***	0.022***	−0.013***
	(0.006)	(0.006)	(0.004)
Frey & Osborne Exposure to Computerization Index (0–1)	−0.025*	0.006	−0.006
	(0.013)	(0.012)	(0.006)
N	27,198	27,198	27,198
Mean Outcome	0.372	0.369	0.032
Panel B: Offshorability	(4)	(5)	(6)
AAIOE_f (Std.) × Post-2010	−0.016***	0.017***	−0.010***
	(0.006)	(0.005)	(0.004)
Blinder & Krueger Offshorability Index (Std.)	0.002	0.004	−0.003
	(0.005)	(0.004)	(0.002)
N	27,595	27,595	27,595
Mean Outcome	0.372	0.374	0.032
Panel C: Skill Specificity	(7)	(8)	(9)
AAIOE_f (Std.) × Post-2010	−0.016***	0.017***	−0.010***
	(0.006)	(0.005)	(0.004)
Cusack, Iversen, & Rehm Skill Specificity Index (Std.)	0.000	0.003***	−0.001
	(0.001)	(0.001)	(0.001)
N	30,685	30,685	30,685
Mean Outcome	0.370	0.366	0.030
Panel D: Labor Market Outsiderness	(10)	(11)	(12)
AAIOE_f (Std.) × Post-2010	−0.016***	0.014***	−0.006*
	(0.006)	(0.005)	(0.003)
Fixed-Term Contract (0/1)	0.001	0.010	−0.006
	(0.011)	(0.008)	(0.004)
N	28,823	28,823	28,823
Mean Outcome	0.387	0.361	0.028
Panel E: Occupational Prestige	(13)	(14)	(15)
AAIOE_f (Std.) × Post-2010	−0.017***	0.021***	−0.013***
	(0.006)	(0.006)	(0.004)
Hughes et al. Occupational Prestige Rating (0–100)	0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)
N	27,969	27,969	27,969
Mean Outcome	0.370	0.368	0.031
Baseline Controls	✓	✓	✓
Respondent FEs	✓	✓	✓
Year FEs	✓	✓	✓
Federal State FEs	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by respondent, in parentheses. Baseline controls: age, years of education, gender, union membership, and frequency of religious activity. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A18. Baseline Longitudinal Results with Additional Socioeconomic Controls

Outcome: Support for...	*Left*	*Mainstream Right*	*Populist Right*
Panel A: Labor Income	(1)	(2)	(3)
AAIOE$_f$ (Std.) × Post-2010	−0.017***	0.017***	−0.009**
	(0.006)	(0.005)	(0.003)
Log Gross Labor Income (euros)	0.000	−0.003	0.000
	(0.005)	(0.004)	(0.002)
N	31,244	31,244	31,244
Mean Outcome	0.371	0.366	0.030
Panel B: Migration Background	(4)	(5)	(6)
AAIOE$_f$ (Std.) × Post-2010	−0.017***	0.016***	−0.006**
	(0.004)	(0.004)	(0.003)
Migration Background (0/1)	0.205	−0.484	0.891
	(1,286.762)	(773.145)	(640.026)
N	39,209	39,209	39,209
Mean Outcome	0.377	0.367	0.030
Panel C: Civil Servant	(7)	(8)	(9)
AAIOE$_f$ (Std.) × Post-2010	−0.017***	0.016***	−0.006**
	(0.004)	(0.004)	(0.003)
Civil Servant (0/1)	−0.012	−0.005	−0.003
	(0.015)	(0.011)	(0.004)
N	39,209	39,209	39,209
Mean Outcome	0.377	0.367	0.030
Panel D: Left-Right Position	(10)	(11)	(12)
AAIOE$_f$ (Std.) × Post-2010	−0.017***	0.016***	−0.006**
	(0.004)	(0.004)	(0.003)
Left-Right Position$_f$ (0–10)	−0.099	0.082	0.840
	(2,370.662)	(1,209.931)	(772.583)
N	36,823	36,823	36,823
Mean Outcome	0.375	0.366	0.032
Baseline Controls	✓	✓	✓
Respondent FEs	✓	✓	✓
Year FEs	✓	✓	✓
Federal State FEs	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by respondent, in parentheses. As left-right position is only included in a handful of SOEP waves, it is measured in year f_i, i.e., the first year available for respondent i. Baseline controls: age, years of education, gender, union membership, and frequency of religious activity. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A19. Baseline Longitudinal Results with Additional Fixed Effects

Outcome: Support for...	*Left*	*Mainstream Right*	*Populist Right*
Panel A: 1-Digit Occupation FEs	(1)	(2)	(3)
AAIOE$_f$ (Std.) $\times$ Post-2010	-0.017***	0.017***	-0.010***
	(0.006)	(0.005)	(0.003)
M	30,717	30,717	30,717
Mean Outcome	0.370	0.366	0.030
1-Digit Occupation FEs	✓	✓	✓
Panel B: 2-Digit Occupation FEs	(4)	(5)	(6)
AAIOE$_f$ (Std.) $\times$ Post-2010	-0.017***	0.016***	-0.009***
	(0.006)	(0.005)	(0.003)
N	30,717	30,717	30,717
Mean Outcome	0.370	0.366	0.030
2-Digit Occupation FEs	✓	✓	✓
Panel C: 3-Digit Occupation FEs	(7)	(8)	(9)
AAIOE$_f$ (Std.) $\times$ Post-2010	-0.017***	0.017***	-0.010***
	(0.006)	(0.005)	(0.003)
N	30,717	30,717	30,717
Mean Outcome	0.370	0.366	0.030
3-Digit Occupation FEs	✓	✓	✓
Panel E: 2-Digit Industry FEs	(10)	(11)	(12)
AAIOE$_f$ (Std.) $\times$ Post-2011	-0.014**	0.013**	-0.005
	(0.007)	(0.006)	(0.004)
N	21,527	21,527	21,527
Mean Outcome	0.340	0.349	0.039
2-Digit Industry FEs	✓	✓	✓
Panel D: Interactive FEs	(13)	(14)	(15)
AAIOE$_f$ (Std.) $\times$ Post-2010	-0.017***	0.016***	-0.005**
	(0.004)	(0.004)	(0.003)
N	39,209	39,209	39,209
Mean Outcome	0.377	0.367	0.030
Federal State $\times$ Year FEs	✓	✓	✓
Baseline Controls	✓	✓	✓
Respondent FEs	✓	✓	✓
Year FEs	✓	✓	✓
Federal State FEs	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by respondent, in parentheses. Baseline controls: age, years of education, gender, union membership, and frequency of religious activity. Occupations are defined according to the ISCO-08 classification, industries according to the NACE classification (Rev.1 before 2013, Rev.2 subsequently). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Single-Difference Estimator

TABLE A20. Results of Single-Difference Specification (Equation 9)

Outcome: Δ Support for...	Left	Mainstream Right	Populist Right
Panel A: 2000-05 – 2016-21	(1)	(2)	(3)
AAIOE_{t_0} (Std.)	-0.021***	0.025***	-0.013**
	(0.007)	(0.008)	(0.005)
N	3,080	3,080	3,080
Mean Outcome	-0.092	0.006	0.049
Panel B: 2000-05 – 2011-21	(4)	(5)	(6)
AAIOE_{t_0} (Std.)	-0.015***	0.015***	-0.005
	(0.003)	(0.004)	(0.003)
N	4,607	4,607	4,607
Mean Outcome	-0.069	0.007	0.026
Panel C: 2000-10 – 2016-21	(7)	(8)	(9)
AAIOE_{t_0} (Std.)	-0.011	0.016**	-0.012*
	(0.007)	(0.007)	(0.006)
N	3,995	3,995	3,995
Mean Outcome	-0.077	0.011	0.045
Panel D: 2000-10 – 2011-21	(10)	(11)	(12)
AAIOE_{t_0} (Std.)	-0.008**	0.010**	-0.004
	(0.004)	(0.005)	(0.005)
N	6,133	6,133	6,133
Mean Outcome	-0.057	0.012	0.022
Baseline Controls	✓	✓	✓
Federal State FEs	✓	✓	✓

Notes: OLS estimates from Equation 9 with robust standard errors, clustered by federal state, in parentheses. Baseline controls: age, years of education, gender, union membership, and frequency of religious activity (all measured during t_0, i.e., the earlier of the two periods). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Alternative Samples

