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Why Artificial Intelligence is not a Salient Issue: Politicizing AI Reduces Mobilization Potential

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Abstract. Technological disruptions have often generated political conflict. Artificial intelligence (AI) is widely expected to transform labor markets as well as economic systems, yet it has not become a strongly polarizing political issue in advanced democracies. This paper investigates why, by fielding a preregistered survey experiment with 11,418 respondents in the United States, Germany and Italy. We examine factual knowledge on AI and automation, beliefs over its economic effects, demand for policy intervention and signatures of online petitions on Change.org. We document limited knowledge, widespread pessimism on their labor-market impact, substantial demand for government intervention and considerable potential for political

mobilization, pointing to an unmet demand for policy responses. We then test the mobilization power of competing political narratives on the economic effects of AI and automation. Overall, across countries and institutional contexts, politicizing AI shifts policy preferences in the expected directions but reduces engagement in political mobilization. In addition, it decreases support for the extreme petitions, thereby reducing polarization. These findings suggest that emerging technologies characterized by high uncertainty and large distributive effects may not follow the historical pattern of polarization associated with past economic shocks. Our results rationalize politicians' hesitation towards increasing the salience of AI and automation. This mismatch between political discourse and voters demand may further enlarge the representation gap between citizens and elected representatives in modern Western democracies, ultimately discouraging political participation.

1 Introduction

Society is being reshaped by recent advances in automation and artificial intelligence (AI). Automation has already had dramatic effects on the labor market in advanced economies (Acemoglu et al. 2022; Pizzinelli et al. 2023; Eloundou et al. 2024; Mäkelä and Stephany 2024; Aghion et al. 2025; Brynjolfsson et al. 2025). Many experts forecast that combining AI with automation will lead to large scale job loss in the near future (e.g., Frey and Osborne 2017). Past episodes of drastic technological transition have caused unrest and spurred backlash, such as the physical destruction of textile machines by Luddites (Johnson and Acemoglu 2023; Acemoglu 2025). Despite the labor market consequences and the increasing attention in the media, political parties and their leaders have not taken strong positions on recent technological change. AI and automation do not feature prominently in either parties' social media communication or party platforms in Europe or the US, as shown in Appendix Figure A1. So far, this is an outlier in an era defined by high political polarization (Autor et al. 2020; Lorenz-Spreen et al. 2023; Boxell et al. 2024).

In the first part of this paper, we examine whether there is unmet voter demand for policies that either promote technological change, restrain it, or compensate for its impact. More specifically, we run a preregistered survey experiment with representative samples from Germany, Italy and the US (N = 11,418) in late 2024 where we ask specific questions about how individuals view automation and AI, and what type of policy interventions they favor in response to current technological change. Evidence on how voters evaluate automation and AI and on the policy responses they would endorse is still scarce, and there are grounds for anticipating both optimistic and pessimistic attitudes. While most of the discussion in the media is about potential negative consequences, AI and automation could lead to productivity gains, price decreases, and improvements in product quality (Borwein et al. 2024b; Magistro et al. 2025; Gambacorta et al. 2025). Furthermore, recent technological advances in computing are largely associated with better economic outcomes and improved quality of life (e.g., Gallego et al. 2022).

Next, building on the fact that political parties are not currently discussing AI and technological change as important parts of their platforms, we explore the effects of narratives on the salience of technological change and its potential to mobilize voters. We do this by randomly showing some individuals either a positive, negative or balanced narrative about the economic and political impacts of automation and AI, and then examining whether this i) changes demand for policies related to technological change; and ii) increases individuals' willingness to sign a public petition on Change.org related to these policy interventions.

We find that knowledge about automation and AI is very low in the general public and individuals tend to be pessimistic about the labor market impacts of these technologies. Demand for policy interventions on these issues is high (64% of people want to intervene) and people are willing to sign a petition on the topic (45% express a willingness). We also find that narratives shape demand for policies in intuitive directions. A techno-optimistic narrative triggers demand for policies that support AI, while a techno-pessimistic narrative spurs demand for policies mitigating potential negative impacts. We also find that being exposed to a non-pessimistic narrative decreases individual willingness to sign a petition on Change.org by approximately 3 percentage points.

Unlike with many current focal topics, narratives on AI and automation appear to *reduce* polarization on the topic with people who have a priori positive beliefs about these technologies more impacted by the negative narrative and vice-versa for those with apriori negative beliefs. Our findings are similar in the US, Germany and Italy even though institutions vary greatly. This may contribute to explaining why parties, who look for polarizing issues, are not using them as a defining political theme of their platforms. An additional motivation could lie in the uncertainty around the impact of new technologies on individuals (König and Wenzelburger 2019; Gallego and Kurer 2022). Given this uncertainty, parties could find it too early to commit to a policy position on this.

Our paper is part of a flourishing research on AI (see, e.g., Acemoglu et al. 2022; Lin et al. 2025; Capraro et al. 2024; Summerfield et al. 2025; Ide and Talamàs 2025; Jones 2024;

Hackenburg et al. 2025). Our results complement recent research that has found mixed evidence of alignment between beliefs about the effect of AI on the labor market and policy preferences (Borwein et al. 2024b; Borwein et al. 2025). For example, Anelli et al. (2025) show that an experimental treatment presenting workers occupation-specific videos of LLMs that perform their most frequent core task affects support for technologically restrictive policies, such as automation tax and AI regulation, but not for classic redistribution. At the same time, Borwein et al. (2024a) find that technological changes such as automation and AI do not drive support for political candidates willing to protect workers, in the same way as do alternative economic shocks, such as offshoring.

We make two key contributions to this emerging literature. First, as opposed to papers focusing on how threats to one's own job impact policy preferences, such as Anelli et al. (2025), we examine how individual opinions are shaped by more general discourse around the impacts of automation and AI. We believe this is more relevant for understanding whether political parties can use opinions about technology to attract voters. Second, beyond asking whether political narratives change what policies individuals support, we examine the impact on people's willingness to sign a real petition on the website Change.org, a well-known online platform. This allows us to examine whether narratives around AI and automation lead to increasing polarization.

2 Knowledge and Opinions about Automation and AI

We first examine individual knowledge about automation and AI and their beliefs about how these technologies impact the labor market. More specifically, we asked survey participants to report the number of industrial robots per 1,000 workers in their country, and then to identify how large language models (LLMs)—such as ChatGPT, Claude and Gemini—operate. Respondents had three choices: i) prediction techniques—the correct answer; ii) a predefined set of rules; or iii) a form of intelligence replicating how the human brain works. These questions

on knowledge were incentivized. We then elicited respondents' beliefs on the impact of these technologies on employment.

The top panel of Figure 1 shows that, overall, there is a very low level of knowledge as well as a widespread pessimism. These questions were asked before the treatment, but for consistency with the other results in this section we show responses that refer to a subsample of our respondents, namely those that are in the experimental control group (N = 3,304, equally split between countries). In any case, results are nearly identical in the entire sample (Appendix Figure A2). Allowing for a margin of error of five robots, the first pie chart shows that only a very small share of respondents (around 12%) knows the correct number of industrial robots per worker in their country, with the absolute majority of respondents overestimating it. In Appendix Figure A3 we also show this is the case for other questions about automation. These results are very similar in all three countries even though the level of robot use is quite different. Turning to the question on AI, less than a quarter of respondents (24%) answered that LLMs work with prediction techniques. Despite the relevance of AI in the public discussion, general knowledge appears to be lacking (Appendix Figure A2 and Figure A4).

Figure 1: Knowledge and Opinions about Automation and AI
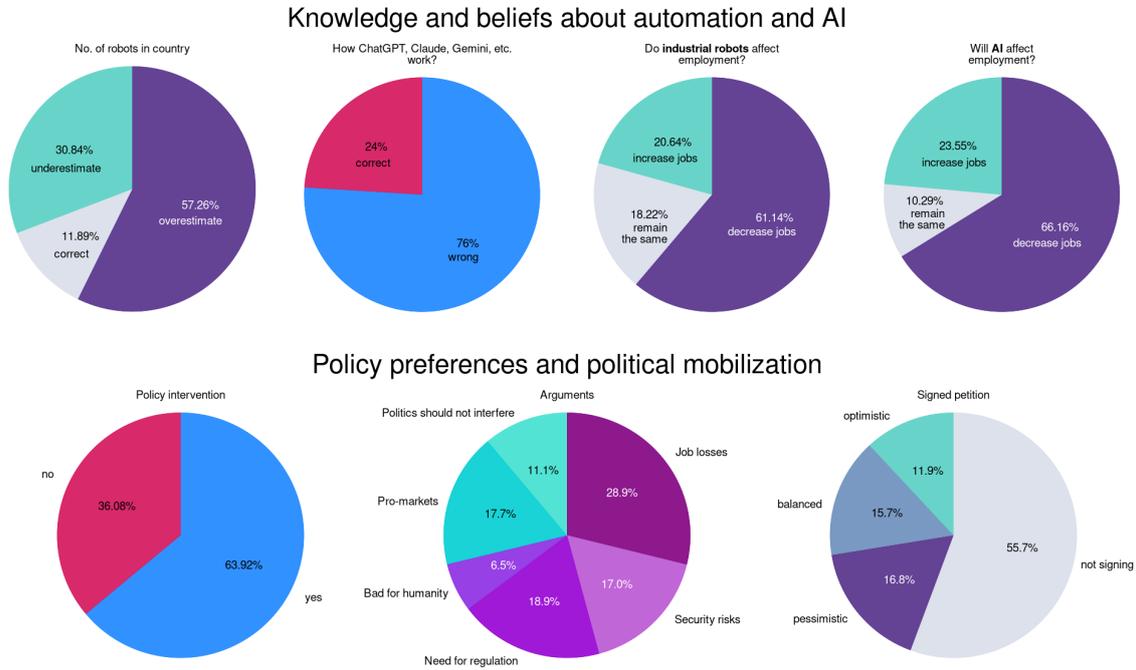
Note. Answers to questions on the number of robots in the country over 1000 workers were recoded so that the "correct" category allows for a deviation of (-5,+5) from the exact number, while answers to questions on how industrial robots and AI will affect employment were recoded so that the "remain the same" category allows for a deviation of (-5, +5) from the value of zero. The sample consists of 3,304 observations from the baseline control treatment (1,160 for the US, 1,064 for Germany and 1,080 for Italy). Arguments in support or against policy intervention come from an open question whose answers were classified with gpt-4o-mini (see section on Methods and Appendix B for more details).

Examining the expected impact on the labor market, the absolute majority of respondents predict that industrial robots (61% of respondents) and AI (66% of respondents) will decrease jobs, while only 21% and 24%, respectively, believe that they will increase jobs. Appendix Figure A5 shows that while beliefs on AI are slightly less pessimistic for high-skilled rather than low-skilled workers, they still remain bleak. Overall, these descriptive results are consistent with existing data on the US from the Pew Research Center (Anderson and Bishop 2025). We also asked an open-ended question on how automation and AI are likely to impact the labor market, which we then classified using OpenAI 4o-mini LLM into optimistic, balanced, pessimistic and a

residual category that includes "don't know" and unclassifiable answers. The relative majority of answers (37%) were pessimistic, followed by don't know (30%), balanced (23%) and, at a substantially lower level, optimistic (11%); see Appendix Table A1.

We next examine the demand for policy intervention related to automation and AI and the willingness to political mobilization among individuals not exposed to our embedded experiment on the impact of political narratives (e.g. the experimental control group). First, we asked whether or not politicians should intervene on these issues. Then, respondents had to write down two arguments about why policymakers should (or should not) intervene. We classified these arguments using OpenAI 4o-mini LLM into replies that mention job losses, other generic anti-AI arguments or pro-market ideas. After the question on policy intervention, we asked respondents if they are willing to sign any of three petitions (optimistic, pessimistic, balanced). The complete text of the petitions is available in Appendix B. They follow directly from the text of the narratives used in the experiment, discussed in the next section.

These results are presented in the bottom panel of Figure 1. Almost two-thirds of respondents demand policy intervention (64%) and mention either concerns about job losses, regulation or general anti-AI feelings as their motivation. Not only are respondents pro-intervention, almost half (45%) are willing to sign a petition on Change.org, suggesting that this topic can mobilize citizens. This is true in all three countries in our survey even though the institutional environments differ (see Appendix Figure A6). Among the different petitions, most respondents choose either the pessimistic (17%) or the balanced petitions (16%) over the optimistic one (12%).

3 Impacts of Political Narratives

3.1 Experimental Design

We next use an embedded experiment to examine the impact of political narratives on the demand for policy interventions and the willingness to political mobilization. Respondents were randomly assigned to read either a techno-optimistic, techno-pessimistic or balanced statement,

or to the control group. Each narrative has three paragraphs and is framed as a fictitious political statement to avoid respondents thinking it is a real speech by an existing political leader. These statements were designed by referencing the related literature in economics and political science, especially that on tech visions (Johnson and Acemoglu 2023).

The techno-optimistic statement posits that the effect on the economy will be positive, with higher productivity and new jobs created. Then, it promises that policies promoting automation and AI will be implemented to remain at the cutting edge of technological progress. The techno-pessimistic statement instead posits that the effect on the economy will be negative, with worse working conditions and a decline in jobs. Then, it promises that policies protecting workers from automation and AI will be implemented to foster a fair and just transition. Finally, the balanced statement posits that the future is uncertain and combines the potential positive and negative effects from the previous statements. Then, it promises that policies that both promote automation and AI and protect workers from these changes will be implemented. The complete text of the statements is available in Appendix B.

3.2   Main results

We first examine the impact of political narratives on policy preferences. As narratives are randomly assigned, we can examine their impact on outcomes using non-parametric tests. However, here we present OLS regression adjusted coefficients which allows us to control for baseline characteristics, and date and country fixed effect, and hence improve the precision of our estimates (see section 5.2 of Methods and Materials for more detail).

Figure 2 shows the impact of each narrative on policy preferences (see Figure A7 for the unadjusted differences across treatments with confidence intervals). We find that exposure to the techno-optimistic statement lowers the probability of demanding any policy intervention on this issue by 2.6 percentage points ($p = 0.033$), and of mentioning concerns about job losses ($e = 2.9$, $p = 0.014$), while increasing the probability of using pro-market arguments in relation to AI ($e = 8.3$, $p < 0.001$). Exposure to the techno-pessimistic statement, on the contrary,

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increases the probability of demanding any policy intervention by a larger 6.7 p.p. ($p < 0.001$) as well as the likelihood of mentioning concerns for job losses ($e = 12.1$, $p < 0.001$). The balanced statement has similar but smaller impacts as the techno-pessimistic one; it leads to higher demand for policy intervention ($e = 4.0$, $p = 0.001$) and higher likelihood of mentioning labor concerns ($e = 5.5$, $p < 0.001$). However, like the techno-optimistic statement, it leads individuals to use slightly more pro-market arguments in relation to AI ($e = 2.9$, $p = 0.009$). All results discussed here are significant with non-parametric tests (see Table A2) and unchanged when adding prior beliefs as additional controls (see Figure A8).

We also asked respondents their preferred policy intervention from among nine alternatives that we group into: i) tax on robots; ii) constraints on big tech; iii) redistribution; iv) education; and v) tax credits. The full list of policies and their grouping is available in Appendix B. The bottom panel of Figure 2 shows that demand for policy intervention does not translate in an obvious way to increased support for specific policies. Interestingly, exposure to any statement, and not just to the pessimistic and balanced ones, marginally increases support for regulation, redistribution and education policies to a similar degree ($p < 0.056$ on regulation, $p < 0.004$ on redistribution, $p < 0.066$ on education policies for all three statements).

Figure 2: Policy Intervention
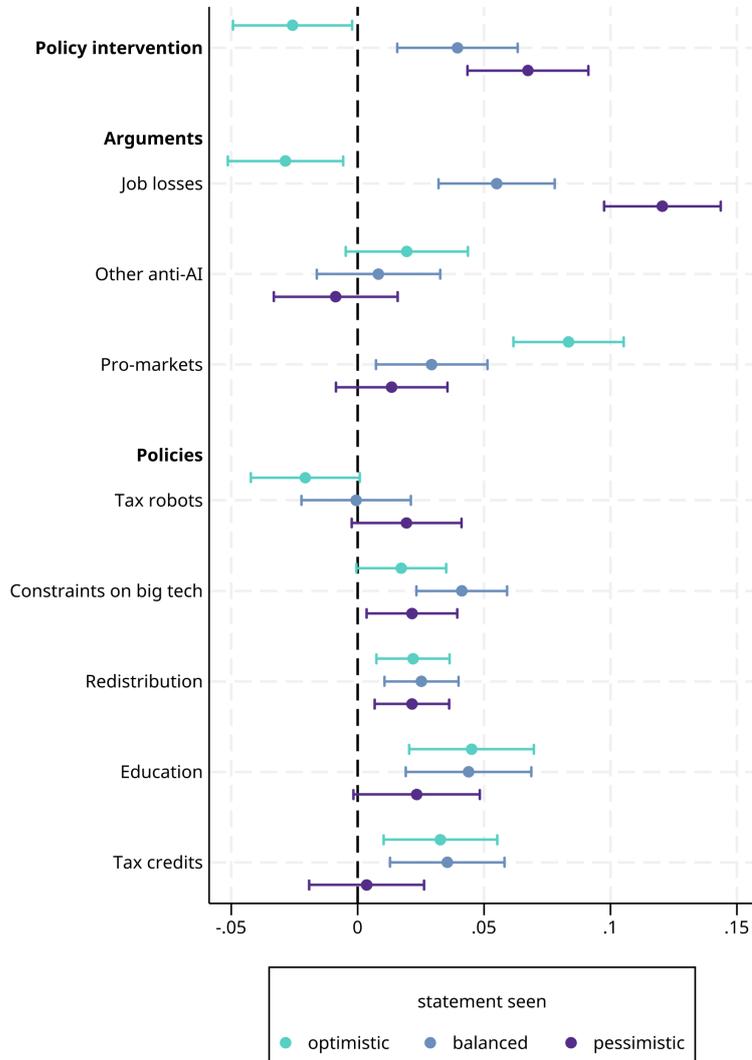
Note. The figure displays the results from separate OLS regressions with each y-axis variable as the dependent variable and treatment indicators shown in the legend as regressors. Full sample of 11,418 observations. Included controls in each regression are age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects. Constraints on big tech includes stronger regulations and breaking up big tech; redistribution includes minimum wages, universal income, lower taxes on labor and increased unemployment benefits.

When we look at more specific policies, we find stronger impacts of the narratives. For example, we find a strongly significant difference in the demand for taxing robots between individuals exposed to the techno-pessimistic and the techno-optimistic statements (Wald test, $F = 12.01$, $p < 0.001$). We also find that respondents exposed to the optimistic or balanced visions become more supportive of tax credits related to innovation ($e = 3.3$, $p = 0.004$, and $e = 3.6$, $p = 0.002$, respectively).

