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The Political Economy of Artificial Intelligence

Evidence from Western Europe

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ABSTRACT

While advances in artificial intelligence (AI) are feared to bring about widespread job losses, workers 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 labor complementarities are expected to outweigh substitution effects—raising income without commensurately intensifying employment risks—exposure to AI should weaken rather than strengthen support for redistributive policies and their political advocates. I test this argument using a combination of observational and original experimental data from Western Europe, finding that occupation-level AI exposure 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.

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

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Abstract

While advances in artificial intelligence (AI) are feared to bring about widespread job losses, workers 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 labor complementarities are expected to outweigh substitution effects—raising income without commensurately intensifying employment risks—exposure to AI should weaken rather than strengthen support for redistributive policies and their political advocates. I test this argument using a combination of observational and original experimental data from Western Europe, finding that occupation-level AI exposure 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

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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 perhaps surprising, therefore, that AI's implications for core distributional questions of political economy—most notably how much redistribution individuals desire, a fundamental determinant of their policy attitudes and voting behavior—have not received more attention.[1] Research on the impact of digital technologies on redistribution preferences has focused primarily on the adoption of robots, computers, and other mechanized devices designed to automate routine occupational tasks. A central finding is that workers more exposed to routine-biased automation tend to 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 emphasizing demand for social protection against the risk of income loss (e.g., Iversen and Soskice 2001; Moene and Wallerstein 2001).[2] Extending this line of inquiry to voting behavior, Gingrich (2019) shows that automation exposure is also associated with greater support for parties on the left of the ideological spectrum, which are defined in large part by their commitment to advancing 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 central 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 systematic relationship between automation risk and redistribution preferences (Jeffrey 2021; Gallego and Kurer 2022; Bicchi, Kuo, and Gallego 2024).

market situation but also on their expected vulnerability to future employment risks. 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 technology-driven productivity gains are expected to raise demand for labor, exposed workers should anticipate higher relative earnings without a commensurate increase in unemployment risk, dampening their demand for redistribution. Mapping these preferences onto the traditional political spectrum, exposure should additionally 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 AI era is that, while public discourse has centered on the threat of widespread job losses, workers with greater exposure to the technology tend to express more optimism about its labor market consequences. This puzzle arises because exposure is a broader concept than displacement risk, capturing a technology's potential to alter the means by which tasks are performed and thus to *complement* as well as substitute for labor. Survey evidence indicates that workers whose jobs are most directly impacted by AI expect their relatively complex roles to be augmented and expanded rather than fully automated, spurring improvements in their future earnings and employment prospects (e.g., BCG GAMMA and Ipsos 2018; Lane, Williams, and Broecke 2023; Pew Research Center 2023; Jitterbit 2024; Stack Overflow 2024).[3] These expectations are consistent with a growing body of research linking AI adoption to higher 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 2021; Fossen and Sorgner 2022;

[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.

Aldasoro et al. 2026), and wage growth (Felten, Raj, and Seamans 2019; Stephany and Teutloff 2024; PwC 2025), while detecting few signs of aggregate 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 proposition that exposure to AI will be associated with weaker support for redistribution, the left, and the populist right but stronger support for the mainstream right. I expect these relationships to materialize after approximately 2010, when a series of breakthroughs in neural network architecture and deep learning triggered rising demand for AI skills 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 redistributive attitudes are well developed and AI adoption is 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 between 2010 and 2024. Controlling for country and survey wave fixed effects as well as standard socioeconomic characteristics, I find that AI exposure is negatively related to preferences for redistribution and voting for the left and the populist right yet positively related to voting for the mainstream right. These relationships emerge early in the sample period and remain robust across a range of specifications, including controls for automation risk and other occupational vulnerabilities associated with digital technologies, within-occupation and within-industry comparisons, and an instrumental variables strategy based on parental occupational characteristics.

A limitation of the ESS is that each wave draws a new sample of respondents, preventing us from accounting for fixed individual characteristics—a key source of potential confounding in observational survey research. While there are, to my knowledge, no longitudinal data sources on Western European attitudes toward redistribution during the period of interest, 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, I thus conduct a within-individual, difference-in-differences-style analysis of the relationship between AI exposure and support for Germany's main party families between 2000 and 2023. The results again comport with expectations: respondents with higher exposure become progressively less likely to support left-wing and right-wing populist parties yet more inclined to back mainstream right-wing parties. These patterns become apparent soon after 2010, mirroring the cross-national findings, and grow stronger in more recent waves.

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 treatments 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 report more positive expectations about AI's impact on their productivity and future earnings, express weaker support for redistribution, and are more likely to vote for the mainstream right-wing Conservative Party than respondents in the control group. By contrast, respondents receiving the substitution frame are less confident that AI will 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 among respondents with greater occupational exposure to AI—measured both objectively and subjectively—for whom the "stakes" of the information provided are higher.

Taken together, 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

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

(Gallego and Kurer 2022). Although often grouped together with "pure" automation techniques, AI is capable of enhancing and expanding human skills in ways that reinforce labor demand—a distinction with critical consequences for how exposed workers evaluate the trade-offs inherent in redistributive and social policy. The political implications are significant: if exposure to AI diminishes 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 routine-biased automation. Similarly, gains in support for the left and the populist right stemming from such demands may be offset by movement toward the mainstream right among AI-exposed workers, potentially increasing electoral polarization. However, these implications are by no means set in stone; rather, as discussed in the concluding section, they reflect contemporary expectations about AI's capabilities and labor market effects 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. New methods, tools, and systems of production can affect the returns to labor both by influencing its efficiency in performing existing tasks and by creating new ones 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 productivity gains are distributed across factors of production and tasks. In the early stages of a technology's adoption, the contours of this distribution are often uncertain and debated—AI representing a clear case in point.

The canonical model of how individuals' economic position shapes 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. If individuals are rational and forward-looking, their redistribution preferences should reflect not only their present financial situation but also their expected *future* earnings (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 economic returns 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 insurance models is that support for redistribution will strengthen with exposure to technologies that heighten the risk of future income loss or economic hardship. As the POUM conjecture implies, however, the desire for social protection need not dominate redistributive motives among rational individuals anticipating technology-induced wage gains. In other words, the expected degree of risk associated with an emerging technology could plausibly influence redistribution attitudes in the opposite direction from expected income gains. Consistent with the negative correlation between income and job insecurity (Cusack, Iversen, and Rehm 2006; Rehm, Hacker, and Schlesinger 2012), these expectations will often push preferences in the same direction, thereby shifting the stance even of risk-neutral individuals. To boost wages, technological change must generate sufficiently sizable gains in worker productivity to raise labor demand in exposed occupations, which typically reduces unemployment risk. Conversely, innovations that primarily substitute for—rather than complement—labor tend to depress wages and employment, increasing the likelihood of job loss. Nevertheless, some workers may anticipate a positive correlation between income and risk (Rehm, Hacker, and Schlesinger 2012), in which case demand for redistribution should depend on the relative size of expected changes along each dimension.[5]

More formally, consider a two-period setting in which individual i seeks to maximize the utility function $u(c_{i0}, c_{i1})$, where c_{i0} depends on y_{i0}, i's pretax income in period 0, and p_{i0}, i's probability of unemployment in period 0; and c_{i1} depends on income y_{i1} and unemployment risk p_{i1} in period 1.[6] Let τ denote a fixed linear tax rate determined at the start of period 0, which finances a lump-sum transfer to the unemployed, b, with a distortionary cost of $D\tau^2$ per person. Assuming that periods 0 and 1 are close enough that discounting is negligible, i's total expected consumption can be written as:

$$c_{i0} + c_{i1} = \overbrace{(1-\tau)[(1-p_{i0})y_{i0} + (1-p_{i1})y_{i1}]}^{\text{after-tax labor income}} + \overbrace{p_{i0}b_0 + p_{i1}b_1}^{\text{government transfer}} - \overbrace{2D\tau^2}^{\text{distortion}} \tag{1}$$

where

$$b_0 = \tau\frac{\overline{(1-p_0)y_0}}{\overline{p_0}} \qquad \text{and} \qquad b_1 = \tau\frac{\overline{(1-p_1)y_1}}{\overline{p_1}}. \tag{2}$$

[5] Of particular interest is the subgroup of workers who anticipate both high earnings *and* high unemployment risk, whose redistributive attitudes are likely to hinge on the availability of private alternatives to social insurance (Busemeyer and Iversen 2020; Iversen and Rehm 2022). Consequently, it may be challenging to empirically disentangle whether their stance reflects expectations about future earnings or a broader preference for social, private, or self-insurance. I return to this issue in the cross-national empirical analysis.

[6] Risk neutrality is assumed to simplify the exposition and avoid biasing conclusions toward either the insurance or the POUM approach.

Differentiating with respect to τ and rearranging yields the optimal tax rate for i:

$$\tau_i^* = \frac{1}{4D}\left(-y_{i0} - y_{i1} + p_{i0}y_{i0} + p_{i1}y_{i1} + p_{i0}\frac{\overline{(1-p_0)y_0}}{\overline{p_0}} + p_{i1}\frac{\overline{(1-p_1)y_1}}{\overline{p_1}}\right). \tag{3}$$

In both periods, the amount of redistribution preferred by i is decreasing in i's income and the society's average probability of unemployment but increasing in i's probability of unemployment and average income.

To characterize the impact of technological change, assume that individual i performs N tasks producing a unique final good, markets are competitive, and the only factors of production are capital and labor, the latter supplied inelastically. Building on the workhorse task-based approach to labor markets (Acemoglu and Restrepo 2018, 2019, 2020; Acemoglu 2024), i's equilibrium wage in period 0 can be expressed as:

$$y_{i0} = \overbrace{\left(\frac{X}{L}\right)^{\frac{1}{\sigma}}}^{\substack{\text{intrinsic}\\ \text{productivity}}} \overbrace{(G(N)A_L)^{\frac{\sigma-1}{\sigma}}}^{\substack{\text{technological}\\ \text{augmentation}}} \overbrace{\left(\int_I^N \gamma_L(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}}^{\text{task allocation}} \tag{4}$$

where X denotes the output produced by tasks $[0, N]$, L is the supply of labor for these tasks, σ is the elasticity of substitution between tasks, G is a general productivity multiplier associated with technology-enabled tasks, A_L indexes labor-augmenting technology specifically, $\gamma_L(z)$ denotes labor productivity in task $z \in [0, N]$, and I is the task threshold above which it is cost-minimizing to employ labor rather than capital.[7] Thus, the first term in Equation 4 represents labor's intrinsic productivity, while the second and third terms capture its marginal productivity from complementary technologies and task allocation, respectively.

[7] Section A.1 of the Supplementary Material provides a more detailed discussion of this setup. I focus on i's earnings because individuals typically lack well-defined expectations about aggregate economic outcomes (Andre et al. 2022; D'Acunto and Weber 2024).

Comparative statics reveal the wage effects of technological change:

$$d \ln y_i = \frac{1}{\sigma} d \ln \left(\frac{X}{L} \right) + \frac{\sigma - 1}{\sigma} (d \ln G + d \ln A_L) + \frac{1}{\sigma} d \ln \left(\int_I^N \gamma_L(z)^{\sigma-1} dz \right). \tag{5}$$

This expression implies that a new technology can influence individual i's earnings by altering multiple dimensions of the production process, most notably i's general and task-specific productivity, the number of tasks i performs, and the share of tasks allocated to labor. The net effect of changes in these parameters determines whether i's wage rises or declines in period 1.

Incorporating unemployment risk into this setup requires relaxing standard assumptions such as perfect competition, inelastic labor supply, and worker mobility across tasks. If filling job vacancies is costly or wages are inflexible, for instance, labor markets may not instantaneously match workers with employers, resulting in a positive probability of unemployment.[8] After-tax income will increase if a technological shock raises earnings ($dy_i > 0$) while reducing unemployment risk ($dp_i < 0$) and will decrease in the reverse scenario:

$$(1 - p_{i1}) y_{i1} \begin{cases} > (1 - p_{i0}) y_{i0} & \text{if } dy_i > 0,\ dp_i < 0 \\ < (1 - p_{i0}) y_{i0} & \text{if } dy_i < 0,\ dp_i > 0. \end{cases} \tag{6}$$

If dy_i and dp_i share the same sign, the net income effect will be indeterminate and depend on the precise ratio of the two changes.

In sum, a new technology that workers expect to improve their position in future income distributions and reduce their risk of job loss by expanding their productivity and range of tasks is likely to weaken their support for redistribution today. An innovation anticipated to lower relative future income and increase unemployment risk by curtailing output and task scope, on the other hand, should strengthen demand for redistribution. Finally, redistribution preferences

[8] Section A.3 of the Supplementary Material provides a brief formal account of how unemployment can arise from search frictions in labor markets.

become more ambiguous when income and risk are expected to move in the same direction, with the net effect hinging on the relative magnitude of each shift.

From Redistribution to Voting 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, numerous 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 of the framework: exposure to technologies anticipated to depress relative future income and increase unemployment risk will be associated with stronger support for the left, whereas exposure to technologies expected to boost relative future income and reduce unemployment risk will be associated with stronger support for the right.[9]

A likely exception to this logic lies at the populist end of the right-wing spectrum, where positions on redistributive policy have evolved substantially 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 stances on established ideological cleavages to broaden their appeal (Rovny 2013). As populist parties have emerged as major political actors over the past 15 years, however, they have predominantly embraced a pro-welfare stance on social policy, albeit one that tends to empha-

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

size assistance for "deserving" recipients (Harteveld 2016; Afonso and Rennwald 2018; Chueri 2022; Rathgeb and Busemeyer 2022). As Chueri (2022, 383) observes, "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 particularly plausible during the past 15 years (Goubin and Hooghe 2022; Enggist and Häusermann 2024).

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) exposure to this innovation in the workplace and (2) expectations about its impact on relative future income and unemployment risk. This section examines each component in the context of AI, allowing us to formulate testable hypotheses about the technology's impact 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 AI based on the technology's capacity to carry out specific standardized tasks.[10] Three such measures 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 core human functions; (2) Brynjolfsson, Mitchell, and Rock's (2018) Suitability for Machine Learning (SML) index, which is based on crowdsourced expert

[10] While technologies influence how tasks are performed, their labor market effects are typically aggregated to the level of occupations—that is, bundles of related tasks requiring specific combinations of skills—where workers are hired, human capital is valued, and key outcomes (such as wages and employment) are measured.

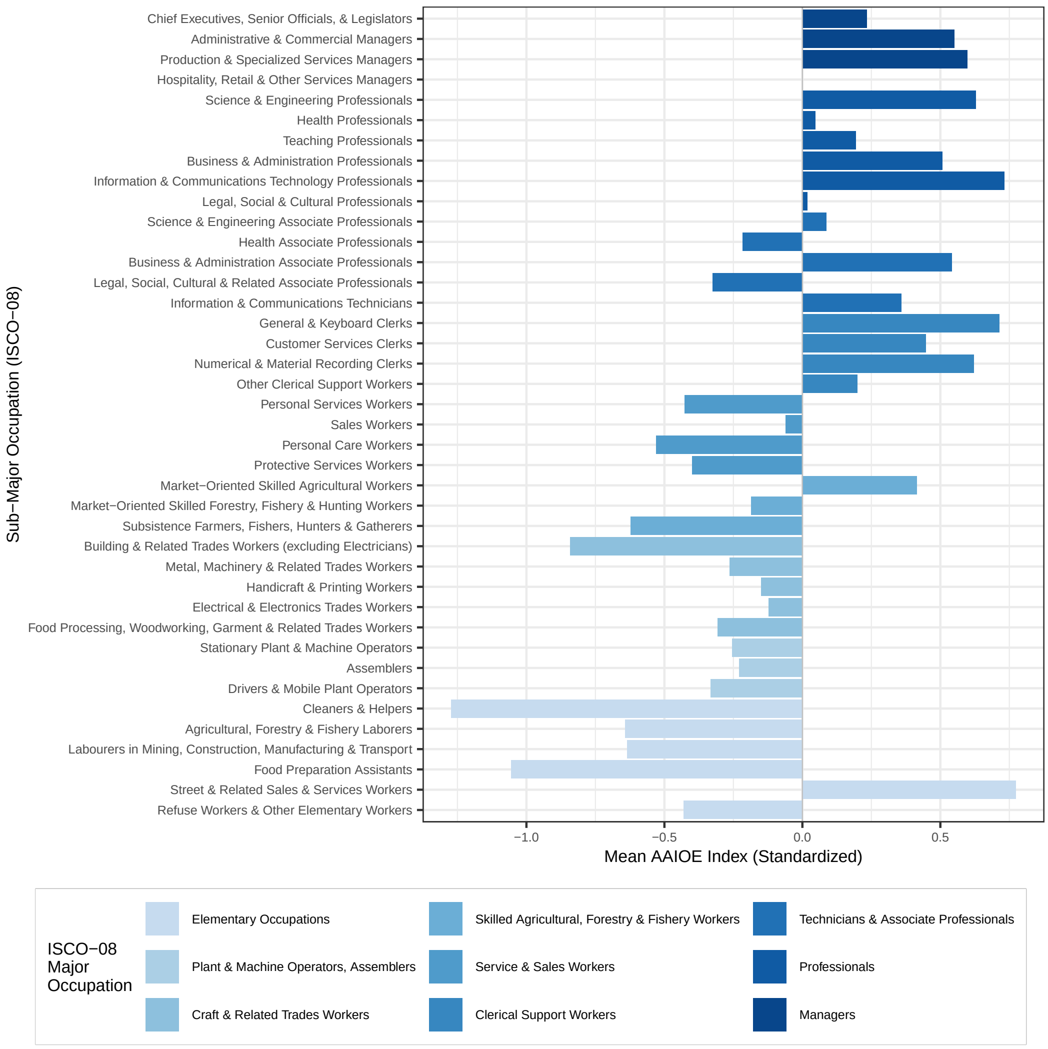
assessments of the potential for work activities to be codified in an algorithmic program; and (3) Webb's (2020) AI exposure index, which is constructed from the text of AI patents filed around the world. As Acemoglu et al. (2022) note, these indices are methodologically and substantively complementary: in addition to drawing on distinct sources of information and expertise, they capture AI's existing as well as potential future capabilities. Since these competences may either enhance labor productivity (by facilitating and creating tasks) or displace workers (by automating all tasks associated with an occupation), the measures are compatible with both substitution and complementarity dynamics. In other words, they provide a neutral metric that allows the direction and magnitude of AI's labor market effects to be determined empirically. I thus make use of all three measures in my empirical investigation, averaging their standardized scores to construct an Aggregate AI Occupational Exposure (AAIOE) index.[11]

Figure 1 provides an overview of exposure to AI based on the AAIOE, displaying its mean scores for "sub-major" (two-digit) categories of the latest International Standard Classification of Occupations (ISCO-08), which are grouped by shading into "major" (one-digit) categories.[12] 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 groups are information and communication technology (ICT) professionals (+0.7 SD relative to the mean AAIOE score), sales and services workers (+0.6 SD), general and keyboard clerks (+0.5 SD), science and engineering professionals (+0.4 SD), and business and administration professionals (+0.3 SD). The five least exposed occupations are cleaners and helpers (− 1.4 SD), food preparation assistants (− 1.2SD), building and related trades workers (−1.1 SD), agricultural, forestry, and fishery laborers (−0.8 SD), and subsistence

[11] The measures are equally weighted: $\text{AAIOE}_o = \frac{1}{3}(\text{AIOE}_o^{std} + \text{SML}_o^{std} + \text{Webb}_o^{std})$, where o denotes an occupation. In the empirical analyses, I standardize the AAIOE again to facilitate interpretation of its regression coefficient.

[12] The three components of the AAIOE are converted from the 2010 Standard Occupational Classification (SOC2010)—the taxonomy used in the United States—to ISCO-08. Figure A1 in the Supplementary Material disaggregates Figure 1 by AAIOE component, revealing reasonably strong correlations between the measures.

FIGURE 1. Exposure to Artificial Intelligence by Occupation



Notes: Mean values 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 (two-digit) ISCO-08 occupations, with shading representing major (one-digit) occupational groups.

farmers, fishers, hunters, and gatherers (−0.8 SD).[13] 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.

Notably, these patterns primarily reflect progress in AI achieved during the past 15 years.

[13]Table A1 in the Supplementary Material enumerates the 25 most and least exposed occupations at the most granular (four-digit) ISCO-08 level.

While many of the concepts underpinning contemporary AI were developed 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).[14] These developments, job postings indicate, precipitated 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).[15] 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.

During periods of rapid AI adoption, dynamic models of redistribution under uncertainty suggest that individuals will update their preferences incrementally as they experience and process new information about the technology's labor market consequences (Piketty 1995; Alesina and Angeletos 2005; Bénabou and Tirole 2006). In theory, attitudes should stabilize once AI becomes a mature technology and uncertainty about its impact diminishes, entrenching a new equilibrium in patterns of voting, party competition, and redistributive policymaking. Nevertheless, over the past 15 years—a period of accelerated AI development—I expect its individual-level effects to gradually intensify over time, reaching their greatest magnitude in recent years.[16] At the population level, this trajectory is less predictable because compositional changes in the workforce may offset or mask within-individual dynamics (for instance, if highly exposed workers who oppose extensive redistribution move into more insulated occupations). Regardless of

[14]Key AI breakthroughs in the early 2010s include the use of NVIDIA graphics processing units (GPUs) 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.

[15]They also prompted a surge in media coverage of AI and its implications for work (Fast and Horvitz 2017), as illustrated with statistics from the Factiva global news database in Figure A2 of the Supplementary Material.

[16]This is particularly plausible in light of heightened public interest in generative AI since the release of the ChatGPT conversational tool in 2022.

their trend, however, aggregate-level effects should remain observable.