TABLE A21. Baseline Longitudinal Results with Alternative Samples

Outcome: Support for...	*Left*	*Mainstream Right*	*Populist Right*
Panel A: Controls Fixed at Year f_i	(1)	(2)	(3)
AAIOE$_f$ (Std.) $\times$ Post-2010	-0.008***	0.012***	-0.006***
	(0.003)	(0.003)	(0.002)
N	146,728	146,728	146,728
Mean Outcome	0.375	0.369	0.032
Panel B: Market Earners Only	(3)	(4)	
AAIOE$_f$ (Std.) $\times$ Post-2010	-0.013**	0.018***	-0.010***
	(0.005)	(0.005)	(0.003)
N	34,671	34,671	34,671
Mean Outcome	0.369	0.368	0.029
Panel C: Design Weights	(5)	(6)	
AAIOE$_f$ (Std.) $\times$ Post-2010	-0.018***	0.018***	-0.010**
	(0.006)	(0.006)	(0.004)
N	38,853	38,853	38,853
Mean Outcome	0.377	0.367	0.031
Baseline Controls	✓	✓	✓
Federal State FEs	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by respondent, in parentheses. Baseline controls: age, years of education, gender, union membership, and frequency of religious activity. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Individual Parties

TABLE A22. Baseline Longitudinal Results with Individual Parties

	Left		Mainstream Right		Populist Right	
Outcome: Support for...	SPD	DL	CDU	CSU	AfD	DH
	(1)	(2)	(3)	(4)	(5)	(6)
AAIOE$_f$ $\times$ Post-2010	-0.015***	-0.002	0.015***	-0.001	-0.008***	0.002
	(0.004)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)
N	39,209	39,209	39,209	39,209	39,209	39,209
Mean Outcome	0.315	0.063	0.308	0.063	0.020	0.011
Baseline Controls	✓	✓	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by respondent, in parentheses. Party names: *Sozialdemokratische Partei Deutschlands* (SPD), *Christlich Demokratische Union Deutschlands* (CDU), *Christlich-Soziale Union in Bayern* (CSU), *Die Linke* (DL), *Die Heimat* (DH), *Alternative für Deutschland* (AfD). Baseline controls: age, years of education, gender, union membership, and frequency of religious activity. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

E Survey Experiment

E.1 Design and Implementation

This study's survey experiment was preregistered with the Open Science Foundation (OSF) on December 21, 2024 and implemented over the following five weeks.[1] The sample comprised 795 working-age adults based in the United Kingdom, who were recruited through two channels: (1) Amazon Mechanical Turk (AMT), a popular crowdsourcing website that permits "Requesters" to specify the location of "Workers"; and (2) advertising on social media networks, primarily British public Facebook groups. Although AMT Workers do not constitute a random sample of the United Kingdom's population, several empirical results based on nationally representative samples have been replicated on the platform (Berinsky, Huber, and Lenz 2012; Clifford, Jewell, and Waggoner 2015; Crump, McDonnell, and Gureckis 2013). Facebook is more widely used and can thus generate samples as representative as those recruited via traditional methods in a variety of contexts (Thornton et al. 2016; Whitaker, Stevelink, and Fear 2017). Importantly, my sample is similar to the wider British population on key demographic characteristics, with male, younger, white, and more educated individuals only marginally overrepresented:

- *Gender*. The male-female ratio in the sample is 1.04, compared with 0.96 in the United Kingdom as a whole.[2]
- *Age*. The proportion of working-age adults in the age groups 18–29 years, 30-39 years, 40-49 years, 50-59 years, and 60-64 years in the sample is 22%, 28.1%, 20.8%, 19.7%, and 9.2%, respectively. The equivalent proportions in the United Kingdom as a whole are 21.6%,[3] 23.7%, 21.3%, 22.9%, and 10.5% (Office for National Statistics 2024).

[1]The pre-analysis plan can be accessed at: `https://osf.io/k5rty/?view_only=fe518f0fc5b3465d8b37779313906a35`.

[2]Office for National Statistics population estimates for the United Kingdom in mid-2022, accessed at: `https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/annualmidyearpopulationestimates/mid2022`.

[3]This figure represents the age group 20-24 years (rather than 18-24 years, for which data are not available).

- *Ethnicity*. The proportion of whites in the sample is 84.3%, compared with an estimated 81.7% in England and Wales.[4]
- *Education level*. The proportion of respondents with an undergraduate degree or equivalent qualification is 47.7%, compared with 43% of the United Kingdom's working-age population (Universities UK 2022, 4).
- *Income*. The median and modal income category in the sample is £25,000–£39,999. In the United Kingdom as a whole, median gross earnings for full-time employees are £37,430.[5]

Summary statistics for the full survey experimental dataset are presented in Table A24.

The survey comprised five sections, which are detailed in Table A23:

1. *Demographic information*. After providing informed consent, respondents were asked to provide basic demographic information: their age, sex, ethnicity, party affiliation, education level, income bracket, and occupational category.
2. *Treatment assignment*. Respondents were either presented with the two primes described in the main text — the "complementarity" prompt and the "substitution" prompt — or transferred to the next stage (the control condition). In total, 257 respondents were assigned the complementarity prompt, 258 were shown the substitution prompt, and 280 were placed in the control group.
3. *Outcomes*. Respondents were posed a series of questions about their redistribution preferences and voting intentions. The order of this and the following section was randomized.
4. *Labor market expectations*. Respondents were asked a series of questions about how they expect AI to impact their productivity, job security, and earnings. The order of this and

[4]Census 2021 data on ethnic groups in England and Wales, accessed at: `https://www.ons.gov.uk/peoplepopulationandcommunity/culturalidentity/ethnicity/bulletins/ethnicgroupenglandandwales/census2021`.

[5]Office for National Statistics data on employee earnings in the United Kingdom in 2024, accessed at: `https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/annualsurveyofhoursandearnings/2024#:~:text=Median%20gross%20annual%20earnings%20for,%2C%20an%20increase%20of%206.9%25`.

TABLE A23. Overview of Survey Experiment

Section	Order	Question Text	Response scale
Demographic information	Pretreatment	1. "What is your gender?" 2. "How old are you (in years)?" 3. "What is your ethnic group?" 4. "In pounds sterling, what is your total annual income?" 5. "What is the highest level of education you have completed?" 6. "Which, if any, of the following political parties do you identify with?" 7. "What is your occupation?" 8. "How compatible are your occupational tasks with AI's current and likely future capabilities?"	1. Categorical: Male; Female; Neither male nor female describe me precisely 2. Categorical: 18–24; 25–29; 30–34; 35–39; 40–44; 45–49; 50–54; 55–59; 60–64; 65+ 3. Categorical: White (English, Welsh, Scottish, Irish, Gypsy, Traveller, Roma, other); Asian (Indian, Pakistani, Bangladeshi, Chinese, Other); Black (Caribbean, African, other); Arab; Mixed (White and Black Caribbean, White and Black African, White and Asian, other); Any other group 4. Categorical: £0–£9,999; £10,000–£24,999; £25,000–£39,999; £40,000–£59,999; £60,000–£79,999; £80,000–£99,999; £10,0000–£149,999; £150,000+ 5. Categorical: No qualification; Primary school; Secondary school up to 16 years; Higher, secondary, or further education; Vocational, trade, or technical training; Undergraduate Degree; Professional Degree; Master's Degree; Doctorate 6. Categorical: Conservative Party; Labour Party; Liberal Democrats; Reform UK; Green Party; None of the above 7. Categorical: ISCO-08 sub-major category (2 digits) 8. Continuous: 0–100 compatibility scale
Treatment assignment		See main text for complementarity and substitution prompts.	N.A.
Redistribution and voting outcomes	Posttreatment (randomized with next section)	"How much do you agree with the following statements?" 1. *The government should take redistributive measures to reduce differences in income levels.* 2. *The government should increase spending on unemployment benefits, even if this requires raising taxes.* 3. *The government should increase spending on public services and social benefits, even if this requires raising taxes.* 4. "If a general election were held tomorrow, which of the following political parties would you vote for?"	1. Continuous: 0–100 Likert scale 2. Continuous: 0–100 Likert scale 3. Continuous: 0–100 Likert scale 4. Categorical: Conservative Party; Labour Party; Liberal Democrats; Reform UK; Green Party; None of the above
Labor market expectations	Posttreatment (randomized with previous section)	"How much do you agree with the following statements?" 1. *The widespread adoption of AI technology will improve my efficiency in performing work tasks.* 2. *The widespread adoption of AI technology will expand my range of work tasks.* 3. *The widespread adoption of AI technology will enhance my ability to find work.* 4. *The widespread adoption of AI technology will increase my future earnings.*	1. Continuous: 0–100 agreement scale 2. Continuous: 0–100 agreement scale 3. Continuous: 0–100 agreement scale 4. Continuous: 0–100 agreement scale

the previous section was randomized.