We next show the impact of narratives on political mobilization. As explained before, we gave respondents the opportunity to express their support for any of three petitions during the survey and then, at the end of the survey, respondents could click on a link redirecting them to the chosen petition on Change.org to eventually sign it. Overall, almost 43 percent of respondents declared that they intended to sign a petition, although only around 3 percent of the sample actually signed it on the website. Although small, when rescaled to the total population, this would amount to 6.8 million signatures in the US, 3.3 million in Germany and 1.8 million in Italy. The most signed petition was by far the balanced one; 52% of individuals who publicly signed on the website choose it. The pessimistic petition followed with 36% of the total; only 12% of individuals in this subset signed the optimistic one. These differences are also strongly statistically significant ($p < 0.01$) when assessed with a Kolmogorov-Smirnov test.

In Figure 3, we show the impact of seeing a particular narrative on being willing to sign a particular petition or to not sign any as recorded within the survey (see Figure A9 for the unadjusted differences across treatments). As this is a categorical outcome variable, we now use a multinomial logit regression to control for baseline and survey variables. Compared to the baseline, exposure to the techno-optimistic statement decreases the probability of signing any petition by 3 p.p. ($p = 0.017$) mainly by significantly decreasing the probability of signing a pessimistic petition by 2.3 p.p. ($p = 0.015$). Exposure to the balanced statement has nearly the same effect on the willingness to sign a petition in both significance and size ($e = 3.5$, $p = 0.005$), but this time at the expense of the probability of signing the optimistic petition ($e = -3.4$, $p < 0.001$). The techno-pessimistic statement does not have significant effects on

signing any of the petitions. Again, results are similar when using non-parametric tests (see Table A3) and when controlling for prior beliefs (see Figure A10).

Figure 3: Political Mobilization
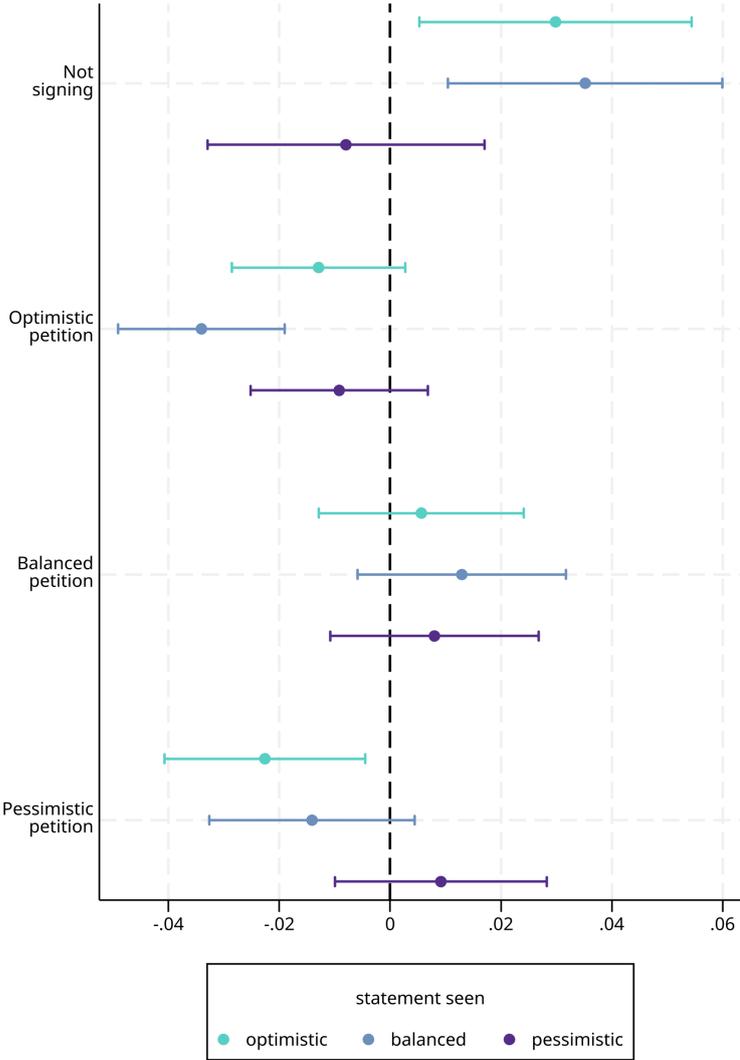
Note. Marginal effects from a multinomial logit regression on the willingness to sign petitions by the statement seen. Full sample of 11,418 observations. Included controls in each regression are age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

As the optimistic and balanced narratives induced respondents to be demobilized and to sign less the optimistic and pessimistic petitions, this indirectly increased the relative success of the balanced petition. This can be seen by looking at the marginal effects of each petition conditional on signing any petition. Multinomial logit regressions reveal that exposure to either the techno-optimistic or the balanced statement significantly increases support for the balanced petition (by 3.9 p.p., $p = 0.036$, and 6.1 p.p., $p = 0.002$, respectively), while the techno-pessimistic statement has no effect ($p = 0.562$). In additional analyses, we find these impacts to be stronger among individuals more concerned about job losses and less pro-market when thinking about technological change (see Table A4). Our findings here along with those on the actual signing of petitions on Change.org indicate that our experiment reduced polarization as defined by the relative frequency of optimistic and pessimistic petitions (see Appendix B for more details on how we measure polarization).

3.3 Mechanisms

A key question about the effect of political narratives is whether they reinforce or undermine prior beliefs. To address this question, we interact each treatment with individual prior beliefs, as elicited by the open question in the previous part of the survey. We find that exposure to narratives largely weakens prior beliefs (Figure 4). More precisely, the negative effect of the techno-optimistic statement on demand for policy intervention and related concerns for job losses is fully driven by respondents with pessimistic preconceptions, and the positive effect of the balanced and techno-pessimistic statements on concerns for job losses is mostly driven by respondents with optimistic preconceptions.

We next examine heterogeneous impacts on mobilization (Figure 5). We find that the reduction in the willingness to sign a petition is driven by those that do not have well-defined priors. Moreover, the decrease in signatures for the optimistic and, to a lesser extent, for the pessimistic petition is driven by individuals with optimistic priors. These individuals converge towards the balanced petition or shy away from signing at all. We further explore these findings

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in our follow-up survey, described in the next section.

Figure 4: Heterogeneity in the Impact of Narratives on Policy Interventions by Prior Beliefs

Figure 5: Heterogeneity in the Impact of Narratives on Political Mobilization by Prior Beliefs

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Note. Marginal effects from a multinomial logit regression on the willingness to sign petitions by the statement seen. Each panel displays the results related to a different value of the categorical variable and treatment indicators are shown in the legend as regressors. Each bar corresponds to the marginal effects related to the prior beliefs (do not know, optimist, balanced or pessimist), such as elicited in the open question from the first part of the survey. Baseline category for the treatments is the baseline control group with no narrative. Full sample of 11,418 observations. Included controls in each regression are age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

Examining other sources of heterogeneity, we do not find significant differences by general risk aversion, lack of knowledge about AI, political ideology, or by the country being surveyed (Appendix Figure A11, Figure A12, Figure A13, Table A5, Table A6 and Table A7). However, we do find heterogeneity in the impacts on polarization. In particular, exposure to narratives lead to more polarization among individuals "not in employment, education, or training" (NEET); over 65; with negative feelings towards technology; and with high exposure to AI as measured with

the vulnerability index from Eloundou et al. (2024). We also investigate whether narratives impacted perceptions about the likelihood of losing one's own job to technology: we find no significant differences across treatments while overall the narratives seemed to make individuals slightly more optimistic about their future prospects (see Appendix Figure A14). Overall, our results are consistent with sociotropic rather than egotropic concerns about job loss, differently from other recent research (Anelli et al. 2025; Borwein et al. 2025).

3.4 Follow-up

In a follow-up fielded between December 2024 and January 2025 (a couple of months later) with a reduced sample of 2,991 respondents, we examined survey respondents' media consumption and political behavior in relation to automation and AI, whether our impacts on policy preferences persisted and respondents' feelings about the particular petitions.

Survey respondents reported a higher interest in the topic. Approximately 40% of respondents read at least one news article or blog post on automation or AI, 25% looked for the position of a political leader on these topics, and 50% of them have either become politically active on the topic or will become in the future, mostly by engaging it with family, friends and colleagues at work. However, even though they reported being more engaged, we found no persistent impact of our narrative priming on policy preferences. With Kruskal-Wallis tests, we now find no differences between treatments either on demand for policy intervention ($p = 0.80$) nor on any specific policy ($p > 0.30$). This is consistent with Stantcheva (2023) that priming interventions are short-lived compared to information ones, especially acknowledging that in the two months between the surveys many game-changing events occurred, like Donald Trump's election in the US and the fall of the Scholz government in Germany.

We then examine how people felt about the petitions to better understand our previous findings. The balanced petition has the strongest association with feelings of happiness and political correctness and weakest association with feelings of anger and fear (Figure A15). Respondents also believe that the balanced and pessimistic petitions will be signed by the most

people, far more likely than the optimistic one (Figure A16). This is true even among individuals who signed the optimistic petition and likely explains why optimistic individuals who see an optimistic narrative are not more likely to sign an optimistic petition.

4 Discussion

Individuals appear to have very little knowledge on AI or automation, they are overly pessimistic about how these new technologies will impact the labor market, and they demand policy intervention out of concerns for job losses. Exposure to political narratives leads to more support for government intervention on AI, but it does not translate into more demand for redistributive policies or regulation of big tech. Exposure also does not increase political polarization; individuals who see any narrative are more likely to sign a balanced petition rather than a pro- or anti-tech one.

While recent work on the US and Canada finds that political preferences are correlated with beliefs about the effect of AI on the labor market (Magistro et al. 2025; Borwein et al. 2024b), politicians do not appear to be employing these issues to define their platforms. Our results contribute to explaining this apparent mismatch between supply and demand of politics.

Populist parties that might be well positioned to build extreme narratives on automation and AI are not incentivized to do so because they observe a general moderate position among the public, differently from other relevant topics. Indeed, previous work has shown that political messages emphasizing the protection of workers are less effective when referred to automation and AI, as compared to alternative economic shocks such as immigration or offshoring (Borwein et al. 2024a). For this reason, it is likely the correct strategy to wait before making these topics more salient in their communication. On the other hand, traditional center-left and center-right parties are unable to capitalize on these generally balanced positions because they cannot employ the traditional toolkit of redistributive and regulatory policies, respectively. Consistent with previous work, we find that political messages on the negative impact of automation and

AI do not increase support for policies protecting workers, not even for those most vulnerable to labor substitution (Bicchi et al. 2025; Haslberger et al. 2025).

The substantial uncertainty surrounding the overall impact of these new technologies on the economy and on the labor market likely increases politicians' caution. Without having a clear idea of who the long-term winners and losers will be, it is difficult for political parties to know who to target. Worryingly, the unmet demand of citizens on such a relevant topic has the potential to enlarge the representation gap between voters and elected representatives, discouraging political participation and reinforcing apathy towards the political system.

5 Methods and Materials

5.1 The Survey

We fielded a preregistered survey experiment with Cint to 11,418 anonymous respondents in the US (N = 3,979), Germany (N = 3,701) and Italy (N = 3,738). The pre-registration can be found on the AEA RCT Registry (AEARCTR-0014322). We received ethical approval for the survey from the Ethical Committee of the Free University of Bozen-Bolzano. Data collection started on the 10th of October and finished on the 4th of November 2024, immediately before the 2024 US Presidential and also before the 2025 German general elections. The survey was programmed with oTree (Chen et al. 2016) and the corresponding programs can be found on a public Github repository. The full text of the questionnaire can be also found in Appendix C. We reached a representative sample of adults (above 18 years old) in each of the three countries in terms of age-groups (6 categories), gender and geographical areas (4 in the US, 7 in Germany and 5 in Italy). Descriptive statistics on our samples by country can be found in Appendix Table A8. Our sample, although slightly skewed towards the young and left-wing individuals, approximately reflects the composition of the general population in terms of gender, age, education, employment status, occupation and voting preferences. We conducted a follow-up survey in January 2025 with 2,991 respondents to test the persistence in demand for policy

intervention and elicit additional beliefs related to the narratives (Appendix D for the text of the questionnaire).

Initial questionnaire: In the first screen of the survey, just after the informed consent, we elicited basic socio-demographic information (age, gender, nationality, education and employment status). Then, we had the non-student respondents fill open questions on the primary tasks associated with their job title and industry of the employer. The answers were classified into 513 O*NET-SOC 2010 occupations and 21 NACE 2.1 industries using OpenAI gpt-4o-mini LLM. See Appendix B for the instructions we used for this classification exercise. We aggregated the occupations into 27 2-digit categories to include them as controls in our regression analyses, while we also associated each of the 513 occupations to measures of exposure to automation and/or AI from Frey and Osborne (2017), Felten et al. (2021), and Eloundou et al. (2024) to derive continuous indexes of exposure to automation and AI. Then, we elicited several questions related to political attitudes, like voting intentions, closeness to a party, left-right political orientation, and cultural worldviews to classify individuals on individualist-communitarian and egalitarian-hierarchical scales using the cultural cognition test (Kahan and Braman 2003; Thompson et al. 1990). We used all the information collected in this part for the heterogeneity analysis.

Facts and beliefs on automation and AI: In the second part of the survey, we first elicited respondents' knowledge on facts on automation and AI. Among the facts on automation, we were mostly interested in the questions about the number of robots for each 1000 workers in the country in 2022, where the corresponding correct number was taken from the International Federation of Robotics (IFR) (2023). Several other questions examine other aspects of automation, such as the country with the highest number of robots or that has increased the number of robots most in the last decade, and the sectors that are most affected by the rise in automation, either across the globe or within the country. On AI, we asked respondents how current LLMs like ChatGPT, Claude, Gemini, etc work between using prediction techniques, a pre-defined set of rules or a form of intelligence replicating how the human brain works. A question among all the aforementioned ones was randomly selected for payment, and a correct answer was paid

0.50 euros/dollars on top of the show-up fee. After that, we elicited beliefs on the impact of automation and AI on the labor market, first focusing on the increase or decrease in the number of jobs due to the introduction of a new industrial robot at the firm and at the aggregate level, then using the same question over AI considering a time span of five years from now for the average worker, and in a separate screen for high-skilled ones and low-skilled ones. Beliefs were also elicited using an open question asking "Please briefly state (max 100 words) your opinion on how automation and AI are shaping the present and future of jobs in terms of number of jobs, their quality and average wage", where answers were classified on one hand into do not know, optimistic, balanced and pessimistic in terms of job creation, quality improvements, or wage increases, and on the other hand into the level of confidence of the judgment, using OpenAI gpt-4o-mini LLM. See Appendix B for the instructions we used for this classification exercise. Table A1 shows the tabulation of this variable according to these two variables.

Political statements: We next introduced an experimental manipulation. With a between-subject design we exposed participants to different statements on automation and AI, framed as fictitious statements by a politician. Respondents were randomly assigned to one of the treatments as they entered the survey. Of our sample pool, 3,304 respondents got randomly assigned to the baseline with no narrative, 2,773 to the optimistic narrative, 2,691 to the balanced one and 2,650 to the pessimistic one. Section 2 already outlined the statements while their full text can be found in Appendix B. To ensure that respondents are attentive to these statements, we included an attention check based on Alesina et al. (2023) that reads as follows: "ATTENTION PLEASE: Do you think you have devoted your full attention to the questions so far? Do you believe, in your honest opinion, that we should use your response for the study?" After respondents read the statements, they had to answer control questions about their content. Respondents could not go on with the survey unless they had answered all questions correctly, but they had the possibility to go back at the text of the narrative to re-read them. We believe these control questions serve two purposes: they ensure that our respondents have carefully read the statements and they also reinforce the optimistic, balanced or pessimistic priming. In our sample,

58.7% of our respondents did not make a single mistake when answering these questions, and 77.4% of them made less than four.

Policy preferences on automation and AI: Immediately after being exposed to the statements, we asked about individual's demand for policy intervention and policy preferences related to automation and AI. In a first screen, we simply ask a yes/no question "Should politicians intervene on automation/AI?" and then we allow respondents to insert two arguments of their choice in favor of or against policy intervention on automation and AI. We then classified the answers with gpt-4o-mini LLM into eight possible categories (job losses, security risks, need for regulation, bad for humanity, mistrust towards AI companies, confidence in automation and AI, pro-market, and mistrust towards politicians), then collapsed to four for the main analysis. See Appendix B for the instructions we used for this classification exercise. On the next screen, we allow individuals to choose preferred policies on these topics among the following ones: minimum wage, universal income, stronger regulations on AI and social media, breaking up big tech monopolies, education policies and training in the workplace, tax credits and subsidies for innovation, lower taxes on labor, taxing firms that use robots treating them similar to labor, unemployment benefits. The precise wording of the policies is available in Appendix B. Respondents could select their preferred policies with no constraints on the number selected.

Willingness to sign a petition on Change.org: We next ask whether individuals are willing to sign one out of three possible petitions on automation and AI on Change.org, a well-known platform for political mobilization, or if they prefer not to sign anything. The text of the petitions mirrors the statements and it is available in Appendix B. Specifically, they were shown the titles of the petitions and they could click on them to see screenshots of the corresponding petitions as they appeared in Change.org. Before the start of the experiment, we added approximately 30 fake signatures to each petition in each country so that individuals would not be worried about being identified. Moreover, experimental evidence on Change.org shows that the previous number of signatures matters for the overall success of the petitions (Van De Rijt et al. 2016). In the final screen of the survey, we gave respondents the opportunity

to click on a link to the petition they had declared they were willing to support on Change.org, so that they could actually sign it. We would have preferred to insert this link at the same time we asked about willingness to sign but the polling company did not allow this. While we cannot trace the actual choice on Change.org back to our treatments, we can observe the number of clicks in our survey to the link to Change.org by treatment and by the petition whom individuals were willing to sign.

Additional outcomes: at the end of the survey we included questions on additional outcomes, such as an individual's perceived chance of losing one's own job in the next five years because of automation or AI (on a 0 to 100% scale) and trust towards several institutions (government, political parties, unions and tech tycoons). We also elicited risk preferences (on a 0-10 scale, following Falk et al. 2018), feelings towards technology and use of AI in daily life.