Expectations about Future Income and Risk

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 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 2025), and management consulting (Dell'Acqua et al. 2023). Firms embracing AI, meanwhile, have enjoyed tangible increases in annual output per worker, accelerating revenue and employment growth (Alderucci et al. 2020; Damioli, Van Roy, and Vertesy 2021; Fossen and Sorgner 2022; Rammer, Fernández, and Czarnitzki 2022; Aldasoro et al. 2026).[17] Similarly, occupations and industries with greater exposure to the technology have experienced systematically faster productivity and wage growth, with AI-related 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 productivity gains do not appear to have come at the expense of aggregate employment (Felten, Raj, and Seamans 2019; Acemoglu et al. 2022; Brynjolfsson, Chandar, and Chen 2025; Humlum and Vestergaard 2025; Hampole et al. 2025), with some analyses finding evidence of *increased* hiring in AI-exposed occupations (Babina et al. 2024; Shen and Zhang 2024; Albanesi et al. 2025; PwC 2025). The task structure of such jobs is increasingly viewed as a

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

key explanation: higher-skilled occupations generally comprise a larger bundle of more diverse, complex, and discretionary tasks, only *some* of which can currently be performed by AI tools. As an OECD review of existing evidence summarizes, "While AI's capabilities have expanded substantially, some bottlenecks to adoption still remain, and many tasks still require humans to carry them out. Thus, much of the impact of AI on jobs is likely to be experienced through the reorganisation of tasks within an occupation, with some workers ultimately complemented in their work by AI, rather than substituted by it" (Lane and Saint-Martin 2021, 9).

Consistent with the previous findings, surveys indicate that workers with higher exposure to AI tend to harbor more positive expectations about its labor market consequences.[18] According to a recent Pew Research Center 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 with almost a quarter of retail trade workers.[19] In a similar vein, OECD surveys reveal that AI programmers in the financial and manufacturing sectors are, on average, more than twice as likely to expect their wages to rise over the next decade as they are to anticipate a decline (Lane, Williams, and Broecke 2023, 49). In cross-national surveys of AI users, large majorities expect the technology to boost their efficiency, salary, and job security in the near future (BCG GAMMA and Ipsos 2018; 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

[18] A general limitation of such evidence is its concentration in recent years: relatively few surveys were conducted in the early 2010s, and many of these conflated AI with earlier automation technologies.

[19] An earlier survey fielded by Gallup and Northeastern University (2018) finds that white-collar Americans are more likely than their blue-collar counterparts to predict that AI will positively affect people's lives over the next decade (78% versus 68%) and to already report such an impact on their own lives (87% versus 73%).

to their job (Stack Overflow 2024).

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 financial 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 better decisions (Lane, Williams, and Broecke 2023, 52).[20] On the employer side of the labor market, around half of AI-adopting firms credit the technology with introducing tasks not previously undertaken by their workforce. This finding echoes an earlier OECD survey of trade union confederations in which nearly two-thirds of respondents cite the creation of "new tasks and jobs" as a key benefit of AI adoption (Kramer and Cazes 2022, 23). Efficiency gains and opportunities to expand occupational skills and responsibilities are likewise highlighted as advantages of AI adoption by a substantial share of participants in the *Global Workforce Hopes and Fears Survey*, the *AI Attitudes Report*, and the *Developer Survey*.

Exposure to earlier automation technologies, by contrast, has been associated with more *negative* perceptions of their labor market effects. In the most comprehensive survey of public attitudes toward industrial robots, conducted by the Eurobarometer in 2012, 75% of manual workers agree that these devices "steal people's jobs," compared with 57% of managers and 68% of other white-collar workers (European Commission 2012, 26). Similarly, an econometric analysis of Pew Research Center's 2017 American Trends Panel finds that workers who perform manual and physical tasks are more likely to report that robots, computers, and digital communication tools have negatively impacted their job or career, whereas managers and data analysts are more

[20] In Lane, Williams, and Broecke's sample, 42% of employers in the financial sector and 29% in the manufacturing sector reported using AI as of 2022, figures consistent with the expectation that exposed workers would already be forming views about its labor market consequences.

apt to report positive effects (Dodel and Mesch 2020).[21] These findings suggest that—owing to their capacity to replicate entire bundles of rule-based, repetitive tasks—pre-AI automation technologies have primarily been viewed as a source of competition rather than productivity gains by exposed workers. In line with this interpretation, computerization and robotization have consistently been linked to the large-scale displacement of routine jobs in academic research (Autor, Levy, and Murnane 2003; Graetz and Michaels 2018; Acemoglu and Restrepo 2020) as well as in public discourse more broadly (Benanav 2020; Estlund 2021). Narratives around AI, on the other hand, have often emphasized themes such as productivity, augmentation, learning, and creativity (Nguyen and Hekman 2024; Petricini 2025; Zai, Rohrbach, and Hänggli Fricker 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 typically anticipate higher future earnings without a proportionate deterioration in their job prospects. These expectations reflect a combination of productivity gains in the performance of existing tasks ($dA_L > 0$) and the emergence of new tasks that rely intensively on human skills ($dN > 0$). The combined effect of these labor-complementing forces is assumed to outweigh any downward pressure on wages

[21] There is also evidence of negative perceptions among individuals directly exposed to these technologies in the workplace: in a 2018 survey of American companies adopting advanced robotics or related forms of automation, a majority of managers report employee concerns about job security (MindEdge Learning 2018).

and employment arising from AI-driven automation (dI):

$$\begin{aligned}
&\overbrace{\frac{\partial \ln y_i}{\partial \ln A_L}\,\Delta \ln A_L}^{\substack{\text{factor}\\ \text{augmentation}}} + \overbrace{\frac{\partial \ln y_i}{\partial N}\,\Delta N}^{\substack{\text{new}\\ \text{tasks}}} + \overbrace{\frac{\partial \ln y_i}{\partial I}\,\Delta I}^{\text{automation}} > 0, \\
&\overbrace{\frac{\partial \ln p_i}{\partial \ln A_L}\,\Delta \ln A_L}^{\substack{\text{factor}\\ \text{augmentation}}} + \overbrace{\frac{\partial \ln p_i}{\partial N}\,\Delta N}^{\substack{\text{new}\\ \text{tasks}}} + \overbrace{\frac{\partial \ln p_i}{\partial I}\,\Delta I}^{\text{automation}} \leq 0.
\end{aligned} \tag{7}$$

[22]

In light of these considerations, two principal hypotheses follow from the framework:

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

Linking redistribution preferences to the left-right dimension of political competition yields an additional three-part hypothesis:

H2 *During the same period, job-related 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.*

Cross-National Evidence from the European Social Survey

The first stage of the empirical investigation draws on ESS data collected in biennial waves, focusing first on redistribution preferences and then on voting behavior. The main analysis includes the 12 Western European countries that have participated in every ESS wave: Belgium, Finland, France, Germany, Ireland, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. As respondents are newly sampled in each wave, my identification strategy relies on variation within country-wave cells rather than within individ-

[22] Sections A.2 and A.3 of the Supplementary Material provide a more detailed explanation of each term in the first and second lines, respectively.

uals, rendering pretreatment survey waves unnecessary from an inferential perspective. Following several studies of AI's labor market effects (e.g., Alekseeva et al. 2021; Acemoglu et al. 2022; Squicciarini and Nachtigall 2021), I thus restrict the sample to waves from 2010 (or slightly earlier) onward, when exposure to the technology becomes empirically and substantively relevant. Each wave comprises between approximately 20,000 and 27,000 respondents, the vast majority of whom (91% on average) are employed at the time of fieldwork and thus eligible for inclusion in the analysis.

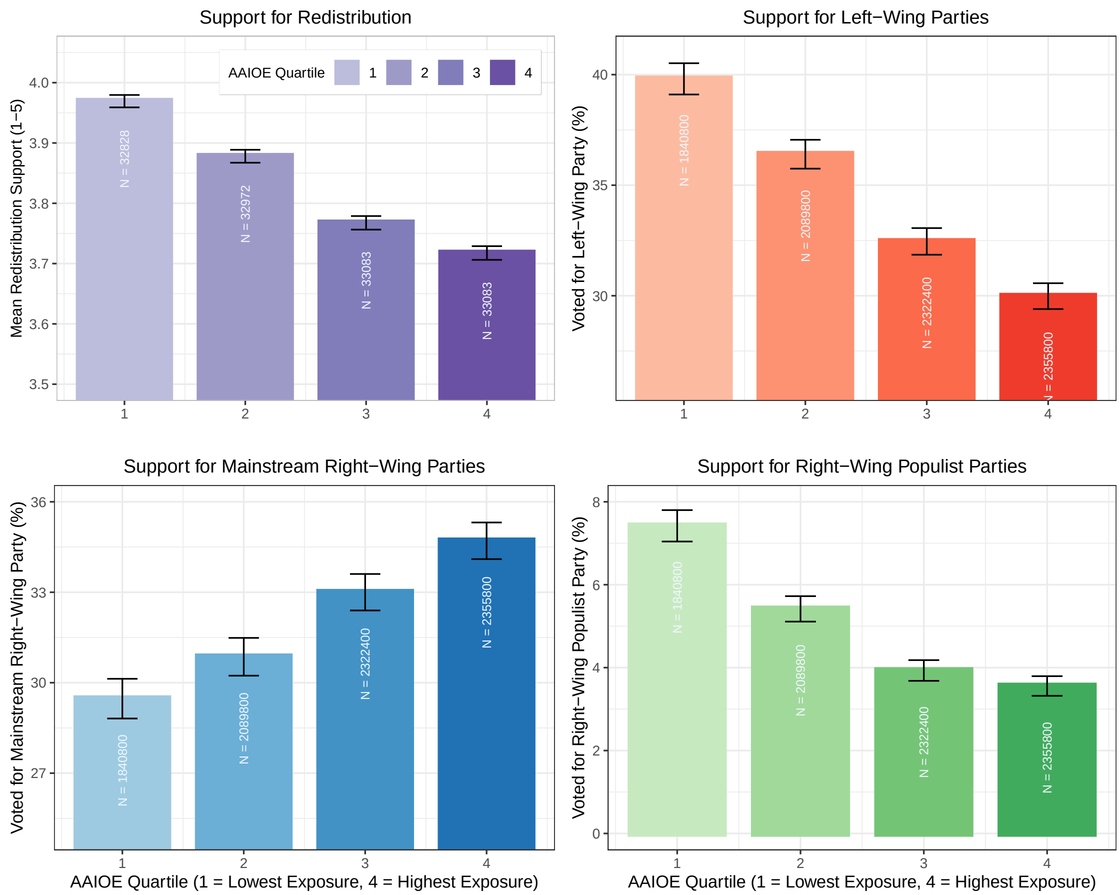
Redistribution Preferences

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."[23] The principal measure of exposure to AI is the AAIOE index described earlier, which I assign to respondents via an ESS item on ISCO-08 occupation scaled at the most granular classification level, namely, four-digit "unit groups" (436 categories).

Suggestively, the upper left panel of Figure 2 shows that support for redistribution is systematically lower among respondents with greater occupational exposure to AI. Averaging over the seven survey waves between 2010 and 2024, the scale mean is 3.97 for respondents in the first quartile of the AAIOE (indicating lowest AI exposure) versus 3.72 for respondents in the

[23] Attitudes toward redistribution are challenging to measure in cross-national settings because they are anchored to a distributional status quo that varies across societies (Beramendi and Rehm 2016). Consequently, as suggested by the country-specific aggregates plotted in Figure A3 in the Supplementary Material, they do not perfectly capture normative beliefs about the acceptable level of societal inequality and state intervention in the economy. Although no survey question can entirely escape distributional reference points, the ESS item I employ is designed to attenuate them by abstracting from specific income distributions and policy instruments. Moreover, as discussed below, my empirical strategy avoids directly comparing redistribution preferences across national contexts by leveraging within-country variation over time.

FIGURE 2. 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 income inequality. In upper right, lower left, and lower right panels, it measures the proportion of such respondents who voted for a left-wing, mainstream right-wing, and right-wing populist party, respectively, in the last national election. Each variable is disaggregated by respondents' AAIOE quartile, with Q1 denoting the bottom 25% of the distribution and Q4 denoting the top 25%. Error bars represent 95% confidence intervals.

fourth quartile (indicating highest AI exposure), a difference that is highly statistically significant ($t = 32.19$, $p < 0.000$).

To more rigorously assess the relationship between AI exposure and support for redistribution, I estimate two sets of OLS regression models that include country-by-wave fixed effects and a battery of individual-level controls, thereby exploiting differences in redistribution preferences among individuals in the same country and survey wave who vary in AI exposure. In both specifications, heteroskedasticity-robust standard errors are clustered at the four-digit ISCO-08 occupation level.

The baseline specification takes the form:

$$R_{ict} = \beta \, \mathrm{AAIOE}_{o(i)} + \boldsymbol{\gamma}' \mathbf{X}_{ict} + \lambda_{ct} + \varepsilon_{ict} \tag{8}$$

where R_{ict} is respondent i's level of support for reducing income differences in country c and wave t; *AAIOE*$_{o(i)}$ is the standardized AI exposure of i's occupation o; $\mathbf{X}_{ict}$ is a vector of socioeconomic control variables common in the redistribution preferences literature, namely, i's age, gender (indicator), years of education, degree of religiosity (1–10 scale), past or present union membership (indicator), residence in an urban area (indicator), household net income decile (1–10 scale), and self-placement on the left-right ideological scale (0–10 scale); and λ_{ct} denotes interactive country-wave fixed effects.[24]

The second specification interacts *AAIOE*$_{o(i)}$ and the controls with the full set of survey wave indicators, allowing us to examine how the relationship between AI exposure and redistribution preferences evolves over time:

$$R_{ict} = \sum_{t \neq 2008} \beta_t \big(\mathrm{AAIOE}_{o(i)} \times \mathbb{1}\{T = t\}\big) + \sum_{t \neq 2008} \boldsymbol{\gamma}_t' \big(\mathbf{X}_{ict} \times \mathbb{1}\{T = t\}\big) + \lambda_{ct} + \varepsilon_{ict}. \tag{9}$$

The 2008–2009 wave, which predates the widespread diffusion and public salience of AI, serves as the reference period. The resulting estimates do not reflect within-individual changes in redistribution and voting preferences—which I expect to intensify over time—but instead capture year-by-year aggregate associations. Although still of interest, these population-level patterns may not fully mirror individual-level dynamics due to compositional shifts in occupational structure across economies (as discussed earlier).

[24]Summary statistics are provided in Table A3 in the Supplementary Material.

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

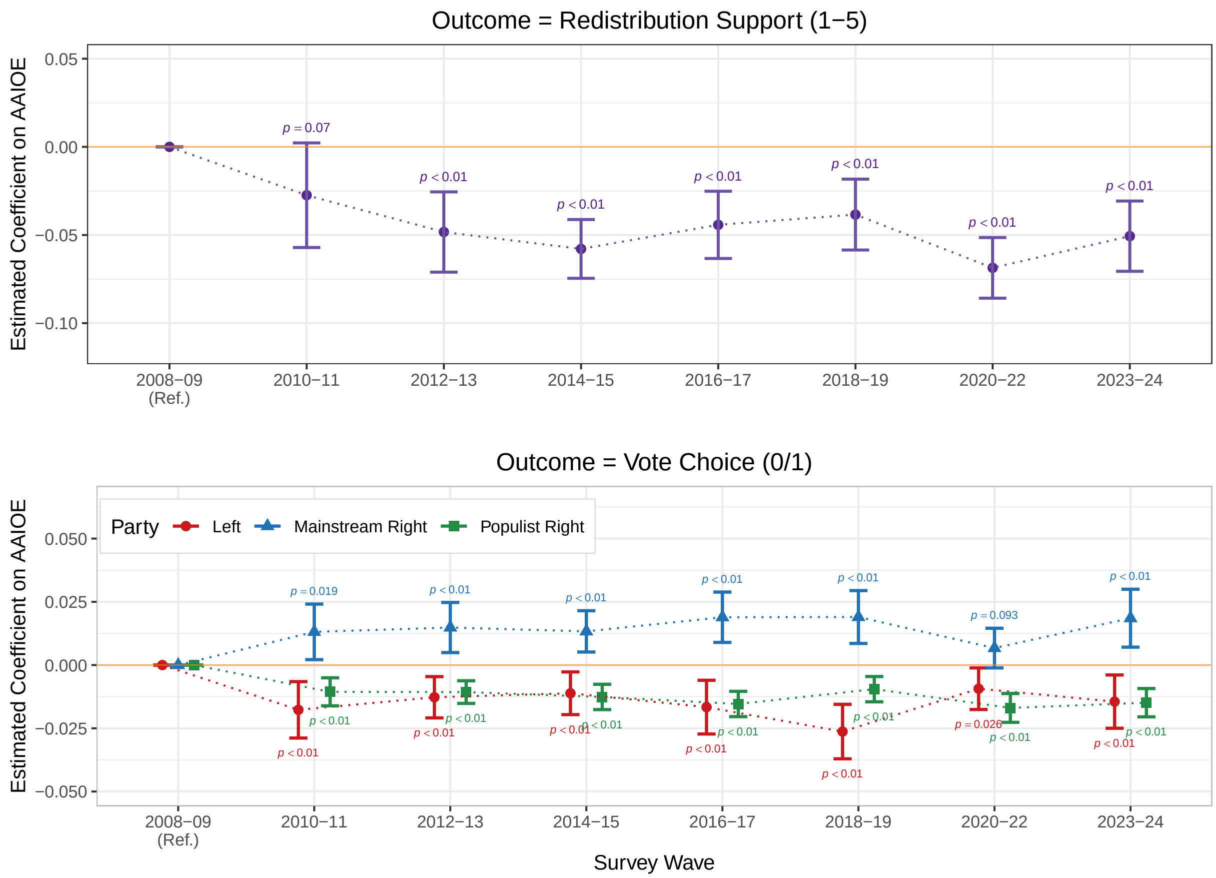
Outcome:	Redistribution Support	Vote Choice: Left	Vote Choice: Mainstream Right	Vote Choice: Populist Right
Panel A: Baseline Specification	(1)	(2)	(3)	(4)
AAIOE (Std.)	-0.048***	-0.016***	0.015***	-0.013***
	(0.007)	(0.003)	(0.002)	(0.002)
N	105,515	73,775	73,775	73,775
Mean Outcome	3.819	0.340	0.316	0.051
Panel B: Automation Risk Control	(5)	(6)	(7)	(8)
AAIOE (Std.)	-0.054***	-0.016***	0.016***	-0.013***
	(0.006)	(0.002)	(0.002)	(0.001)
Goos et al. RTI Index (Std.)	0.032***	0.011***	0.001	0.003*
	(0.005)	(0.002)	(0.002)	(0.002)
N	94,436	65,388	65,388	65,388
Mean Outcome	3.811	0.343	0.317	0.054
Socioeconomic Controls	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by four-digit ISCO-08 occupation, in parentheses. Socioeconomic controls: age, years of education, gender, union membership, religiosity, urban residence, household income decile, and left-right ideology. Full results are reported in Table A4 in the Supplementary Material. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Results The key estimates from Equation 8 are reported in column 1 of Table 1. In line with **H1**, there is a negative relationship between AI exposure and support for redistribution that is statistically significant at the 0.1% level. A one-standard-deviation increase in a respondent's AAIOE score—roughly equivalent to the difference in exposure between nursing assistants and insurance clerks—is associated with a 0.05-point decline in the redistribution support scale, which also represents 0.05 standard deviations.

The results of the wave-by-wave specification, plotted in the upper panel of Figure 3, indicate that this negative association becomes clearly visible in the 2012-2013 wave and holds throughout the remainder of the sample period. The wave-specific coefficient on $AAIOE_{o(i)}$ follows a modest downward trend, consistent with a strengthening of AI's impact at the population level. Moving one standard deviation up the AAIOE distribution lowers support for

FIGURE 3. Results of Wave-by-Wave Cross-National Analysis



Notes: OLS estimates with 95% confidence intervals based on robust standard errors clustered by four-digit ISCO-08 occupation; *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, urban residence, household income, and left-right ideology—which are interacted with survey wave indicators—and include country-by-wave fixed effects.

redistribution by 0.03 standard deviations in the 2010–2011 wave, compared to 0.05 standard deviations in 2023–2024.

Voting Behavior

Data and Model Turning to **H2**, I replace the outcome variable in Equation 8 with V_{ictp}, an indicator for whether respondent i voted for a party in category p (left, mainstream right, or populist right) in the previous national election as of wave t.[25] Party categorizations follow the

[25]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 substantively similar results.

ParlGov (Döring, Huber, and Manow 2022) and PopuList (Rooduijn et al. 2023) databases.[26] To ensure meaningful vote choice comparisons, abstainers are omitted from the sample (Rueda and Stegmueller 2019). As before, the wave-by-wave specification interacts $AAIOE_{o(i)}$ and all controls with survey wave indicators, using 2008–2009 as the reference period.

As illustrated in Figure 2, descriptive evidence accords with **H2**. Respondents in higher AAIOE quartiles are consistently less likely to support the left (upper right panel) and the populist right (lower right panel) and more likely to favor the mainstream right (lower left panel). On average, 40%, 7%, and 30% of respondents in the lowest quartile voted for a left-wing, right-wing populist, and mainstream right-wing party in the most recent national election, respectively, versus 30%, 4%, and 35% of respondents in the highest quartile. These differences are again statistically significant in two-sample t tests.

Results The regression estimates, presented in columns 2–4 of Table 1, offer more systematic evidence for **H2**. The coefficient on $AAIOE_{o(i)}$ is negative and statistically significant when the outcome is left-wing (column 2) and right-wing populist (column 4) voting but positive and significant when the outcome is mainstream right-wing voting (column 3). Each standard-deviation increase in a respondent's AAIOE score lowers the probability of voting for the left and the populist right by 1.6 and 1.4 percentage points, respectively, while raising the probability of voting for the mainstream right by 1.5 percentage points.