The average survey completion time was 11 minutes (658 seconds).

E.2 Ethical Considerations

The survey received ethics approval from the author's institution on December 19, 2024. In general, the research did not raise any ethical issues specific to the British context — in which the questions were unlikely to be perceived as particularly sensitive or controversial — or pose physical or psychological risks to the research team. Respondents were provided with an informed consent form detailing the purpose of the research, the survey procedure, the right to withdraw, confidentiality arrangements, remuneration, the complaints procedure, and contact information. Compensation was slightly higher than the British minimum wage (£2 for an activity typically taking around 10 minutes). As discussed earlier, the sample was approximately representative of the British population on several demographic variables, reducing the likelihood that participation differentially benefited or harmed any specific group.

E.3 Departures from Pre-Analysis Plan

Aside from some minor changes in the wording of questions, implementation of the survey only deviated from my pre-analysis plan in one way: rather than recruiting all participants through AMT, I employed a combination of this platform and advertising on social media (principally Facebook). I made this decision shortly after launching the survey, when it became clear that the AMT sample was less representative of the British population than anticipated. Since social media networks are widely used in the United Kingdom, I believed that incorporating them into my recruitment strategy would help to address this problem. This deviation neither concerns my hypotheses nor materially alters the empirical strategy set out in the pre-analysis plan.

E.4 Summary Statistics

TABLE A24. Summary Statistics for Survey Experimental Dataset

Statistic	N	Mean	St. Dev.	Min	Max
Complementarity Treatment	795	0.323	0.468	0	1
Substitution Treatment	795	0.325	0.468	0	1
Agree: Reduce Income Differences	791	69.282	25.039	0	100
Agree: Increase Unemployment Benefits	791	67.912	24.696	0	100
Agree: Increase Social Spending	790	68.665	24.569	0	100
Vote Choice: Labour	795	0.278	0.448	0	1
Vote Choice: Conservative	795	0.201	0.401	0	1
Vote Choice: Reform UK	795	0.289	0.454	0	1
Female	795	0.489	0.500	0	1
White	795	0.843	0.364	0	1
Party ID: Conservative	795	0.249	0.433	0	1
Party ID: Labour	795	0.262	0.440	0	1
Party ID: Liberal Democrats	795	0.128	0.335	0	1
Party ID: Reform UK	795	0.231	0.422	0	1
Party ID: Green	795	0.048	0.213	0	1
Age: 18–24	795	0.102	0.303	0	1
Age: 25–29	795	0.118	0.323	0	1
Age: 30–34	795	0.135	0.342	0	1
Age: 35–39	795	0.146	0.353	0	1
Age: 40–44	795	0.104	0.306	0	1
Age: 45–49	795	0.104	0.306	0	1
Age: 50–54	795	0.098	0.298	0	1
Age: 55–59	795	0.099	0.299	0	1
Age: 60–64	795	0.092	0.289	0	1
Income: £0–£9,999	795	0.088	0.284	0	1
Income: £10,000–£24,999	795	0.229	0.420	0	1
Income: £25,000–£39,999	795	0.260	0.439	0	1
Income: £40,000–£59,999	795	0.158	0.365	0	1
Income: £60,000–£79,999	795	0.113	0.317	0	1
Income: £80,000–£99,999	795	0.093	0.291	0	1
Income: £100,000–£149,999	795	0.050	0.219	0	1
Income: £150,000+	795	0.003	0.050	0	1
Education: Doctorate	795	0.009	0.093	0	1
Education: Secondary/Further	795	0.205	0.404	0	1
Education: Master's Degree	795	0.138	0.345	0	1
Education: No Qualification	795	0.052	0.221	0	1
Education: Primary School	795	0.068	0.252	0	1
Education: Professional Degree	795	0.122	0.328	0	1
Education: Secondary School up to 16 Years	795	0.114	0.319	0	1
Education: Undergraduate Degree	795	0.208	0.406	0	1
Education: Vocational	795	0.084	0.278	0	1
AAIOE	767	0.149	0.887	−2.034	1.237
Subjective AI Exposure	767	61.806	30.023	0	100

Notes: The sample comprises 795 working-age adults based in the United Kingdom, who were recruited through a combination of AMT and advertising on social media in late 2024 and early 2025.

TABLE A25. Balance Table for Survey Experiment

Covariate	Control Group Mean	Complementarity Treatment Group Mean	Complementarity Std. Difference in Means	Substitution Treatment Group Mean	Substitution Std. Difference in Means
Female	0.439	0.494	0.055	0.539	0.099
White	0.846	0.821	-0.025	0.860	0.014
Age: 18-24	0.093	0.097	0.004	0.116	0.023
Age: 25-29	0.136	0.109	-0.027	0.109	-0.027
Age: 30-34	0.136	0.132	-0.003	0.136	0.000
Age: 35-39	0.139	0.132	-0.007	0.167	0.027
Age: 40-44	0.082	0.113	0.031	0.120	0.038
Age: 45-49	0.079	0.152	0.073	0.085	0.007
Age: 50-54	0.107	0.089	-0.018	0.097	-0.010
Age: 55-59	0.107	0.086	-0.022	0.105	-0.002
Age: 60-64	0.118	0.089	-0.028	0.066	-0.052
Income: £0-£9,999	0.086	0.105	0.019	0.074	-0.012
Income: £10,000-£24,999	0.236	0.198	-0.037	0.252	0.016
Income: £25,000-£39,999	0.261	0.265	0.004	0.256	-0.005
Income: £40,000-£59,999	0.154	0.160	0.006	0.163	0.009
Income: £60,000-£79,999	0.104	0.113	0.009	0.124	0.020
Income: £80,000-£99,999	0.093	0.109	0.016	0.078	-0.015
Income: £100,000-£149,999	0.054	0.047	-0.007	0.050	-0.003
Income: £150,000+	0.000	0.004	0.004	0.004	0.004
Education: No Qualification	0.054	0.062	0.009	0.039	-0.015
Education: Primary School	0.057	0.082	0.025	0.066	0.009
Education: Secondary School Up to 16 Years	0.225	0.206	-0.019	0.182	-0.043
Education: Secondary/Further	0.118	0.097	-0.021	0.128	0.010
Education: Vocational	0.089	0.089	0.000	0.074	-0.016
Education: Undergraduate Degree	0.218	0.160	-0.058	0.244	0.026
Education: Master's Degree	0.121	0.156	0.034	0.140	0.018
Education: Professional Degree	0.114	0.140	0.026	0.112	-0.002
Education: Doctorate	0.004	0.008	0.004	0.016	0.012
Party ID: Conservative	0.186	0.257	0.071	0.310	0.124
Party ID: Labour	0.211	0.257	0.046	0.322	0.111
Party ID: Liberal Democrats	0.132	0.136	0.004	0.116	-0.016
Party ID: Reform UK	0.314	0.218	-0.096	0.155	-0.159
Party ID: Green	0.054	0.051	-0.003	0.039	-0.015

Notes: Mean covariate values for the control and treatment groups in the survey experiment. The fourth and sixth columns report unadjusted standardized mean differences between the treatment and control groups; values between -0.2 and 0.2 indicate that a covariate is well balanced. The sample comprises 795 working-age adults based in the United Kingdom, who were recruited through a combination of AMT and advertising on social media in late 2024 and early 2025 (see Table A24 for summary statistics).