5.2 Empirical Analysis

As we are examining the impact of an experiment, we can use conventional non-parametric tests or regression adjusted estimates. In the paper, we present the regressions results, while the results from non-parametric tests are reported in Table A2 and Table A3. Our regression model can be written as:

$$Outcome_i = \alpha + \beta_0 TechVision_i + \beta_1 X_i + \epsilon_i \tag{1}$$

where $Outcome_i$ is one of the following variables: an indicator variable for demand for policy intervention, for arguments in support or against policy intervention, for specific preferred policies; or a categorical variable for the choice related to the petition, between not supporting any petition, signing the techno-optimistic, the techno-pessimistic or the balanced petition for respondent i. $TechVision_i$ identifies the treatment that each respondent was assigned to, i.e. either the baseline with no narrative, the techno-optimistic, the techno-pessimistic or the balanced one. X_i is a vector of baseline controls including categorical variables for age-groups

(under 35, between 35 and 65, and over 65), gender (male, female and other), education (primary school, high school, vocational, and university), income (above and below the country-level median income), employment status (out of the job market, unemployed, employee, self-employed, retired and student), industry (21 categories) and occupation (27 categories). We also include fixed effects for country, date and hour at which the respondents completed the survey. We employ an OLS estimation for all outcome variables except for signing the petitions, where we estimate a multinomial logit model given the categorical nature of the choice. Figure 2 presents the impact on policy preferences, while Figure 3 presents the marginal effects of $TechVision_i$ on political mobilization based on this model.

For further analyses on the mechanisms, this model is extended with interaction terms between $TechVision_i$ and prior beliefs, which are then also included as controls (Figure 4 and Figure 5). In additional analyses, we interact the treatments with individual exposure to automation/AI, several individual characteristics, political orientation, cultural worldviews or attitudes (Table A7, Figure A11, Figure A12, Figure A13).

5.3 Robustness

We examined whether our experimental results are sensitive to data 'quality'. First, we redo our main results using the subsample of individuals who made less than three mistakes in the control questions about the statements. This reduces the sample from 11,418 to 8,846 individuals. While these individuals may have been more serious in the completion of the survey, they may also constitute a self-selected sample in terms of attention and social preferences. The coefficients from both our regressions on policy preferences and political mobilization approximately double in size and remain significant. This suggests that our reported results may be a lower bound of the potential effect of political messages. Next, we restrict our sample to those that passed the attention check from Alesina et al. (2023) which drops a further 541 respondents. Our results are unaffected. See Appendix Table A9 and Table A10.

Regarding attrition, only 4% of our sample dropped out at the landing page. The overall

attrition is 32.7%, which is broadly in line with other survey experiments (Stantcheva 2023). 9% of this attrition rate is at the control questions' screen though. Although there are no significant differences across the treatments with narratives, the sample is slightly imbalanced compared to the baseline in terms of age, education and employment status, as younger, less educated, lower income and not in the labour force respondents were more likely to drop out of the survey at the control questions (see Appendix Table A11). We then performed our main analysis re-weighting observations in each treatment with respect to the baseline in terms of age, gender, education, income and employment status. Results in Appendix Figure A17 and Figure A18 are reassuring that our main results were not driven by differential attrition; they even are slightly stronger. We also asked individuals whether they thought the survey was politically oriented; 83.8% said no, while among the remaining respondents an equal number declared it was left- vs right-wing oriented with no differences across treatments (Chi-squared, $p = 0.29$).

5.4   Evidence on Low Salience of AI & Automation Topic

Figure A1 provides motivational evidence on the scarcity of mentions of recent technological advances in social media communication and electoral programs of the two main parties in the three countries of our study. For social media, we obtained access to the official Meta Content Library on November 21, 2025 and we collected the Facebook posts of the leaders of these parties from 2020 onward. We collected all content published in the official pages of Donald Trump, Joe Biden and Kamala Harris for the US; Giorgia Meloni (FDI), Elly Schlein (PD), Giuseppe Conte (M5S) and Matteo Salvini (Lega) for Italy; Olaf Scholz and Lars Klingbeil (SPD), Friedrich Merz (CDU), Alice Weidel and Tino Chrupalla (AfD), Sahra Wagenknecht (BSW) for Germany. The top panel of Figure A1 displays the share of Facebook posts for each topic by all the leaders we collected for the US, by Giorgia Meloni and Elly Schlein for Italy and by Friedrich Merz, Olaf Scholz and Lars Klingbeil for Germany. Figure A19 and Figure A20 show that leaders of other large parties also do not put emphasis on this issue. The analysis uses a keyword dictionary approach to assign each post to its dominant topic, defined as the category with the greatest

number of matched terms. The choice of topics is based on the political science literature (Laver and Garry 2000; Baumgartner et al. 2019, e.g.) with the addition of the "AI & Automation" category. We employed Claude Sonnet 3.5 to create comprehensive lists of words for each topic, based on these seminal studies. Since the other categories are admittedly broader, we add another category "Technology" that includes the category "AI & Automation".

For the electoral programs, we collected the official programs of these parties in the last national electoral campaign. More precisely, we examined the platforms of the Democratic and Republican parties for the 2024 presidential election in the United States (Democratic National Committee 2024; Republican National Committee 2024), the federal election manifestos of the SPD and CDU/CSU for the 2025 Bundestag election in Germany (Sozialdemokratische Partei Deutschlands 2025; Christlich Demokratische Union Deutschlands 2025) and the electoral programs of Partito Democratico and Fratelli d'Italia for the 2022 parliamentary election in Italy (Partito Democratico 2022; Fratelli d'Italia 2022). The bottom panel of Figure A1 uses the same methodology and displays the share of assigned content for each topic in the most recent electoral programs of these parties.

References

Acemoglu, Daron (2025). "Nobel Lecture: Institutions, Technology, and Prosperity". *American Economic Review* 115.6, pp. 1709–1748.

Acemoglu, Daron, Autor, David, Hazell, Jonathon, and Restrepo, Pascual (2022). "Artificial intelligence and jobs: Evidence from online vacancies". *Journal of Labor Economics* 40.S1, S293–S340.

Aghion, Philippe, Bunel, Simon, Jaravel, Xavier, Mikaelsen, Thomas, Roulet, Alexandra, and Søgaard, Jakob (2025). "How different uses of AI shape labor demand: evidence from France". *AEA Papers and Proceedings*. Vol. 115. American Economic Association, pp. 62–67.

Alesina, Alberto, Miano, Armando, and Stantcheva, Stefanie (2023). "Immigration and redistribution". *The Review of Economic Studies* 90.1, pp. 1–39.

Anderson, Monica and Bishop, William (Nov. 2025). *Republicans, Democrats Now Equally Concerned About AI in Daily Life, but Views on Regulation Differ*. Accessed: 2025-12-12. URL: https://www.pewresearch.org/short-reads/2025/11/06/republicans-democrats-now-equally-concerned-about-ai-in-daily-life-but-views-on-regulation-differ/.

Anelli, Massimo, Colantone, Italo, Gallego, Aina, and Stanig, Piero (2025). "What If You See It? Workers' Perceptions of and Reactions to LLMs". Unpublished manuscript. URL: https://sites.google.com/view/italocolantone/working-papers.

Autor, David, Dorn, David, Hanson, Gordon, and Majlesi, Kaveh (2020). "Importing political polarization? The electoral consequences of rising trade exposure". *American Economic Review* 110.10, pp. 3139–3183.

Baumgartner, Frank R, Breunig, Christian, and Grossman, Emiliano (2019). *Comparative policy agendas: Theory, tools, data*. Oxford University Press.

Bicchi, Nicolas, Kuo, Alexander, and Gallego, Aina (2025). "Unpacking technological risks: Different sources of concern and policy preferences". *Political Studies* 73.3, pp. 1054–1077.

Borwein, Sophie, Bonikowski, Bart, Loewen, Peter John, Lee-Whiting, Blake, and Magistro, Beatrice (2025). "Perceived technological threat and vote choice: evidence from 15 European democracies". *West european politics* 48.3, pp. 534–561.

Borwein, Sophie, Bonikowski, Bart, Loewen, Peter, Magistro, Beatrice, and Lee-Whiting, Blake (2024a). "Who can assert ownership over automation? Workplace technological change, populist and ethno-nationalist rhetoric, and candidate support". *Political Behavior* 46.4, pp. 2191–2214.

Borwein, Sophie, Magistro, Beatrice, Alvarez, R Michael, Bonikowski, Bart, and Loewen, Peter John (2024b). "The Potential for Political Backlash Against AI".

Boxell, Levi, Gentzkow, Matthew, and Shapiro, Jesse M (2024). "Cross-country trends in affective polarization". *Review of Economics and Statistics* 106.2, pp. 557–565.

Brynjolfsson, Erik, Chandar, Bharat, and Chen, Ruyu (2025). "Canaries in the coal mine? six facts about the recent employment effects of artificial intelligence". *Stanford Digital Economy Lab. Published August.*

Capraro, Valerio, Lentsch, Austin, Acemoglu, Daron, Akgun, Selin, Akhmedova, Aisel, Bilancini, Ennio, Bonnefon, Jean-François, Brañas-Garza, Pablo, Butera, Luigi, Douglas, Karen M, et al. (2024). "The impact of generative artificial intelligence on socioeconomic inequalities and policy making". *PNAS nexus* 3.6, pgae191.

Chen, Daniel L., Schonger, Martin, and Wickens, Chris (2016). "oTree, An open-source platform for laboratory, online, and field experiments". *Journal of Behavioral and Experimental Finance* 9.C, pp. 88–97. DOI: 10.1016/j.jbef.2015.12.001. URL: https://ideas.repec.org/a/eee/beexfi/v9y2016icp88-97.html.

Christlich Demokratische Union Deutschlands (2025). *Politikwechsel für Deutschland: Wahlprogramm von CDU und CSU.* https://www.cdu.de/. Accessed January 2025.

Democratic National Committee (2024). *2024 Democratic Party Platform.* https://democrats.org/where-we-stand/party-platform/. Accessed January 2025.

Eloundou, Tyna, Manning, Sam, Mishkin, Pamela, and Rock, Daniel (2024). "GPTs are GPTs: Labor market impact potential of LLMs". *Science* 384.6702, pp. 1306–1308.

Falk, Armin, Becker, Anke, Dohmen, Thomas, Enke, Benjamin, Huffman, David, and Sunde, Uwe (2018). "Global evidence on economic preferences". *The quarterly journal of economics* 133.4, pp. 1645–1692.

Felten, Edward, Raj, Manav, and Seamans, Robert (2021). "Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses". *Strategic Management Journal* 42.12, pp. 2195–2217.

Fratelli d'Italia (2022). *Pronti a risollevare l'Italia*. https://www.fratelli-italia.it/programma/. Accessed January 2025.

Frey, Carl Benedikt and Osborne, Michael A (2017). "The future of employment: How susceptible are jobs to computerisation?" *Technological forecasting and social change* 114, pp. 254–280.

Gallego, Aina, Kuo, Alexander, Manzano, Dulce, and Fernández-Albertos, José (2022). "Technological risk and policy preferences". *Comparative Political Studies* 55.1, pp. 60–92.

Gallego, Aina and Kurer, Thomas (2022). "Automation, digitalization, and artificial intelligence in the workplace: implications for political behavior". *Annual Review of Political Science* 25, pp. 463–484.

Gambacorta, Leonardo, Jappelli, Tullio, and Oliviero, Tommaso (Oct. 2025). *Exploring Household Adoption and Usage of Generative AI: New Evidence from Italy*. CEPR Discussion Paper 20762. Centre for Economic Policy Research. URL: https://cepr.org/publications/dp20762.

Hackenburg, Kobi, Tappin, Ben M, Hewitt, Luke, Saunders, Ed, Black, Sid, Lin, Hause, Fist, Catherine, Margetts, Helen, Rand, David G, and Summerfield, Christopher (2025). "The levers of political persuasion with conversational artificial intelligence". *Science* 390.6777, eaea3884.

Haslberger, Matthias, Gingrich, Jane, and Bhatia, Jasmine (2025). "Rage against the machine? Generative AI exposure, subjective risk, and policy preferences". *Journal of European Public Policy*, pp. 1–28.

Ide, Enrique and Talamàs, Eduard (2025). "Artificial Intelligence in the Knowledge Economy". *Journal of Political Economy* 133.12, pp. 3762–3800.

Johnson, Simon and Acemoglu, Daron (2023). *Power and Progress: Our Thousand-Year Struggle Over Technology and Prosperity— Winners of the 2024 Nobel Prize for Economics*. Hachette UK.

Jones, Charles I (2024). "The AI dilemma: Growth versus existential risk". *American Economic Review: Insights* 6.4, pp. 575–590.

Kahan, Dan M and Braman, Donald (2003). "More statistics, less persuasion: A cultural theory of gun-risk perceptions". *University of Pennsylvania Law Review* 151.4, pp. 1291–1327.

König, Pascal D and Wenzelburger, Georg (2019). "Why parties take up digitization in their manifestos: An empirical analysis of eight Western European economies". *Journal of European Public Policy* 26.11, pp. 1678–1695.

Laver, Michael and Garry, John (2000). "Estimating policy positions from political texts". *American Journal of Political Science*, pp. 619–634.

Lin, Hause, Czarnek, Gabriela, Lewis, Benjamin, White, Joshua P, Berinsky, Adam J, Costello, Thomas, Pennycook, Gordon, and Rand, David G (2025). "Persuading voters using human–artificial intelligence dialogues". *Nature*, pp. 1–8.

Lorenz-Spreen, Philipp, Oswald, Lisa, Lewandowsky, Stephan, and Hertwig, Ralph (2023). "A systematic review of worldwide causal and correlational evidence on digital media and democracy". *Nature human behaviour* 7.1, pp. 74–101.

Magistro, Beatrice, Borwein, Sophie, Alvarez, R Michael, Bonikowski, Bart, and Loewen, Peter John (2025). "Attitudes toward artificial intelligence (AI) and globalization: Common microfoundations and political implications". *American Journal of Political Science*.

Mäkelä, Elina and Stephany, Fabian (2024). "Complement or substitute? How AI increases the demand for human skills". *arXiv preprint arXiv:2412.19754*.

Partito Democratico (2022). *Insieme per un'Italia democratica e progressista.* Electoral program for the 2022 Italian general election.

Pizzinelli, Carlo, Panton, Augustus J, Tavares, Ms Marina Mendes, Cazzaniga, Mauro, and Li, Longji (2023). *Labor market exposure to AI: Cross-country differences and distributional implications.* International Monetary Fund.

Republican National Committee (2024). *2024 Republican Party Platform.* https://www.presidency.ucsb.edu/documents/2024-republican-party-platform. Accessed January 2025.

Sozialdemokratische Partei Deutschlands (2025). *Regierungsprogramm 2025: Mehr für dich.* https://mehr.spd.de/. Accessed January 2025.

Stantcheva, Stefanie (2023). "How to run surveys: A guide to creating your own identifying variation and revealing the invisible". *Annual Review of Economics* 15.1, pp. 205–234.

Summerfield, Christopher, Argyle, Lisa P, Bakker, Michiel, Collins, Teddy, Durmus, Esin, Eloundou, Tyna, Gabriel, Iason, Ganguli, Deep, Hackenburg, Kobi, Hadfield, Gillian K, et al. (2025). "The impact of advanced AI systems on democracy". *Nature Human Behaviour* 9.12, pp. 2420–2430.

Thompson, M., Ellis, R.J., and Wildavsky, A. (1990). *Cultural Theory.* Political cultures. Avalon Publishing. ISBN: 9780813378633. URL: https://books.google.it/books?id=8t62AAAAIAAJ.

Van De Rijt, Arnout, Akin, Idil Afife, Willer, Robb, and Feinberg, Matthew (2016). "Success-breeds-success in collective political behavior: Evidence from a field experiment". *Sociological Science* 3, pp. 940–950.

Appendix A - Tables and Figures

Table A1: Prior Beliefs - Open Question

Certainty	Beliefs				
	Don't Know	Optimistic	Balanced	Pessimistic	Total
Low	3,331	265	117	374	4,087
	[100]	[20.80]	[4.55]	[8.90]	[35.91]
Medium	0	503	1,905	1,566	3,974
	[0]	[39.48]	[74.04]	[37.27]	[34.92]
High	0	506	551	2,262	3,319
	[0]	[39.72]	[21.41]	[53.83]	[29.17]
Total	3,331	1,274	2,573	4,202	11,380
	[29.27]	[11.20]	[22.61]	[36.92]	[100]

Frequencies [percentages in brackets] of beliefs by their level of certainty from the open question "Please briefly state (max. 100 words) your opinion on how automation and AI are shaping the present and future of jobs in terms of number of jobs, their quality, and average wages." Answers to the question are classified using gpt-4o-mini (see more details in Appendix B).

Table A2: Non-parametric tests on Policy Preferences

	Arguments					Policies			
	Policy intervention	Job losses	Other anti-AI	Pro-markets	Tax robots	Constraints on big tech	Redistr	Educat	Tax credits
optimistic	0.095	0.023	0.027	0.000	0.065	0.006	0.027	0.000	0.002
balanced	0.000	0.000	0.121	0.003	0.944	0.000	0.000	0.000	0.000
pessimistic	0.000	0.000	0.930	0.138	0.076	0.001	0.001	0.018	0.466

p-values from Kolmogorov-Smirnov tests on the equality of distribution in the outcome variables (dummy variables identifying the choice of preferred policies) when exposed to a statement (listed in the row headers) compared to non exposure (the baseline condition). Full sample of 11,418 observations.

Table A3: Non-parametric tests on Willingness to Sign a Petition

	not signing	optimistic	balanced	pessimistic
optimistic	0.013	0.094	0.486	0.009
balanced	0.004	0.000	0.112	0.071
pessimistic	0.581	0.218	0.331	0.402

p-values from Chi-squared tests on the equality of distribution in the outcome variables (dummy variables identifying the choice of not signing, signing the optimistic petition, signing the balanced petition or signing the pessimistic petition) when exposed to a statement (listed in the row headers) compared to non exposure (the baseline condition). Full sample of 11,418 observations.