The lower panel of Figure 3 displays estimates from the wave-by-wave specification. Similarly to before, the hypothesized associations appear in the early 2010s and remain evident in all subsequent waves. In the case of mainstream and populist right-wing voting, they also strengthen slightly over time, offering additional evidence that AI's political effects intensify even at the population level.

[26] Parties in ParlGov's "Christian democracy" and "conservative" families are coded as mainstream right-wing, while those in its "social democracy" and "communist/socialist" families are coded as left-wing. For a full list of parties by category, see Table A2 in the Supplementary Material. Regional and single-issue parties are excluded.

Robustness and Extensions

I now extend the baseline analyses in several directions to probe the robustness of the main findings and explore additional issues of interest. Unless otherwise indicated, the results are reported in Section C.3 of the Supplementary Material.

Additional Controls and Fixed Effects I begin by incorporating an expanded set of controls into the analyses. 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, while the coefficient on the RTI index mostly points in the opposite direction and reaches statistical significance (in keeping with Gingrich 2019; Thewissen and Rueda 2019; Dermont and Weisstanner 2020; Busemeyer and Sahm 2022). Table A5 documents similar results when adding proxies for other occupational risks associated with digitalization: susceptibility to computerization (Frey and Osborne 2017), the potential for offshoring (Blinder and Krueger 2013), skill specificity (Cusack, Iversen, and Rehm 2006), and labor market "outsiderness," which I measure using an ESS-based indicator for fixed-term employment (Thewissen and Rueda 2019). The findings are also robust to the inclusion of survey-based ratings of occupational prestige (Hughes et al. 2024), which capture status-related 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) perceived job security (1–4 scale); (2) trust in politicians (0–10 scale); (3) employment in the public sector (indicator); and (4) ethnic minority status (indicator). The findings remain intact (Table A6).

Third, following previous analyses of redistribution preferences (e.g., Burgoon, Koster, and Van Egmond 2012; Burgoon 2014; Rueda 2018; Thewissen and Rueda 2019), I control for three country-level variables, each lagged by one year: (1) social spending as a percentage of GDP; (2)

the unemployment rate; and (3) the share of foreign-born residents in the total population.[27] Again, the results are substantively unchanged (Table A7).

Fourth, I introduce fixed effects for ISCO-08 major groups and Nomenclature of Economic Activities (NACE) sections (one digit), thus leveraging variation in AI exposure *within* occupational and industrial categories. Robustness to these more demanding specifications would indicate that the hypothesized relationships obtain even among individuals who perform similar tasks (e.g., technicians or clerical support staff) and who produce similar goods and services (e.g., manufacturing workers or financial professionals). In addition, I include region fixed effects at the NUTS-2 level, given the role played by economic geography in shaping redistribution preferences (Beramendi 2012), and add—rather than interact—the country and wave fixed effects.[28] Finally, I replicate the approach of Thewissen and Rueda (2019) by excluding all fixed effects and estimating a multilevel specification with random intercepts for countries via maximum likelihood estimation. Across all specifications, **H1** and **H2** continue to receive support (Tables A8 and A9).

Instrumental Variables Analysis In the absence of longitudinal data, a common strategy for identifying the causal effect of occupational attributes is to instrument them with corresponding characteristics of an individual's parents during adolescence. The intuition is that parental occupation strongly predicts respondents' career choices through the intergenerational transmission of skills, networks, and expectations, while remaining plausibly exogenous to adult outcomes of interest. Building on Fletcher and Sindelar (2009) and Kelly et al. (2014), I instrument $AAIOE_{o(i)}$ with the occupational skill level of respondent i's father when i was 14 years old, as captured by an ESS item on paternal job type.[29] The key identifying assumption is that, conditional

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

[28] Relatedly, clustering standard errors by country instead of ISCO-08 user group does not materially alter estimated significance levels.

[29] I reorder the item's nine-point scale from most skilled ("professional and technical occupations") to least skilled ("unskilled worker").

on the baseline controls—which account for plausible direct pathways through which paternal occupation may influence political preferences, such as education, ideology, and income—the instrument only affects the outcome variables through i's own occupation.[30] I estimate each model using two-stage least squares (2SLS), again finding evidence concordant with **H1** and **H2** (Table A10).[31]

Alternative Samples The results are also robust to several modifications of the baseline sample (Tables A12 and A13). First, I incorporate the five Western European countries that have not participated in every ESS wave (Austria, Denmark, Greece, Iceland, and Italy).[32] Second, I include the three Eastern European countries that *have* featured in all waves (Hungary, Poland, and Slovenia).[33] Third, I restrict the sample to respondents from households whose primary source of income is market earnings (wages, salaries, self-employment income, and capital income) as opposed to social transfers. Fourth, I focus on individuals in the top two deciles of their country's household income distribution.[34] Fifth, I adopt the survey's recommended sampling weights to account for differences in selection probabilities arising from country-specific sampling designs. Lastly, in the 2010–2011 voting sample, I exclude respondents from countries whose most recent national election occurred prior to this wave.

Placebo Tests Reassuringly, replacing the outcome variables with proxies for a range of attitudes not directly related to AI's labor market consequences—including views on immigration,

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

[31] First-stage F-statistics, also conveyed in Table A10, indicate a strong association between paternal skill and respondent AI exposure.

[32] I exclude Luxembourg, which only took part in the first two waves.

[33] The additional parties included in this and the previous sample are listed in Table A14.

[34] Within this group, AI exposure is unrelated to the belief that the government is responsible for maintaining living standards for the unemployed (see Table A12), suggesting that weak demand for redistribution does not simply reflect a preference for private or self-insurance. This interpretation is further supported by the inclusion of household income in all specifications, which ensures that the coefficient on $AAIOE_{o(i)}$ captures variation within income groups rather than the preferences of high earners only.

climate change, same-sex relationships, European integration, interpersonal trust, authoritarian leadership, and life satisfaction—yields null results (Table A15).[35]

Alternative Party Classifications Table A11 confirms that the negative relationship between exposure to AI and support for the left persists when the analysis is limited to each country's principal left-wing party as well as to far left parties. Likewise, the positive relationship between such exposure and support for the mainstream right remains when focusing on each country's principal right-wing party.[36]

Disaggregating Artificial Intelligence Table A16 shows that the results remain comparable when $AAIOE_{o(i)}$ is disaggregated into its three constituent indices, albeit with a modest reduction in coefficient size. The same is true when we employ two more recently developed measures of occupational AI exposure: Pizzinelli et al.'s (2024) Complementarity-Adjusted AI Occupational Exposure (C-AIOE) index, which modifies Felten, Raj, and Seamans's AIOE to more explicitly account for potential labor complementarities; and Gmyrek, Berg, and Bescond's (2023) generative AI exposure index, restricted to the two most recent survey waves). Finally, because AI is not a single technique but a diverse collection of models and algorithms, one might wonder whether the findings vary across its different applications. Usefully for this purpose, the AIOE aggregates measures of compatibility between occupational abilities and 10 distinct AI applications ranging from image recognition to language modeling. Substituting these 10 application-specific measures for $AAIOE_{o(i)}$ produces similar results, though estimated effects are slightly larger in the case of reading comprehension, visual interpretation, and abstract strategy games (Table A17).

[35] Given that some of these attitudes may nevertheless vary across broad occupational categories, I include one-digit ISCO-08 fixed effects in the specification.

[36] See the fifth column of Table A2 for these classifications.

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 renders the estimates primarily correlational, with no way of ruling out confounding by time-invariant individual attributes. For example, respondents with personality or genetic traits associated with opposition to redistribution may self-select into occupations with greater exposure to AI. Alternatively, respondents predisposed toward progressive attitudes may be more likely to leave or lose high-exposure jobs (while retaining their political orientations).

Drawing on the German SOEP, I address these concerns by conducting a longitudinal analysis of political preferences that exploits within-individual variation over time. Although 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 close comparators—it is unique in classifying occupations according to the ISCO-08 scheme rather than an earlier, less granular taxonomy. Furthermore, its annual panel is substantially larger than that of the UKHLS (by an average of more than 50% per wave since 2000) and the SHP (by more than twofold). I include all SOEP waves from 2000 to 2023, allowing us to account for preexisting trends in political attitudes as well as to mitigate potential bias arising from selection into AI-exposed occupations.

Data and Specification

As a large, diversified, and generally stable economy with strengths in high-end manufacturing and engineering—sectors relatively exposed to AI—Germany represents a promising testing ground for my argument. Moreover, the country's proportional electoral system and multiparty structure ensure that citizens can choose among a wide range of redistributive platforms. As in the cross-national analysis, I group Germany's federal parties into three categories: (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 *Alternative für Deutschland* (AfD) and *Die Heimat* (DH).[37]

Figure A4 in the Supplementary Material plots average support for each party category over the 2000–2023 period based on responses to the SOEP question: "Which party do you lean toward?" The expected patterns only emerge consistently after around 2010: support for left-wing and right-wing populist parties is stronger among respondents in lower AAIOE quartiles, whereas support for mainstream right-wing parties is stronger among those in higher AAIOE quartiles.

My baseline specification is a two-way fixed effects model in which AAIOE scores are interacted with a linear time trend to estimate differential within-individual trends in political preferences across levels of AI exposure. To avoid bias from endogenous occupational changes during the sample period, I fix the AAIOE at its value when respondent i first enters the panel (survey wave f_i). The estimating equation, which resembles a continuous difference-in-differences design, is:

$$\mathrm{S}_{itp} = \beta(\mathrm{AAIOE}_{o(i)f_i} \times \mathrm{trend}_t) + \theta_i + \phi_t + \epsilon_{itp} \tag{10}$$

where S_{itp} indicates whether respondent i supports a member of party category p in wave t; $AAIOE_{o(i)f_i}$ is the standardized AI exposure of i's occupation o measured at panel entry; $trend_t$ is a linear time trend; and θ_i and ϕ_t denote respondent and wave fixed effects, respectively. The coefficient β thus captures whether respondents in more exposed occupations experience steeper changes in support for p over time.[38] I initially exclude the individual-level controls from the cross-national analysis because they are largely time-invariant over a respondent's panel

[37] *Bündnis 90/Die Grünen*, a green party, and *Freie Demokratische Partei* (FDP), a liberal party, do not clearly fit into these categories and are thus excluded from the analysis.

[38] Since $AAIOE_{o(i)f_i}$ does not vary within individuals, its lower-order term is collinear with the respondent fixed effects and hence not separately identified.

tenure and thus absorbed by θ_i. Robust standard errors are clustered by respondent.

As in the cross-national analysis, I also estimate a wave-by-wave version of Equation 10 in which $AAIOE_{o(i)f_i}$ is interacted with survey wave indicators, relaxing the linear functional form constraint imposed by the time trend:

$$S_{itp} = \sum_{t \neq 2000} \beta_t \big(\text{AAIOE}_{o(i)f_i} \times \mathbb{1}\{T = t\}\big) + \theta_i + \phi_t + \varepsilon_{itp}. \tag{11}$$

Unlike before, this specification allows for a direct assessment of whether the relationship between individual-level AI exposure and party support strengthens over time. Furthermore, if the wave-specific coefficient β_t is statistically indistinguishable from zero during the first decade of the sample, the analysis would provide support for the central identifying assumption underlying Equation 10: in the absence of AI, party support would have followed a similar trajectory across respondents with varying levels of exposure.

Results

Panel A of Table 2 reports the baseline estimates from Equation 10. In accordance with **H2**, the coefficient on $AAIOE_{o(i)f_i} \times \text{trend}_t$ is negative and statistically significant when the outcome is support for the left (column 1) and the populist right (column 3) but positive and significant when the outcome is support for the mainstream right (column 2). With each additional year, a one-standard-deviation rise in AI exposure is associated with a 0.1-percentage-point decline in the likelihood of favoring a left-wing or right-wing populist party and a 0.1-percentage-point increase in the probability of backing a mainstream right-wing party. Over the 2010–2023 period, these estimates imply cumulative changes of -1.2 percentage points for left-wing support, -1.3 percentage points for right-wing populist support, and +1.5 percentage points for mainstream right-wing support.

Figure 4 plots the results of the wave-by-wave specification. During the 2000s, the estimated

TABLE 2. Longitudinal Results: AI Exposure and Political Preferences in Germany

Outcome: Support for...	Left	Mainstream Right	Populist Right
Panel A: Baseline Specification	(1)	(2)	(3)
AAIOE_f (Std.) $\times$ Trend	-0.001***	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
N	168,530	168,530	168,530
Mean Outcome	0.363	0.360	0.035
Panel B: Automation Risk Control	(4)	(5)	(6)
AAIOE_f (Std.) $\times$ Trend	-0.001*	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Goos et al. RTI Index	0.001	-0.001	0.000
	(0.002)	(0.002)	(0.001)
N	112,598	112,598	112,598
Mean Outcome	0.358	0.367	0.036
Respondent FEs	✓	✓	✓
Survey Wave FEs	✓	✓	✓

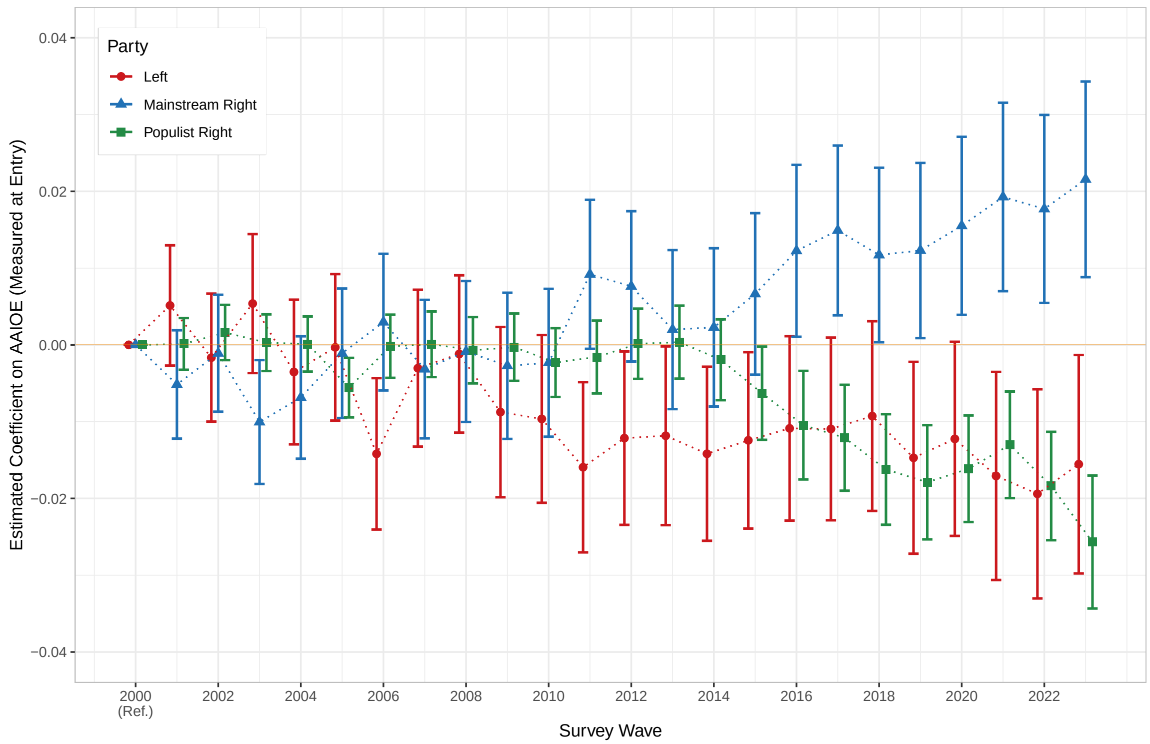
Notes: OLS estimates from Equation 10 with robust standard errors, clustered by respondent, in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

wave-specific coefficients on $AAIOE_{o(i)f_i}$ are close to zero and fluctuate in sign, indicating that AI exposure does not systematically predict support for any party category. After 2010, these estimates become increasingly negative for left-wing and right-wing populist support and increasingly positive for the mainstream right-wing support. Effect sizes grow over time, with the 2023 coefficient almost three times as large as that in 2015, on average. Overall, the wave-by-wave results provide evidence for both the parallel trends assumption and the expectation that AI's political consequences intensify over time.

Robustness and Extensions

The baseline findings are robust to a variety of alternative specifications, including the key robustness checks from the cross-national analysis. The results are summarized in this section and, unless noted otherwise, reported in full in Section D.2 of the Supplementary Material.

FIGURE 4. Results of Wave-by-Wave Longitudinal Analysis



Notes: OLS estimates from Equation 11 with 95% confidence intervals based on robust standard errors clustered by respondent. The reference period is 2000. All models include respondent and survey wave fixed effects.

I start by introducing a series of basic, time-varying socioeconomic controls that are not fully absorbed by the respondent fixed effects: age, log gross labor income (in euros), left-right ideology (0–10 scale), current union membership (indicator), and residence in an urban area (indicator). The results, reported in Table A18, are essentially unchanged.

Next, 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 A19 (for the remaining proxies), the results remain closely comparable. The coefficient on the RTI index is small and statistically insignificant across all three models, implying that within-individual changes in exposure to routine-biased automation—unlike stable cross-sectional differences—are not meaningfully associated with political preferences during the sample period. Given the empirical setup, this pattern is not particularly surprising: most respondents do not remain in the SOEP panel for the full 2000–2023 period, job transitions are relatively infrequent, and the RTI index is time-invariant at the occupation level, resulting in limited identifying variation.

Third, turning to other socioeconomic characteristics, I add SOEP-based measures of perceived job security (1-3 scale), possession of a migrant background (indicator), employment in the civil service (indicator), and concern about immigration (1-3 scale). The findings continue to hold (Table A20).

Fourth, Table A21 establishes that the findings survive the inclusion of one-digit occupation and industry fixed effects as well as federal state (*Bundesland*) indicators. Nor are they sensitive to the removal of respondent fixed effects, which allows the analysis to exploit between-individual variation in AI exposure within the same year (in a manner analogous to the cross-national analysis).[39]

Fifth, 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:

$$\Delta \mathrm{S}_{i,t_1-t_0,p} = \beta \mathrm{AAIOE}_{it_0} + \eta_b + \epsilon_{i,t_1-t_0} \tag{12}$$

where $\Delta S_{i,t_1-t_0,p}$ denotes the change in respondent i's support for party category p between periods t_0 and t_1; and η_b represents federal state fixed effects. With each respondent now contributing a single observation, I cluster robust standard errors by federal state. The results, presented in Table A22 for a variety of temporal windows, are consistent with the main findings.[40]

Finally, I demonstrate robustness to four adjustments to the baseline sample (Table A23): (1) measuring AAIOE scores at wave t rather than at entry point f_i; (2) excluding respondents

[39] Estimated effect sizes are comparable to those in the cross-national context: a one-standard-deviation increase in AI exposure is associated with cumulative changes in the probability of voting for the left, the mainstream right, and the populist right of -2.2, +1.1, and -2.6 percentage points, respectively.

[40] To smooth annual fluctuations in political preferences and maximize sample size, I designate t_0 and t_1 as multiyear intervals—averaging each variable over these periods—rather than single waves.

from households that derive the majority of their income from nonmarket sources; (3) applying the SOEP's recommended weighting factor to compensate for differential sampling probabilities and panel attrition; and (4) restricting the analysis to the principal party within each ideological category, namely, the SPD, the CDU, and the AfD.[41]

Experimental Evidence from the United Kingdom

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

Using a combination of the widely used Amazon Mechanical Turk crowdsourcing platform and advertising on social media, I administered the survey to almost 800 adults based in the United Kingdom in late 2024 and early 2025. As a setting for evaluating my hypotheses, the United Kingdom offers comparable analytical advantages to Germany. In addition to being a sizable and varied economy, it has emerged as a global leader in AI development and adoption over the past decade, particularly in high-skilled financial, professional, and business services. Despite its majoritarian electoral system, moreover, it increasingly functions as a multiparty democracy with significant parties on the left (the Labour Party), the mainstream right (the Conservative Party), and the populist right (Reform UK). As discussed in Section E.1 of the Supplementary Material, the survey sample is reasonably representative of the British population, exhibiting

[41] The last modification yields stronger results, which is to be expected: voters are likely to be more familiar with the social policy platforms of more prominent parties, in addition to the fact that statistical relationships are easier to detect in larger samples.

only a modest bias toward younger, male, and more educated respondents.

Respondents were randomly assigned in roughly equal proportion to one of two treatment groups or to a control group. The first treatment group ($n = 257$) was presented with a "complementarity" frame emphasizing 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 treatment group ($n = 258$) was exposed to a "substitution" perspective highlighting AI's potential to disrupt labor markets and 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."*

The control group ($n = 280$) received no vignette.