E.5 Additional Results

TABLE A26. Full Survey Experiment Results: Support for Redistribution Outcomes

Outcome = Agree the Government Should...	Reduce Income Differences		Increase Unemployment Benefits		Increase Social Spending	
	(1)	(2)	(3)	(4)	(5)	(6)
Complementarity Treatment	−10.219***		−10.670***		−10.087***	
	(2.079)		(2.042)		(1.990)	
Substitution Treatment		8.174***		8.296***		8.933***
		(1.721)		(1.630)		(1.659)
Female	−5.138**	−1.576	−4.283*	−1.145	−3.549	−1.805
	(2.315)	(1.892)	(2.274)	(1.792)	(2.217)	(1.825)
White	6.575**	5.706**	5.991**	3.772	8.503***	5.414**
	(2.880)	(2.467)	(2.828)	(2.336)	(2.755)	(2.377)
Age: 18–24	2.832	−2.224	4.127	1.948	4.834	−1.441
	(4.840)	(3.966)	(4.754)	(3.756)	(4.629)	(3.821)
Age: 25–29	6.771	0.547	5.374	0.859	7.765*	3.110
	(4.378)	(3.668)	(4.300)	(3.474)	(4.187)	(3.534)
Age: 30–34	11.983***	−2.211	12.152***	−2.665	14.123***	−2.711
	(4.366)	(3.742)	(4.288)	(3.544)	(4.176)	(3.605)
Age: 35–39	8.960**	4.481	6.865	5.809*	11.786***	5.843*
	(4.372)	(3.653)	(4.293)	(3.460)	(4.181)	(3.519)
Age: 40–44	0.557	3.462	−2.684	5.123	1.493	4.093
	(4.608)	(3.826)	(4.525)	(3.623)	(4.407)	(3.685)
Age: 45–49	−3.329	0.429	−3.326	3.486	−2.848	0.095
	(4.404)	(4.040)	(4.325)	(3.826)	(4.212)	(3.892)
Age: 50–54	−1.753	−2.933	−0.682	−1.925	2.268	−0.160
	(4.541)	(3.765)	(4.460)	(3.565)	(4.367)	(3.648)
Age: 55–59	−0.561	0.908	−1.058	−1.119	−0.245	−0.415
	(4.568)	(3.791)	(4.486)	(3.590)	(4.369)	(3.651)
Income: £0–£9,999	−0.212	−2.170	2.338	−5.486	3.579	−1.030
	(5.617)	(4.745)	(5.516)	(4.494)	(5.372)	(4.571)
Income: £10,000–£24,999	13.469***	7.936**	15.601***	6.901*	15.654***	8.106**
	(4.741)	(3.801)	(4.656)	(3.600)	(4.537)	(3.662)
Income: £100,000–£149,999	1.989	10.360**	6.273	11.426***	3.960	11.411**
	(5.704)	(4.659)	(5.602)	(4.413)	(5.456)	(4.488)
Income: £150,000+	22.254	26.519	19.708	30.549*	20.413	25.046
	(23.838)	(19.434)	(23.412)	(18.406)	(22.800)	(18.720)
Income: £25,000–£39,999	7.506*	5.948	14.401***	9.670***	9.781**	6.350*
	(4.438)	(3.754)	(4.358)	(3.555)	(4.244)	(3.618)
Income: £40,000–£59,999	11.034**	6.226*	13.547***	4.788	11.888***	3.821
	(4.410)	(3.707)	(4.331)	(3.511)	(4.218)	(3.571)
Income: £60,000–£79,999	1.158	2.944	3.656	0.872	4.289	3.866
	(4.640)	(3.757)	(4.557)	(3.558)	(4.438)	(3.619)
Education: Primary School	−12.210**	6.058	−12.477**	−0.857	−12.294**	1.540
	(6.063)	(5.392)	(5.954)	(5.106)	(5.799)	(5.194)
Education: Secondary School up to 16 Years	−14.596***	2.575	−17.971***	−3.706	−14.436***	0.569
	(5.625)	(4.824)	(5.524)	(4.568)	(5.379)	(4.646)
Education: Secondary/Further	−16.830***	1.002	−14.023***	−2.285	−13.672***	0.318
	(5.195)	(4.566)	(5.102)	(4.324)	(4.972)	(4.401)
Education: Vocational	−15.474***	2.785	−15.191***	−1.019	−15.157***	−2.675
	(5.819)	(5.181)	(5.715)	(4.907)	(5.565)	(4.991)
Education: Undergraduate Degree	−9.311*	2.751	−6.698	0.339	−7.264	1.090
	(5.563)	(4.767)	(5.464)	(4.514)	(5.321)	(4.591)
Education: Professional Degree	−8.817	10.257**	−5.021	3.519	−8.424	5.353
	(5.946)	(5.178)	(5.840)	(4.904)	(5.687)	(4.988)
Education: Master's Degree	−8.537	7.041	−2.333	6.509	−3.097	8.167*
	(5.890)	(5.114)	(5.785)	(4.844)	(5.634)	(4.926)
Education: Doctorate	14.486	14.597	16.633	10.076	13.198	8.731
	(14.993)	(9.904)	(14.725)	(9.380)	(14.340)	(9.540)
Party ID: Conservative	−7.926*	−1.881	−4.640	2.417	−8.876**	−2.379
	(4.160)	(3.583)	(4.085)	(3.393)	(3.978)	(3.451)
Party ID: Labour	0.333	−1.587	3.759	3.253	1.115	−0.931
	(4.130)	(3.568)	(4.056)	(3.379)	(3.950)	(3.437)
Party ID: Liberal Democrats	−1.391	−4.664	1.642	1.859	−0.517	−2.212
	(4.588)	(4.024)	(4.506)	(3.811)	(4.389)	(3.876)
Party ID: Reform UK	6.708	2.759	9.959**	8.367**	6.894*	4.637
	(4.189)	(3.678)	(4.114)	(3.484)	(4.006)	(3.544)
Party ID: Green	−8.383	−4.660	−6.721	3.569	−4.030	3.476
	(5.796)	(5.040)	(5.692)	(4.774)	(5.614)	(4.923)
Constant	82.721***	72.420***	75.826***	65.823***	72.448***	66.041***
	(14.812)	(10.257)	(14.547)	(9.714)	(14.168)	(9.880)
N	533	534	533	534	532	533
Mean Outcome	74.515	74.515	73.275	73.275	73.951	73.951

Notes: Full results from the top panel of Figure 6. OLS estimates with robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A27. Full Survey Experiment Results: Vote Choice Outcomes