Table A4: Heterogeneity: Willingness to Sign by Policy preferences

	(1) not signing	(2) optimistic	(3) balanced	(4) pessimistic
Baseline N=11417				
optimistic	0.030**	-0.013	0.006	-0.023**
	(0.013)	(0.008)	(0.009)	(0.009)
balanced	0.035***	-0.034***	0.013	-0.014
	(0.013)	(0.008)	(0.010)	(0.009)
pessimistic	-0.008	-0.009	0.008	0.009
	(0.013)	(0.008)	(0.010)	(0.010)
Policy intervention N=7559				
optimistic	0.033**	-0.010	0.006	-0.029**
	(0.016)	(0.010)	(0.012)	(0.012)
balanced	0.045***	-0.040***	0.013	-0.018
	(0.016)	(0.009)	(0.012)	(0.012)
pessimistic	0.012	-0.018*	0.005	0.002
	(0.016)	(0.010)	(0.012)	(0.012)
Job losses N=3469				
optimistic	-0.029	0.002	0.048**	-0.021
	(0.025)	(0.014)	(0.019)	(0.020)
balanced	-0.012	-0.031***	0.046***	-0.003
	(0.023)	(0.012)	(0.017)	(0.019)
pessimistic	-0.020	-0.008	0.021	0.007
	(0.022)	(0.012)	(0.016)	(0.018)
Other anti-AI N=4405				
optimistic	0.051***	-0.023**	-0.019	-0.009
	(0.020)	(0.011)	(0.015)	(0.014)
balanced	0.037*	-0.030***	-0.001	-0.007
	(0.020)	(0.011)	(0.016)	(0.014)
pessimistic	-0.008	-0.009	-0.003	0.021
	(0.021)	(0.011)	(0.016)	(0.015)
Pro-markets N=2966				
optimistic	-0.030	0.000	0.023	0.007
	(0.024)	(0.016)	(0.018)	(0.016)
balanced	0.011	-0.027*	0.028	-0.013
	(0.025)	(0.016)	(0.020)	(0.017)
pessimistic	-0.022	0.012	0.016	-0.006
	(0.026)	(0.017)	(0.020)	(0.017)

*** p<.01, ** p<.05, * p<.1

Marginal effects from multinomial logit regressions over the subsample specified at the top of each panel. Included controls are age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

Table A5: Policy Preferences by Country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			Arguments				**Policies**		
	Policy	Job	Other	Pro-	Tax	Constraints	Redistr	Educat	Tax
	intervention	losses	anti-AI	markets	robots	on big tech			credits
				United States					
optimistic	-0.057***	-0.033*	0.049**	0.098***	-0.011	0.025	0.013	0.059***	0.045**
	(0.021)	(0.020)	(0.020)	(0.020)	(0.018)	(0.015)	(0.013)	(0.021)	(0.019)
balanced	0.028	0.073***	0.015	0.024	0.009	0.056***	0.019	0.068***	0.043**
	(0.021)	(0.020)	(0.021)	(0.020)	(0.019)	(0.016)	(0.013)	(0.022)	(0.019)
pessimistic	0.063***	0.115***	0.016	0.005	0.034*	0.030*	0.036***	0.053**	-0.000
	(0.021)	(0.020)	(0.021)	(0.020)	(0.018)	(0.016)	(0.013)	(0.021)	(0.019)
R-squared	0.057	0.074	0.083	0.075	0.029	0.073	0.052	0.093	0.053
Obs	3979	3979	3979	3979	3979	3979	3979	3979	3979
				Germany					
optimistic	-0.024	-0.032*	0.007	0.071***	-0.027	0.026*	0.015	0.005	0.011
	(0.022)	(0.019)	(0.022)	(0.020)	(0.019)	(0.016)	(0.012)	(0.022)	(0.020)
balanced	0.003	0.007	0.017	0.064***	0.013	0.035**	0.023*	0.027	0.014
	(0.022)	(0.019)	(0.022)	(0.020)	(0.019)	(0.016)	(0.012)	(0.022)	(0.020)
pessimistic	0.027	0.070***	0.008	0.033	-0.014	0.010	0.001	0.013	-0.012
	(0.023)	(0.020)	(0.022)	(0.021)	(0.020)	(0.016)	(0.012)	(0.023)	(0.020)
R-squared	0.033	0.047	0.043	0.041	0.033	0.074	0.051	0.082	0.041
Obs	3701	3701	3701	3701	3701	3701	3701	3701	3701
				Italy					
optimistic	0.004	-0.014	-0.003	0.080***	-0.020	0.003	0.041***	0.073***	0.038*
	(0.020)	(0.022)	(0.022)	(0.018)	(0.020)	(0.016)	(0.014)	(0.022)	(0.021)
balanced	0.085***	0.087***	-0.012	0.004	-0.022	0.030*	0.033**	0.035	0.048**
	(0.020)	(0.022)	(0.022)	(0.018)	(0.020)	(0.016)	(0.014)	(0.022)	(0.021)
pessimistic	0.108***	0.173***	-0.052**	0.003	0.035*	0.022	0.027*	0.003	0.028
	(0.020)	(0.022)	(0.022)	(0.018)	(0.020)	(0.016)	(0.014)	(0.022)	(0.021)
R-squared	0.050	0.057	0.055	0.037	0.033	0.061	0.051	0.063	0.035
Obs	3738	3738	3738	3738	3738	3738	3738	3738	3738

*** p<.01, ** p<.05, * p<.1

OLS regressions on the subsample of participants from each country separately. Included controls are age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

Table A6: Mobilization: Willingness to Sign by Country

	Signatures			
	(1)	(2)	(3)	(4)
	Not Signing	Optimistic	Balanced	Pessimistic
United States				
optimistic	0.051**	-0.009	0.010	-0.052***
	(0.021)	(0.015)	(0.016)	(0.016)
balanced	0.051**	-0.034**	0.027	-0.044***
	(0.022)	(0.014)	(0.017)	(0.017)
pessimistic	-0.024	-0.016	0.018	0.022
	(0.021)	(0.015)	(0.017)	(0.018)
Obs	3979	3979	3979	3979
Germany				
optimistic	0.014	-0.018	-0.006	0.010
	(0.022)	(0.014)	(0.016)	(0.015)
balanced	0.022	-0.039***	0.001	0.015
	(0.022)	(0.013)	(0.016)	(0.015)
pessimistic	-0.012	0.004	-0.005	0.012
	(0.022)	(0.015)	(0.016)	(0.016)
Obs	3700	3700	3700	3700
Italy				
optimistic	0.019	-0.015	0.015	-0.019
	(0.022)	(0.013)	(0.017)	(0.016)
balanced	0.030	-0.031**	0.010	-0.009
	(0.022)	(0.013)	(0.017)	(0.017)
pessimistic	0.007	-0.017	0.013	-0.004
	(0.022)	(0.013)	(0.017)	(0.017)
Obs	3738	3738	3738	3738

*** p<.01, ** p<.05, * p<.1

Marginal effects from multinomial logit regressions on the subsample of participants from each country separately. Included controls are age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

Table A7: Heterogeneity: Willingness to Sign

	(1) not signing	(2) optimistic	(3) balanced	(4) pessimistic
baseline N=11417				
optimistic	0.030**	-0.013	0.006	-0.023**
	(0.013)	(0.008)	(0.009)	(0.009)
balanced	0.035***	-0.034***	0.013	-0.014
	(0.013)	(0.008)	(0.010)	(0.009)
pessimistic	-0.008	-0.009	0.008	0.009
	(0.013)	(0.008)	(0.010)	(0.010)
female N=5729				
optimistic	0.004	-0.004	0.012	-0.012
	(0.017)	(0.011)	(0.013)	(0.013)
balanced	0.036**	-0.038***	0.020	-0.019
	(0.018)	(0.010)	(0.013)	(0.013)
pessimistic	-0.016	-0.013	0.007	0.022
	(0.018)	(0.011)	(0.013)	(0.014)
under 35 N=3070				
optimistic	0.050**	-0.033*	0.003	-0.020
	(0.024)	(0.018)	(0.018)	(0.018)
balanced	0.048*	-0.042**	0.018	-0.024
	(0.025)	(0.018)	(0.018)	(0.019)
pessimistic	0.018	-0.025	0.003	0.004
	(0.024)	(0.018)	(0.018)	(0.019)
over 65 N=2664				
optimistic	0.010	-0.004	-0.015	0.009
	(0.026)	(0.014)	(0.021)	(0.017)
balanced	0.015	-0.035***	-0.017	0.037**
	(0.026)	(0.012)	(0.021)	(0.018)
pessimistic	-0.067**	-0.000	-0.010	0.077***
	(0.026)	(0.014)	(0.021)	(0.019)
university N=3883				
optimistic	0.032	-0.012	0.009	-0.028*
	(0.021)	(0.014)	(0.017)	(0.015)
balanced	0.022	-0.028**	0.009	-0.002
	(0.022)	(0.014)	(0.017)	(0.016)
pessimistic	-0.024	0.002	0.022	0.000
	(0.022)	(0.015)	(0.018)	(0.017)
blue collar N=1303				
optimistic	-0.035	0.012	0.057**	-0.033
	(0.037)	(0.024)	(0.027)	(0.030)
balanced	0.008	-0.024	0.047*	-0.031
	(0.038)	(0.022)	(0.027)	(0.030)
pessimistic	-0.001	-0.008	0.061**	-0.052*
	(0.036)	(0.022)	(0.026)	(0.028)
neet N=3867				
optimistic	-0.008	0.000	0.011	-0.003
	(0.021)	(0.012)	(0.017)	(0.014)
balanced	0.028	-0.021*	-0.013	0.005
	(0.021)	(0.012)	(0.016)	(0.015)
pessimistic	-0.051**	0.002	-0.003	0.052***
	(0.022)	(0.013)	(0.017)	(0.016)
exposed to AI N=5703				
optimistic	0.009	-0.026**	0.018	-0.000
	(0.018)	(0.011)	(0.013)	(0.013)
balanced	0.013	-0.040***	0.023*	0.004
	(0.018)	(0.011)	(0.014)	(0.013)
pessimistic	-0.006	-0.018	-0.004	0.029**
	(0.018)	(0.012)	(0.013)	(0.014)
individualist N=5303				
optimistic	0.016	-0.003	0.009	-0.022
	(0.018)	(0.011)	(0.013)	(0.013)
balanced	0.039**	-0.024**	0.013	-0.027**
	(0.018)	(0.010)	(0.014)	(0.013)
pessimistic	-0.030	0.004	0.008	0.018
	(0.019)	(0.011)	(0.014)	(0.014)
egalitarian N=6535				
optimistic	0.007	0.007	0.008	-0.022*
	(0.017)	(0.010)	(0.013)	(0.012)
balanced	0.020	-0.026***	0.012	-0.006
	(0.017)	(0.009)	(0.013)	(0.013)
pessimistic	-0.027	0.003	0.004	0.019
	(0.017)	(0.010)	(0.013)	(0.013)
low knowledge on auto/AI N=7473				
optimistic	0.016	-0.010	0.019	-0.025**
	(0.016)	(0.010)	(0.012)	(0.012)
balanced	0.030*	-0.035***	0.021*	-0.016
	(0.016)	(0.009)	(0.012)	(0.012)
pessimistic	-0.002	-0.006	0.003	0.005
	(0.016)	(0.010)	(0.011)	(0.012)
risk averse N=5396				
optimistic	0.032*	-0.008	-0.005	-0.020
	(0.018)	(0.010)	(0.013)	(0.013)
balanced	0.034*	-0.024**	0.006	-0.016
	(0.018)	(0.010)	(0.013)	(0.013)
pessimistic	-0.014	-0.004	-0.005	0.023*
	(0.018)	(0.011)	(0.013)	(0.014)
neg. feelings towards tech N=2194				
optimistic	0.064**	-0.030*	-0.001	-0.033
	(0.028)	(0.017)	(0.019)	(0.021)
balanced	0.066**	-0.060***	-0.016	0.010
	(0.028)	(0.016)	(0.018)	(0.023)
pessimistic	0.009	-0.026	-0.029	0.045*
	(0.028)	(0.017)	(0.018)	(0.023)

*** p<.01, ** p<.05, * p<.1

Marginal effects from multinomial logit regressions over the subsample specified at the top of each panel defined by having a specific characteristic. Included controls are age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

Table A8: Sample Characteristics by Country

	Germany	Italy	US	Total
N	3701	3738	3979	11418
Gender				
male	50.3%	49.8%	48.3%	49.4%
female	49.5%	49.9%	51.1%	50.2%
other	0.2%	0.3%	0.6%	0.4%
Age				
Mean	48.7	49.7	47.7	48.7
Std. dev.	(16.8)	(16.3)	(17.8)	(17.0)
Under 35	27.0%	23.2%	30.2%	26.9%
Over 65	23.3%	25.4%	21.3%	23.3%
Education				
primary school or nothing	9.3%	9.8%	8.2%	9.1%
high school	38.5%	52.2%	50.6%	47.2%
vocational	23.9%	5.9%	0.0%	9.7%
university	28.3%	32.0%	41.2%	34.0%
Employment				
employed	49.5%	43.4%	38.1%	43.5%
self-employed	8.6%	13.8%	9.0%	10.4%
unemployed	4.8%	7.4%	9.8%	7.4%
out of job market	3.9%	4.0%	7.6%	5.2%
retired	24.4%	21.8%	25.9%	24.1%
student	4.2%	5.2%	4.2%	4.6%
other	4.6%	4.4%	5.3%	4.8%
Blue collar	12.6%	8.9%	12.7%	11.4%
Service worker	26.8%	29.0%	28.8%	28.2%
Voting intention				
far-left	12.6%	24.4%	0.0%	12.1%
centre-left	24.9%	29.5%	44.3%	33.1%
centre-right	27.3%	15.3%	37.4%	26.9%
far-right	17.8%	28.4%	0.0%	15.1%
do not know	17.3%	2.4%	18.3%	12.8%

Voting intentions: far-left includes Bündnis Sahra Wagenknecht and Die Linke in Germany, and the Five Stars Movement and Greens/Left in Italy. Centre-left includes the Democrats in the US, Die Grünen and SPD in Germany, and Azione, Italia Viva, +Europa and the Democratic Party in Italy. Centre-right includes the Republicans in the US, CDU/CSU and FDP in Germany, and Forza Italia in Italy. Far-right includes the AfD in Germany, and Lega and Brothers of Italy in Italy.

Table A9: Policy Preferences for Attentive Respondents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			Arguments				**Policies**		
	Policy intervention	Job losses	Other anti-AI	Pro-markets	Tax robots	Constraints on big tech	Redistr	Educat	Tax credits
				Less than 3 mistakes in the control questions					
optimistic	-0.026*	-0.005	0.059***	0.113***	-0.019	0.044***	0.050***	0.081***	0.048***
	(0.013)	(0.013)	(0.014)	(0.013)	(0.012)	(0.010)	(0.008)	(0.014)	(0.013)
balanced	0.061***	0.099***	0.043***	0.062***	0.011	0.087***	0.057***	0.094***	0.047***
	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)	(0.010)	(0.009)	(0.014)	(0.013)
pessimistic	0.089***	0.165***	0.034**	0.038***	0.049***	0.046***	0.059***	0.082***	0.020
	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.010)	(0.009)	(0.015)	(0.013)
R-squared	0.044	0.055	0.044	0.053	0.019	0.052	0.060	0.066	0.031
Obs	8846	8846	8846	8846	8846	8846	8846	8846	8846
				Attention check					
optimistic	-0.015	-0.024**	0.029**	0.091***	-0.016	0.024***	0.027***	0.057***	0.038***
	(0.012)	(0.012)	(0.013)	(0.011)	(0.011)	(0.009)	(0.008)	(0.013)	(0.012)
balanced	0.055***	0.065***	0.018	0.036***	0.005	0.048***	0.029***	0.051***	0.039***
	(0.012)	(0.012)	(0.013)	(0.012)	(0.011)	(0.009)	(0.008)	(0.013)	(0.012)
pessimistic	0.078***	0.133***	-0.001	0.019*	0.024**	0.025***	0.027***	0.033**	0.004
	(0.012)	(0.012)	(0.013)	(0.012)	(0.011)	(0.009)	(0.008)	(0.013)	(0.012)
R-squared	0.041	0.052	0.045	0.044	0.014	0.049	0.053	0.061	0.028
Obs	10877	10877	10877	10877	10877	10877	10877	10877	10877

*** p<.01, ** p<.05, * p<.1

OLS regressions on the subsample of individuals who either answered correctly to the control questions within the third attempt or who declared to be attentive at our attention check. Included controls are age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

Table A10: Mobilization: Willingness to Sign for Attentive Respondents

	Signatures			
	(1)	(2)	(3)	(4)
	Not signing	Optimistic	Balanced	Pessimistic
Less than 3 mistakes in the control questions				
optimistic	0.064***	-0.036***	0.007	-0.035***
	(0.014)	(0.008)	(0.010)	(0.010)
balanced	0.065***	-0.055***	0.010	-0.020*
	(0.014)	(0.008)	(0.011)	(0.011)
pessimistic	0.016	-0.028***	0.004	0.008
	(0.015)	(0.009)	(0.011)	(0.011)
Obs	8846	8846	8846	8846
Attention check				
optimistic	0.023*	-0.015*	0.011	-0.019**
	(0.013)	(0.008)	(0.010)	(0.009)
balanced	0.032**	-0.036***	0.017*	-0.013
	(0.013)	(0.008)	(0.010)	(0.010)
pessimistic	-0.013	-0.008	0.011	0.009
	(0.013)	(0.008)	(0.010)	(0.010)
Obs	10876	10876	10876	10876

*** p<.01, ** p<.05, * p<.1

Marginal effects from multinomial logit regressions on the subsample of individuals who either answered correctly to the control questions within the third attempt or who declared to be attentive at our attention check. Included controls are age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

Table A11: Balance of characteristics compared to the baseline

|	baseline	optimistic		balanced		pessimistic	
	Mean/(SE)	Mean/(SE)	Mean diff	Mean/(SE)	Mean diff	Mean/(SE)	Mean diff
Under 35	0.280	0.259	-0.021*	0.260	-0.020*	0.275	-0.005
	(0.008)	(0.008)		(0.008)		(0.009)	
Over 65	0.236	0.228	-0.008	0.236	-0.000	0.232	-0.004
	(0.007)	(0.008)		(0.008)		(0.008)	
Male	0.496	0.478	-0.018	0.498	0.002	0.505	0.008
	(0.009)	(0.009)		(0.010)		(0.010)	
Female	0.500	0.519	0.019	0.498	-0.002	0.489	-0.011
	(0.009)	(0.009)		(0.010)		(0.010)	
Other gender	0.004	0.003	-0.001	0.004	0.000	0.006	0.003
	(0.001)	(0.001)		(0.001)		(0.002)	
Primary education or nothing	0.101	0.088	-0.013*	0.087	-0.013*	0.086	-0.015**
	(0.005)	(0.005)		(0.005)		(0.005)	
High School	0.478	0.462	-0.016	0.458	-0.020	0.489	0.011
	(0.009)	(0.009)		(0.010)		(0.010)	
Vocational School	0.099	0.097	-0.002	0.099	0.000	0.092	-0.006
	(0.005)	(0.006)		(0.006)		(0.006)	
University	0.323	0.353	0.030**	0.356	0.033***	0.333	0.010
	(0.008)	(0.009)		(0.009)		(0.009)	
Employed	0.421	0.446	0.025*	0.435	0.014	0.442	0.021
	(0.009)	(0.009)		(0.010)		(0.010)	
Self-employed	0.106	0.110	0.005	0.096	-0.010	0.105	-0.001
	(0.005)	(0.006)		(0.006)		(0.006)	
Unemployed	0.071	0.065	-0.006	0.080	0.009	0.081	0.010
	(0.004)	(0.005)		(0.005)		(0.005)	
Out of job market	0.055	0.053	-0.002	0.055	-0.000	0.045	-0.011*
	(0.004)	(0.004)		(0.004)		(0.004)	
Retired	0.242	0.235	-0.007	0.246	0.004	0.239	-0.003
	(0.007)	(0.008)		(0.008)		(0.008)	
Student	0.051	0.040	-0.011**	0.046	-0.005	0.044	-0.007
	(0.004)	(0.004)		(0.004)		(0.004)	
Other employment status	0.054	0.050	-0.004	0.042	-0.012**	0.045	-0.009
	(0.004)	(0.004)		(0.004)		(0.004)	
Low income	0.496	0.464	-0.033**	0.472	-0.024*	0.465	-0.031**
	(0.009)	(0.009)		(0.010)		(0.010)	

*** p<.01, ** p<.05, * p<.1

Observations are 3304 in the baseline, 2773 in the optimistic, 2691 in the balanced and 2650 in the pessimistic treatments. Stars identify p-values of pairwise t-tests between the distribution of the characteristic in the treatment compared to the baseline.