All respondents were then asked two sets of questions: (1) how strongly 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 the proposed mechanism, respondents were also posed a series of questions about how they expect growing AI adoption to impact their job performance and wages.[42]

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

$$Y_i = \alpha + \beta \begin{cases} C_i \\ \\ S_i \end{cases} + \gamma' \mathbf{X}_i + \eta \mathrm{PID}_{ip} + \epsilon_i \tag{13}$$

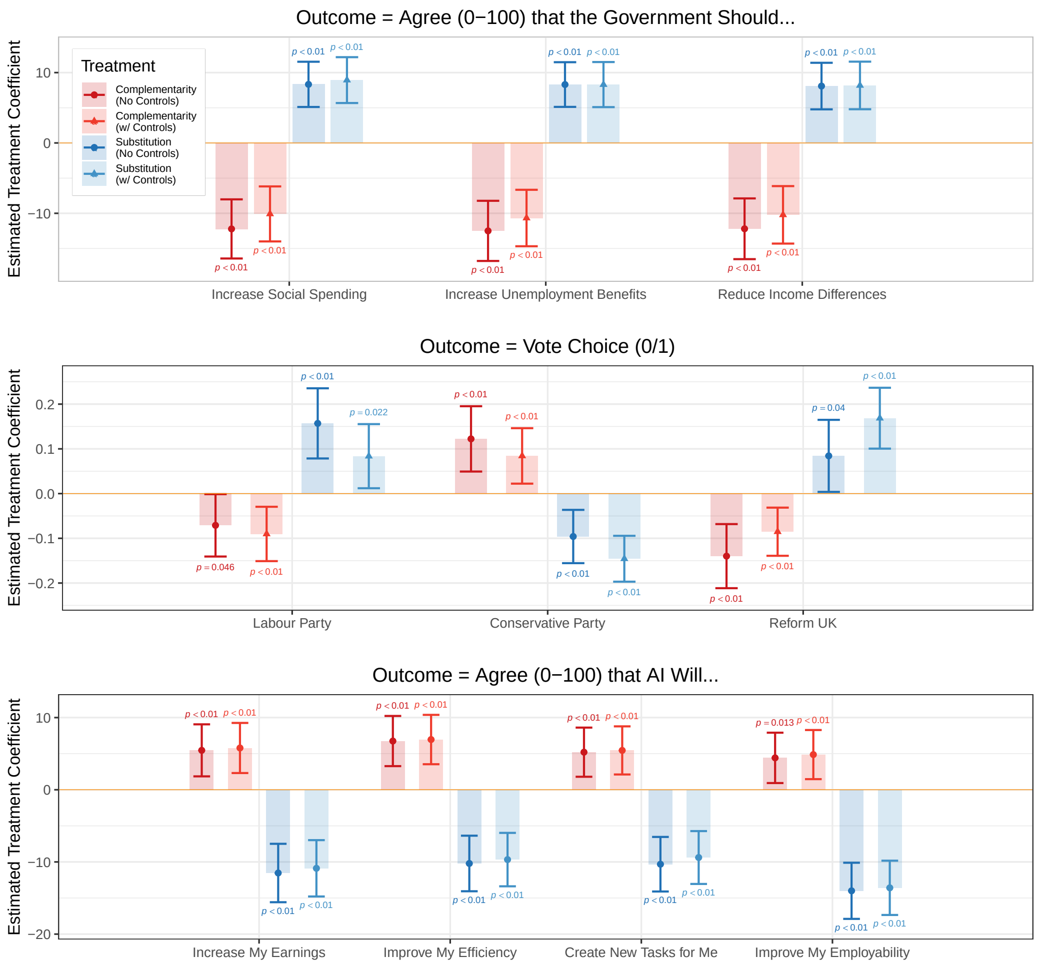
where Y_i is respondent i's outcome value; C_i and S_i are indicators for whether i is assigned the complementarity frame and the substitution frame, respectively; $\mathbf{X}_i'$ is a vector of controls for i's age (10 categories), gender (indicator for female), ethnicity (indicator for white), income (eight categories), and education (nine categories); and PID_{ip} is an indicator for whether i identifies with political party p (six categories).[43] The specification is estimated separately for C_i and S_i, excluding respondents assigned to the alternative treatment condition so that parameters are estimated relative to the control group.

Main Hypotheses The results are presented in Figure 5. The top panel provides robust support for **H1**: whether control variables are included or excluded, assignment to the complementarity frame is negatively and significantly related to support for reducing income differences, expanding unemployment benefits, and increasing social spending. In line with **H2**, the complementarity treatment also has a strong negative association with the intention to vote for the Labour Party and Reform UK but a strong positive association with the intention to vote for the Conservative Party (middle panel). These relationships are exactly reversed under the substitution

[42] The order of these three sets of posttreatment questions was randomized. The survey structure is described in detail in Section E.1 of the Supplementary Material.

[43] Table A26 in the Supplementary Material confirms that these covariates are well balanced across the treatment and control groups. Table A25 reports summary statistics for the full dataset.

FIGURE 5. Experimental Effects of AI Framing: Evidence from the United Kingdom



Notes: OLS estimates from Equation 13 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 A27–A29 in the Supplementary Material.

treatment.[44] The estimated effects are substantively large, particularly for the complementarity treatment. For example, agreement that the government should reduce income differences is 10.2 percentage points lower among respondents receiving the complementarity frame, while the probability of voting for the Conservative Party is 8.4 percentage points higher.

[44]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.

Causal Mechanism To assess whether the previous findings reflect the hypothesized mechanism, I replace the outcome variable in Equation 13 with responses to the aforementioned questions about AI's anticipated impact on work. In keeping with the argument, exposure to the complementarity frame is positively and significantly associated with expectations that AI will increase respondents' earnings, efficiency, range of tasks, and ability to find employment (bottom panel of Figure 5). As in the main analysis, assignment to the substitution treatment yields effects in the opposite direction. A formal mediation analysis, summarized in Table A31 in the Supplementary Material, indicates that expectations about AI's labor market consequences constitute a central channel through which the treatments influence redistribution preferences. These attitudes, in turn, strongly mediate the treatment effects on the three vote choice outcomes.

Controlling for Automation Risk Adding the RTI index to the vector of controls does not alter any of the previous findings (see Table A30 in the Supplementary Material), though the complementarity treatment effects on redistribution preferences are slightly weakened. Since the complementarity frame is randomly assigned and purely informational, this attenuation is more likely to reflect the RTI measure's coarseness and relatively high level of missingness (171 observations) than genuine overlap between the treatment and exposure to routine-biased automation. The RTI coefficients themselves point in the expected direction but are generally small and statistically insignificant.

Heterogeneity Across and Within Occupations Another notable implication of my argument is that the treatment effects will be stronger among respondents with higher real-world exposure to AI, whose livelihoods are more directly impacted by the technology. To evaluate this proposition, I interact C_i and S_i with respondent i's AAIOE score, computed using a pretreatment survey item on occupation (scaled at the two-digit ISCO-08 level). Figure A5 in the Supplementary Material shows that the marginal effects of both treatments on the redistribution and voting outcomes strengthen with AI exposure, attaining significance only at medium or high AAIOE values. Figure A6 displays similar patterns when the moderator is a subjective measure of exposure constructed from a pretreatment question on the compatibility between i's tasks and AI's current and anticipated capabilities—a measure strongly correlated with AAIOE scores ($r = 0.88$).[45]

Finally, I take advantage of exogenous treatment assignment to test a related implication of the argument: the complementarity treatment will exert larger effects 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).[46] This conjecture also finds support: controlling for ISCO-08 fixed effects, the marginal effects of C_i on the redistribution, voting, and work-related outcomes grow with respondent i's level of education (see Figure A7).[47]

Discussion

Advances in AI are poised to reshape advanced labor markets in the coming years and decades, with potentially profound consequences for the distribution of economic opportunity and material resources within societies. Surprisingly little is known, however, about how this transformation is influencing preferences over the allocation of resources among citizens—a central driver of voting behavior and social policy outcomes in canonical models of political economy. Previous research on the distributional politics of digitalization has concentrated on routine-

[45]Based on a representative survey from Great Britain, Green et al. (2025) also report a positive correlation between subjective and objective measures of AI exposure. They find only a modest correlation between subjective exposure and opposition to redistribution but emphasize that their analysis is descriptive rather than causal.

[46]Random assignment ensures that treatment status is independent of both observed and unobserved potential outcomes, permitting a causal interpretation of subgroup differences. In observational settings, such heterogeneity may reflect selection into subgroups or unobserved confounding rather than genuine variation in treatment effects.

[47]There is less reason to expect comparable heterogeneity under the substitution treatment: while skilled workers may face elevated displacement risks from AI, they are also better positioned to adapt to structural occupational change and secure alternative employment.

biased automation methods pioneered in the 1980s and 1990s, generally finding that exposed workers display greater affinity 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 potential to enhance human productivity by facilitating, creating, and restructuring occupational tasks—complementarities that exposed workers widely expect to raise their relative future income without jeopardizing their employment prospects. Analyses of observational and experimental data from Western Europe furnish 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 document 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 dynamic, eroding demand for a social safety net from the relatively skilled, wealthy, and politically influential set of workers who stand 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 gravitate toward mainstream right-wing parties favoring lower taxes and a more limited welfare state (Mares 2003).[48] The precise electoral consequences of such realignments 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 future iterations of the technology may come to be perceived as less complementary to skilled labor, particularly if they assume a broader range of tasks without creating enough new productive activities to sustain mass employment. It bears emphasizing, therefore, that this study's argument and results only pertain to recent expectations about AI's labor market consequences. Although these effects are only now becoming visible—and remain contested—the observational findings suggest that expectations about AI began to shift soon after the major advances in neural networks and deep learning of the early 2010s. This gap between perception, technological progress, and economic reality opens up interesting avenues for further research: How do views of AI emerge and diffuse across workers, firms, and policymakers? How accurately do such beliefs predict subsequent technological and labor market developments? At what point will AI become sufficiently mature that political preferences, redistributive policy, and voter behavior align to generate a self-sustaining equilibrium? The broader takeaway is that the political economy of AI is not only about what the technology *can* do but also about what actors *think* it can do—beliefs that may change well in advance of observable labor market outcomes and shape political behavior accordingly.

Nor, on the "supply side" of the political equation, will party strategy necessarily remain static during the AI era. Although mainstream parties are unlikely to fundamentally revise their positions on redistributive issues, they may develop packages of AI-specific policies that more directly shape the economic prospects of exposed workers (e.g., regulations on AI deployment or

[48] 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 amplified by populist appeals to feelings of "status anxiety" among workers excluded from the benefits of AI (Gingrich 2019).

subsidies for AI development). Non-mainstream parties, meanwhile, may be willing and able to adjust core policy commitments in response to labor market—and broader societal—upheavals wrought by the AI revolution. Looking ahead, a nuanced grasp of the interplay between progress in AI technology, changes in labor market structure, and party responses to these trends will be crucial for understanding the fast-changing political economy of digitalization in industrialized democracies.

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Online Appendices for:

The Political Economy of Artificial Intelligence: Evidence from Western Europe

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Contents

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A Formal Details

A.1 Task-Based Model of Labor Markets

The main text's formal exposition of the labor market implications of technological change is informed by the task-based approach developed by Daron Acemoglu and collaborators (e.g., Acemoglu and Autor 2011; Acemoglu and Restrepo 2018, 2019, 2020; Acemoglu 2024). To keep the model as parsimonious as possible, I draw on the single-sector, static version of the task-based framework, in which a homogeneous final good is assembled by combining N tasks according to the production function:

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

where $x(z)$ denotes the output from task $z \in [0, N]$ and the remaining notation follows the main text. I assume that individual i performs the full range of tasks $[0, N]$, which are gross complements ($0 < \sigma < 1$). The case $\sigma = 1$ corresponds to a Cobb–Douglas production function, in which the share of each task in value added is fixed and the substitution effect vanishes. I focus on the strict gross-complements case $\sigma < 1$, consistent with available estimates of the elasticity of substitution between capital and labor.

Tasks are completed by a fixed quantity of labor — supplied inelastically — or capital via the production functions:

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

where $l(z)$ and $k(z)$ are the amounts of labor and capital allocated to task z, respectively. Following the modeling convention that labor has a comparative advantage in higher-indexed tasks

— formally, $\gamma_L(z)/\gamma_K(z)$ increases with z — there exists some threshold I above which it is cost-minimizing to employ labor. While tasks below I can technically be performed by either factor, capital is the lower-cost choice for firms, yielding an equilibrium where labor performs the $(N-I)$ tasks in $(I, N]$ and capital the tasks in $[0, I]$.

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 (i.e., price adjustment to match supply with demand). 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 $(N-I)$ tasks performed by labor must meet the requirement:

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

where w_L is the price of labor, that is, the equilibrium wage. Combining Equations A3 and A4 yields Equation 4, the expression for individual i's employment income in period 0.

A.2 Wage 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 widespread AI adoption is expected to primarily 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.

Let $\Gamma(I, N)$ be the labor task content (i.e., the share of tasks allocated to labor, adjusted for relative productivities); $s_L \equiv w_L L/X$ be the labor share; R be the rental rate of capital; and A_K

be capital-augmenting technology. Following Acemoglu and Restrepo (2019), the labor share can be written as:

$$s_L = \frac{1}{1 + \frac{1-\Gamma(I,N)}{\Gamma(I,N)} \left(\frac{R/A_K}{w_L/A_L}\right)^{1-\sigma}}. \tag{A5}$$

A labor-augmenting shock leaves the task boundaries fixed ($\partial I/\partial A_L = \partial N/\partial A_L = 0$), affecting the equilibrium wage through two offsetting channels:

$$\frac{d \ln y_i}{d \ln A_L} = \overbrace{s_L}^{\substack{\text{productivity}\\ \text{effect}}} + \overbrace{\frac{\sigma - 1}{\sigma}(1 - s_L)}^{\text{substitution effect}} = \frac{s_L + \sigma - 1}{\sigma}. \tag{A6}$$

Since greater labor efficiency raises output, the productivity effect ($d \ln X/d \ln A_L = s_L$) is positive. The substitution effect is negative when $\sigma < 1$, as higher wages reduce the relative price of capital and thus expand its share of production. The net effect is positive if and only if $\sigma > 1 - s_L$.

AI can also increase earnings by creating new tasks in which labor has a comparative advantage:

$$\frac{d \ln y_i}{d N} = \overbrace{\frac{1}{\sigma}\frac{d \ln (X/L)}{d N} + \frac{\sigma - 1}{\sigma}\frac{G'(N)}{G(N)}}^{\text{productivity effect}} + \overbrace{\frac{1}{\sigma}\frac{\gamma_L(N)^{\sigma-1}}{\left(\int_I^N \gamma_L(z)^{\sigma-1}dz\right)}}^{\text{reinstatement effect}}. \tag{A7}$$

Beyond improving productivity, this process "reinstates" labor by raising its share of tasks — the mirror image of the substitution effect in Equation A6. Reinstatement effects are especially strong when new tasks render the entire production process more efficient by raising G. While the second productivity term is negative when $\sigma < 1$ — the same $\frac{\sigma-1}{\sigma}$ force that drives the substitution effect — the reinstatement effect is unambiguously positive. The net effect of task creation on the equilibrium wage is hence positive because new tasks both raise productivity and shift task content toward labor.

Finally, AI involves an automation component:

$$\frac{d \ln y_i}{dI} = \overbrace{\frac{1}{\sigma}\frac{d \ln (X/L)}{dI}}^{\text{productivity effect}} - \overbrace{\frac{1}{\sigma}\frac{\gamma_L(I)^{\sigma-1}}{\left(\int_I^N \gamma_L(z)^{\sigma-1}dz\right)}}^{\text{displacement effect}}. \tag{A8}$$

Here, the productivity effect reflects cost savings enabled by automation as well as the resulting rise in labor demand in non-automated tasks. The negative displacement effect stems from the replacement of labor with capital in existing tasks, which raises the latter's share of production. Which effect dominates is unclear ex ante, depending on the relative productivity and rental rates of labor and capital in automated tasks.

As captured by the first line of Equation 7 in the main text, if AI is expected to raise future earnings through a combination of labor augmentation and task creation, the productivity effects in Equations A6–A8 plus the reinstatement effect in Equation A7 must outweigh the substitution effect in Equation A6 plus the displacement effect in Equation A8.

A.3 Unemployment Effects of Artificial Intelligence

Unemployment does not arise in Section A.1's task-based model due to several common simplifying assumptions, most notably perfect competition and inelastic labor supply. Since workers are always willing to accept employment and labor markets clear, wages adjust instantaneously to eliminate any imbalance between supply and demand. Building on the canonical search-and-matching framework in labor economics (e.g., Diamond 1982; Mortensen and Pissarides 1994; Pissarides 2000), this section introduces a simple extension in which unemployment emerges from frictions and delays in matching workers to vacancies.

In a standard search-and-matching model, the flow of new jobs is determined by a matching function, m, whose inputs are the number of unemployed workers, U, and the number of vacant jobs, V. This function is often assumed to take a Cobb-Douglas form: $m(U, V) = \kappa U^{\alpha} V^{1-\alpha}$, where $\kappa > 0$ and $\alpha \in (0, 1)$. The job-finding rate, f, is the ratio of matches to vacancies in a given period:

$$f \equiv \frac{m(U, V)}{U}.^{1} \tag{A9}$$

The counterpart to f is the job separation rate, s, defined as the fraction of employed workers who lose or leave their job during the same period. In a steady state, the unemployment rate is increasing in s and decreasing in f:

$$u^* = \frac{s}{s+f}. \tag{A10}$$

To analyze AI's impact on unemployment, suppose that the job-finding and separation rates are functions of q, an exogenous labor market parameter capturing the extent of its adoption. Differentiating the steady-state unemployment rate with respect to q yields:

$$\frac{du^*}{dq} = \frac{f\frac{ds}{dq} - s\frac{df}{dq}}{(s+f)^2}. \tag{A11}$$

Unemployment thus increases if AI raises s while reducing f and decreases if the reverse holds. The magnitude of the overall change depends on the relative strength of the "separation effect" and "matching effect." This can be seen more clearly by rewriting Equation A11 as follows:

$$\frac{du^*}{dq} = \overbrace{\frac{f\frac{ds}{dq}}{(s+f)^2}}^{\text{separation effect}} - \overbrace{\frac{s\frac{df}{dq}}{(s+f)^2}}^{\text{matching effect}}. \tag{A12}$$

How are AI-driven changes in the three labor market parameters analyzed in Section A.2 — A_L (labor-augmenting productivity), N (the number of tasks), and I (the threshold above which tasks are performed by labor) — likely to affect the job-finding and separation rates? In general, f should increase with A_L, since higher labor productivity strengthens incentives to form matches and post vacancies, but decrease with I, as labor demand declines when a larger

[1]This rate is sometimes expressed as a function of labor market "tightness," the ratio of vacancies to unemployment: $\theta \equiv v/u$.

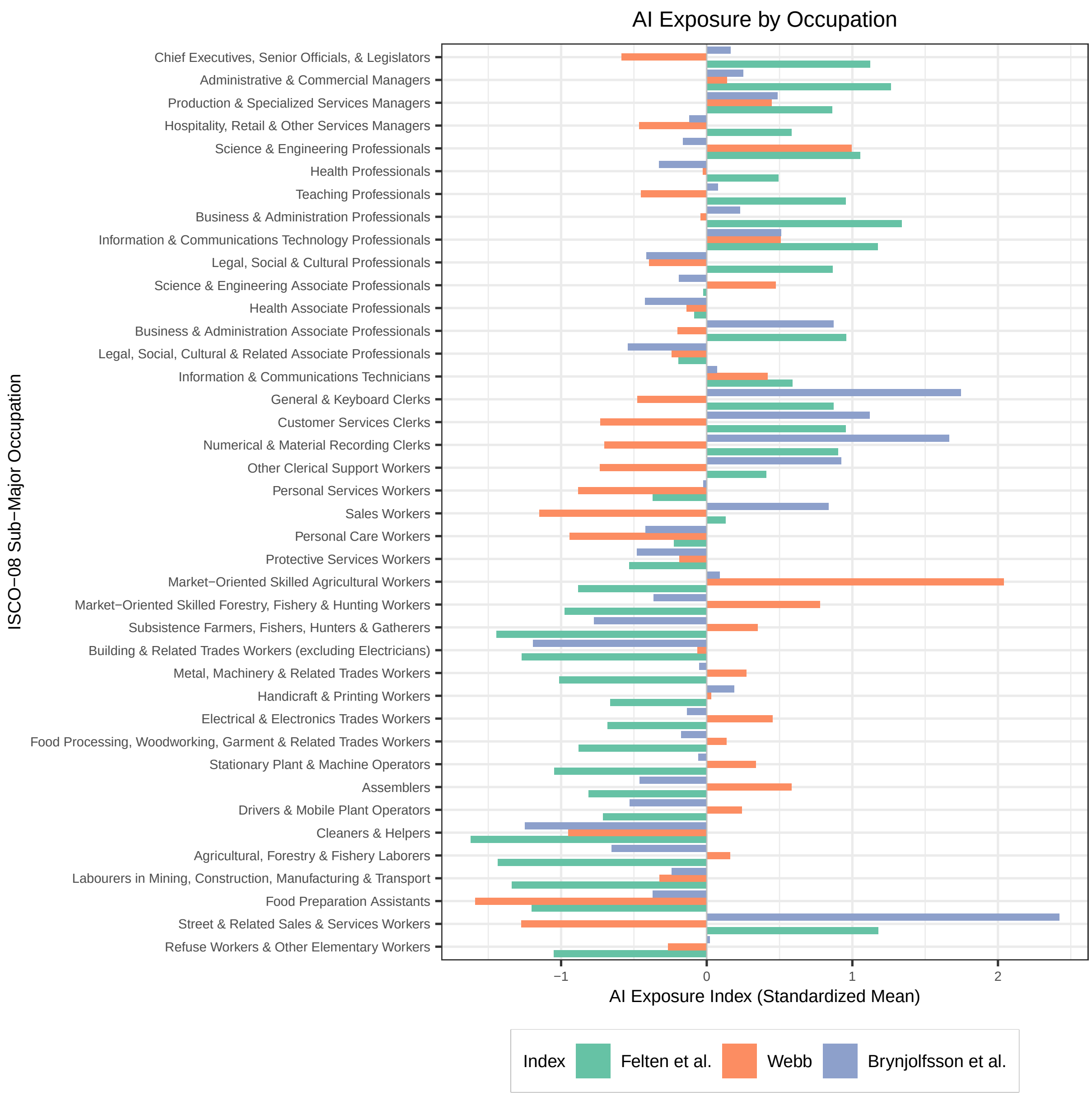
share of tasks is performed by capital. The relationship between f and N depends on the nature of new tasks created by AI: if these activities rely heavily on human skills, they will raise f by boosting demand for workers; if not, they should be automated by firms, leaving f largely unchanged.