Outcome = Vote Choice	Labour Party		Conservative Party		Reform UK	
	(1)	(2)	(3)	(4)	(5)	(6)
Complementarity Treatment	−0.090***		0.084***		−0.085***	
	(0.031)		(0.032)		(0.027)	
Substitution Treatment		0.084**		−0.146***		0.169***
		(0.036)		(0.026)		(0.035)
Female	0.012	0.019	−0.008	−0.021	−0.034	−0.003
	(0.034)	(0.040)	(0.035)	(0.029)	(0.030)	(0.038)
White	0.004	−0.005	0.013	−0.005	−0.013	−0.005
	(0.043)	(0.052)	(0.044)	(0.037)	(0.038)	(0.050)
Age: 18–24	0.309	0.329	−0.261	−0.273	0.046	0.038
	(0.406)	(0.469)	(0.415)	(0.336)	(0.360)	(0.446)
Age: 25–29	0.316	0.362	−0.405	−0.355	0.057	0.016
	(0.403)	(0.466)	(0.411)	(0.333)	(0.357)	(0.442)
Age: 30–34	0.343	0.294	−0.283	−0.293	−0.030	−0.011
	(0.402)	(0.465)	(0.411)	(0.333)	(0.357)	(0.441)
Age: 35–39	0.316	0.307	−0.297	−0.310	0.042	0.000
	(0.402)	(0.464)	(0.411)	(0.332)	(0.357)	(0.441)
Age: 40–44	0.274	0.350	−0.310	−0.341	0.021	0.033
	(0.405)	(0.468)	(0.414)	(0.335)	(0.359)	(0.444)
Age: 45–49	0.373	0.408	−0.279	−0.298	0.002	−0.047
	(0.405)	(0.469)	(0.413)	(0.336)	(0.359)	(0.446)
Age: 50–54	0.443	0.479	−0.330	−0.359	0.045	−0.041
	(0.405)	(0.468)	(0.413)	(0.335)	(0.359)	(0.444)
Age: 55–59	0.375	0.407	−0.325	−0.324	0.041	−0.011
	(0.405)	(0.467)	(0.413)	(0.335)	(0.359)	(0.444)
Age: 60–64	0.301	0.377	−0.243	−0.340	−0.045	−0.038
	(0.405)	(0.469)	(0.414)	(0.335)	(0.359)	(0.445)
Income: £0–£9,999	−0.195	−0.408	−0.705***	−0.484**	0.048	0.124
	(0.225)	(0.267)	(0.230)	(0.191)	(0.199)	(0.254)
Income: £10,000–£24,999	−0.098	−0.333	−0.778***	−0.547***	0.088	0.186
	(0.226)	(0.263)	(0.230)	(0.188)	(0.200)	(0.250)
Income: £100,000–£149,999	−0.206	−0.436	−0.666***	−0.559***	0.168	0.291
	(0.236)	(0.276)	(0.241)	(0.197)	(0.209)	(0.262)
Income: £150,000+	−0.190	−0.692	−0.809*	−0.992***	0.334	0.876*
	(0.419)	(0.487)	(0.428)	(0.349)	(0.371)	(0.463)
Income: £25,000–£39,999	−0.166	−0.396	−0.757***	−0.549***	0.027	0.173
	(0.225)	(0.262)	(0.229)	(0.187)	(0.199)	(0.249)
Income: £40,000–£59,999	−0.112	−0.366	−0.798***	−0.515***	0.075	0.143
	(0.228)	(0.265)	(0.233)	(0.190)	(0.202)	(0.252)
Income: £60,000–£79,999	−0.187	−0.348	−0.802***	−0.603***	0.148	0.221
	(0.231)	(0.271)	(0.236)	(0.194)	(0.205)	(0.257)
Income: £80,000–£99,999	−0.258	−0.431	−0.724***	−0.569***	0.074	0.233
	(0.233)	(0.272)	(0.237)	(0.195)	(0.206)	(0.258)
Education: Primary School	−0.079	0.076	0.051	0.021	−0.009	−0.121
	(0.090)	(0.114)	(0.092)	(0.082)	(0.080)	(0.108)
Education: Secondary School up to 16 Years	−0.144*	0.162	0.089	−0.065	0.031	−0.146
	(0.084)	(0.102)	(0.085)	(0.073)	(0.074)	(0.097)
Education: Secondary/Further	−0.093	0.136	0.065	−0.059	0.012	−0.134
	(0.077)	(0.097)	(0.079)	(0.069)	(0.068)	(0.092)
Education: Vocational	−0.164*	0.211*	0.068	−0.070	0.062	−0.167
	(0.087)	(0.110)	(0.088)	(0.079)	(0.077)	(0.104)
Education: Undergraduate Degree	−0.118	0.082	0.116	−0.025	0.033	−0.079
	(0.083)	(0.101)	(0.084)	(0.072)	(0.073)	(0.096)
Education: Professional Degree	−0.136	0.166	0.235***	−0.032	0.029	−0.133
	(0.088)	(0.110)	(0.090)	(0.079)	(0.078)	(0.104)
Education: Master's Degree	−0.162*	0.110	−0.009	−0.111	0.182**	−0.021
	(0.088)	(0.108)	(0.089)	(0.078)	(0.078)	(0.103)
Education: Doctorate	0.015	0.187	−0.309	−0.115	0.322	−0.197
	(0.223)	(0.210)	(0.228)	(0.150)	(0.198)	(0.199)
Party ID: Conservative	0.083	0.124	0.627***	0.492***	−0.002	0.050
	(0.062)	(0.076)	(0.063)	(0.054)	(0.055)	(0.072)
Party ID: Labour	0.583***	0.537***	0.129**	0.029	0.024	0.090
	(0.061)	(0.076)	(0.063)	(0.054)	(0.054)	(0.072)
Party ID: Liberal Democrats	0.056	0.036	0.084	0.106*	−0.022	−0.044
	(0.068)	(0.085)	(0.070)	(0.061)	(0.060)	(0.081)
Party ID: Reform UK	0.095	−0.033	0.004	0.006	0.613***	0.697***
	(0.062)	(0.078)	(0.064)	(0.056)	(0.055)	(0.074)
Party ID: Green	0.014	0.026	0.009	0.025	−0.006	0.025
	(0.086)	(0.107)	(0.088)	(0.076)	(0.076)	(0.101)
Constant	0.015	0.187	0.691	0.885***	0.322	−0.197
	(0.412)	(0.452)	(0.421)	(0.324)	(0.365)	(0.429)
N	537	538	537	538	537	538
Mean Outcome	0.325	0.325	0.147	0.147	0.348	0.348

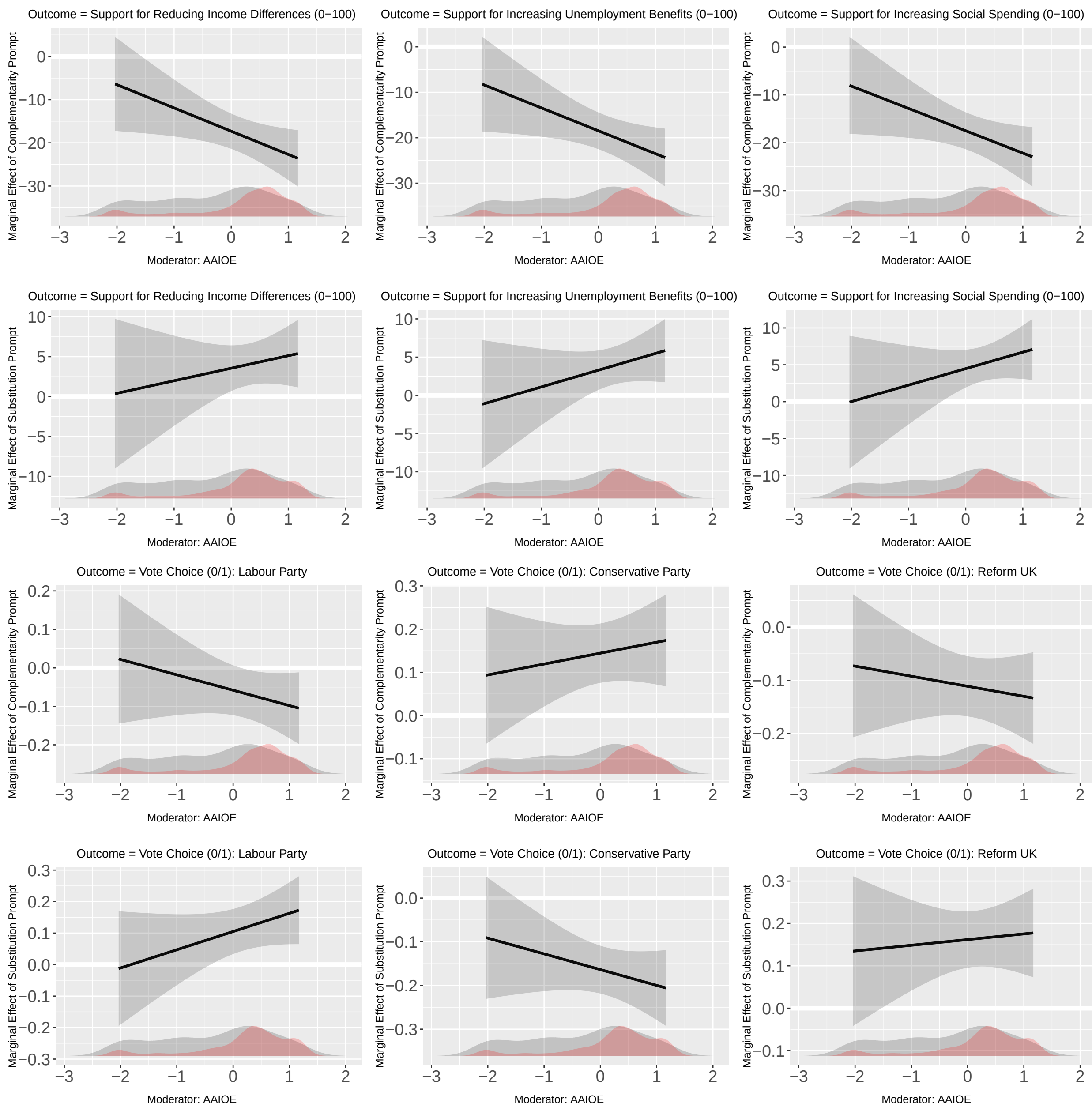
Notes: Full results from the middle panel of Figure 6. OLS estimates with robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A28. Full Survey Experiment Results: Work Performance Outcomes