Figure A1: Prevalence of AI/Automation Topics in Facebook Posts and Electoral Programs
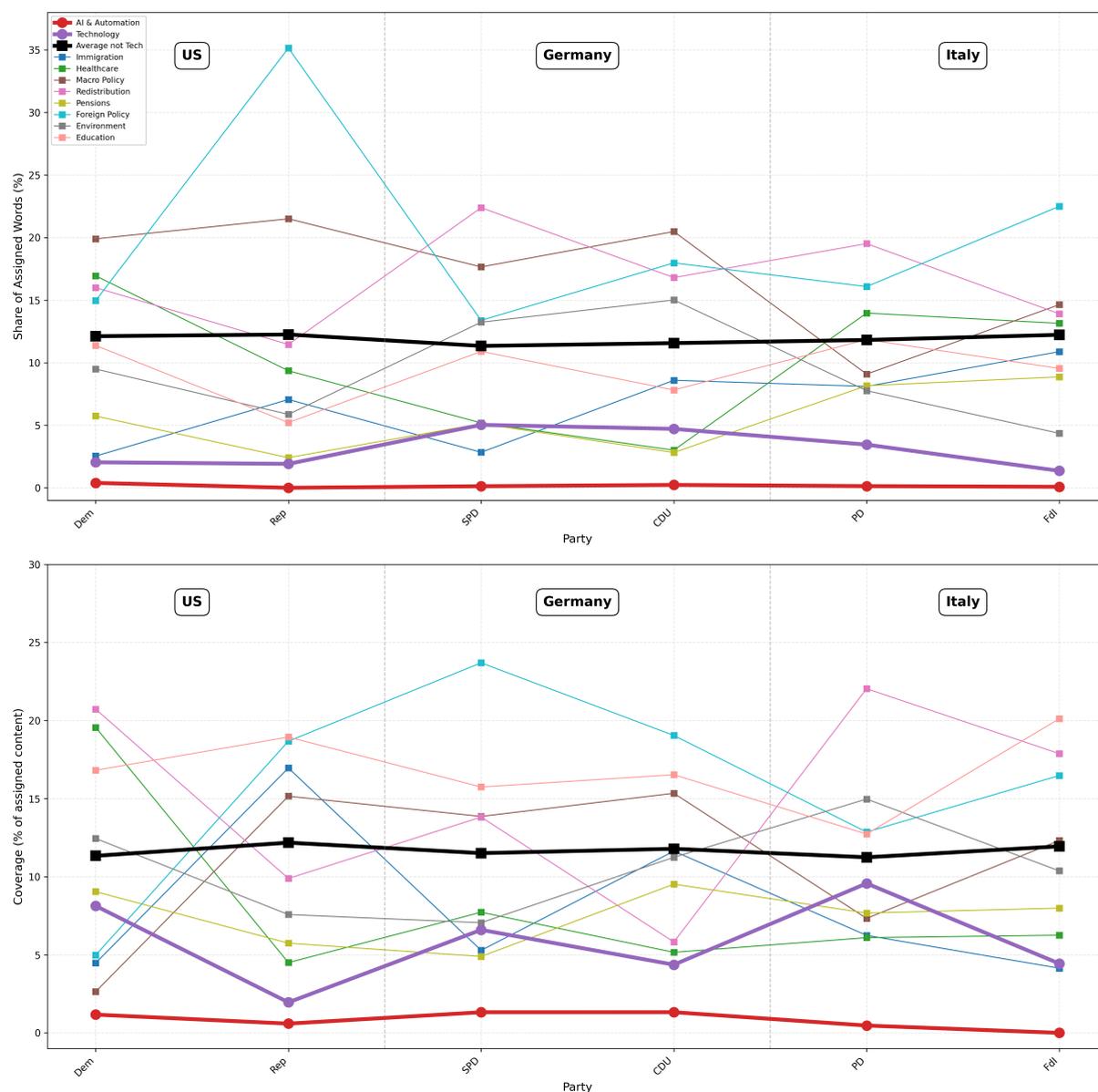

Note. The top panel displays the share of Facebook posts for each topic by leaders of the two main parties in US, Germany and Italy. The bottom panel displays the share of words for each topic in the programs of the two main parties in US, Germany and Italy in the last national electoral campaign. The category "Technology" includes the category "AI & Automation". More details on the construction of these graphs can be found in the Methods section.

Figure A2: Factual Knowledge and Beliefs
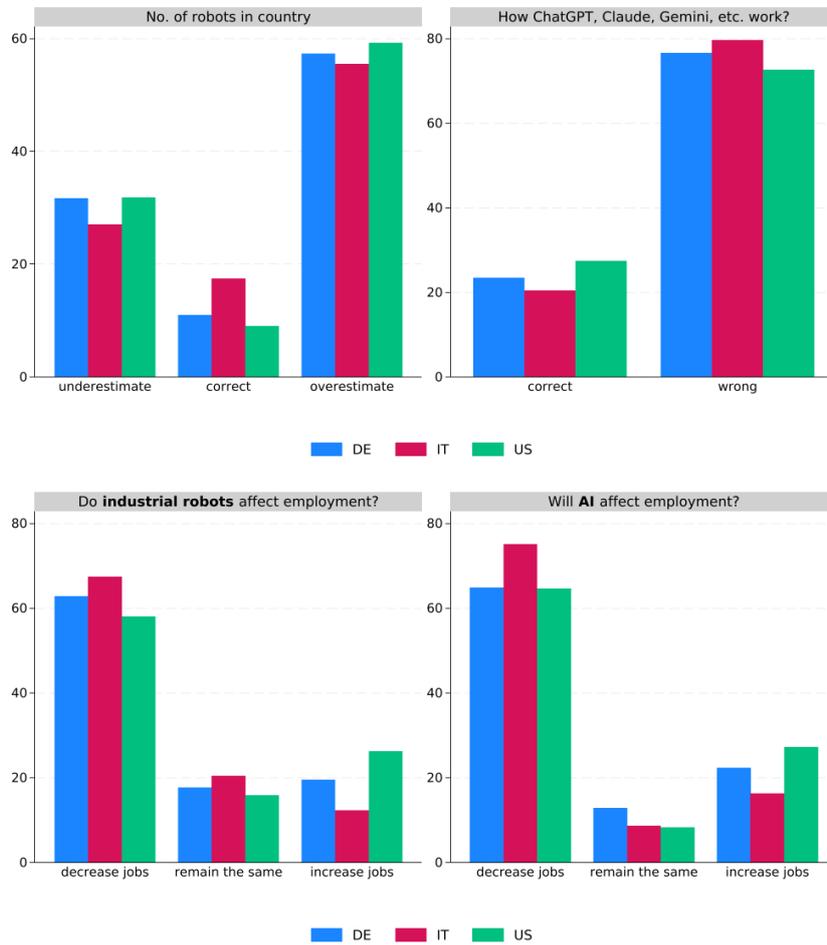
Note. In the top panel, answers to questions on the number of robots in the country over 1000 workers were recoded so that the "correct" category allows for a deviation of (-5,+5) from the exact number, while answers to questions on how LLMs work were recoded between correct (prediction techniques) and wrong (the other two possible answers). In the bottom panel, answers to questions on how industrial robots and AI will affect employment were recoded so that the "remain the same" category allows for a deviation of (-5, +5) from the value of zero. Full sample of 11,418 observations.

Figure A3: Additional Questions on Knowledge
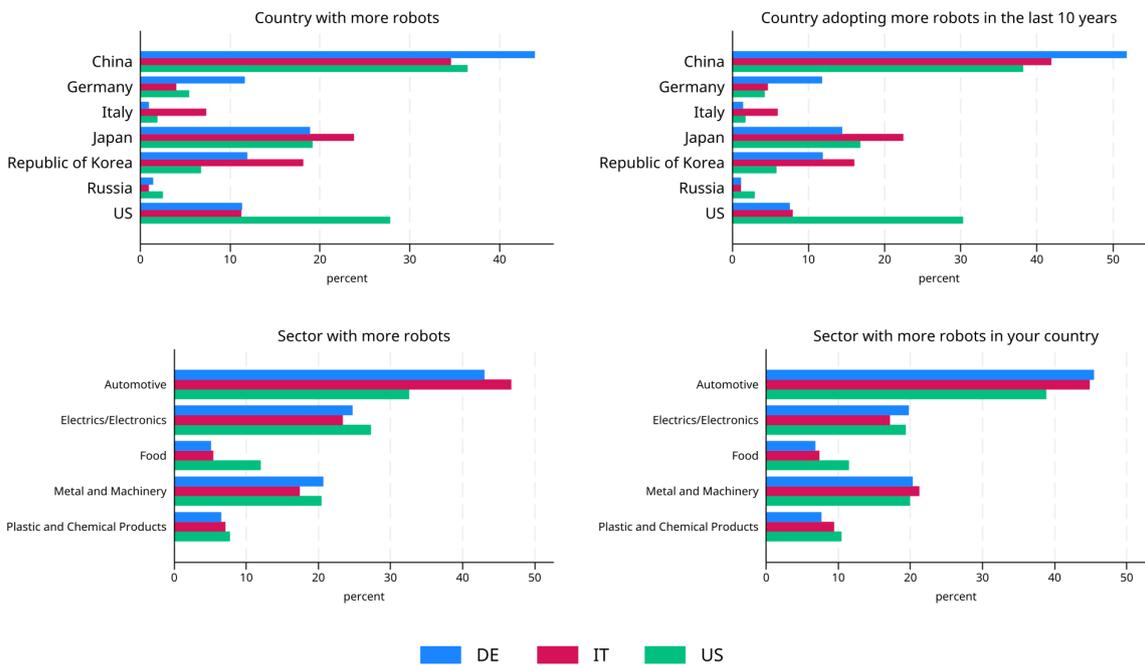
Note. Answers to questions on the country with the highest number of robots or that has increased the number of robots most in the last decade, and the sectors that are most affected 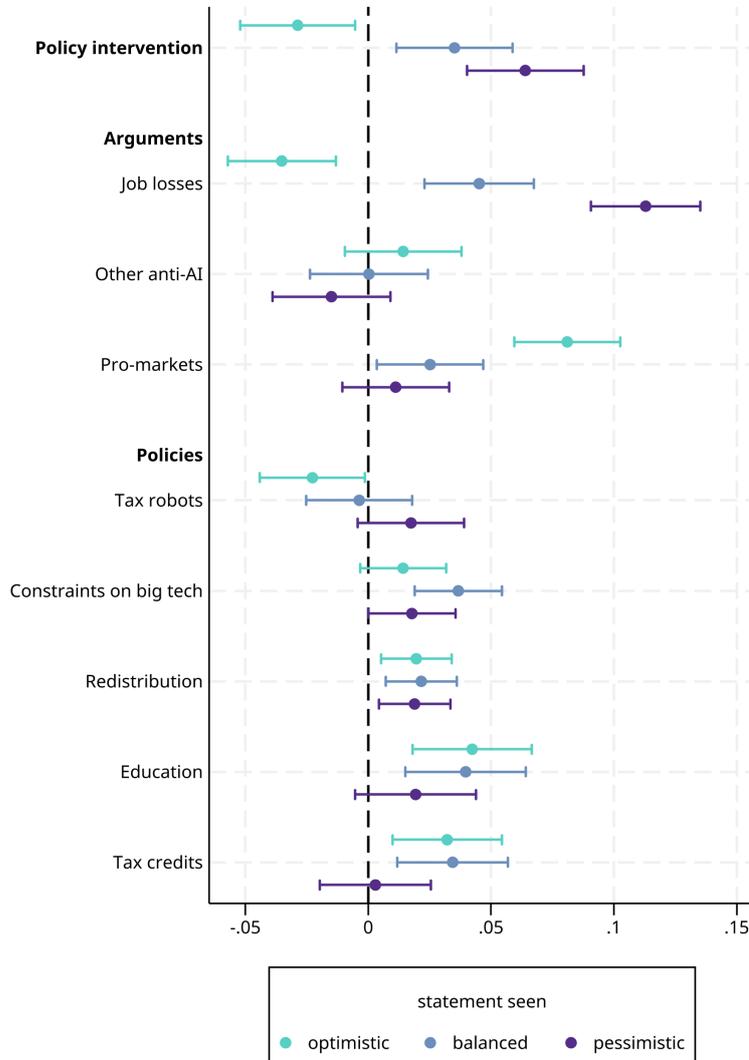by the rise in automation either in all the world or within the country. Sample of 3,304 observations from the baseline control treatment (1,160 for the US, 1,064 for Germany and 1,080 for Italy).

Figure A4: Functioning of AI
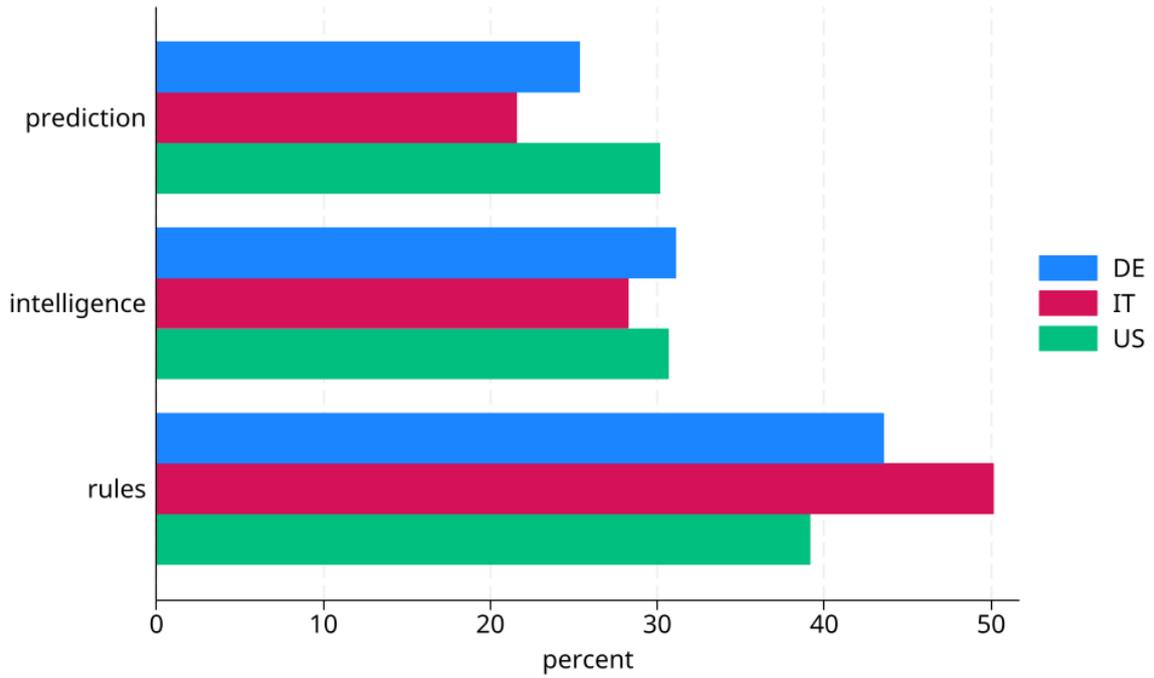
Figure A5: Beliefs on AI by Skills

Will **AI** affect
employment of **low-skilled** individuals?

Will **AI** affect
employment of **high-skilled** individuals?

26.09%

9.715%

64.19%

38.2%

13.47%

48.34%

decrease jobs   remain the same   increase jobs

Note. Answers to questions on how AI will affect employment between low-skilled workers (on the left) or high-skilled workers (on the right) in the next 5 years recoded so that the "remain the same" category allows for a deviation of (-5, +5) from the value of zero. Sample of 3,304 observations from the baseline control treatment (1,160 for the US, 1,064 for Germany and 1,080 for Italy).

Figure A6: Policy Preferences and Mobilization by Country
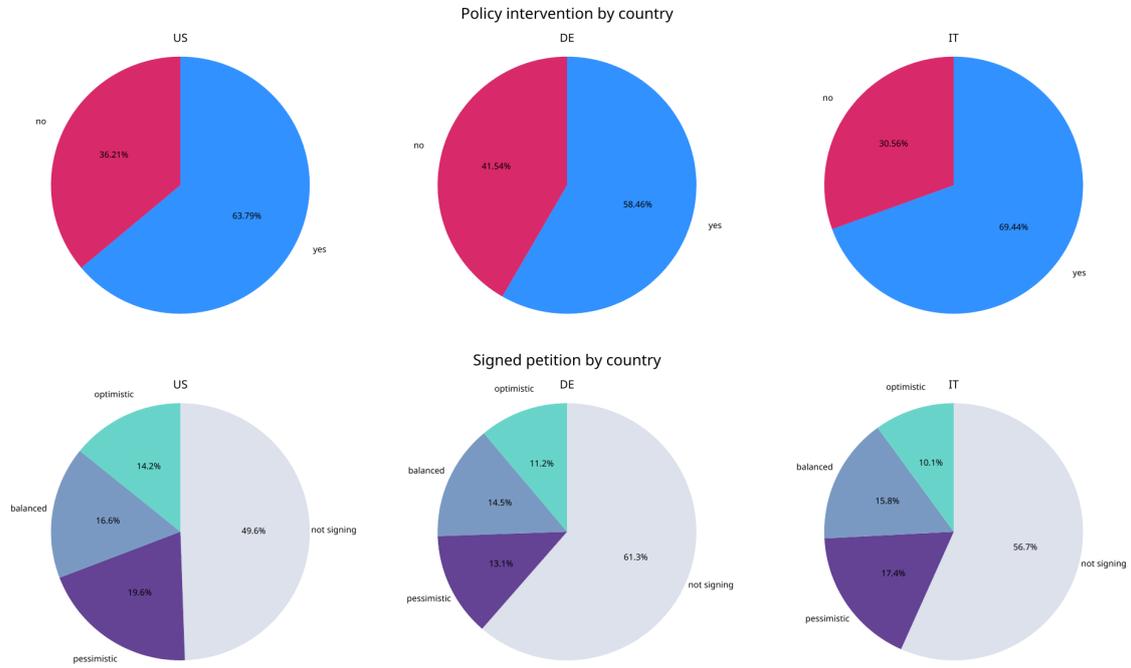
Note. Sample of 3,304 observations from the baseline control treatment (1,160 for the US, 1,064 for Germany and 1,080 for Italy).