The implications for job separation are more mixed. Increases in A_L and N could plausibly lower s by bolstering labor demand and introducing complementary tasks that facilitate the rapid reemployment of displaced workers. An increase in I, on the other hand, is likely to elevate s as AI-based automation displaces workers from previously labor-intensive tasks.

For AI not to intensify unemployment risk, the second line of Equation 7 in the main text implies that the combined rise in f stemming from growth in A_L and N must offset any increase in s due to growth in I.

B Exposure to Artificial Intelligence

FIGURE A1. Occupational Exposure to AI by AAIOE Component



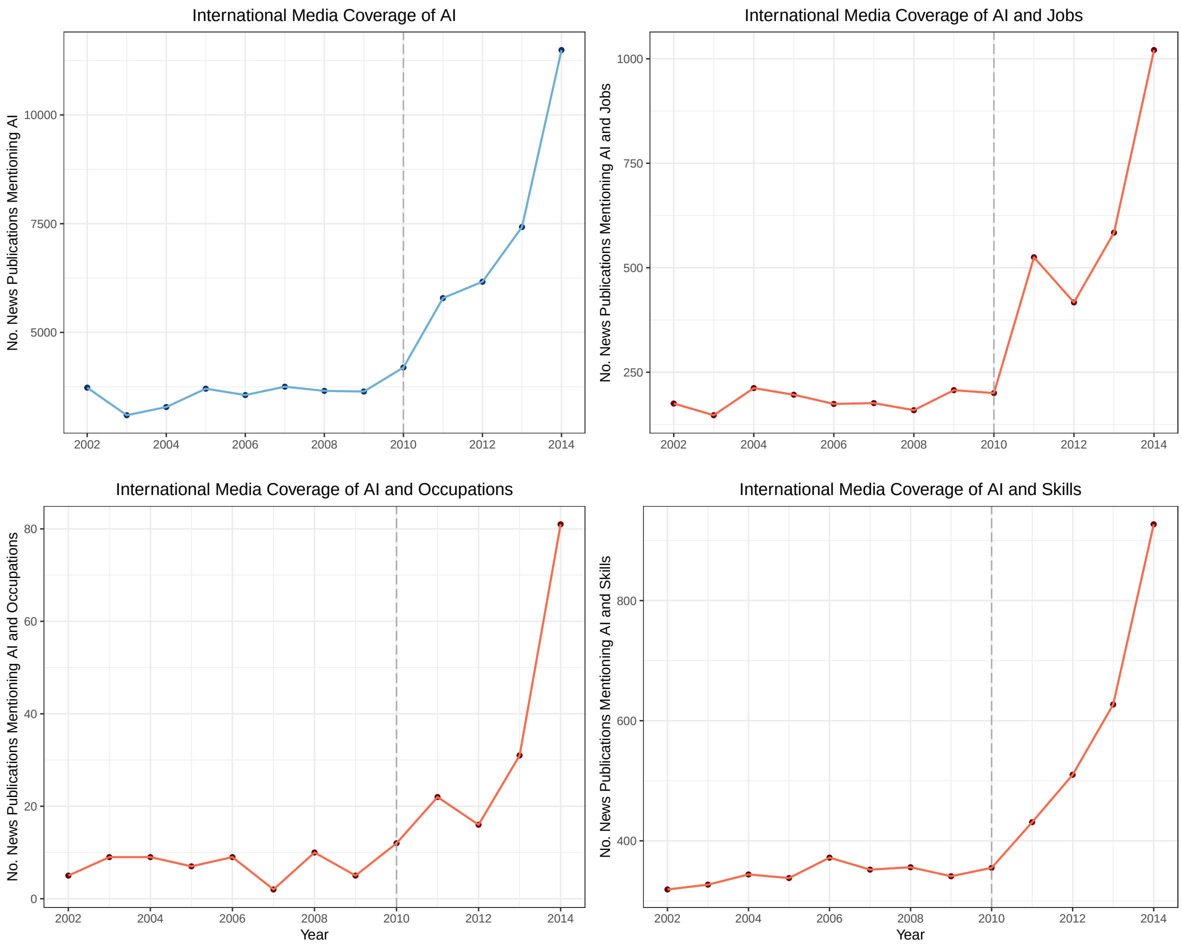
Notes: This figure disaggregates Figure 1 by the three component measures of the AAIOE: (1) Felten, Raj, and Seamans' (2021) AIOE index; (2) Brynjolfsson, Mitchell, and Rock's (2018) SML index; and (3) Webb's (2020) AI exposure index.

TABLE A1. Four-Digit Occupations Most and Least Exposed to AI

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
Cleaners 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, four-digit occupations — with the lowest (left column) and highest (right column) exposure to AI according to 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).

FIGURE A2. International Media Coverage of AI and Work Before and After 2010

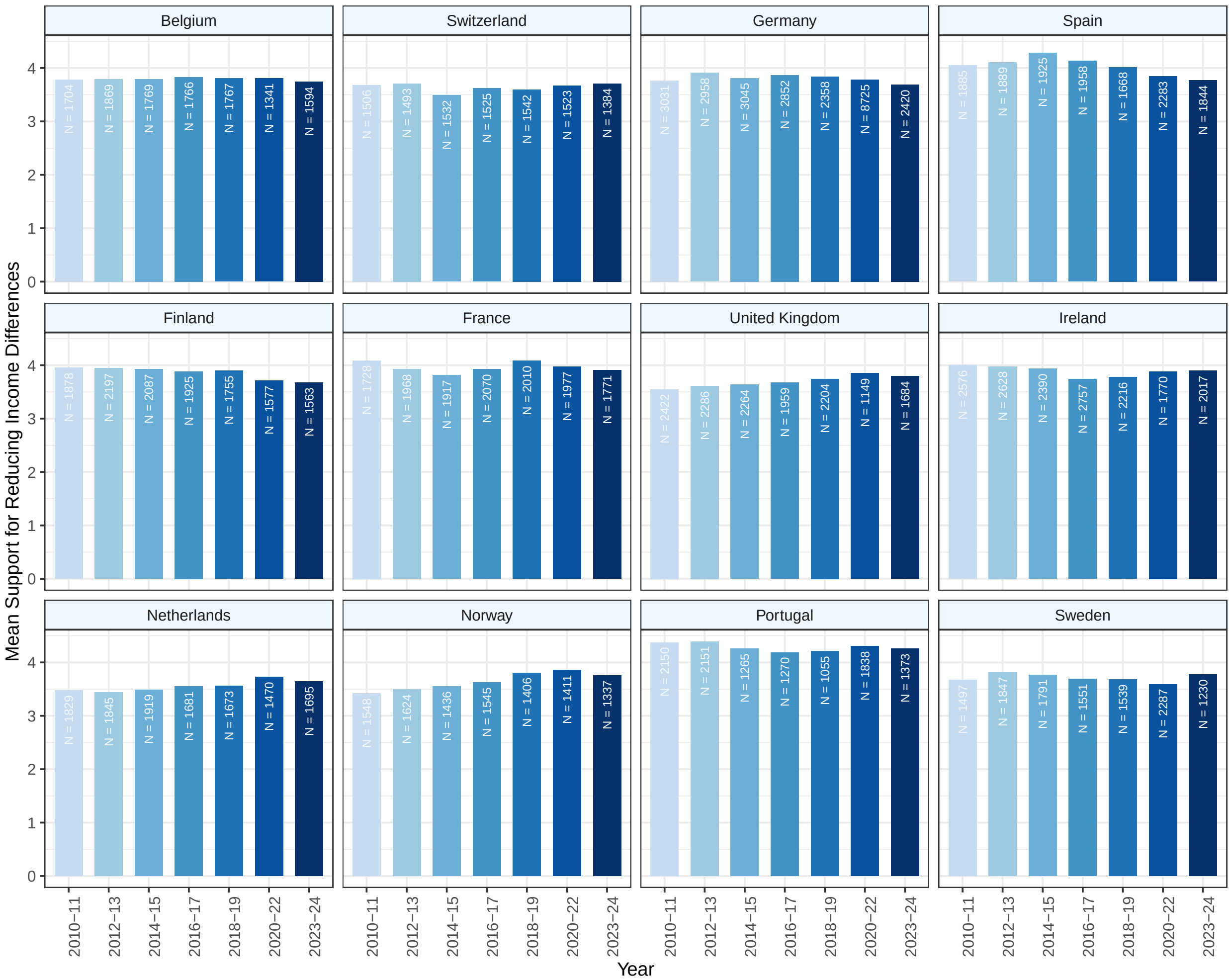


Notes: This figure plots the number of English-language media publications (print and online) containing the term "artificial intelligence" (upper left panel) plus "jobs" (upper right), "occupations" (lower left), and "skills" (lower right) between 2002 and 2014. Source: Dow Jones Factiva global news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

C Cross-National Analysis

C.1 Descriptive Data

FIGURE A3. Support for Redistribution in 12 Western European Countries, 2010–2024



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-wave is reported within bars.

TABLE A2. List of Political Parties in Cross-National Analysis

Party	Acronym	Country	Category	Principal
Christen-Democratisch en Vlaams	CD&V	Belgium	Mains. right	
Vooruit	Vooruit	Belgium	Mains. left	✓ (L)
Volksunie	VU	Belgium	Mains. right	
Partij Van De Arbeid van België/Parti du Travail de Belgique	PVDA-PTB	Belgium	Far left	
Vlaams Belang	VB	Belgium	Populist right	
Centre Démocrate Humaniste	CDH	Belgium	Mains. right	
Parti Socialiste	PS	Belgium	Mains. left	✓ (L)
Front National	FN	Belgium	Populist right	
Nieuw-Vlaamse Alliantie	N-VA	Belgium	Mains. right	✓ (R)
Parti Populaire	PP	Belgium	Populist right	
Christlichdemokratische Volkspartei der Schweiz/Parti Démocrate-Chrétien	CVP/PDC	Switzerland	Mains. right	
Sozialdemokratische Partei der Schweiz/Parti Socialiste Suisse	SP/PS	Switzerland	Mains. left	✓ (L)
Landesring der Unabhängigen	LdU	Switzerland	Mains. left	
Evangelische Volkspartei der Schweiz/Parti Evangelique Suisse	EVP/PEV	Switzerland	Mains. right	
Christlich-Soziale Partei/Parti Chrétien-Social	CSP/PCS	Switzerland	Mains. right	
Partei der Arbeit der Schweiz/Parti Suisse du Travail	PdA/PST	Switzerland	Far left	
Schweizer Demokraten/Démocrates Suisses	SD/DS	Switzerland	Populist right	
Eidgenössisch-Demokratische Union/Union Démocratique Fédérale	EDU/UDF	Switzerland	Mains. right	
Freiheits-Partei der Schweiz/Parti Suisse de la Liberté	FPS/PSL	Switzerland	Populist right	
Lega dei Ticinesi	Lega	Switzerland	Populist right	
Bürgerlich-Demokratische Partei Schweiz/Parti Bourgeois Démocratique Suisse	BDP/PBD	Switzerland	Mains. right	
Mouvement Citoyens Genevois	MCG	Switzerland	Populist right	
Alternative Linke	AL	Switzerland	Mains. left	
solidaritéS	Sol	Switzerland	Far left	
Partido Popular	PP	Spain	Mains. right	✓ (R)
Partido Socialista Obrero Español	PSOE	Spain	Mains. left	✓ (L)
Izquierda Unida	IU	Spain	Far left	
Podemos	Podemos	Spain	Far left	
Vox	Vox	Spain	Populist right	
Sumar	SMR	Spain	Mains. left	
Más País	MP	Spain	Mains. left	
Kansallinen Kokoomus	Kok	Finland	Mains. right	
Kristillisdemokraatit	KD	Finland	Mains. right	
Sosialidemokraatit	SDP	Finland	Mains. left	✓ (L)
Vasemmistoliitto	Vas	Finland	Far left	

Suomen Kommunistinen Puolue	SKP	Finland	Far left	
Kommunistinen Työväenpuolue	KTP	Finland	Far left	
Kansalaisliitto	KaL	Finland	Mains. left	
Köyhien Asialla	KA	Finland	Mains. left	
Suomen Työväenpuolue	STP	Finland	Far left	
Muutos 2011	M11	Finland	Populist right	
Seitsemän Tähden Liike	STL	Finland	Populist right	
Suomen Kansa Ensin	SKE	Finland	Populist right	
Kansalaispuolue	KP	Finland	Mains. right	
Korjausliike	Korjausliike	Finland	Mains. right	
Valta Kuuluu Kansalle	VKK	Finland	Populist right	
Vapauden Liitto	VL	Finland	Populist right	
Rassemblement National	RN	France	Populist right	
Ligue Communiste Révolutionnaire	LCR	France	Far left	
Lutte Ouvrière	LO	France	Far left	
Mouvement des Citoyens	MDC	France	Far left	
Mouvement pour la France	MPF	France	Mains. right	
Parti Communiste Français	PCF	France	Far left	
Parti Socialiste	PS	France	Mains. left	
Rassemblement du Peuple Français	RPF	France	Mains. right	
Union pour un Mouvement Populaire	UMP	France	Mains. right	
Union pour la Démocratie Française	UDF	France	Mains. right	
Parti Radical de Gauche	PRG	France	Mains. left	
Parti Radical	PR	France	Mains. right	
Nouveau Parti Anticapitaliste	NPA	France	Far left	
Mouvement Démocrate	MoDem	France	Mains. right	
La France Insoumise	LFI	France	Far left	✓ (L)
Les Républicains	LR	France	Mains. right	✓ (R)
Reconquête	R!	France	Populist right	
Conservative Party	Conservatives	UK	Mains. right	✓ (R)
Labour Party	Labour	UK	Mains. left	✓ (L)
UK Independence Party	UKIP	UK	Populist right	
Reform UK	Reform	UK	Populist right	
Fianna Fáil	FF	Ireland	Mains. right	
Fine Gael	FG	Ireland	Mains. right	✓ (R)
Labour Party	Labour	Ireland	Mains. left	
Sinn Féin	SF	Ireland	Mains. left	✓ (L)
People Before Profit	PBP	Ireland	Far left	
Socialist Party	SP	Ireland	Far left	
Social Democrats	Soc Dems	Ireland	Mains. left	
Centre Party of Ireland	Centre Party	Ireland	Mains. right	
Aontú	Aontú	Ireland	Mains. right	
Independents 4 Change	I4C	Ireland	Far left	
Workers' Party	WP	Ireland	Far left	
Christen-Democratisch Appèl	CDA	Netherlands	Mains. right	
Partij van de Arbeid	PvdA	Netherlands	Mains. left	✓ (L)
Lijst Pim Fortuyn	LPF	Netherlands	Populist right	
Socialistische Partij	SP	Netherlands	Mains. left	
ChristenUnie	CU	Netherlands	Mains. right	

Leefbaar Nederland	LN	Netherlands	Populist right	
Staatkundig Gereformeerde Partij	SGP	Netherlands	Mains. right	
Partij voor de Vrijheid	PVV	Netherlands	Populist right	
Trots op Nederland	TON	Netherlands	Populist right	
Denk	DENK	Netherlands	Mains. left	
Forum voor Democratie	FvD	Netherlands	Populist right	
Bij1	BIJ1	Netherlands	Far left	
JA21	JA21	Netherlands	Populist right	
Sosialistisk Venstreparti	SV	Norway	Far left	
Arbeiderpartiet	Ap	Norway	Mains. left	✓ (L)
Kristelig Folkeparti	KrF	Norway	Mains. right	
Høyre	H	Norway	Mains. right	✓ (R)
Fremskrittspartiet	Frp	Norway	Populist right	
Rødt	R	Norway	Far left	
Bloco de Esquerda	BE	Portugal	Far left	
CDS - Partido Popular	CDS-PP	Portugal	Mains. right	
Partido Comunista Português	PCP	Portugal	Far left	
Partido Comunista dos Trabalhadores Portugueses	PCTP/MRPP	Portugal	Far left	
Partido Operário de Unidade Socialista	POUS	Portugal	Far left	
Partido Socialista	PS	Portugal	Mains. left	✓ (L)
Partido Trabalhista Português	PTP	Portugal	Mains. left	
Livre	L	Portugal	Mains. left	
Cidadania e Democracia Cristã	PPV/CDC	Portugal	Mains. right	
Alternativa Democrática Nacional	ADN	Portugal	Mains. right	
Aliança	A	Portugal	Mains. right	
Chega	CH	Portugal	Populist right	
Movimento Alternativa Socialista	MAS	Portugal	Far left	
Kristdemokraterna	KD	Sweden	Mains. right	
Moderata Samlingspartiet	M	Sweden	Mains. right	✓ (R)
Vänsterpartiet	V	Sweden	Far left	
Sverigedemokraterna	SD	Sweden	Populist right	
Socialdemokratiska Arbetarpartiet	S	Sweden	Mains. left	✓ (L)
Sozialdemokratische Partei Deutschlands	SPD	Germany	Mains. left	✓ (L)
Christlich Demokratische Union Deutschlands/Christlich-Soziale Union in Bayern	CDU/CSU	Germany	Mains. right	✓ (R)
Partei des Demokratischen Sozialismus	PDS	Germany	Far left	
Die Republikaner	REP	Germany	Populist right	
Die Linke	LINKE	Germany	Far left	
Alternative für Deutschland	AfD	Germany	Populist right	

Notes: This table lists all national left-wing, mainstream right-wing, and right-wing populist parties in 12 Western European countries that appear as response options in the ESS vote choice question, Rounds 5-11 (2008-2024). Liberal, green, regional and single-issue parties are excluded. Party categorizations are based on the ParlGov (Döring, Huber, and Manow 2022) and PopuList (Rooduijn et al. 2023) databases, supplemented by the author's coding for a small number of additional cases. The fifth column identifies the principal left-wing (L) and right-wing (R) party in each country; in Belgium, Flemish and Francophone parties are treated as separate systems.

TABLE A3. Summary Statistics for Cross-National Analysis

	N	Mean	St. Dev.	Min	Max
Panel A: Full Sample					
Redistribution Support	160,950	3.824	1.014	1	5
AAIOE	133,408	0.000	1.000	−3.084	2.685
Age	162,176	49.937	18.842	14	114
Female	162,775	0.517	0.500	0	1
Years of Education	160,659	13.221	4.390	0	76
Degree of Religiosity	162,287	4.289	3.086	0	10
Urban Resident	162,696	0.617	0.486	0	1
Union Member	160,133	0.204	0.403	0	1
Household Income Decile	136,166	5.464	2.799	1	10
Left-Right Ideology	149,885	4.971	2.143	0	10
Panel B: Voting Analysis Only					
Vote Choice: Left	100,548	0.344	0.475	0	1
Vote Choice: Mainstream Right	100,548	0.327	0.469	0	1
Vote Choice: Populist Right	100,548	0.049	0.216	0	1

Notes: The sample comprises 12 Western European countries: Belgium, Finland, France, Germany, Ireland, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. Source: ESS, Rounds 5-11 (2010-2024).