Outcome = Agree AI Will...	Increase My Earnings		Improve My Efficiency		Create New Tasks for Me		Improve My Employability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Complementarity Prompt	5.789***		6.958***		5.452***		4.873***	
	(1.767)		(1.740)		(1.696)		(1.732)	
Substitution Treatment		−10.882***		−9.675***		−9.388***		−13.588***
		(1.987)		(1.883)		(1.864)		(1.914)
Female	3.852*	−0.739	1.080	−2.112	1.289	−0.604	1.841	−0.193
	(1.968)	(2.184)	(1.941)	(2.070)	(1.885)	(2.043)	(1.929)	(2.105)
White	4.199*	10.495***	4.889**	11.567***	1.890	9.684***	5.089**	13.002***
	(2.448)	(2.847)	(2.407)	(2.699)	(2.359)	(2.688)	(2.399)	(2.739)
Age: 18–24	5.321	4.574	2.981	1.826	5.089	4.020	4.722	1.153
	(4.114)	(4.578)	(4.065)	(4.339)	(3.951)	(4.297)	(4.032)	(4.403)
Age: 25–29	3.261	2.426	3.191	2.181	4.428	2.100	4.723	1.389
	(3.722)	(4.234)	(3.659)	(4.013)	(3.564)	(3.959)	(3.647)	(4.073)
Age: 30–34	6.548*	7.921*	6.274*	7.163*	5.263	7.356*	6.953*	5.331
	(3.711)	(4.319)	(3.649)	(4.094)	(3.553)	(4.038)	(3.637)	(4.154)
Age: 35–39	7.774**	12.781***	6.160*	10.579***	5.866*	10.421***	8.828**	12.347***
	(3.716)	(4.217)	(3.653)	(3.997)	(3.558)	(3.943)	(3.642)	(4.055)
Age: 40–44	0.739	−0.613	0.767	−0.595	2.297	−1.370	0.004	0.043
	(3.917)	(4.416)	(3.851)	(4.185)	(3.751)	(4.129)	(3.839)	(4.246)
Age: 45–49	1.582	3.945	−1.563	0.810	1.479	4.330	1.348	2.972
	(3.744)	(4.663)	(3.681)	(4.420)	(3.584)	(4.361)	(3.669)	(4.515)
Age: 50–54	2.160	−0.611	−0.426	−3.313	0.676	−1.402	2.148	−1.719
	(3.860)	(4.345)	(3.795)	(4.119)	(3.696)	(4.062)	(3.783)	(4.179)
Age: 55–59	−0.801	−3.434	−5.395	−5.281	−2.835	−3.991	−2.038	−4.467
	(3.883)	(4.375)	(3.817)	(4.147)	(3.717)	(4.090)	(3.805)	(4.207)
Income: £0–£9,999	−4.568	−3.067	−6.192	−2.102	−3.905	−0.803	−2.485	0.959
	(4.775)	(5.477)	(4.702)	(5.191)	(4.626)	(5.174)	(4.679)	(5.302)
Income: £10,000–£24,999	−2.868	−0.272	−2.462	2.121	−0.915	3.231	−0.589	2.764
	(4.030)	(4.388)	(3.963)	(4.159)	(3.866)	(4.108)	(3.949)	(4.219)
Income: £100,000–£149,999	−0.118	−12.062**	−4.697	−7.412	0.271	−6.621	−1.656	−7.779
	(4.849)	(5.378)	(4.767)	(5.098)	(4.642)	(5.028)	(4.752)	(5.172)
Income: £150,000+	1.132	−11.948	4.085	−7.204	3.643	−3.561	6.154	−0.169
	(20.263)	(22.432)	(19.922)	(21.262)	(19.400)	(20.971)	(19.859)	(21.570)
Income: £25,000–£39,999	0.531	3.508	−2.476	3.712	1.219	5.126	0.640	4.614
	(3.772)	(4.333)	(3.710)	(4.107)	(3.616)	(4.055)	(3.697)	(4.167)
Income: £40,000–£59,999	−5.537	−0.973	−4.551	1.975	−1.194	0.064	−1.846	0.086
	(3.749)	(4.279)	(3.686)	(4.056)	(3.590)	(4.001)	(3.674)	(4.115)
Income: £60,000–£79,999	−6.057	−4.413	−5.439	−3.208	−4.440	−2.356	−3.485	−1.205
	(3.944)	(4.336)	(3.878)	(4.110)	(3.777)	(4.054)	(3.866)	(4.170)
Education: Primary School	−0.563	2.444	−0.880	6.766	−6.204	−1.083	−4.340	2.389
	(5.154)	(6.223)	(5.068)	(5.899)	(4.936)	(5.818)	(5.051)	(5.985)
Education: Secondary School up to 16 Years	7.026	0.118	3.185	1.204	2.085	−0.913	3.801	0.849
	(4.781)	(5.568)	(4.730)	(5.277)	(4.584)	(5.205)	(4.686)	(5.363)
Education: Higher/Further	2.468	1.823	2.367	4.351	−0.602	−0.022	−1.153	0.180
	(4.416)	(5.270)	(4.344)	(4.996)	(4.233)	(4.934)	(4.328)	(5.068)
Education: Vocational	8.468*	−0.474	1.731	−2.061	3.326	−0.211	4.201	−0.644
	(4.946)	(5.980)	(4.865)	(5.668)	(4.742)	(5.591)	(4.847)	(5.751)
Education: Undergraduate Degree	14.451***	10.276*	10.121**	10.191*	8.050*	7.327	9.302**	10.098*
	(4.729)	(5.502)	(4.652)	(5.215)	(4.559)	(5.145)	(4.635)	(5.291)
Education: Professional Degree	16.609***	14.428**	13.121***	14.662***	10.701**	11.432**	12.104**	13.103**
	(5.054)	(5.977)	(4.970)	(5.665)	(4.880)	(5.609)	(4.954)	(5.748)
Education: Master's Degree	16.942***	16.463***	13.211***	17.801***	13.621***	16.244***	12.927***	15.440***
	(5.007)	(5.903)	(4.925)	(5.595)	(4.811)	(5.521)	(4.907)	(5.677)
Education: Doctorate	−8.686	8.681	−12.339	5.998	−1.741	9.671	−4.822	8.793
	(12.745)	(11.431)	(12.530)	(10.835)	(12.213)	(10.690)	(12.490)	(10.994)
Party ID: Conservative	8.989**	5.951	4.521	−4.322	4.880	−0.694	5.457	2.107
	(3.536)	(4.135)	(3.476)	(3.920)	(3.393)	(3.881)	(3.465)	(3.977)
Party ID: Labour	2.587	−2.503	0.604	−11.495***	1.924	−6.361*	1.317	−3.715
	(3.510)	(4.118)	(3.456)	(3.903)	(3.361)	(3.852)	(3.440)	(3.960)
Party ID: Liberal Democrats	0.266	3.657	−2.500	−7.992*	−1.436	−1.454	0.993	−0.243
	(3.900)	(4.645)	(3.835)	(4.403)	(3.734)	(4.344)	(3.822)	(4.481)
Party ID: Reform UK	8.631**	11.389***	2.824	−2.027	7.168**	7.102*	6.743*	8.136**
	(3.561)	(4.246)	(3.501)	(4.024)	(3.410)	(3.973)	(3.490)	(4.083)
Party ID: Green	−0.710	−1.086	−4.981	−11.521**	−3.348	−6.207	−2.485	−3.897
	(4.927)	(5.818)	(4.844)	(5.514)	(4.717)	(5.439)	(4.829)	(5.595)
Constant	41.074***	56.223***	45.419***	60.721***	55.222***	61.294***	49.438***	56.809***
	(12.591)	(11.839)	(12.379)	(11.221)	(12.056)	(11.069)	(12.339)	(11.390)
N	533	534	532	534	531	531	533	533
Mean Outcome	64.566	64.566	63.526	63.526	63.928	63.928	63.912	63.912