Figure A7: Policy Preferences
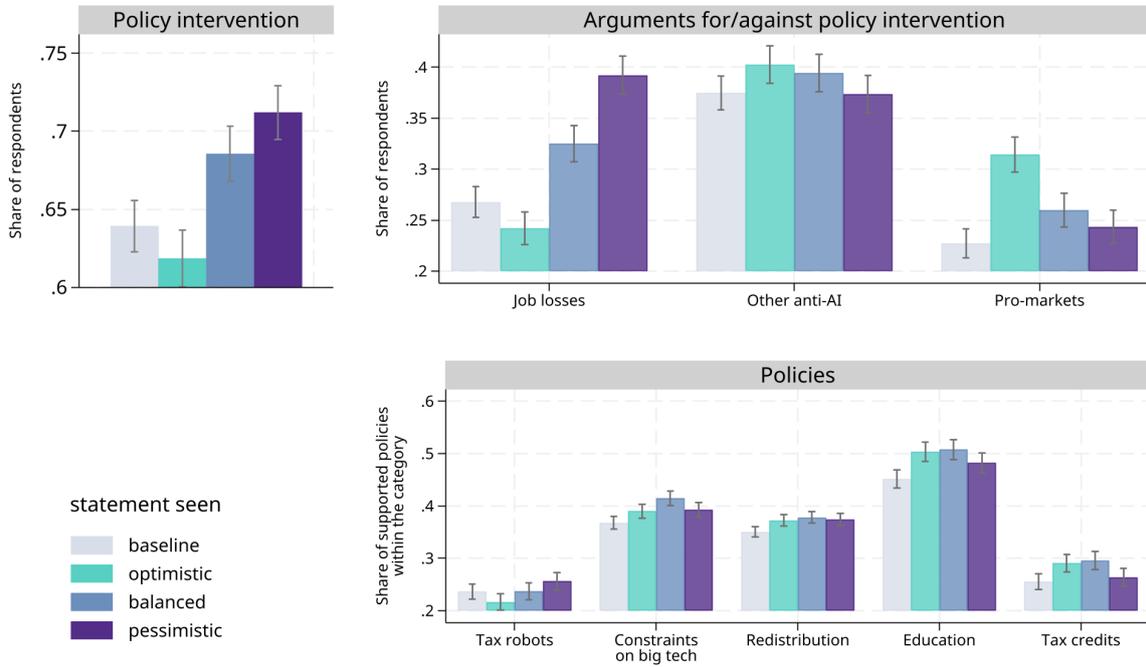
Note. Confidence intervals at 95% level. Full sample of 11,418 observations. Constraints on big tech includes stronger regulations and breaking up big tech; redistribution includes minimum wages, universal income, lower taxes on labour and increased unemployment benefits.

Figure A8: Policy Intervention controlling for Prior Beliefs

Note. The figure displays the results from separate OLS regressions with each y-axis variable as the dependent variable and treatment indicators shown in the legend as regressors. Full sample of 11,418 observations. Included controls in each regression are prior beliefs such as elicited from the open question and classified by gpt-4o-mini into do not know, optimistic, pessimistic and balanced beliefs, age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects. Constraints on big tech includes stronger regulations and breaking up big tech; redistribution includes minimum wages, universal income, lower taxes on labour and increased unemployment benefits.

Figure A9: Political Mobilization
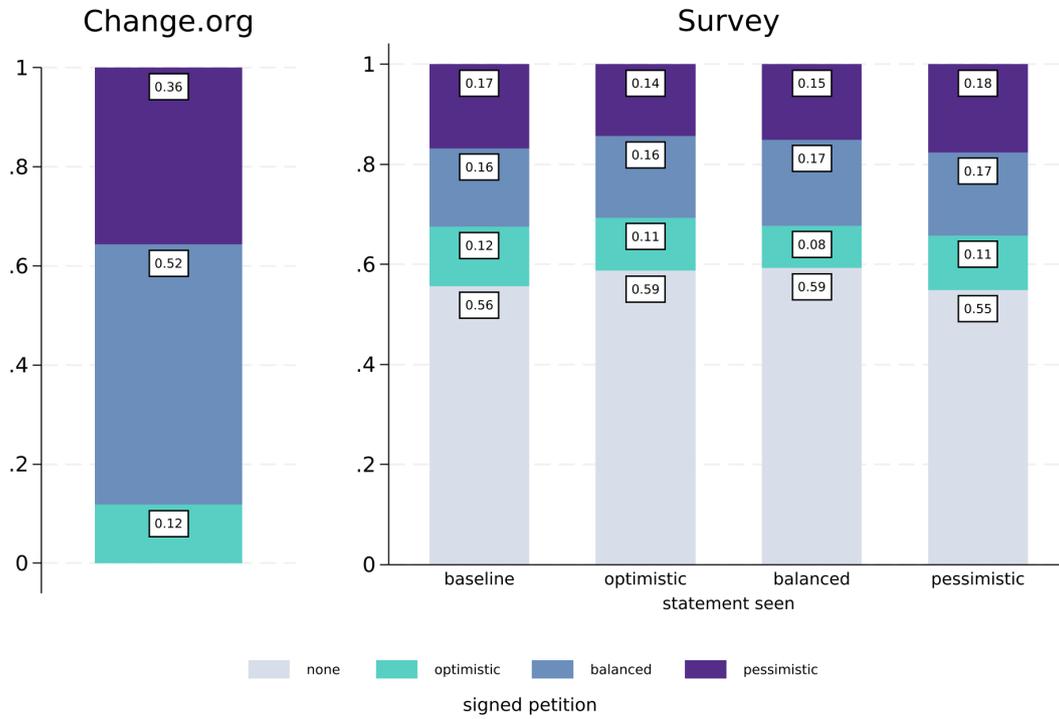
Note. On the left panel, share of signatures on Change.org by petition signed, considering the restricted sample of 320 respondents who signed a petition on the website. On the right, share of signatures within the survey by statement seen, considering the full sample of 11,418 observations.

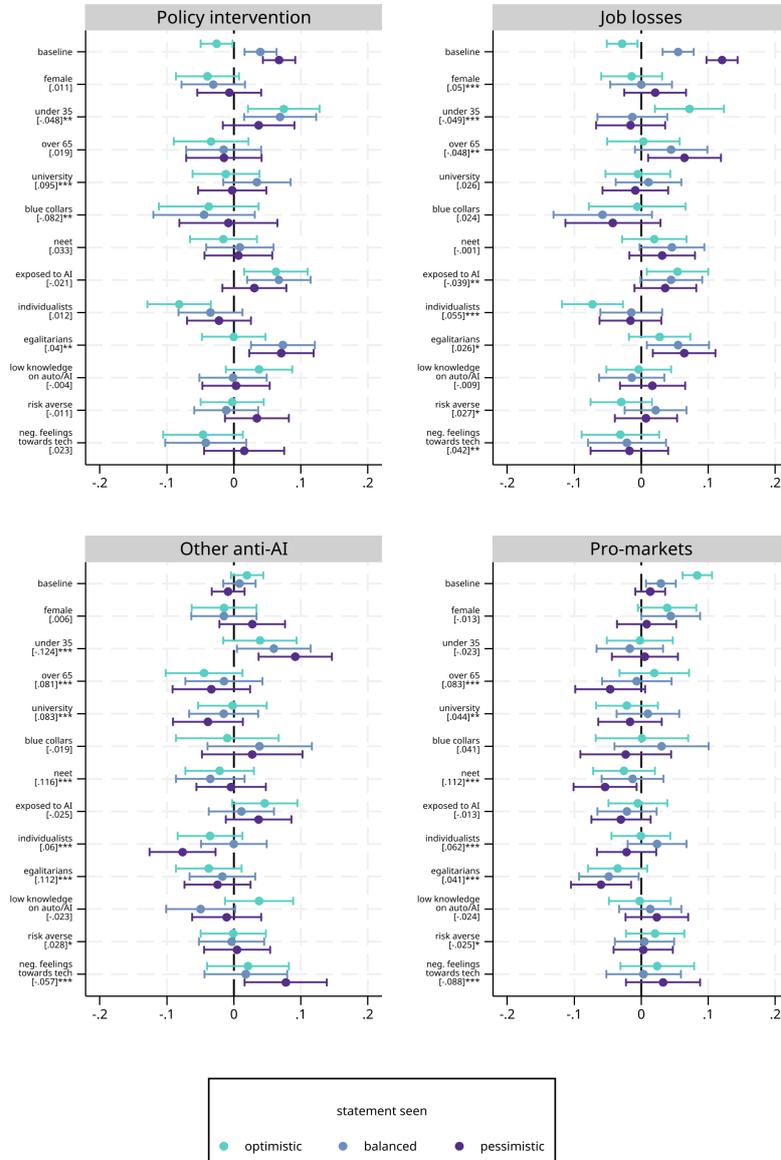Figure A10: Political Mobilization controlling for Prior Beliefs
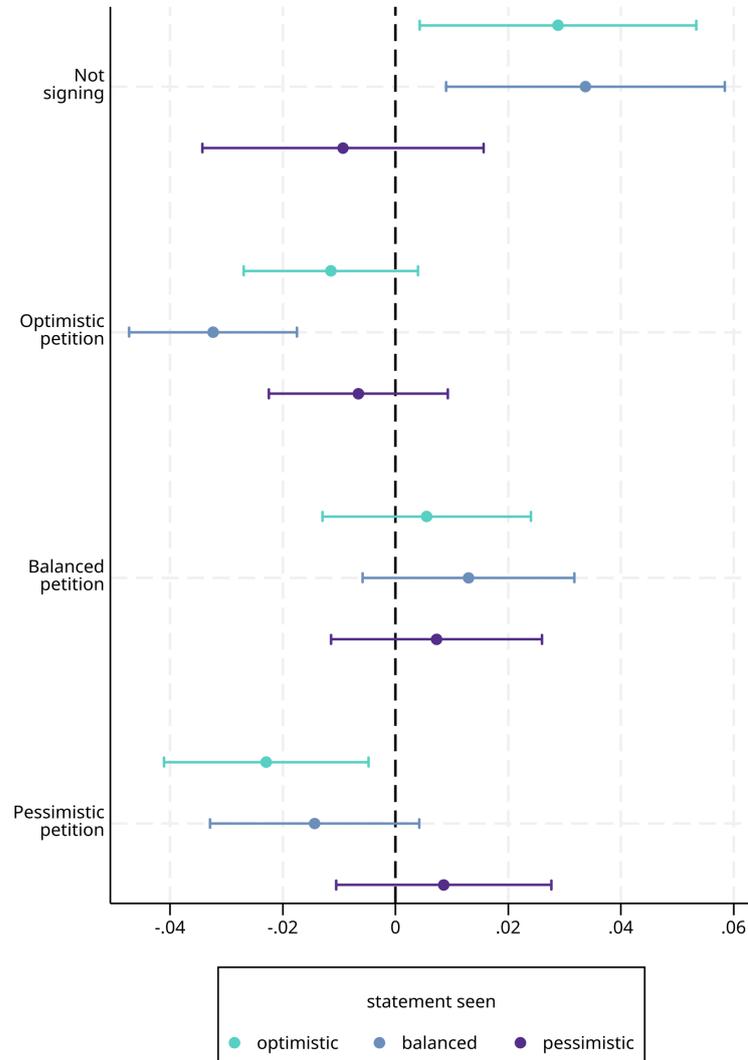
Note. Marginal effects from a multinomial logit regression on the willingness to sign petitions by the statement seen. Full sample of 11,418 observations. Included controls in each regression are prior beliefs such as elicited from the open question and classified by gpt-4o-mini into do not know, optimistic, pessimistic and balanced beliefs, age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

Figure A11: Heterogeneity in Policy Intervention by Political Orientation
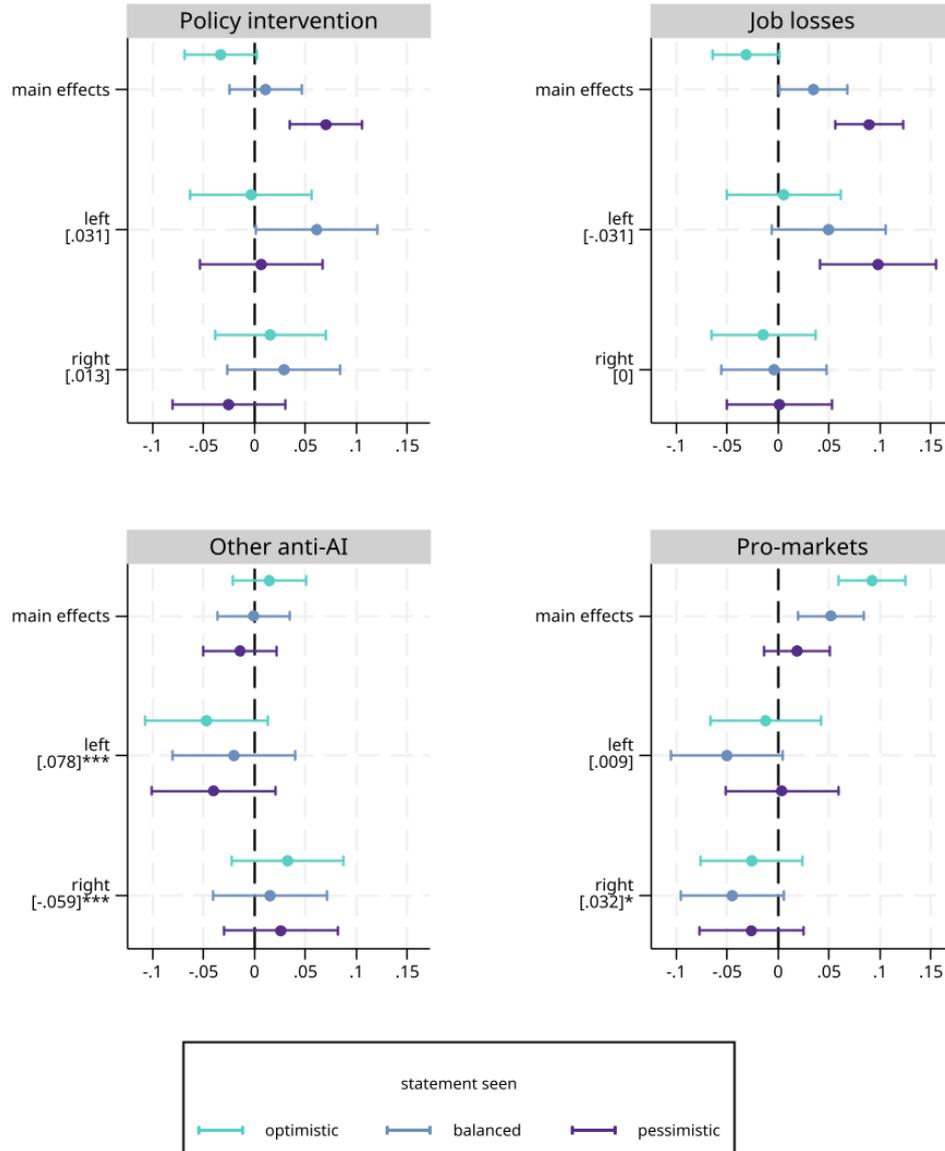
Note. Each panel displays the results from a separate OLS regression with each variable in the title as dependent variable and treatment indicators shown in the legend as regressors. Each bar corresponds to either the main effects or to the interaction coefficients of the main effects with political orientation (left-wing, right-wing or center), such as elicited from the self-declared left/right political orientation scale in the first part of the survey. Baseline categories are the baseline control group with no narrative (for the treatments) and center (for political orientation). The numbers in square brackets represent the coefficients of the association between political orientation and the corresponding outcome variable in the title, with the stars representing their significance. Full sample of 11,418 observations. Included controls in each regression are age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

Figure A12: Heterogeneity: Policies

Figure A13: Heterogeneity in Political Mobilization by Political Orientation
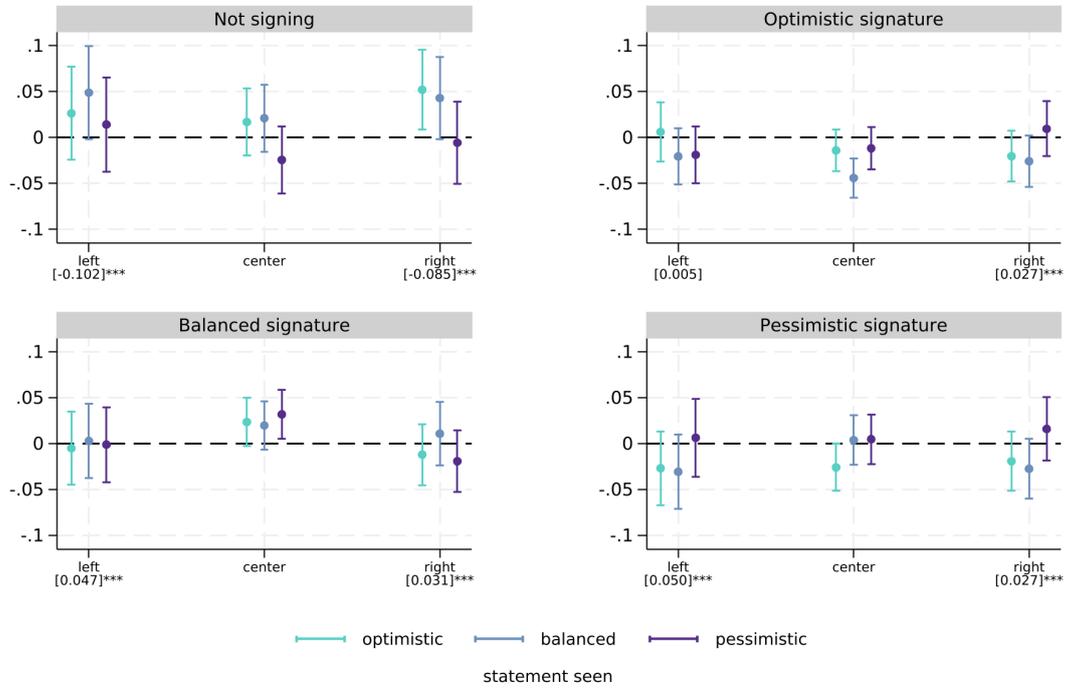
Note. Marginal effects from a multinomial logit regression on the willingness to sign petitions by the statement seen. Full sample of 11,418 observations. Each panel displays the results related to a different value of the categorical variable and treatment indicators are shown in the legend as regressors. Each bar corresponds to the marginal effect of the treatments by political orientation (left-wing, right-wing or center), such as elicited from the self-declared left/right political orientation scale in the first part of the survey. Baseline category is the baseline control group with no narrative. The numbers in square brackets represent the coefficients of the association between political orientation and the corresponding outcome variable, with the stars representing their significance. Full sample of 11,418 observations. Included controls in each regression are age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