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.)	−0.048***	−0.016***	0.015***	−0.013***
	(0.007)	(0.003)	(0.002)	(0.002)
Age	0.004***	0.001***	0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.110***	−0.005	0.000	−0.018***
	(0.011)	(0.004)	(0.004)	(0.002)
Years of Education	−0.007***	−0.007***	0.002***	−0.004***
	(0.001)	(0.000)	(0.000)	(0.000)
Degree of Religiosity	−0.002*	−0.007***	0.016***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.000)
Urban Resident	−0.018***	0.051***	−0.019***	−0.004**
	(0.006)	(0.004)	(0.004)	(0.002)
Union Member	0.120***	0.057***	−0.021***	0.003
	(0.009)	(0.004)	(0.004)	(0.002)
Household Income	−0.048***	−0.007***	0.008***	−0.004***
	(0.002)	(0.001)	(0.001)	(0.000)
Left-Right Position	−0.122***	−0.097***	0.076***	0.018***
	(0.005)	(0.001)	(0.001)	(0.001)
N	105,515	73,775	73,775	73,775
Mean Outcome	3.819	0.340	0.316	0.051
Panel B: Controlling for Automation Risk				
	(5)	(6)	(7)	(8)
AAIOE (Std.)	−0.054***	−0.016***	0.016***	−0.013***
	(0.006)	(0.002)	(0.002)	(0.001)
Goos et al. RTI Index (Std.)	0.032***	0.011***	0.001	0.003*
	(0.005)	(0.002)	(0.002)	(0.002)
Age	0.004***	0.001***	0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.110***	−0.010**	0.002	−0.019***
	(0.011)	(0.004)	(0.004)	(0.003)
Years of Education	−0.007***	−0.007***	0.002***	−0.004***
	(0.001)	(0.000)	(0.000)	(0.000)
Degree of Religiosity	−0.003**	−0.006***	0.015***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.000)
Urban Resident	−0.017***	0.049***	−0.023***	−0.005***
	(0.006)	(0.004)	(0.004)	(0.002)
Union Member	0.124***	0.056***	−0.022***	0.003
	(0.009)	(0.005)	(0.004)	(0.002)
Household Income	−0.046***	−0.008***	0.009***	−0.004***
	(0.002)	(0.001)	(0.001)	(0.000)
Left-Right Position	−0.119***	−0.097***	0.076***	0.019***
	(0.005)	(0.001)	(0.001)	(0.001)
N	94,436	65,388	65,388	65,388
Mean Outcome	3.811	0.343	0.317	0.054
Country × Wave FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by four-digit ISCO-08 occupation, in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

C.3 Extensions and Robustness

Additional Controls and Fixed Effects

TABLE A5. 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.)	-0.047^{***}	-0.017^{***}	0.015^{***}	-0.014^{***}
	(0.006)	(0.003)	(0.002)	(0.001)
Frey & Osborne Exposure to Computerization Index (Std.)	0.030^{***}	0.010^{***}	-0.002	0.005^{***}
	(0.007)	(0.002)	(0.002)	(0.001)
N	101,129	70,512	70,512	70,512
Mean Outcome	3.821	0.341	0.315	0.052
Panel B: Offshorability	(5)	(6)	(7)	(8)
AAIOE (Std.)	-0.048^{***}	-0.015^{***}	0.016^{***}	-0.012^{***}
	(0.007)	(0.003)	(0.003)	(0.002)
Blinder and Krueger Offshorability Index (Std.)	-0.001	0.003	0.001	-0.001
	(0.006)	(0.002)	(0.002)	(0.002)
N	94,436	65,388	65,388	65,388
Mean Outcome	3.811	0.343	0.317	0.054
Panel C: Skill Specificity	(9)	(10)	(11)	(12)
AAIOE (Std.)	-0.048^{***}	-0.015^{***}	0.015^{***}	-0.013^{***}
	(0.007)	(0.003)	(0.002)	(0.002)
Cusack, Iversen, and Rehm Skill Specificity Index (Std.)	0.001	0.004^{**}	-0.002	0.002
	(0.005)	(0.002)	(0.002)	(0.001)
N	105,257	73,595	73,595	73,595
Mean Outcome	3.819	0.341	0.316	0.051
Panel D: Labor Market Outsiderness	(13)	(14)	(15)	(16)
AAIOE (Std.)	-0.052^{***}	-0.016^{***}	0.017^{***}	-0.014^{***}
	(0.007)	(0.003)	(0.003)	(0.002)
Fixed-Term Contract (0/1)	0.025^{***}	-0.009^{*}	-0.009^{**}	0.004
	(0.009)	(0.006)	(0.005)	(0.003)
N	92,891	64,514	64,514	64,514
Mean Outcome	3.839	0.357	0.307	0.051
Panel E: Occupational Prestige	(17)	(18)	(19)	(20)
AAIOE (Std.)	-0.036^{***}	-0.011^{***}	0.014^{***}	-0.011^{***}
	(0.008)	(0.003)	(0.003)	(0.001)
Hughes et al. Occupational Prestige Rating (0-100)	-0.003^{***}	-0.001^{***}	0.000^{*}	-0.001^{***}
	(0.001)	(0.000)	(0.000)	(0.000)
N	105,408	73,716	73,716	73,716
Mean Outcome	3.819	0.340	0.316	0.051
Baseline Controls	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by four-digit ISCO-08 occupation, in parentheses. Baseline controls: age, years of education, gender, union membership, degree of religiosity, urban residence, household income decile, and left-right ideology. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A6. Cross-National Results with Additional Socioeconomic Controls

Outcome:	*Redistribution Support*	*Vote Choice: Left*	*Vote Choice: Mainstream Right*	*Vote Choice: Populist Right*
Panel A: Perceived Job Security	(1)	(2)	(3)	(4)
AAIOE (Std.)	−0.039*	−0.022***	0.025***	−0.012***
	(0.021)	(0.007)	(0.007)	(0.004)
Job Security (1-4)	−0.026**	0.002	0.004	−0.005*
	(0.013)	(0.007)	(0.006)	(0.003)
N	5,612	3,890	3,890	3,890
Mean Outcome	3.716	0.356	0.324	0.042
Panel B: Trust in Politicians	(5)	(6)	(7)	(8)
AAIOE (Std.)	−0.046***	−0.016***	0.014***	−0.012***
	(0.007)	(0.003)	(0.002)	(0.001)
Trust in Politicians (0-10)	−0.017***	0.002***	0.009***	−0.016***
	(0.002)	(0.001)	(0.001)	(0.001)
N	105,040	73,596	73,596	73,596
Mean Outcome	3.819	0.340	0.316	0.051
Panel C: Public-Sector Employee	(9)	(10)	(11)	(12)
AAIOE (Std.)	−0.046***	−0.015***	0.015***	−0.014***
	(0.006)	(0.003)	(0.002)	(0.002)
Public-Sector Employee (0/1)	0.060***	0.023***	−0.017***	−0.008***
	(0.009)	(0.005)	(0.004)	(0.002)
N	105,211	73,595	73,595	73,595
Mean Outcome	3.819	0.340	0.316	0.051
Panel D: Ethnic Minority	(13)	(14)	(15)	(16)
AAIOE (Std.)	−0.044***	−0.017***	0.016***	−0.012***
	(0.007)	(0.003)	(0.003)	(0.002)
Ethnic Minority (0/1)	−0.051**	0.129***	−0.091***	−0.010*
	(0.020)	(0.012)	(0.009)	(0.005)
N	74,712	52,526	52,526	52,526
Mean Outcome	3.820	0.341	0.340	0.047
Baseline Controls	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by four-digit ISCO-08 occupation, in parentheses. Baseline control variables: age, years of education, gender, union membership, degree of religiosity, urban residence, household income decile, and left-right ideology. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A7. 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.)	−0.048***	−0.016***	0.015***	−0.013***
	(0.007)	(0.003)	(0.002)	(0.002)
Social Spending (% of GDP), Lagged	−0.058	0.013	0.001	−0.028*
	(0.056)	(0.022)	(0.028)	(0.015)
N	105,515	73,775	73,775	73,775
Mean Outcome	3.819	0.340	0.316	0.051
Panel B: Unemployment	(5)	(6)	(7)	(8)
AAIOE (Std.)	−0.048***	−0.016***	0.015***	−0.013***
	(0.007)	(0.003)	(0.002)	(0.002)
Unemployment Rate (% of Workforce), Lagged	−0.083	−0.021	0.010	−0.011*
	(0.054)	(0.024)	(0.023)	(0.006)
N	105,515	73,775	73,775	73,775
Mean Outcome	3.819	0.340	0.316	0.051
Panel C: Migration	(9)	(10)	(11)	(12)
AAIOE (Std.)	−0.050***	−0.016***	0.015***	−0.015***
	(0.007)	(0.003)	(0.003)	(0.002)
Foreign-Born Population (% of Total), Lagged	0.363	0.434***	−0.087	−0.071
	(0.416)	(0.068)	(0.068)	(0.072)
N	93,321	66,219	66,219	66,219
Mean Outcome	3.795	0.334	0.298	0.056
Baseline Controls	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by four-digit ISCO-08 occupation, in parentheses. Baseline control variables: age, years of education, gender, union membership, degree of religiosity, urban residence, household income decile, and left-right ideology. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A8. Cross-National Results with Alternative Fixed Effects

Outcome:	*Redistribution Support*	*Vote Choice: Left*	*Vote Choice: Mainstream Right*	*Vote Choice: Populist Right*
Panel A: Occupation FEs	(1)	(2)	(3)	(4)
AAIOE (Std.)	-0.031***	-0.006**	0.009***	-0.005***
	(0.007)	(0.003)	(0.003)	(0.001)
N	105,515	73,775	73,775	73,775
Mean Outcome	3.819	0.340	0.316	0.051
Baseline Controls	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓
1-Digit Occupation FEs	✓	✓	✓	✓
Panel B: Industry FEs	(5)	(6)	(7)	(8)
AAIOE (Std.)	-0.037***	-0.013***	0.013***	-0.013***
	(0.007)	(0.003)	(0.002)	(0.001)
N	103,892	72,632	72,632	72,632
Mean Outcome	3.820	0.340	0.316	0.051
Baseline Controls	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓
1-Digit Industry FEs	✓	✓	✓	✓
Panel C: Region FEs	(9)	(10)	(11)	(12)
AAIOE (Std.)	-0.046***	-0.015***	0.014***	-0.013***
	(0.007)	(0.003)	(0.002)	(0.001)
N	105,515	73,775	73,775	73,775
Mean Outcome	3.819	0.340	0.316	0.051
Baseline Controls	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓
NUTS-2 FEs	✓	✓	✓	✓
Panel D: Country + Wave FEs	(13)	(14)	(15)	(16)
AAIOE (Std.)	-0.048***	-0.016***	0.016***	-0.013***
	(0.006)	(0.003)	(0.002)	(0.002)
N	105,515	73,775	73,775	73,775
Mean Outcome	3.819	0.340	0.316	0.051
Baseline Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Wave FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by four-digit ISCO-08 occupation, in parentheses. Baseline controls: age, years of education, gender, union membership, degree of religiosity, urban residence, household income decile, and left-right ideology. Occupations are defined according to the ISCO-08 classification, industries according to the NACE Rev.2 classification. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A9. Cross-National Results Replicating Thewissen and Rueda's Approach

Outcome:	*Redistribution Support*	*Vote Choice: Left*	*Vote Choice: Mainstream Right*	*Vote Choice: Populist Right*
AAIOE (Std.)	-0.062***	-0.019**	0.019***	-0.013***
	(0.003)	(0.002)	(0.002)	(0.001)
Goos et al. RTI Index (Std.)	0.035***	0.012***	0.001	0.003**
	(0.003)	(0.002)	(0.002)	(0.001)
N	99,461	66,806	66,806	66,806
Mean Outcome	3.824	0.344	0.327	0.049
Thewissen and Rueda Controls	✓	✓	✓	✓

Notes: Multilevel OLS estimates with random country intercepts; robust standard errors, clustered by four-digit ISCO-08 occupation, are in parentheses. The control variables follow Thewissen and Rueda's (2019) baseline specification (column 4, Table 2): age, years of education, gender, union membership, degree of religiosity, urban residence, household income decile, employment status, and lagged country-level social spending and unemployment. Design weights are included to adjust for differential respondent selection probabilities. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Instrumental Variables Analysis

TABLE A10. Cross-National Instrumental Variables Results

Outcome:	*Redistribution Support* (1)	*Vote Choice: Left* (2)	*Vote Choice: Mainstream Right* (3)	*Vote Choice: Populist Right* (4)
AAIOE (Std.) [Instrumented]	-0.627***	-0.247***	0.135***	-0.121***
	(0.107)	(0.045)	(0.032)	(0.020)
N	93,857	66,344	66,344	66,344
Mean Outcome	3.807	0.334	0.319	0.050
First-Stage F-Statistic	392.381	271.078	271.078	271.078
Baseline Controls	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓

Notes: 2SLS estimates with robust standard errors, clustered by four-digit ISCO-08 occupation, in parentheses. The instrument is the occupational skill level of respondent i's father when i was 14 years old. Baseline controls: age, years of education, gender, union membership, degree of religiosity, urban residence, household income decile, and left-right ideology. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Different Party Categorizations

TABLE A11. Cross-National Vote Choice Results with Different Party Categorizations

Outcome = Vote Choice:	*Main Left* (1)	*Far Left* (2)	*Main Right* (3)
AAIOE (Std.)	−0.015***	−0.006***	0.016***
	(0.003)	(0.001)	(0.003)
N	73,775	73,775	73,775
Mean Outcome	0.245	0.061	0.291
Baseline Controls	✓	✓	✓
Country × Wave FEs	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by four-digit ISCO-08 occupation, in parentheses. Baseline controls: age, years of education, gender, union membership, degree of religiosity, urban residence, household income decile, and left-right ideology. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Alternative Samples

TABLE A12. Cross-National Results for High-Income Respondents Only

Outcome:	*Redistribution Support* (1)	*Public Provision for Unemployed* (2)	*Vote Choice: Left* (3)	*Vote Choice: Mains. Right* (4)	*Vote Choice: Populist Right* (5)
AAIOE (Std.)	−0.048***	−0.020	−0.015***	0.015***	−0.013***
	(0.007)	(0.018)	(0.003)	(0.002)	(0.001)
N	105,515	15,822	73,775	73,775	73,775
Mean Outcome	3.819	6.620	0.340	0.316	0.051
Baseline Controls	✓	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by four-digit ISCO-08 occupation, in parentheses. The sample is restricted to respondents in the top two deciles of their country's household net income distribution. Baseline controls: age, years of education, gender, union membership, degree of religiosity, urban residence, household income decile, and left-right ideology. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A13. 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.)	−0.046***	−0.015***	0.014***	−0.014***
	(0.006)	(0.003)	(0.002)	(0.002)
N	127,686	90,407	90,407	90,407
Mean Outcome	3.824	0.338	0.303	0.066
Panel B: + Hungary, Poland, Slovenia	(5)	(6)	(7)	(8)
AAIOE (Std.)	−0.048***	−0.013***	0.013***	−0.013***
	(0.007)	(0.002)	(0.002)	(0.001)
N	123,971	86,124	86,124	86,124
Mean Outcome	3.852	0.324	0.360	0.092
Panel C: Market Earners Only	(9)	(10)	(11)	(12)
AAIOE (Std.)	−0.053***	−0.014***	0.014***	−0.014***
	(0.007)	(0.003)	(0.002)	(0.002)
N	70,631	48,217	48,217	48,217
Mean Outcome	3.749	0.322	0.306	0.053
Panel D: Analysis Weights	(13)	(14)	(15)	(16)
AAIOE (Std.)	−0.041***	−0.015***	0.015***	−0.014***
	(0.007)	(0.003)	(0.003)	(0.002)
N	105,515	73,775	73,775	73,775
Mean Outcome	3.819	0.340	0.316	0.051
Panel E: No Pre-2010 Elections in 2010-11 Wave		(17)	(18)	(19)
AAIOE (Std.)		−0.015***	0.015***	−0.013***
		(0.003)	(0.002)	(0.001)
N		69,378	69,378	69,378
Mean Outcome		0.337	0.317	0.052
Baseline Controls	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by four-digit ISCO-08 occupation, in parentheses. Baseline controls: age, years of education, gender, union membership, degree of religiosity, urban residence, household income decile, and left-right ideology. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A14. List of Political Parties in Supplementary Cross-National Analyses

Party	Acronym	Country	Category
Panel A: Additional Western European Countries			
Sozialdemokratische Partei Österreichs	SPÖ	Austria	Left
Österreichische Volkspartei	ÖVP	Austria	Right
Freiheitliche Partei Österreichs	FPÖ	Austria	Populist right
Bündnis Zukunft Österreich	BZÖ	Austria	Populist right
Kommunistische Partei Österreichs	KPÖ	Austria	Far left
Socialdemokratiet	S	Denmark	Left
Det Konservative Folkeparti	C	Denmark	Right
Centrum Demokraterne	CD	Denmark	Right
Dansk Folkeparti	DF	Denmark	Populist right
Kristendemokraterne	K	Denmark	Right
Enhedslisten - De Rød-Grønne	EL	Denmark	Far left
Panellinio Sosialistiko Kinima - Kínima Allagís	PASOK-KINAL	Greece	Left
Néa Dimokratía	ND	Greece	Right
Kommounistikó Kómma Elládas	KKE	Greece	Far left
Dimokratiko Koinoniko Kinima	DIKKI	Greece	Left
Laikós Orthódoxos Synagermós	LAOS	Greece	Populist right
Sinaspismós Rizospastikís Aristerás	SYRIZA	Greece	Far left
Laïkós Sýndesmos – Chrysí Avgí	XA	Greece	Populist right
Antikapitalistiki Aristeri Synergasia gia tin Anatropi	ANTARSYA	Greece	Far left
Ellinikí Lýsi	EL	Greece	Populist right
Métopo Evropaikís Realistikís Anypakoís	MeRA25	Greece	Far left
Plefsi Eleftherias	PE	Greece	Left
Énosi Kentróon	EK	Greece	Left
Néa Aristerá	NEAR	Greece	Far left
Dimiourgía	Dimiourgía	Greece	Right
Samfylkingin	S	Iceland	Left
Sjálfstæðisflokkurinn	D	Iceland	Right
Alþýðufylkingin	PFI	Iceland	Far left
Viðreisn	Viðreisn	Iceland	Right
Húmanistaflokkurinn	H	Iceland	Far left
Sósíalistaflokkurinn	SFÍ	Iceland	Far left
Democratici di Sinistra	DS	Italy	Left
Partito dei Comunisti Italiani	PdCI	Italy	Far left
Partito della Rifondazione Comunista	PRC	Italy	Far left
Forza Italia	FI	Italy	Right
Alleanza Nazionale	AN	Italy	Right
Lega Nord	LN	Italy	Populist right
Nuovo Partito Socialista Italiano	NPSI	Italy	Left
Democrazia Europea	DE	Italy	Right
Partito Democratico	PD	Italy	Left
Sinistra Ecologia Libertà	SEL	Italy	Far left
Unione di Centro	UdC	Italy	Right
Fratelli d'Italia	FdI	Italy	Populist right
Civica Popolare	CP	Italy	Right
Noi con l'Italia	NcI	Italy	Right

Potere al Popolo!	PaP	Italy	Far left
Italexit per l'Italia	Italexit	Italy	Populist right
Panel B: Eastern European Countries			
Magyar Demokrata Fórum	MDF	Hungary	Right
Független Kisgazdapárt	FKgP	Hungary	Right
Magyar Igazság és Élet Pártja	MIÉP	Hungary	Populist right
Magyar Szocialista Párt	MSZP	Hungary	Left
Magyar Munkáspárt	Munkáspárt	Hungary	Far left
Fidesz – Magyar Polgári Szövetség	Fidesz	Hungary	Populist right
Kereszténydemokrata Néppárt	KDNP	Hungary	Right
Jobbik Magyarországért Mozgalom	Jobbik	Hungary	Populist right
Magyarországi Szociáldemokrata Párt	MSZDP	Hungary	Far left
Demokratikus Koalíció	DK	Hungary	Left
Momentum Mozgalom	Momentum	Hungary	Right
Mi Hazánk Mozgalom	Mi Hazánk	Hungary	Populist right
Sojusz Lewicy Demokratycznej	SLD	Poland	Left
Prawo i Sprawiedliwość	PiS	Poland	Populist right
Platforma Obywatelska	PO	Poland	Right
Polska Wspólnota Narodowa	PWN	Poland	Right
Polska Partia Socjalistyczna	PPS	Poland	Left
Centrum dla Polski	CdP	Poland	Right
Liga Polskich Rodzin	LPR	Poland	Right
Inicjatywa Rzeczpospolitej Polskiej	IRP	Poland	Left
Kongres Nowej Prawicy	KNP	Poland	Populist right
Polska Konfederacja – Godność i Praca	PKGiP	Poland	Far left
Polska Partia Pracy	PPP	Poland	Left
Socjaldemokracja Polska	SDPL	Poland	Left
Polska Jest Najważniejsza	PJN	Poland	Right
Polska Partia Pracy – Sierpień 80	PPP–Sierpień 80	Poland	Far left
Koalicja Odnowy Rzeczypospolitej Wolność i Nadzieja	KORWiN	Poland	Populist right
Kukiz'15	K'15	Poland	Populist right
Partia Razem	Razem	Poland	Left
Konfederacja Wolność i Niepodległość	Konfederacja	Poland	Populist right
Nowa Lewica	NL	Poland	Left
Slovenska Ljudska Stranka	SLS	Slovenia	Right
Slovenska Demokratska Stranka	SDS	Slovenia	Right
Nova Slovenija – Krščanski Demokrati	NSi	Slovenia	Right
Socialni Demokrati	SD	Slovenia	Left
Lipa	L	Slovenia	Populist right
Zares – Socialno-Liberalni	Zares	Slovenia	Left
Pozitivna Slovenija	PS	Slovenia	Left
Stranka za trajnostni razvoj Slovenije	TRS	Slovenia	Left
Stranka Modernega Centra	SMC	Slovenia	Left
Verjamem – Stranka Igorja Šoltesa	Verjamem	Slovenia	Left
Stranka Alenke Bratušek	SAB	Slovenia	Left
Levica	L	Slovenia	Far left
Lista Marjana Šarca	LMŠ	Slovenia	Left
Gibanje Svoboda	GS	Slovenia	Left

Notes: This table lists all additional Western and Eastern European political parties included in the supplementary analyses presented in panels A and B of Table A13. Party categorizations are based on the ParlGov (Döring, Huber, and Manow 2022) and PopuList (Rooduijn et al. 2023) databases, supplemented by the author's coding for a small number of additional cases.