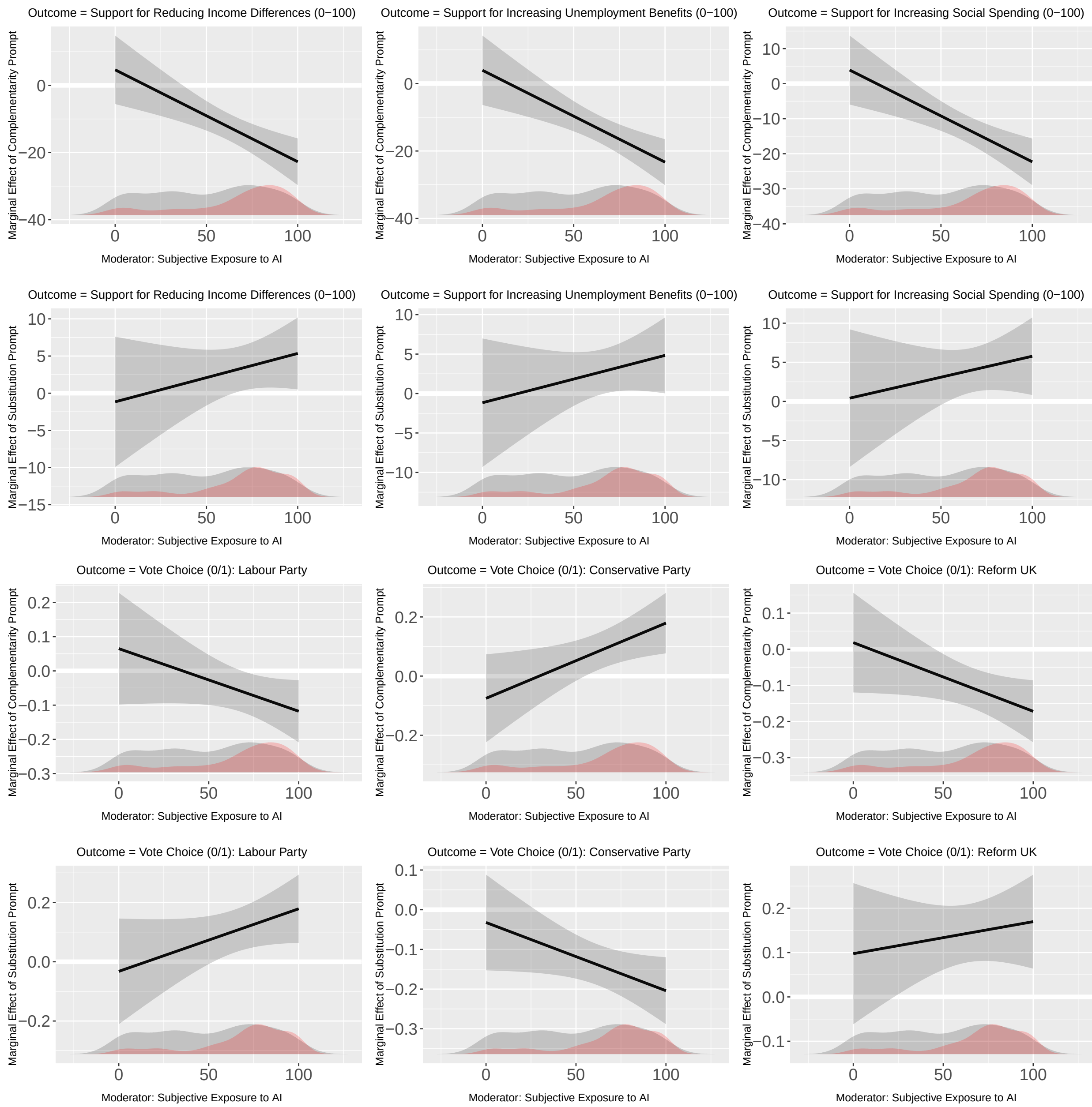
Notes: Full results from the bottom panel of Figure 6. OLS estimates with robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

FIGURE A4. Survey Experimental Treatment Effects Moderated by Occupational Exposure to AI



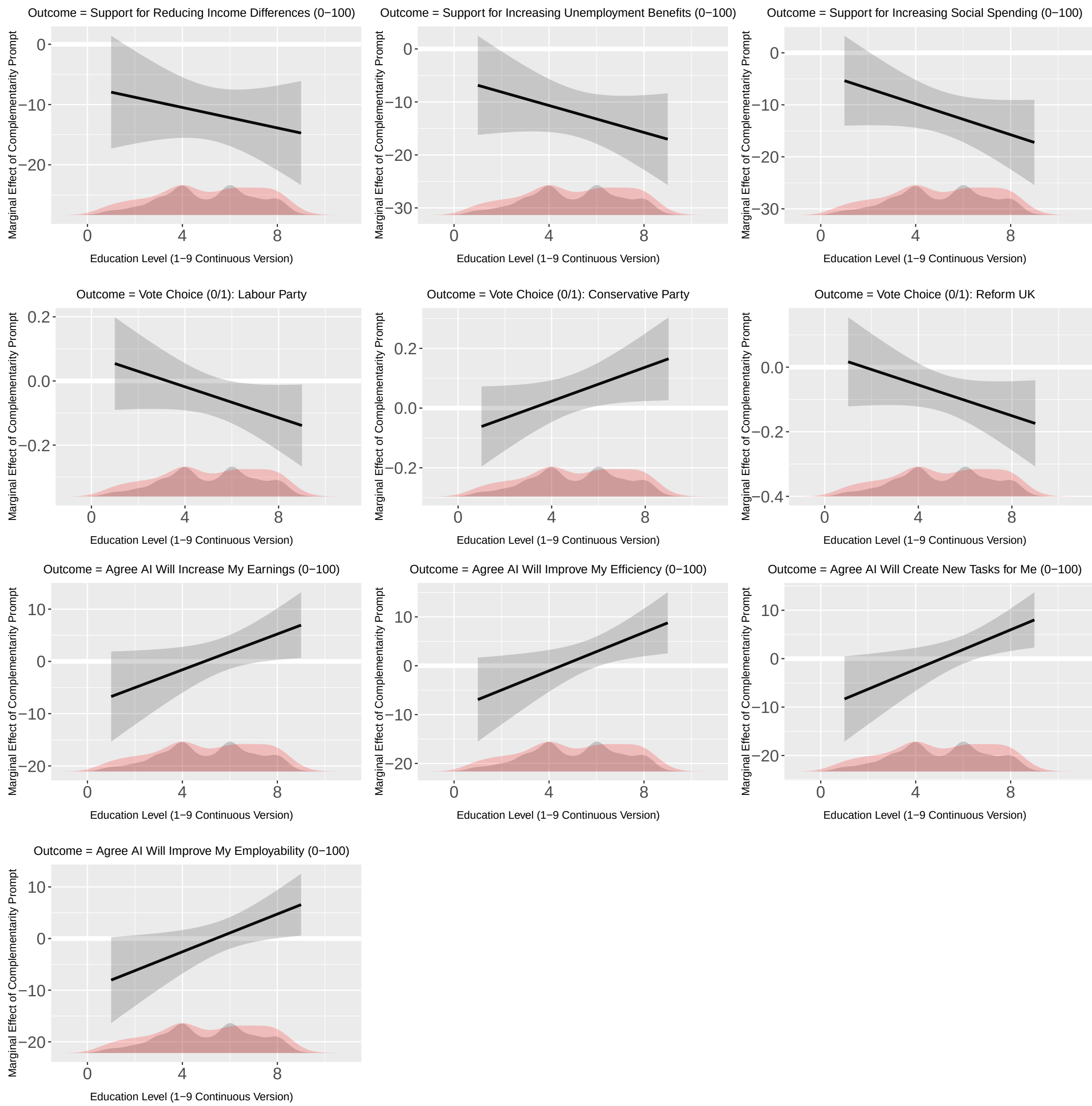
Notes: Marginal effect estimates from a modified version of Equation 10 in which C_i and S_i are interacted with respondent i's AAIOE score (at the 2-digit ISCO-08 level). Shaded bands represent 95% confidence intervals. All models control for age, gender, ethnicity, income, education level, and party identification. Estimates are computed with the **interflex** package in R (Hainmueller, Mummolo, and Xu 2019).

FIGURE A5. Survey Experimental Treatment Effects Moderated by Subjective Occupational Exposure to AI



Notes: Marginal effect estimates from a modified version of Equation 10 in which C_i and S_i are interacted with respondent i's response to a survey question about the compatibility between i's occupational tasks and AI's current and likely future capabilities. Shaded bands represent 95% confidence intervals. All models control for age, gender, ethnicity, income, education level, and party identification. Estimates are computed with the **interflex** package in R (Hainmueller, Mummolo, and Xu 2019).