Figure A14: Perceptions about own job loss
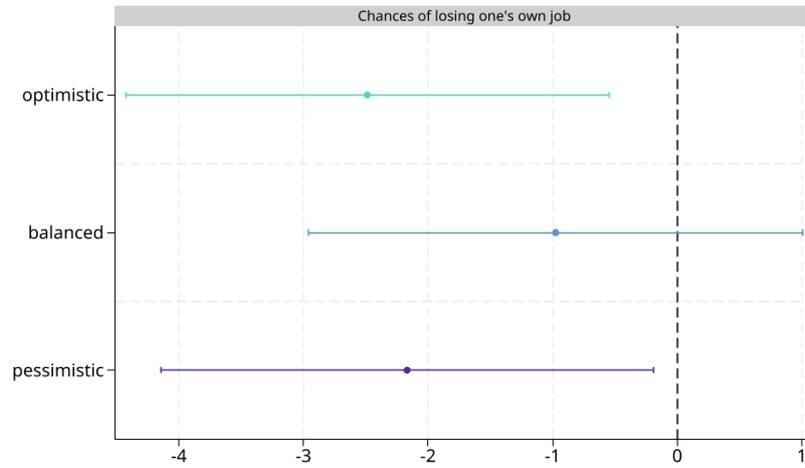
Note. OLS regression on chances of losing one's own job in 5 years (from 0 to 100). Sample restricted to 6,160 observations that exclude students and retired individuals. Included controls in the regression are age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

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Figure A15: Emotions and Political Correctness Associated to the Statements
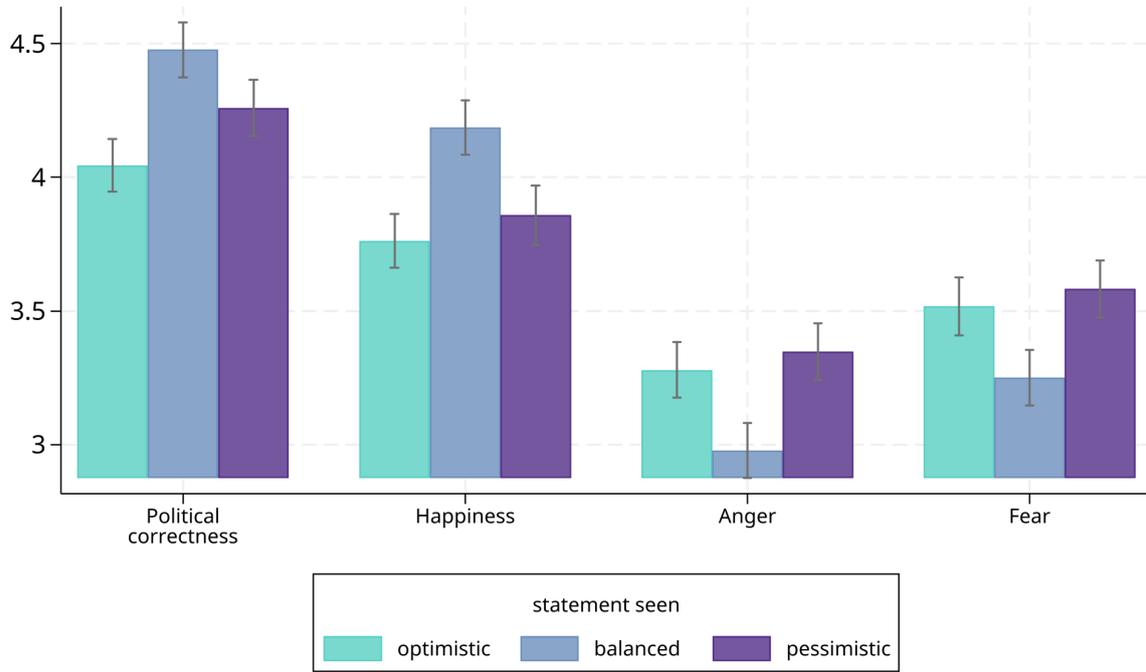
Note. Political correctness and emotions elicited in the follow-up survey on a scale from 1 to 7 with a between-subject design over a sample of 2,991 respondents. Each participant was only seeing and reporting on one statement only. Confidence intervals at 95% level.

Figure A16: Beliefs on the Most Signed Petition by the Petition Signed
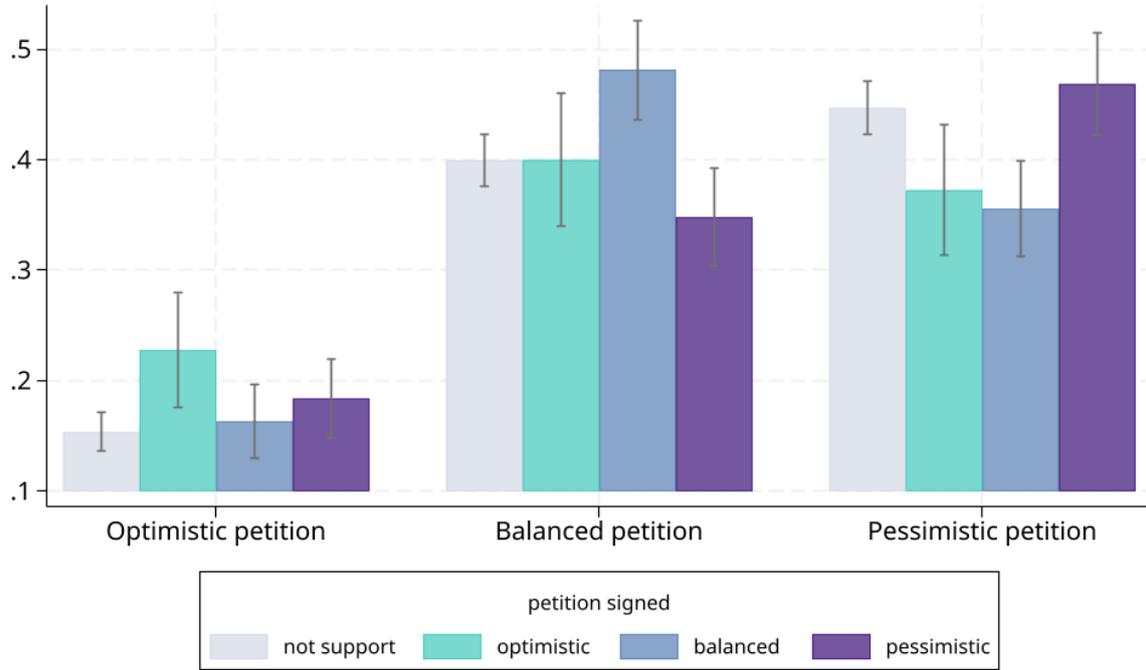
Note. The figure displays the share of respondents from the follow-up survey that believes each petition to be the most signed, by willingness to sign each petition in the main survey. Sample of 2,991 respondents. Confidence intervals at 95% level.

Figure A17: Policy Intervention weighting for the baseline sample
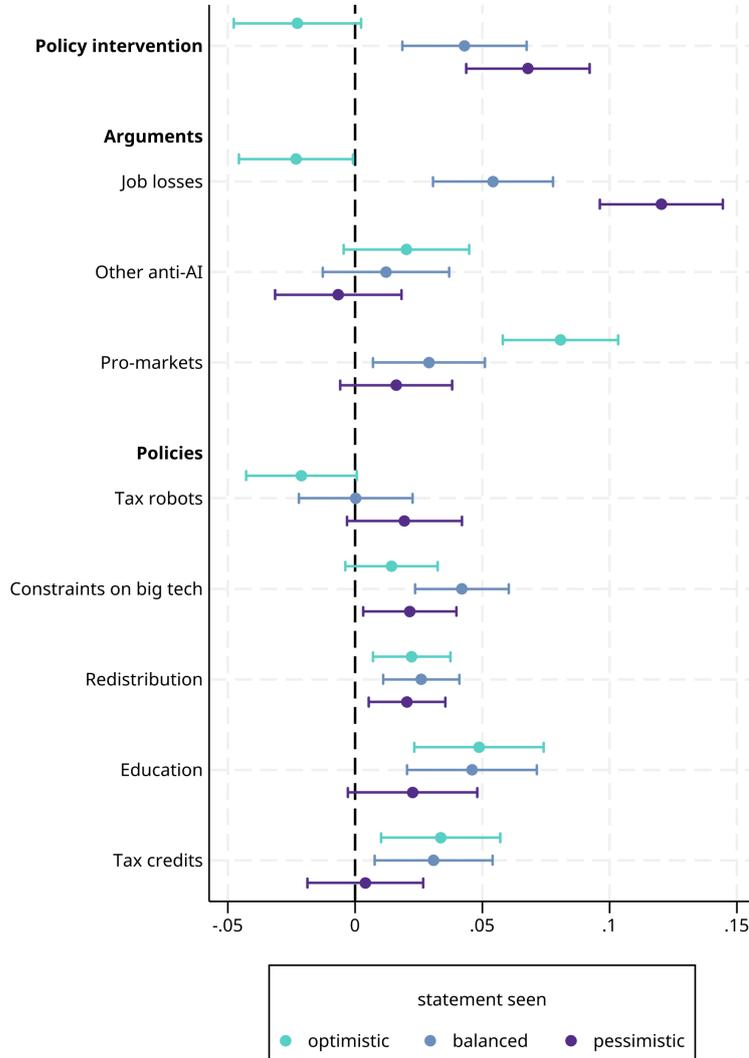
Note. The figure displays the results from separate OLS regressions with each y-axis variable as the dependent variable and treatment indicators shown in the legend as regressors. Each observation in each treatment is weighted with respect to the baseline with the weight determined by the relative frequency in each cell built on age-groups, gender, low/high income, education and employment status. Full sample of 11,418 observations. Included controls in each regression are prior beliefs such as elicited from the open question and classified by gpt-4o-mini into do not know, optimistic, pessimistic and balanced beliefs, age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects. Constraints on big tech includes stronger regulations and breaking up big tech; redistribution includes minimum wages, universal income, lower taxes on labour and increased unemployment benefits.

Figure A18: Political Mobilization weighting for the baseline sample
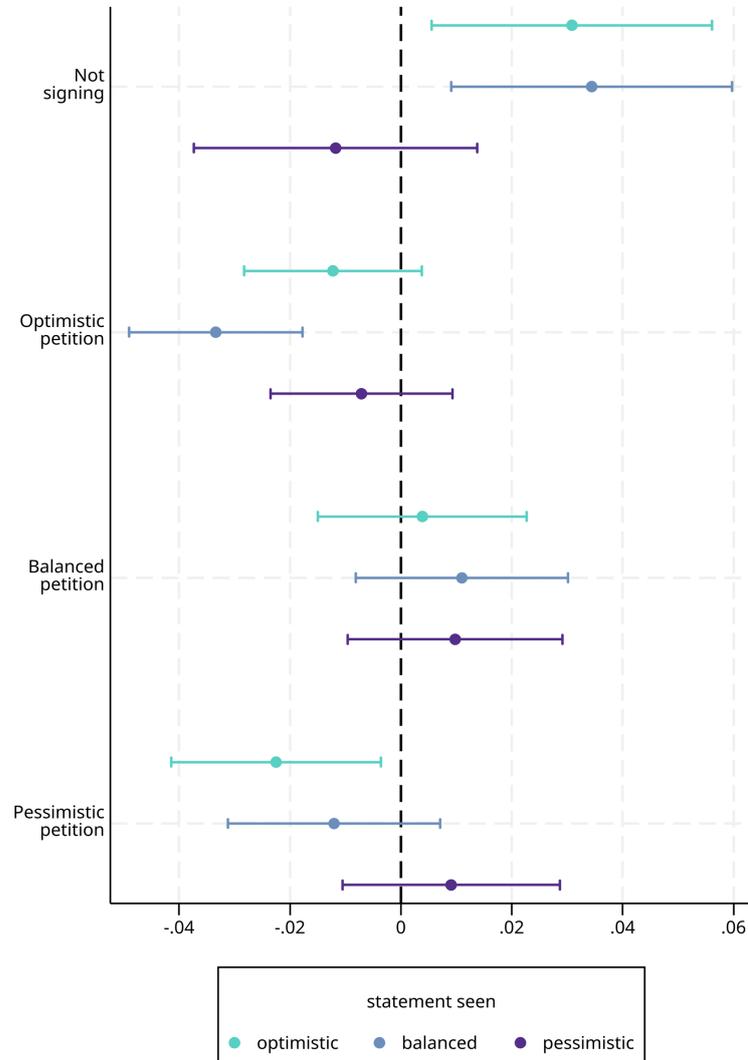
Note. Marginal effects from a multinomial logit regression on the willingness to sign petitions by the statement seen. Each observation in each treatment is weighted with respect to the baseline with the weight determined by the relative frequency in each cell built on age-groups, gender, low/high income, education and employment status. Full sample of 11,418 observations. Included controls in each regression are prior beliefs such as elicited from the open question and classified by gpt-4o-mini into do not know, optimistic, pessimistic and balanced beliefs, age-groups (under 35 and over 65), gender, education (4 categories), income (low income), employment status (7 categories), industry (21 categories), occupation (27 categories), country, date and hour fixed effects.

Figure A19: Prevalence of AI/Automation Topics in Facebook Posts: Germany
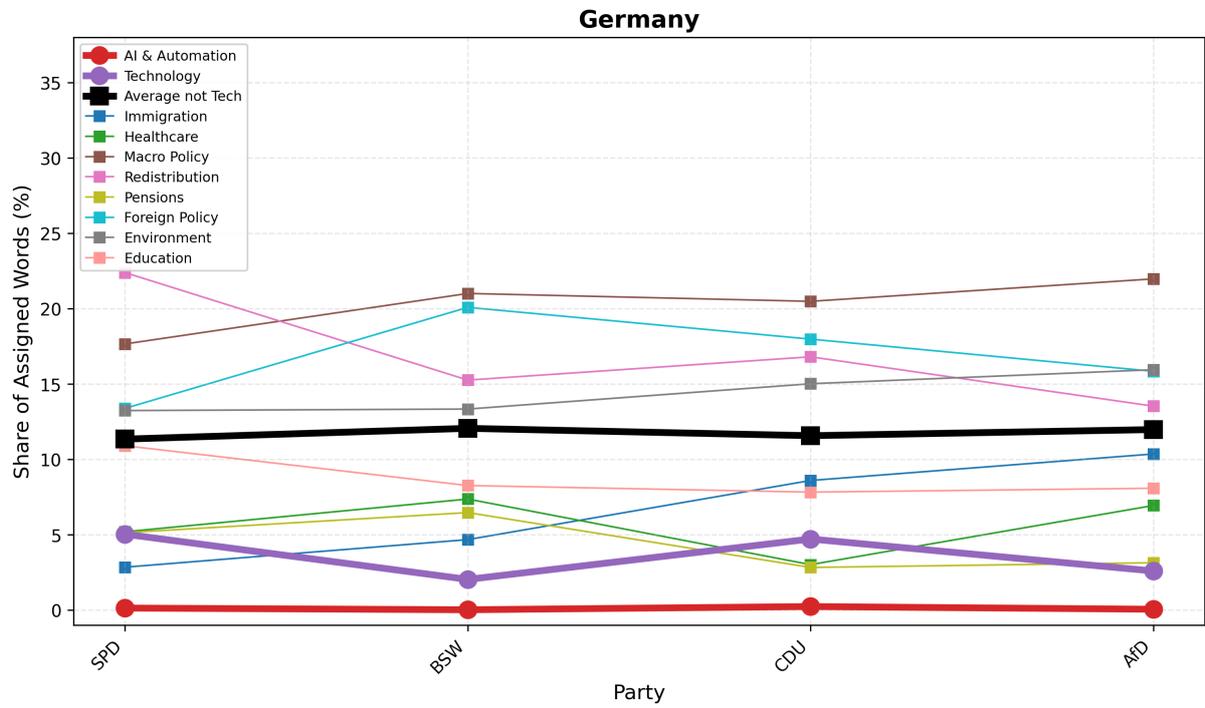
Note. The graph displays the share of Facebook posts for each topic by leaders of the four main parties in Germany. The category "Technology" includes the category "AI & Automation". More details on the construction of these graphs can be found in the Methods section.