Placebo Tests

TABLE A15. Cross-National Results with Placebo Outcomes

Outcome:	*Immigration Beneficial*	*Worried About Climate*	*LGBTQ+ Stigma*	*Support for EU Integration*	*People Are Trustworthy*	*People Are Fair*	*Leader Above the Law*	*Life Satisfaction*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AAIOE (Std.)	0.003	−0.004	0.010	0.005	0.018	0.001	−0.014	−0.004
	(0.017)	(0.007)	(0.007)	(0.015)	(0.014)	(0.030)	(0.028)	(0.008)
N	104,866	46,142	61,608	91,266	105,939	15,170	16,554	105,961
Mean Outcome	5.499	3.304	4.433	5.240	5.617	7.429	1.567	7.452
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓	✓	✓	✓	✓
1-Digit Occupation FEs	✓	✓	✓	✓	✓	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by four-digit ISCO-08 occupation, in parentheses. Baseline controls: age, years of education, gender, union membership, degree of religiosity, urban residence, household income decile, and left-right ideology. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A16. 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)	(17)	(18)	(19)	(20)
AIOE (Std.)	−0.061***					−0.017***					0.018***					−0.017***				
	(0.007)					(0.003)					(0.002)					(0.002)				
SML (Std.)		−0.010*					−0.002					0.012***					−0.008***			
		(0.006)					(0.003)					(0.002)					(0.001)			
Webb (Std.)			−0.028***					−0.012***					0.001					−0.002		
			(0.008)					(0.003)					(0.002)					(0.002)		
C-AIOE (Std.)				−0.009					0.001					0.006***					−0.007***	
				(0.007)					(0.002)					(0.002)					(0.002)	
Gmyrek et al. (Std.)					−0.033***					−0.006*					0.011***					−0.011***
					(0.010)					(0.003)					(0.003)					(0.003)
N	105,515	105,515	105,515	105,515	30,199	73,775	73,775	73,775	73,775	20,906	73,775	73,775	73,775	73,775	20,906	73,775	73,775	73,775	73,775	20,906
Mean Outcome	3.824	3.824	3.824	3.824	3.812	0.344	0.344	0.344	0.344	0.345	0.327	0.327	0.327	0.327	0.269	0.049	0.049	0.049	0.049	0.062
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sample Start Year	2010	2010	2010	2010	2020	2010	2010	2010	2010	2020	2010	2010	2010	2010	2020	2010	2010	2010	2010	2020

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; (4) Pizzinelli et al.'s (2024) C-AIOE index; and (5) Gmyrek, Berg, and Bescond's (2023) generative AI exposure index (restricted to ESS waves from 2020 onward). Baseline controls: age, years of education, gender, union membership, degree of religiosity, urban residence, household income decile, and left-right ideology. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A17. Cross-National Results for Different AI Applications

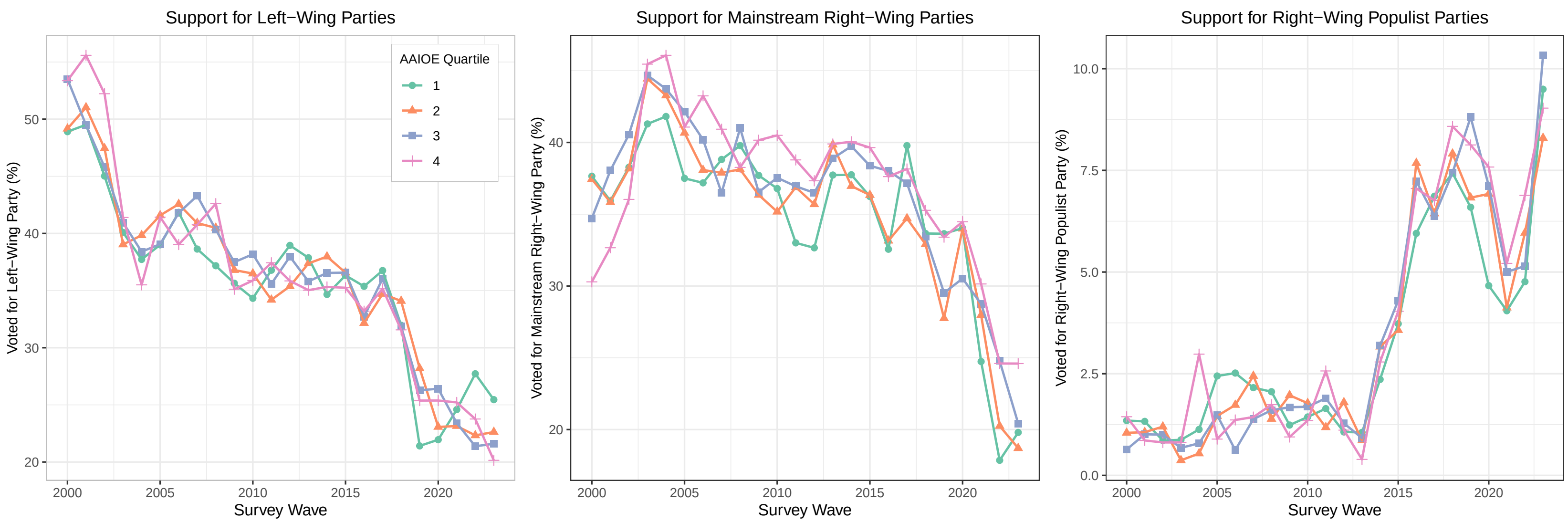
Outcome:	*Redistribution Support*	*Vote Choice: Left*	*Vote Choice: Mainstream Right*	*Vote Choice: Populist Right*
	(1)	(2)	(3)	(4)
Abstract Strategy Games (Std.)	−0.067***	−0.018***	0.018***	−0.016***
	(0.007)	(0.003)	(0.002)	(0.002)
	(5)	(6)	(7)	(8)
Real-Time Video Games (Std.)	−0.055***	−0.015***	0.014***	−0.011***
	(0.007)	(0.003)	(0.003)	(0.001)
	(9)	(10)	(11)	(12)
Image Recognition (Std.)	−0.056***	−0.015***	0.011***	−0.009***
	(0.006)	(0.002)	(0.003)	(0.002)
	(13)	(14)	(15)	(16)
Visual Question Answering (Std.)	−0.064***	−0.017***	0.016***	−0.013***
	(0.007)	(0.003)	(0.002)	(0.002)
	(17)	(18)	(19)	(20)
Image Generation (Std.)	−0.066***	−0.019***	0.015***	−0.013***
	(0.006)	(0.003)	(0.003)	(0.002)
	(21)	(22)	(23)	(24)
Reading Comprehension (Std.)	−0.061***	−0.016***	0.018***	−0.018***
	(0.007)	(0.003)	(0.002)	(0.002)
	(25)	(26)	(27)	(28)
Language Modeling (Std.)	−0.055***	−0.015***	0.017***	−0.017***
	(0.007)	(0.003)	(0.002)	(0.002)
	(29)	(30)	(31)	(32)
Translation (Std.)	−0.055***	−0.015***	0.017***	−0.017***
	(0.007)	(0.003)	(0.002)	(0.002)
	(33)	(34)	(35)	(36)
Speech Recognition (Std.)	−0.053***	−0.015***	0.017***	−0.016***
	(0.007)	(0.003)	(0.002)	(0.002)
	(37)	(38)	(39)	(40)
Instrumental Track Recognition (Std.)	−0.051***	−0.015***	0.016***	−0.015***
	(0.007)	(0.003)	(0.002)	(0.002)
N	105,515	73,775	73,775	73,775
Mean Outcome	3.819	0.340	0.316	0.051
Baseline Controls	✓	✓	✓	✓
Country × Wave FEs	✓	✓	✓	✓

Notes: This table shows that the results in Table 1 remain substantively similar when Felten, Raj, and Seamans' (2021) AIOE index is disaggregated into its 10 components, which measure exposure to specific AI applications. OLS estimates are reported with robust standard errors, clustered by four-digit ISCO-08 occupation, in parentheses. Baseline controls: age, years of education, gender, union membership, degree of religiosity, urban residence, household income decile, and left-right ideology. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D Longitudinal Analysis of German Political Preferences

D.1 Descriptive Data

FIGURE A4. Support for German Political Parties by AI Exposure Quartile, 2000-2023



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). Each variable is disaggregated by respondents' AAIOE quartile, with Q1 corresponding to the bottom 25% of the distribution (i.e., lowest AI exposure) and Q4 corresponding to the top 25% (i.e., highest AI exposure).

D.2 Extensions and Robustness

Additional Controls and Fixed Effects

TABLE A18. Baseline Longitudinal Results with Basic Socioeconomic Controls

Outcome: Support for...	*Left*	*Mainstream Right*	*Populist Right*
Panel A: Age	(1)	(2)	(3)
AAIOE_f (Std.) $\times$ Trend	–0.001***	0.001***	–0.001***
Age	–0.002	0.003	0.000
N	165,876	165,876	165,876
Mean Outcome	0.364	0.360	0.035
Panel B: Log Gross Income	(4)	(5)	(6)
AAIOE_f (Std.) $\times$ Trend	–0.001**	0.001***	–0.001***
	(0.000)	(0.000)	(0.000)
Log Labor Income (euros)	0.001	–0.003	–0.001
	(0.002)	(0.002)	(0.001)
N	131,040	131,040	131,040
Mean Outcome	0.355	0.358	0.035
Panel C: Union Member	(7)	(8)	(9)
AAIOE_f (Std.) $\times$ Trend	–0.001***	0.001***	–0.001***
	(0.000)	(0.000)	(0.000)
Union Member (0/1)	–0.001	0.000	–0.004
	(0.009)	(0.007)	(0.004)
N	45,694	45,694	45,694
Mean Outcome	0.360	0.353	0.038
Panel D: Urban Resident	(10)	(11)	(12)
AAIOE_f (Std.) $\times$ Trend	–0.001***	0.001***	–0.001***
	(0.000)	(0.000)	(0.000)
Urban Resident (0/1)	0.000	–0.016**	–0.002
	(0.009)	(0.008)	(0.005)
N	168,281	168,281	168,281
Mean Outcome	0.363	0.361	0.035
Panel E: Left-Right Position	(10)	(11)	(12)
AAIOE_f (Std.) $\times$ Trend	–0.001**	0.001*	–0.001**
	(0.000)	(0.000)	(0.000)
Left-Right Position (0–10)	–0.030***	0.024***	0.010***
	(0.002)	(0.002)	(0.002)
N	29,765	29,765	29,765
Mean Outcome	0.345	0.364	0.037
Respondent FEs	✓	✓	✓
Survey Wave FEs	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by respondent, in parentheses. Controls are entered into the specification separately due to high levels of missingness in the ideology and union membership measures. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A19. 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.) × Trend	-0.001*	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Frey and Osborne Exposure to Computerization Index (0-1)	0.001	-0.001	0.000
	(0.002)	(0.002)	(0.001)
N	112,598	112,598	112,598
Mean Outcome	0.358	0.367	0.036
Panel B: Offshorability	(4)	(5)	(6)
AAIOE_f (Std.) × Trend	-0.001***	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Blinder and Krueger Offshorability Index (Std.)	0.002**	-0.002**	0.000
	(0.001)	(0.001)	(0.000)
N	153,484	153,484	153,484
Mean Outcome	0.365	0.363	0.036
Panel C: Skill Specificity	(7)	(8)	(9)
AAIOE_f (Std.) × Trend	-0.001*	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Cusack, Iversen, and Rehm Skill Specificity Index (Std.)	0.004**	-0.001	-0.001
	(0.002)	(0.002)	(0.001)
N	112,598	112,598	112,598
Mean Outcome	0.358	0.367	0.036
Panel D: Labor Market Outsiderness	(10)	(11)	(12)
AAIOE_f (Std.) × Trend	-0.001*	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Fixed-Term Contract (0/1)	0.009**	-0.001	-0.002
	(0.004)	(0.003)	(0.002)
N	120,952	120,952	120,952
Mean Outcome	0.368	0.353	0.033
Panel E: Occupational Prestige	(13)	(14)	(15)
AAIOE_f (Std.) × Trend	-0.001***	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Hughes et al. Occupational Prestige Rating (0-100)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
N	157,042	157,042	157,042
Mean Outcome	0.363	0.362	0.035
Respondent FEs	✓	✓	✓
Survey Wave FEs	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by respondent, in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A20. Longitudinal Results with Additional Socioeconomic Controls

Outcome: Support for...	*Left*	*Mainstream Right*	*Populist Right*
Panel A: Job Security	(1)	(2)	(3)
AAIOE_f (Std.) × Trend	-0.001**	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Perceived Job Security (1-3)	-0.001	0.001	-0.002**
	(0.002)	(0.002)	(0.001)
N	129,014	129,014	129,014
Mean Outcome	0.356	0.355	0.035
Panel B: Migration Background	(4)	(5)	(6)
AAIOE_f (Std.) × Trend	-0.001***	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Migration Background (0/1)	-0.756	-0.934	2.000
	(9,357.726)	(8,433.478)	(4,895.242)
N	168,530	168,530	168,530
Mean Outcome	0.363	0.360	0.035
Panel C: Civil Servant	(7)	(8)	(9)
AAIOE_f (Std.) × Trend	-0.001***	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Civil Servant (0/1)	-0.027***	0.006	0.003
	(0.007)	(0.006)	(0.002)
N	168,472	168,472	168,472
Mean Outcome	0.363	0.360	0.034
Panel D: Immigration Concern	(10)	(11)	(12)
AAIOE_f (Std.) × Trend	-0.001***	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Worried about Immigration (1-3)	0.005***	-0.005***	-0.009***
	(0.001)	(0.001)	(0.001)
N	165,882	165,882	165,882
Mean Outcome	0.364	0.359	0.035
Respondent FEs	✓	✓	✓
Survey Wave FEs	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by respondent, in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A21. Baseline Longitudinal Results with Alternative Fixed Effects

Outcome: Support for...	*Left*	*Mainstream Right*	*Populist Right*
Panel A: Occupation FEs	(1)	(2)	(3)
AAIOE_f (Std.) $\times$ Trend	-0.001*	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
N	125,619	125,619	125,619
Mean Outcome	0.357	0.359	0.034
1-Digit Occupation FEs	✓	✓	✓
Respondent FEs	✓	✓	✓
Survey Wave FEs	✓	✓	✓
Panel B: Industry FEs	(4)	(5)	(6)
AAIOE_f (Std.) $\times$ Trend	-0.001	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
N	66,914	66,914	66,914
Mean Outcome	0.364	0.351	0.033
1-Digit Industry FEs	✓	✓	✓
Respondent FEs	✓	✓	✓
Survey Wave FEs	✓	✓	✓
Panel C: Federal State FEs	(7)	(8)	(9)
AAIOE_f (Std.) $\times$ Trend	-0.001***	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
N	168,529	168,529	168,529
Mean Outcome	0.363	0.360	0.035
Respondent FEs	✓	✓	✓
Survey Wave FEs	✓	✓	✓
Federal State FEs	✓	✓	✓
Panel D: No Respondent FEs	(10)	(11)	(12)
AAIOE_f (Std.) $\times$ Trend	-0.002**	0.001*	-0.002***
	(0.001)	(0.000)	(0.000)
N	168,529	168,529	168,529
Mean Outcome	0.363	0.360	0.035
Survey Wave FEs	✓	✓	✓
Federal State FEs	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by respondent in panels A–C and by federal state in panel D, in parentheses. Occupations are defined according to the ISCO-08 classification, industries according to the NACE classification (Rev.1 before 2013, Rev.2 subsequently). $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Single-Difference Estimator

TABLE A22. Results of Longitudinal Single-Difference Specification (Equation 12)

Outcome: Δ Support for...	Left	Mainstream Right	Populist Right
Panel A: 2000-05 – 2016-21	(1)	(2)	(3)
AAIOE_{t_0} (Std.)	−0.015**	0.022***	−0.021***
	(0.006)	(0.007)	(0.006)
N	3,205	3,205	3,205
Mean Outcome	−0.097	0.001	0.049
Panel B: 2000-05 – 2011-21	(4)	(5)	(6)
AAIOE_{t_0} (Std.)	−0.015***	0.015***	−0.009*
	(0.004)	(0.005)	(0.004)
N	4,770	4,770	4,770
Mean Outcome	−0.072	0.005	0.027
Panel C: 2000-10 – 2016-21	(7)	(8)	(9)
AAIOE_{t_0} (Std.)	−0.004	0.016**	−0.017***
	(0.006)	(0.007)	(0.006)
N	4,962	4,962	4,962
Mean Outcome	−0.074	0.006	0.045
Panel D: 2000-10 – 2011-21	(10)	(11)	(12)
AAIOE_{t_0} (Std.)	−0.008*	0.012**	−0.007
	(0.004)	(0.005)	(0.005)
N	7,313	7,313	7,313
Mean Outcome	−0.053	0.008	0.025
Federal State FEs	✓	✓	✓

Notes: OLS estimates from Equation 12 with robust standard errors, clustered by federal state, in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Alternative Samples

TABLE A23. Baseline Longitudinal Results with Alternative Samples

Outcome: Support for...	*Left*	*Mainstream Right*	*Populist Right*
Panel A: Measuring AIIOE at Wave t	(1)	(2)	(3)
AAIOE_f (Std.) × Trend	−0.0004**	0.0005**	−0.0005***
	(0.0002)	(0.0002)	(0.0001)
N	113,731	113,731	113,731
Mean Outcome	0.356	0.360	0.035
Panel B: Market Earners Only	(3)	(4)	(5)
AAIOE_f (Std.) × Trend	−0.001*	0.001***	−0.001***
	(0.000)	(0.000)	(0.000)
N	145,815	145,815	145,815
Mean Outcome	0.354	0.359	0.033
Panel C: Design Weights	(5)	(6)	(7)
AAIOE_f (Std.) × Trend	−0.001***	0.001***	−0.001***
	(0.000)	(0.000)	(0.000)
N	165,485	165,485	165,485
Mean Outcome	0.363	0.360	0.035
Panel D: Outcome is Support for...	SPD	CDU	AfD
	(8)	(9)	(10)
AAIOE_f (Std.) × Trend	−0.001***	0.001***	−0.001***
	(0.000)	(0.000)	(0.000)
N	168,530	168,530	168,530
Mean Outcome	0.298	0.301	0.025
Respondent FEs	✓	✓	✓
Survey Wave FEs	✓	✓	✓

Notes: OLS estimates with robust standard errors, clustered by respondent, in parentheses. Full party names in panel D: *Sozialdemokratische Partei Deutschlands* (SPD), *Christlich Demokratische Union Deutschlands* (CDU), and *Alternative für Deutschland* (AfD). $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

E Survey Experiment

E.1 Design and Implementation

The survey experiment presented in the main text was preregistered with the Open Science Foundation (OSF) on December 21, 2024 and implemented over the following five weeks.[2] The sample comprised 795 working-age adults residing 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, primarily British public Facebook groups. Although AMT Workers do not constitute a random sample of the United Kingdom's population, numerous findings obtained from nationally representative samples have been successfully replicated on the platform (Berinsky, Huber, and Lenz 2012; Clifford, Jewell, and Waggoner 2015; Crump, McDonnell, and Gureckis 2013). Facebook has broader reach across demographic groups and can thus generate samples as representative as those recruited via traditional methods in many contexts (Thornton et al. 2016; Whitaker, Stevelink, and Fear 2017). Indeed, my sample closely resembles the broader British population on key demographic characteristics, with male, younger, white, and more educated individuals only marginally overrepresented:

- *Gender*. The male-to-female ratio in the sample is 1.04, compared with 0.96 in the United Kingdom as a whole.[3]
- *Age*. The proportion of working-age adults in the age groups 18–29, 30–39, 40–49, 50–59, and 60–64 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%,[4] 23.7%, 21.3%, 22.9%, and 10.5% (Office for

[2] The pre-analysis plan is available at: `https://osf.io/k5rty/?view_only=fe518f0fc5b3465d8b37779313906a35`.

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

[4] This figure corresponds to the 20–24 age group (rather than 18–24, for which comparable data are unavailable).

National Statistics 2024).

- *Ethnicity*. The proportion of whites is 84.3%, relative to an estimated 81.7% in England and Wales.[5]
- *Education level*. The proportion of respondents with an undergraduate degree or equivalent qualification is 47.7%, in comparison 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.[6]

Summary statistics for the full survey experimental dataset are presented in Table A25.

The survey comprises five sections, detailed in Table A24:

1. *Demographic information*. After providing informed consent, respondents were asked to supply basic demographic information: age, sex, ethnicity, party affiliation, education level, income bracket, and occupational category.
2. *Treatment assignment*. Respondents were randomly assigned either to one of the two treatment conditions — the "complementarity" frame and the "substitution" frame — or to the control condition, in which they proceeded directly to the next stage. In total, 257 respondents received the complementarity frame, 258 were shown the substitution frame, and 280 were placed in the control group.
3. *Outcomes*. Respondents were asked about their redistribution preferences and voting intentions. The order of this and the following section was randomized.
4. *Labor market expectations*. Respondents were posed a series of questions about how they expect AI to affect their productivity, job security, and earnings.

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

[6] Office for National Statistics data on employee earnings in the United Kingdom in 2024, available 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 A24. 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 average survey completion time was 11 minutes (658 seconds).

E.2 Ethical Considerations

The survey received ethics approval from the University of Oxford's Department of Politics and International Relations Research Ethics Committee (reference SSH/DPIR_24_995386) on December 19, 2024. In general, the research did not raise any ethical issues specific to the British context — in which the questions are unlikely to be perceived as particularly sensitive or controversial — or pose physical or psychological risks to the research team. At the outset, respondents were provided with an informed consent form outlining the purpose of the research, the survey procedures, their right to withdraw, confidentiality protections, remuneration, the complaints procedure, and the author's contact information. Compensation was slightly higher than the British minimum wage (£2 for an activity typically taking around 10 minutes). As discussed above, the sample was broadly representative of the British population across several demographic dimensions, reducing the likelihood that participation disproportionately benefited or harmed any particular group.

E.3 Departures from Pre-Analysis Plan

Aside from some minor changes to question wording, implementation of the survey only deviated from my pre-analysis plan in one respect: instead of recruiting all participants through AMT, I employed a combination of this platform and targeted 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, incorporating them into my recruitment strategy was intended to mitigate this problem. The deviation alters neither the hypotheses nor the empirical strategy set out in the pre-analysis plan.

E.4 Summary Statistics

TABLE A25. 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	0.093	0.555	−1.273	0.774
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 A26. Balance Table for Survey Experimental Treatment and Control Groups

Covariate	Control Group Mean	Complementarity		Substitution	
		Treatment Group Mean	Std. Difference in Means	Treatment Group Mean	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 treatment and control groups in the survey experiment. The fourth and sixth columns report unadjusted standardized mean differences between treatment and control; values between -0.2 and 0.2 indicate adequate covariate balance. The sample comprises 795 working-age adults residing 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 A25 for summary statistics).