FIGURE A6. Within-Occupation Survey Experimental Treatment Effects Moderated by Education Level



Notes: Marginal effect estimates from a modified version of Equation 10 in which C_i is interacted with respondent i's level of education (converted from a categorical to a continuous scale) and 2-digit ISCO-08 fixed effects are included. Shaded bands represent 95% confidence intervals. All models control for age, gender, ethnicity, income, and party identification. Estimates are computed with the **interflex** package in R (Hainmueller, Mummolo, and Xu 2019).

TABLE A29. Results of Survey Experimental Mediation Analyses

Treatment Variable		Mediator Variable		Outcome Variable	Average Causal Mediation Effect Estimate	95% CIs	Average Direct Effect Estimate	95% CIs
Randomized Prompt		Agree AI Will. . .		Agree the Government Should. . .	*Panel A: Explaining Redistribution Preferences*			
Complementarity	⟶	Increase My Earnings	⟶	Reduce Income Differences	1.069**	[0.268, 2.170]	-17.483***	[-21.559, -12.930]
Complementarity	⟶	Improve My Efficiency	⟶	Reduce Income Differences	1.290***	[0.532, 2.190]	-18.220***	[-21.333, -14.800]
Complementarity	⟶	Create New Tasks for Me	⟶	Reduce Income Differences	1.112***	[0.517, 1.900]	-17.763***	[-21.549, -13.890]
Complementarity	⟶	Improve my Employability	⟶	Reduce Income Differences	1.371***	[0.333, 2.570]	-17.819***	[-21.479, -13.620]
Complementarity	⟶	Increase My Earnings	⟶	Increase Unemployment Benefits	1.481***	[0.593, 2.430]	-17.704***	[-21.410, -13.570]
Complementarity	⟶	Improve My Efficiency	⟶	Increase Unemployment Benefits	1.329***	[0.609, 2.250]	-17.903***	[-21.075, -13.980]
Complementarity	⟶	Create New Tasks for Me	⟶	Increase Unemployment Benefits	1.224**	[0.393, 2.150]	-17.996***	[-21.486, -13.810]
Complementarity	⟶	Improve my Employability	⟶	Increase Unemployment Benefits	1.788***	[0.947, 2.750]	-18.264***	[-22.665, -14.590]
Complementarity	⟶	Increase My Earnings	⟶	Increase Social Spending	0.878***	[0.202, 1.680]	-17.284***	[-20.623, -13.430]
Complementarity	⟶	Improve My Efficiency	⟶	Increase Social Spending	1.063***	[0.279, 1.870]	-17.285***	[-21.291, -12.780]
Complementarity	⟶	Create New Tasks for Me	⟶	Increase Social Spending	1.013***	[0.300, 1.770]	-17.117***	[-20.443, -13.300]
Complementarity	⟶	Improve my Employability	⟶	Increase Social Spending	1.448***	[0.577, 2.540]	-17.859***	[-21.608, -14.300]
Substitution	⟶	Increase My Earnings	⟶	Reduce Income Differences	-1.596***	[-2.652, -0.500]	15.756***	[11.875, 19.710]
Substitution	⟶	Improve My Efficiency	⟶	Reduce Income Differences	-1.621***	[-2.478, -0.700]	15.855***	[12.682, 19.470]
Substitution	⟶	Create New Tasks for Me	⟶	Reduce Income Differences	-1.430**	[-2.975, -0.290]	15.673***	[12.619, 18.450]
Substitution	⟶	Improve my Employability	⟶	Reduce Income Differences	-2.522***	[-3.937, -1.220]	16.681***	[13.123, 20.620]
Substitution	⟶	Increase My Earnings	⟶	Increase Unemployment Benefits	-2.076***	[-3.394, -1.010]	16.590***	[13.518, 20.370]
Substitution	⟶	Improve My Efficiency	⟶	Increase Unemployment Benefits	-1.652***	[-2.829, -0.530]	16.132***	[13.193, 19.500]
Substitution	⟶	Create New Tasks for Me	⟶	Increase Unemployment Benefits	-1.793***	[-3.046, -0.680]	16.213***	[12.803, 19.390]
Substitution	⟶	Improve my Employability	⟶	Increase Unemployment Benefits	-3.281***	[-4.730, -1.920]	17.807***	[14.742, 20.880]
Substitution	⟶	Increase My Earnings	⟶	Increase Social Spending	-1.386***	[-2.545, -0.340]	15.923***	[12.860, 18.830]
Substitution	⟶	Improve My Efficiency	⟶	Increase Social Spending	-1.272**	[-2.289, -0.140]	16.096***	[13.284, 19.670]
Substitution	⟶	Create New Tasks for Me	⟶	Increase Social Spending	-1.452***	[-2.538, -0.550]	15.866***	[12.924, 18.940]
Substitution	⟶	Improve my Employability	⟶	Increase Social Spending	-2.472***	[-3.892, -1.370]	17.045***	[14.136, 19.950]
Randomized Prompt		Agree the Government Should. . .		Vote Choice	*Panel B: Explaining Voting Preferences*			
Complementarity	⟶	Reduce Income Differences	⟶	Labour Party	-0.038***	[-0.064, -0.020]	-0.111***	[-0.195, -0.050]
Complementarity	⟶	Increase Unemployment Benefits	⟶	Labour Party	-0.039***	[-0.058, -0.020]	-0.107***	[-0.162, -0.030]
Complementarity	⟶	Increase Social Spending	⟶	Labour Party	-0.045***	[-0.065, -0.030]	-0.104**	[-0.165, -0.040]
Complementarity	⟶	Reduce Income Differences	⟶	Conservative Party	0.0674***	[0.044, 0.090]	0.106***	[0.043, 0.180]
Complementarity	⟶	Increase Unemployment Benefits	⟶	Conservative Party	0.064***	[0.041, 0.090]	0.112***	[0.044, 0.170]
Complementarity	⟶	Increase Social Spending	⟶	Conservative Party	0.075***	[0.052, 0.100]	0.101***	[0.052, 0.170]
Complementarity	⟶	Reduce Income Differences	⟶	Reform UK	-0.055***	[-0.086, -0.030]	-0.126***	[-0.176, -0.070]
Complementarity	⟶	Increase Unemployment Benefits	⟶	Reform UK	-0.059***	[-0.086, -0.040]	-0.122***	[-0.189, -0.070]
Complementarity	⟶	Increase Social Spending	⟶	Reform UK	-0.055***	[-0.081, -0.030]	-0.125***	[-0.189, -0.060]
Substitution	⟶	Reduce Income Differences	⟶	Labour Party	0.030***	[0.014, 0.040]	0.167***	[0.094, 0.230]
Substitution	⟶	Increase Unemployment Benefits	⟶	Labour Party	0.031***	[0.013, 0.040]	0.166***	[0.101, 0.250]
Substitution	⟶	Increase Social Spending	⟶	Labour Party	0.037***	[0.020, 0.050]	0.162***	[0.097, 0.210]
Substitution	⟶	Reduce Income Differences	⟶	Conservative Party	-0.059***	[-0.081, -0.030]	-0.099***	[-0.149, -0.040]
Substitution	⟶	Increase Unemployment Benefits	⟶	Conservative Party	-0.060***	[-0.084, -0.040]	-0.092***	[-0.146, -0.040]
Substitution	⟶	Increase Social Spending	⟶	Conservative Party	-0.066***	[-0.090, -0.050]	-0.086***	[-0.141, -0.040]
Substitution	⟶	Reduce Income Differences	⟶	Reform UK	0.050***	[0.033, 0.070]	0.107**	[0.040, 0.170]
Substitution	⟶	Increase Unemployment Benefits	⟶	Reform UK	0.055***	[0.036, 0.080]	0.099**	[0.030, 0.170]
Substitution	⟶	Increase Social Spending	⟶	Reform UK	0.051***	[0.024, 0.080]	0.101**	[0.024, 0.180]

Notes: Average causal mediation effect (ACME) and average direct effect (ADE) estimates with 95% confidence intervals, based on a quasi-Bayesian Monte Carlo simulation method, in brackets. All estimates are computed using the **mediation** package in R (Tingley et al. 2014). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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