E.5 Additional Results

TABLE A27. Full Survey Experimental 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 5. OLS estimates with robust standard errors in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A28. Full Survey Experimental 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 5. OLS estimates with robust standard errors in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE A29. Full Survey Experimental 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 Treatment	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 5. OLS estimates with robust standard errors in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

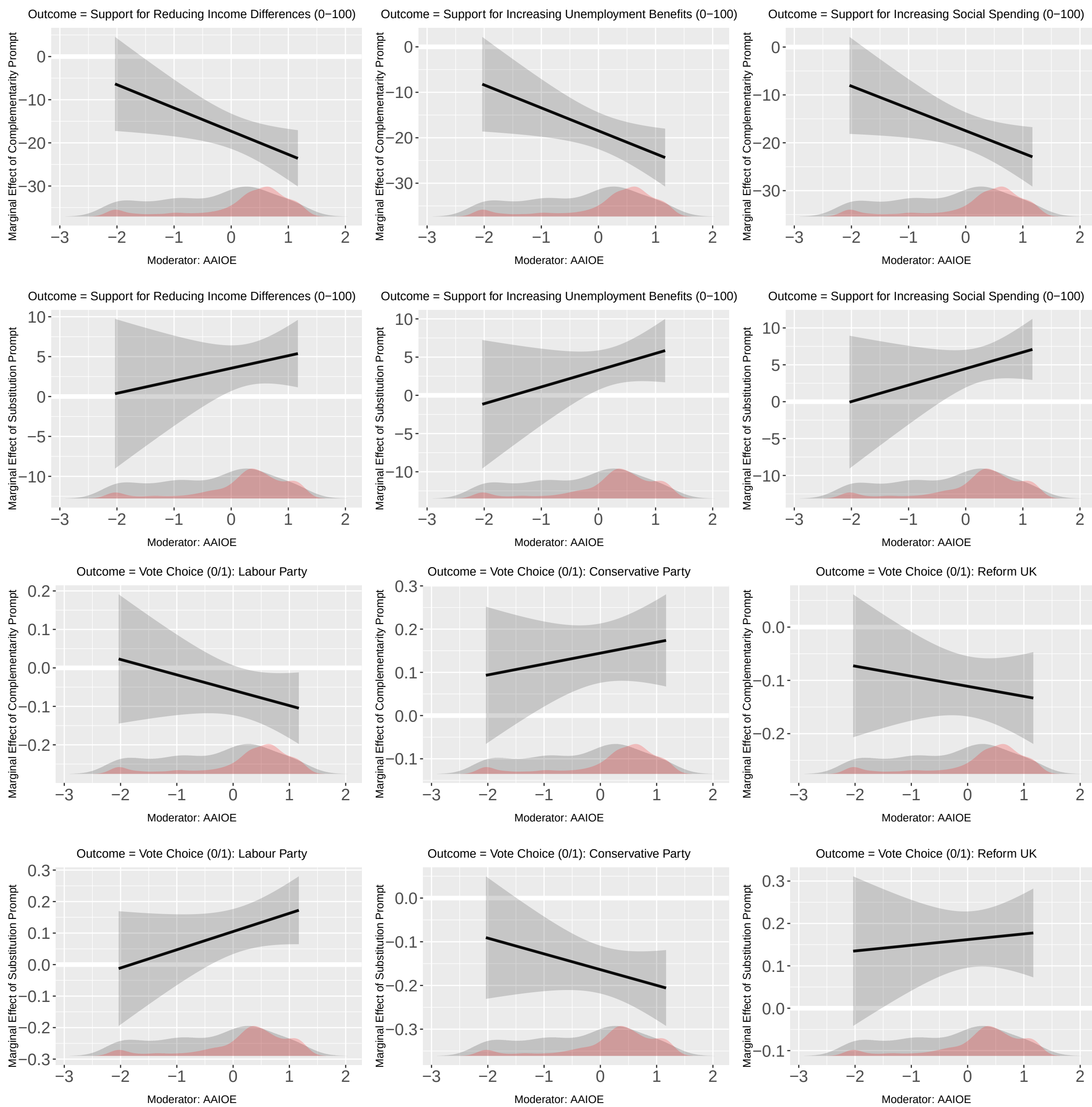
TABLE A30. Survey Experimental Results Including Automation Risk Control

Panel A: Redistribution Preferences						
Outcome = Agree the Govt. Should...	Reduce Income Differences		Increase Unemployment Benefits		Increase Social Spending	
	(1)	(2)	(3)	(4)	(5)	(6)
Complementarity Treatment	−7.096***		−8.288***		−7.216***	
	(2.341)		(2.282)		(2.257)	
Substitution Treatment		10.017***		10.398***		10.883***
		(1.960)		(1.870)		(1.972)
Goos et al. RTI Index	1.136	2.859**	0.283	1.749	0.057	2.609**
	(1.446)	(1.180)	(1.410)	(1.126)	(1.392)	(1.186)
N	424	413	424	413	423	412
Mean Outcome	75.126	75.126	74.092	74.092	74.218	74.218
Baseline Controls	✓	✓	✓	✓	✓	✓

Panel B: Voting Intentions						
Outcome = Vote Choice:	Labour Party		Conservative Party		Reform UK	
	(1)	(2)	(3)	(4)	(5)	(6)
Complementarity Treatment	−0.075**		0.134***		−0.107***	
	(0.035)		(0.035)		(0.031)	
Substitution Treatment		0.101**		−0.139***		0.150***
		(0.042)		(0.030)		(0.039)
Goos et al. RTI Index	0.010	0.021	−0.038*	−0.025	0.020	0.031
	(0.022)	(0.025)	(0.022)	(0.018)	(0.019)	(0.024)
N	424	413	424	413	424	413
Mean Outcome	0.304	0.337	0.141	0.131	0.367	0.349
Baseline Controls	✓	✓	✓	✓	✓	✓

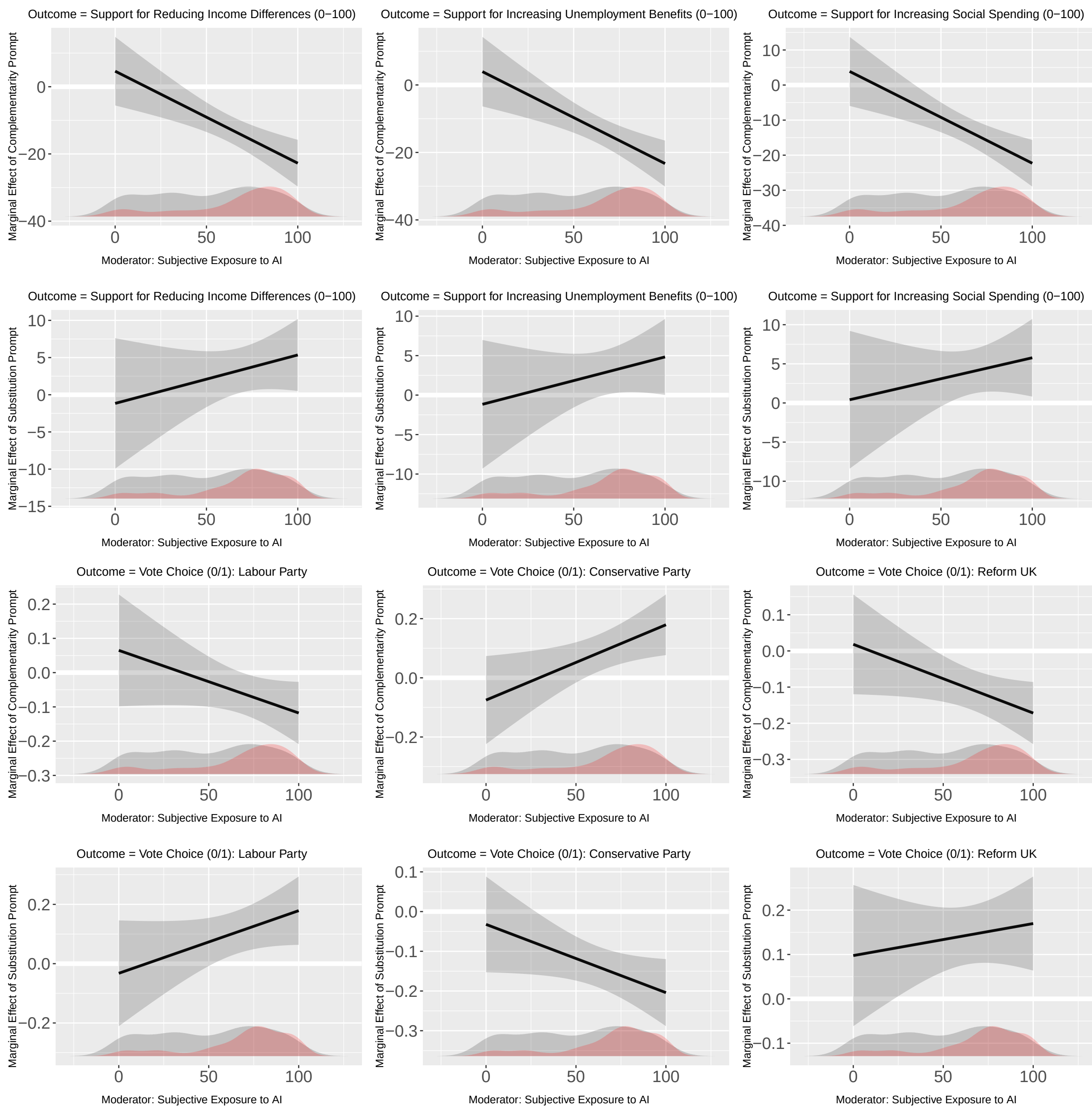
Notes: OLS estimates with robust standard errors in parentheses. Baseline controls: age, gender, ethnicity, income, education level, and party identification. The RTI index is merged with the survey experimental dataset at the two-digit level using a probabilistic crosswalk between the ISCO-88 and ISCO-08 classification systems, which draws on detailed descriptions of occupational activities and tasks as well as established harmonization procedures. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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



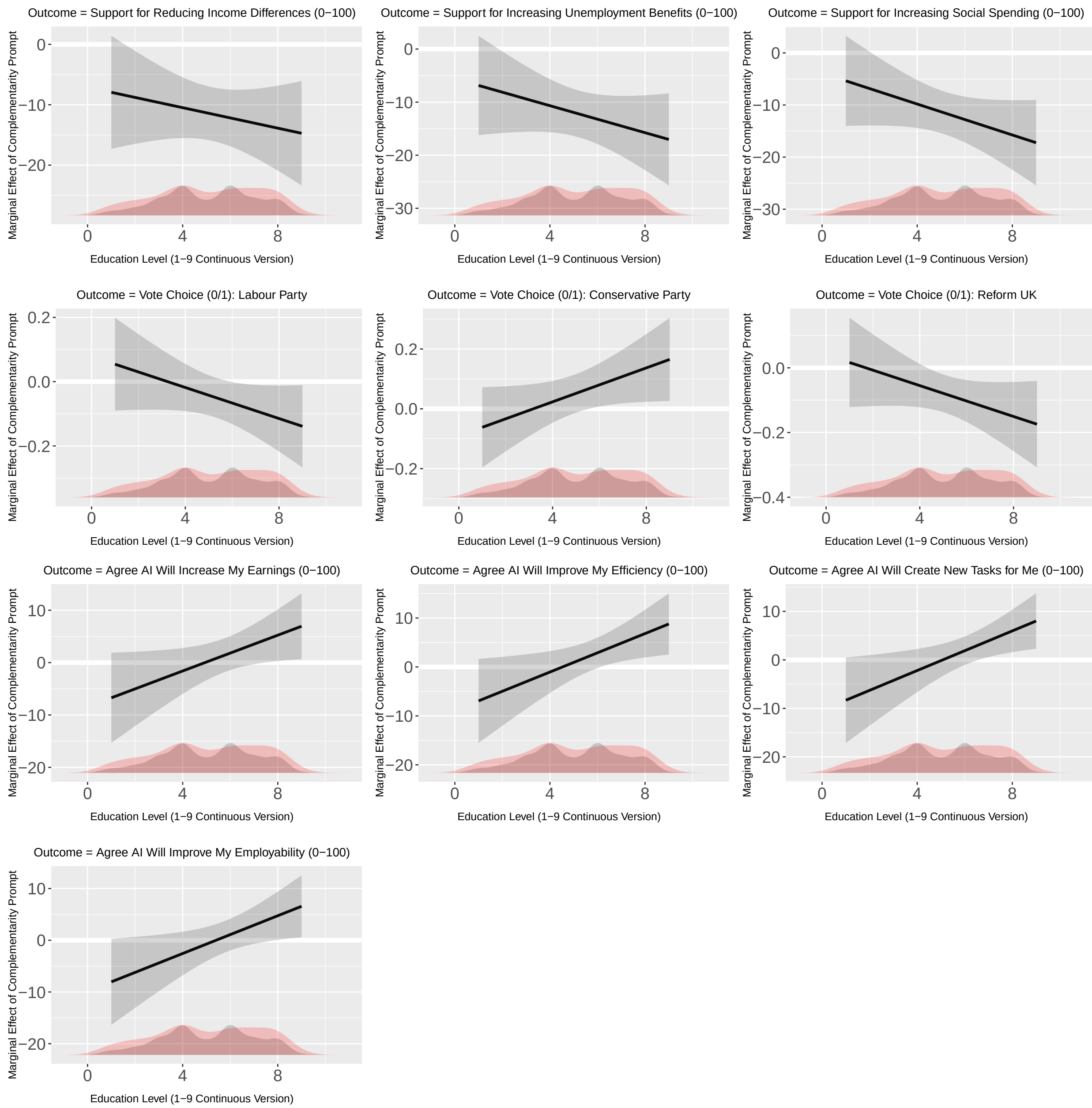
Notes: Marginal effect estimates from a modified version of Equation 13 in which C_i and S_i are interacted with respondent i's AAIOE score (at the two-digit ISCO-08 level). Shaded bands represent 95% confidence intervals. All models control for age, gender, ethnicity, income, education level, and party identification. Estimates are computed using the **interflex** package in R (Hainmueller, Mummolo, and Xu 2019).

FIGURE A6. Survey Experimental Treatment Effects Moderated by Subjective Occupational Exposure to AI



Notes: Marginal effect estimates from a modified version of Equation 13 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 anticipated capabilities. Shaded bands represent 95% confidence intervals. All models control for age, gender, ethnicity, income, education level, and party identification. Estimates are computed using the **interflex** package in R (Hainmueller, Mummolo, and Xu 2019).

FIGURE A7. Within-Occupation Survey Experimental Treatment Effects Moderated by Education Level



Notes: Marginal effect estimates from a modified version of Equation 13 in which C_i is interacted with respondent i's level of education (converted from a categorical to a continuous scale) and two-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 using the **interflex** package in R (Hainmueller, Mummolo, and Xu 2019).

TABLE A31. Results of Survey Experimental Mediation Analyses

Treatment Variable		Mediator Variable		Outcome Variable	Average Causal Mediation Effect		Average Direct Effect	
					Estimate	95% CIs	Estimate	95% CIs
Randomized Prompt		Agree AI Will. . .		Agree the Government Should. . .	*Panel A: Explaining Redistribution Preferences*			
Complementarity	⟶	Increase My Earnings	⟶	Reduce Income Differences	1.045**	[0.212, 2.053]	-17.502***	[-21.726, -13.747]
Complementarity	⟶	Improve My Efficiency	⟶	Reduce Income Differences	1.380***	[0.382, 2.556]	-17.814***	[-22.027, -13.698]
Complementarity	⟶	Create New Tasks for Me	⟶	Reduce Income Differences	1.056**	[0.210, 2.025]	-17.516***	[-21.812, -13.458]
Complementarity	⟶	Improve My Employability	⟶	Reduce Income Differences	1.408***	[0.480, 2.429]	-17.935***	[-22.166, -13.836]
Complementarity	⟶	Increase My Earnings	⟶	Increase Unemployment Benefits	1.431***	[0.528, 2.476]	-18.040***	[-22.025, -13.687]
Complementarity	⟶	Improve My Efficiency	⟶	Increase Unemployment Benefits	1.352***	[0.414, 2.377]	-17.888***	[-21.887, -13.919]
Complementarity	⟶	Create New Tasks for Me	⟶	Increase Unemployment Benefits	1.285***	[0.462, 2.313]	-17.854***	[-22.141, -13.764]
Complementarity	⟶	Improve My Employability	⟶	Increase Unemployment Benefits	1.788***	[0.825, 2.914]	-18.280***	[-22.109, -14.419]
Complementarity	⟶	Increase My Earnings	⟶	Increase Social Spending	0.897**	[0.077, 1.790]	-17.413***	[-21.443, -13.315]
Complementarity	⟶	Improve My Efficiency	⟶	Increase Social Spending	1.058**	[0.148, 2.065]	-17.446***	[-21.321, -13.669]
Complementarity	⟶	Create New Tasks for Me	⟶	Increase Social Spending	1.019**	[0.196, 1.992]	-17.481***	[-21.447, -13.371]
Complementarity	⟶	Improve My Employability	⟶	Increase Social Spending	1.370***	[0.551, 2.324]	-17.624***	[-21.993, -13.642]
Substitution	⟶	Increase My Earnings	⟶	Reduce Income Differences	-1.577***	[-2.950, -0.407]	15.793***	[12.373, 19.159]
Substitution	⟶	Improve My Efficiency	⟶	Reduce Income Differences	-1.687***	[-2.926, -0.609]	15.861***	[12.795, 19.278]
Substitution	⟶	Create New Tasks for Me	⟶	Reduce Income Differences	-1.558***	[-2.841, -0.428]	15.894***	[12.575, 19.307]
Substitution	⟶	Improve My Employability	⟶	Reduce Income Differences	-2.627***	[-4.133, -1.262]	16.760***	[13.279, 20.181]
Substitution	⟶	Increase My Earnings	⟶	Increase Unemployment Benefits	-2.065***	[-3.423, -0.926]	16.506***	[13.418, 19.612]
Substitution	⟶	Improve My Efficiency	⟶	Increase Unemployment Benefits	-1.651***	[-2.837, -0.581]	16.041***	[13.058, 18.885]
Substitution	⟶	Create New Tasks for Me	⟶	Increase Unemployment Benefits	-1.769***	[-2.961, -0.756]	16.174***	[13.084, 19.487]
Substitution	⟶	Improve My Employability	⟶	Increase Unemployment Benefits	-3.213***	[-4.808, -1.876]	17.655***	[14.480, 20.677]
Substitution	⟶	Increase My Earnings	⟶	Increase Social Spending	-1.377**	[-2.519, -0.367]	15.827***	[12.599, 19.371]
Substitution	⟶	Improve My Efficiency	⟶	Increase Social Spending	-1.281***	[-2.365, -0.250]	15.790***	[12.568, 18.824]
Substitution	⟶	Create New Tasks for Me	⟶	Increase Social Spending	-1.466***	[-2.551, -0.474]	15.893***	[12.598, 19.314]
Substitution	⟶	Improve My Employability	⟶	Increase Social Spending	-2.574***	[-4.065, -1.224]	17.037***	[13.943, 20.299]
Randomized Prompt		Agree the Government Should. . .		Vote Choice	*Panel B: Explaining Voting Preferences*			
Complementarity	⟶	Reduce Income Differences	⟶	Labour Party	-0.040***	[-0.064, -0.020]	-0.106***	[-0.173, -0.038]
Complementarity	⟶	Increase Unemployment Benefits	⟶	Labour Party	-0.040***	[-0.064, -0.020]	-0.106***	[-0.175, -0.043]
Complementarity	⟶	Increase Social Spending	⟶	Labour Party	-0.045***	[-0.068, -0.025]	-0.102***	[-0.168, -0.035]
Complementarity	⟶	Reduce Income Differences	⟶	Conservative Party	0.068***	[0.043, 0.097]	0.107***	[0.046, 0.169]
Complementarity	⟶	Increase Unemployment Benefits	⟶	Conservative Party	0.066***	[0.042, 0.094]	0.110***	[0.043, 0.177]
Complementarity	⟶	Increase Social Spending	⟶	Conservative Party	0.074***	[0.047, 0.104]	0.102***	[0.037, 0.171]
Complementarity	⟶	Reduce Income Differences	⟶	Reform UK	-0.055***	[-0.080, -0.034]	-0.131***	[-0.198, -0.065]
Complementarity	⟶	Increase Unemployment Benefits	⟶	Reform UK	-0.060***	[-0.085, -0.039]	-0.125***	[-0.186, -0.062]
Complementarity	⟶	Increase Social Spending	⟶	Reform UK	-0.053***	[-0.078, -0.032]	-0.132***	[-0.200, -0.067]
Substitution	⟶	Reduce Income Differences	⟶	Labour Party	0.032***	[0.016, 0.050]	0.165***	[0.088, 0.236]
Substitution	⟶	Increase Unemployment Benefits	⟶	Labour Party	0.031***	[0.015, 0.049]	0.166***	[0.095, 0.241]
Substitution	⟶	Increase Social Spending	⟶	Labour Party	0.036***	[0.020, 0.054]	0.160***	[0.088, 0.235]
Substitution	⟶	Reduce Income Differences	⟶	Conservative Party	-0.061***	[-0.086, -0.039]	-0.095***	[-0.149, -0.041]
Substitution	⟶	Increase Unemployment Benefits	⟶	Conservative Party	-0.059***	[-0.085, -0.037]	-0.099***	[-0.153, -0.046]
Substitution	⟶	Increase Social Spending	⟶	Conservative Party	-0.067***	[-0.095, -0.043]	-0.089***	[-0.141, -0.035]
Substitution	⟶	Reduce Income Differences	⟶	Reform UK	0.051***	[0.033, 0.071]	0.100***	[0.030, 0.172]
Substitution	⟶	Increase Unemployment Benefits	⟶	Reform UK	0.055***	[0.036, 0.077]	0.096***	[0.020, 0.170]
Substitution	⟶	Increase Social Spending	⟶	Reform UK	0.051***	[0.033, 0.072]	0.101***	[0.025, 0.173]

Notes: Average causal mediation effect (ACME) and average direct effect (ADE) estimates with 95% confidence intervals, generated via a nonparametric bootstrap method (1,000 simulations), in brackets. All estimates are computed using the **mediation** package in R (Tingley et al. 2014). $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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