Figure A20: Prevalence of AI/Automation Topics in Facebook Posts: Italy
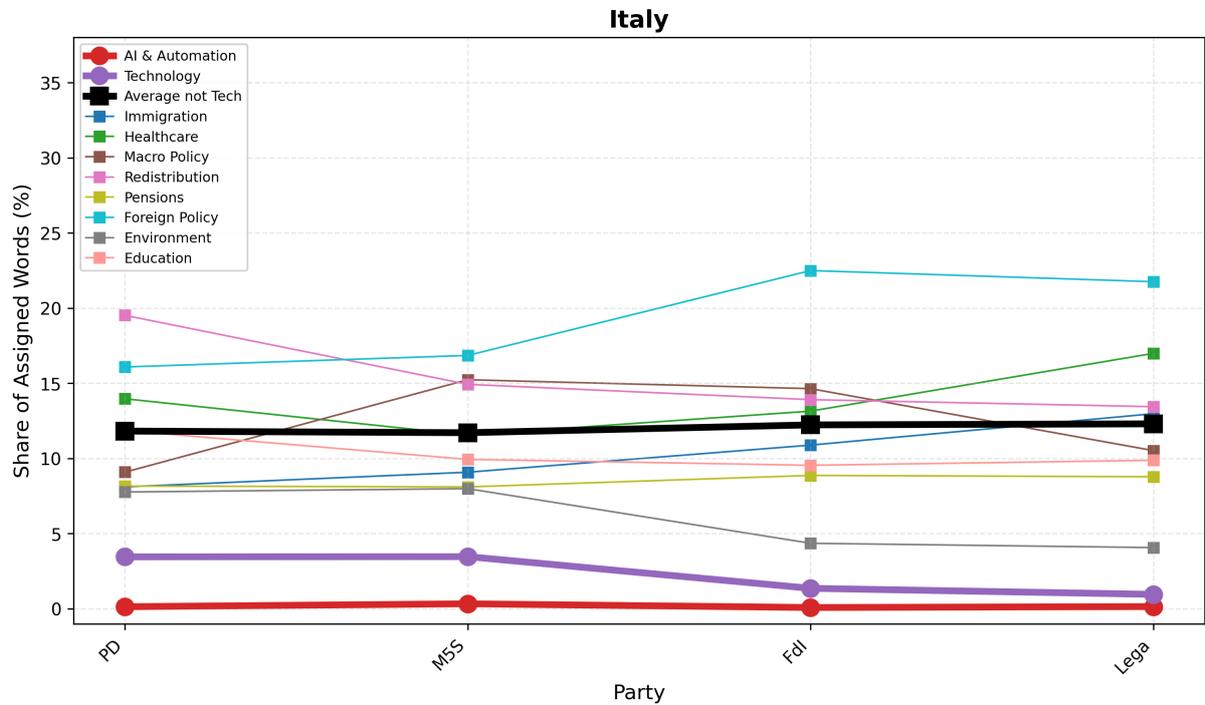
Note. The graph displays the share of Facebook posts for each topic by leaders of the four main parties in Italy. The category "Technology" includes the category "AI & Automation". More details on the construction of these graphs can be found in the Methods section.

Appendix B - Additional Material

Text of the Narratives - US Version

Optimistic:

Ladies and Gentlemen, Fellow Citizens,

The advancement of automation and artificial intelligence will lead to a better future. Productivity will increase and new jobs will be created. The automation of routine tasks will allow workers to focus on what truly matters—on the meaningful, creative, innovative part of their jobs. The economy will expand increasing opportunities for everyone.

Our response to this challenge will define the character of our nation for generations to come.

My commitment to you is to ensure that the march of technology is not stopped because of misplaced fears. We will implement policies that promote automation and artificial intelligence and ensure we are at the cutting edge of technological progress.

Our goal is clear: a future where every American can thrive in an economy that is as humane as it is advanced.

Pessimistic:

Ladies and Gentlemen, Fellow Citizens,

The advancement of automation and artificial intelligence will lead to a worse future. Certain occupations will become outdated, leading to a worrying decline in available employment opportunities, worse working conditions and lower wages. Benefits will be increasingly concentrated in the hands of tech tycoons.

Our response to this challenge will define the character of our nation for generations to come.

My commitment to you is to ensure that the march of technology does not trample on the livelihoods of our citizens. We will implement policies that protect workers from the advancement of automation and artificial intelligence and foster a fair and just transition.

Our goal is clear: a future where every American can thrive in an economy that is as humane as it is advanced.

Balanced:

Ladies and Gentlemen, Fellow Citizens,

The impact of automation and artificial intelligence is uncertain. On one hand, advancements

promise to enhance productivity, create new jobs and free workers from the repetitive tasks. On the other hand, these changes will potentially lead to job loss and a lower quality of remaining jobs, with most benefits concentrated in the hands of tech tycoons.

Our response to this challenge will define the character of our nation for generations to come. My commitment to you is to navigate this uncertain terrain with thoughtful interventions. We will implement balanced policies that, on one hand, promote automation and artificial intelligence, but, on the other hand, protect workers from these advancements and foster a fair and just transition.

Our goal is clear: a future where every American can thrive in an economy that is as humane as it is advanced.

Text of the Petitions - US Version

Optimistic:

Let's promote policies that favor technological change!

The integration of automation and artificial intelligence represents the biggest opportunity of our age to transform our economy and create a better future for every American worker. Advancements in automation and AI hold the promise to enhance productivity and create better jobs. As has happened in the past, this will generate new types of jobs without increasing unemployment. The automation of routine tasks will allow all American workers to focus on what truly matters—on the meaningful, creative, innovative part of their jobs.

For these reasons, the political response to technological change will define the future character of our nation for generations to come. The march of technology should not be stopped because of misplaced fears. We should convince our political leaders to implement policies that promote automation and artificial intelligence and ensure we are at the cutting edge of technological progress.

Please sign this petition to help convince policymakers to promote automation and artificial

intelligence and ensure that we are at the frontier of the technical revolution!

Pessimistic:

Let's promote policies that protect workers from technological change!

The rapid progress of automation and artificial intelligence poses profound challenges to our economy that will lead to a worse future for all American workers. Certain occupations will become outdated, substantially decreasing the number of available employment opportunities. Moreover, the remaining jobs will have both worse working conditions and lower wages. The economic benefits will be increasingly concentrated in the hands of tech tycoons.

For these reasons, the political response to technological change will define the future character of our nation for generations to come. The march of technology should not trample on the livelihoods of our citizens. We should convince our political leaders to implement policies that protect workers from the advancement of automation and artificial intelligence and foster a fair and just transition.

Please sign this petition to help convince policymakers to protect workers from automation and artificial intelligence, and ensure that all citizens benefit from these advancements!

Balanced:

Let's promote policies that take a balanced approach to technological change!

The impact of automation and artificial intelligence on the labor market is both a very important and very uncertain topic. This technological revolution puts the future of every American worker at stake. On one hand, it offers a promising future, holding the promise to enhance productivity and potentially allowing all workers to focus on what truly matters— on the meaningful, creative,

innovative part of their jobs. However, automation and AI-driven technologies could also lead to job loss, and to a lower quality of remaining jobs. The benefits of these technologies may end up concentrated in the hands of tech tycoons.

For these reasons, the political response to technological change will define the future character of our nation for generations to come. We should convince our political leaders to implement balanced policies that, on one hand, promote automation and artificial intelligence, but, on the other hand, protect workers from these advancements and foster a fair and just transition.

Please sign this petition to convince policymakers to take a balanced approach that both ensure that we are at the frontier of the technical revolution and that all citizens benefit from these advancements!

List of Policies

This is the complete list of policies that appears in random order in the survey. We then aggregate policies 2) and 3) into the "Constraints on big tech" category and policies 4) 5) 6) and 7) into the "Redistribution" category.

1) Directly taxing firms that use robots treating them similar to a type of labor.

2) Breaking up big tech monopolies, meaning splitting the big tech monopolists of the digital markets that are currently dominating the AI revolution (Microsoft, Amazon, Facebook, Google, etc.).

3) Stronger regulations on AI and social media, to strengthen the protection of user privacy, prevent massive data collection from users, avoid mass face recognition, help achieve data ownership and limit spreading information on the web without consent.

4) Minimum wage, meaning a minimum level of hourly wages set by law and that applies for all jobs.

5) Universal income, meaning a social welfare provision that guarantees all citizens or families an income sufficient to live on.

6) Lower taxes on labour, meaning reducing payroll taxes on income related to human labour.

7) More generous unemployment benefits, meaning an increase in benefits associated to losing the job compared to the current levels

8) Education policies and training in the workplace, meaning adapting the educational system to provide the workers with the necessary skills for an automation/AI labour market and retraining current workers with skills that are complementary to the ma-chines.

9) Tax credits and subsidies for innovation, meaning a reduction in taxes or an additional support for firms who are willing to invest in innovation.

Polarization Measure

Bottom line: Polarization over automation/AI decreases when individuals are exposed to the tech visions. We estimate the simplest index of polarization:

$$Index\_polarization_{ct} = 4 * Optimistic_{ct} * Pessimistic_{ct}$$

where $Optimistic$ and $Pessimistic$ are, within each treatment t, the share of individuals in each context c, where c can be either prior beliefs, signed petitions within the survey or signed petitions on Change.org. On Change.org t is unknown, so we only calculate the aggregate index.

The average prior polarization is 0.331. Rescaled to the change in the baseline, the change in polarization when people are asked to sign the petitions are -0.037 when exposed to the optimistic statement, -0.095 when exposed to the balanced one and 0.013 when exposed to the pessimistic one. In Change.org, polarization almost halves by -0.162. If we impute signatures on Change.org by treatment based on proportions of clicks to the final link in the survey, all treatments - baseline included - lead to this reduction in polarization on Change.org. Of this decrease, based on the clicks 26.8% should be imputed to the baseline, 20.7% to the optimistic, 34% to the balanced and 18.5% to the pessimistic treatment. So two things lead to lower polarization: exposure to the statements and going from private to public mobilization.

Prompts for classifying the open questions

To build quantitative variables from the information in the answers to the open questions in the survey, we employed gpt-4o-mini. Prompts were first written by us, then refined using ChatGPT, then piloted on a subsample of 50 entries before being applied to the whole sample. We had a research assistant do an independent classification on a subsample of 1000 entries of job tasks and the accuracy score of gpt-4o-mini was at 89%.

O*NET prompt

Below is the description of a coding exercise. The input consists of descriptions of job tasks collected from a survey. As these descriptions come from survey responses, they may be incomplete or poorly written.

You will be provided with a codebook containing a list of jobs classified by O*NET Center. Each job entry includes the O*NET-SOC code, job title, and job description. Entries in the codebook are delimited by semicolons.

Your task is to assign the O*NET-SOC code that best matches the input description of job tasks based on the information in the codebook. Follow these special rules:

- If the input describes a retired individual and does not include any job-related tasks, respond with "Retired";

- If the input describes a housewife and does not mention any job outside the home, respond with "Housewife";

- If the input describes a disabled person and does not mention any job outside the home, respond with "Disabled";

- For all other cases, use the O*NET-SOC code from the codebook.

Your responses should include **only the O*NET-SOC code**. Do not include job titles, job descriptions, or any other information from the inputs or codebook.

The 2010 SOC codebook was also attached to the prompt for each query.

Prior beliefs' prompt

Below is the description of a coding exercise. The input consists of answers to the following open-ended survey question:

"Now, please briefly state (max 100 words) your opinion on how automation and AI are shaping the present and future of jobs in terms of number of jobs, their quality, and average wage."

Since these responses come from survey participants, they may be incomplete or poorly written.

Classification Task:

You must classify each response based on **two dimensions**:

1. **Forecast on the present and future of jobs**:

   - **Optimistic** $\rightarrow$ The response suggests a positive impact (e.g., job creation, quality improvements, or wage increases).

   - **Pessimistic** $\rightarrow$ The response suggests a negative impact (e.g., job losses, lower quality, or wage reductions).

   - **Balanced** $\rightarrow$ The response acknowledges both positive and negative aspects.

   Note: If the response does not explicitly discuss job impact but still expresses a **positive** or **negative** judgment of automation and AI, classify it as **Optimistic** (positive judgment) or **Pessimistic** (negative judgment).

2. **Certainty Level** (how confident the respondent appears in their forecast):

   - **High** $\rightarrow$ The response expresses a strong opinion with clear reasoning.

- **Medium** → The response expresses an opinion but with some uncertainty.

- **Low** → The response is vague, hesitant, or lacks a clear stance.

Special Cases:

- If the response is **gibberish** or **not related** to the question, classify it as: **"Not related, low"**.

- If the response is **I don't know** or similar, classify it as: **"Uncertain, low"**.

Examples:

Response	Classification
"AI automatic workers are taking the jobs of humans. The future is uncertain."	**Pessimistic, medium**
"Automation is creating new jobs and increasing the quality of existing ones."	**Optimistic, high**
"I don't know."	**Uncertain, low**
"AI can benefit quality and wages, but the number of jobs may decrease."	**Balanced, medium**
"Some people will lose jobs because of AI and automation. But there will be job creation because of AI."	**Balanced, high**

Output Format:

Your response should contain **only the two classifications, separated by a comma**, with no extra text or comments.

Example Output: `Optimistic, high`

Arguments' prompt

Below is the description of a coding exercise. The input consists of answers to the following open-ended survey question:

"*Please write down two arguments (one for each field) as to why, in your opinion, policymakers should or should not intervene on automation and AI.*"

Since these responses come from survey participants, they may be incomplete or poorly written.

Classification Task:

Classify each argument according to its main theme:

Negative themes:

- **Labour**: The response focuses on the negative impact of automation and AI on jobs, wages, working conditions, or other labour-related concerns.

- **Security**: The response concerns risks related to safety, surveillance, privacy, or broader existential threats.

- **Humanity**: The response focuses on considering AI/automation as fundamentally corrupting humanity and human values (e.g. making humans less intelligent, more lazy, reducing social interactions).

- **Regulation**: The response focuses on the need for regulation and intervention by policy-makers.

- **Mistrust towards AI companies**: The argument reflects distrust in AI companies (e.g., profit motives, lack of transparency, collusion).

Positive themes:

- **Confidence in automation and AI**: The argument suggests AI/automation is beneficial or at least not harmful and that, because of that, intervention is unnecessary.

- **Market**: The response defends market forces, suggesting they will handle issues better than policy-makers.

- **Mistrust towards politicians and the government**: The argument reflects distrust in politicians or institutions (e.g., inefficiency, incompetence, corruption).

Special Cases:

- If the response is **gibberish** or **not related** to the question, classify it as: Not related.

- If the response is **I don't know** or similar, classify it as: I do not know.

Try not to classify responses as *Not related* or *I do not know* unless you really have no other possibility. Some answers may be very short or poorly written, or may not mention AI or automation explicitly—still, by interpreting their meaning, they may fall within one of the main categories.

Hard-to-Classify Examples (Still Classifiable):

Response	Classification
"The economy will decline"	Labour
"to set controls"	Security
"It's not good for our society"	Humanity
"Because there's too many policies"	Mistrust towards politicians and the government
"it's not their business"	Mistrust towards politicians and the government
"Company decision"	Market
"We must move forward into the future"	Confidence in automation and AI
"Spreads misinformation"	Security

Regular Examples:

Response	Classification
"Bc it's going to take everyone job"	Labour
"I think they let the companies do as they wish"	Market
"I don't know."	I do not know
"Policy makers aren't engineers"	Mistrust towards politicians and the government
"Should: could destroy Earth and human civilization"	Security
"We the people are smarter and more compassionate than machines."	Humanity

Output Format:

Your response should contain **only the classification**, with no extra text or comments.

Example Output: Labour

Example Output: Mistrust towards politicians and the government

Appendix C - The text of the surveys

Questionnaire for the Research

Page 1: Informed Consent

Dear participant, our names are Federico Boffa, Steven Stillman and Eugenio Levi. We are researchers at the Free University of Bozen-Bolzano in Italy.

The goal of this study is to survey public opinion in the US over a range of topics relevant

for our society – in particular technological change, automation, and Artificial Intelligence. If you decide to participate, you will be asked to complete a research survey about your views and attitudes over such topics. The survey will take approximately 15 minutes, and you will be paid according to the standard rate of compensation for this time. You can earn additional money if you answer some questions correctly.

In addition, you will be asked some basic demographic questions including your political orientation and voting intention in the next Presidential elections. Occasionally, you will also be asked some questions just to check your attention.

Your participation in this study is purely voluntary and your data will be treated confidentially by our research team. The questionnaire is fully anonymous and we have implemented all necessary technical and organisational security measures to guarantee the anonymity of participants. Except for the initial questions, you are free not to answer some of the questions, but we would really be grateful if you answered all of them. Your opinion matters to us and remember, the questionnaire is fully anonymous. We kindly ask you not to include any personal data (name, e-mail, phone number, home or work address, the name of your employer, etc.) in the answers to open questions. Nevertheless, in case you do, the personal data provided are not processed for research purposes. You are free to opt out of the survey at any time, but in that case you will forfeit your payment. The results of the study may be published or presented at professional meetings, but only group characteristics will be discussed. All payments are managed through the company that contacted you and we will never contact you directly.

We will be happy to answer any questions you have about the study. You may contact us by phone: xxxxxxxxxxxx or by e-mail at xxxxxxxxxxxxx. Thank you for your consideration. If you would like to participate, please click the button below. When you are done, simply click *Finish* to complete the survey.

Page 2: Initial Questionnaire

Note: questions are slightly adjusted in each country.

- How old are you? *(integer)*

- Please indicate your gender.

  (radio, vertical: Female / Man / Other)

- Please indicate your nationality.

  (radio, vertical: US nationality / US and other nationality / US citizenship)

- What is your highest educational qualification?

  (No degree / Primary Education / High school diploma / University degree / Master's degree / Ph.D.)

- What is your current employment situation? (If you have more than one job, please indicate only your main job.)

  (Employed / Self-employed / Currently not employed and not looking for work / Looking for work but currently unemployed / Student / Retired / Apprentice and trainee / Other)

Page 3: Employment Details

Conditional on not having answered "Student" to the previous question:

- Can you tell us the job title of your current or most recent job? *(open question)*

- What are your primary tasks in that job? For example, if you are a waiter, you could write "taking food orders, serving food at the table". *(open question)*

- In what industry is your employer? *(open question)*

Page 4: Voting

Note: questions are slightly adjusted in each country.

- Are you eligible to vote in the upcoming Presidential elections?

  (radio, vertical: Yes / No)

- Which party do you think you will vote for in the next Presidential elections?

  (Republican / Democrat / Do not know)

- How close do you feel to that party?

  (Likert scale 1–7: 1 = not close at all, 7 = very close)

- Many people use the terms 'left' and 'right' when referring to different political attitudes. Thinking about your own political views, where would you rank those views on this scale?

  (Likert scale 0–10: 0 = left, 10 = right)

Page 5: Additional Questions – Individual Liberty

People in our society often disagree about how far to let individuals go in making decisions for themselves. How strongly do you agree or disagree with each of the following statements? *(agree/disagree scale)*

IINTRSTRS The government interferes far too much in our everyday lives.

CHARM Sometimes government needs to make laws that keep people from hurting themselves.

IPROTECT It's not the government's business to try to protect people from themselves.

IPRIVACY The government should stop telling people how to live their lives.

CPROTECT The government should do more to advance society's goals, even if that means limiting the freedom and choices of individuals.

CLIMCHOI Government should put limits on the choices individuals can make so they don't get in the way of what's good for society.

Page 6: Additional Questions – Equality

People in our society often disagree about issues of equality and discrimination. How strongly do you agree or disagree with each of the following statements? *(agree/disagree scale)*

HEQUAL We have gone too far in pushing equal rights in this country.

EWEALTH Our society would be better off if the distribution of wealth was more equal.

ERADEQ We need to dramatically reduce inequalities between the rich and the poor, whites and people of colour, and men and women.

EDISCRIM Discrimination against minorities is still a very serious problem in our society.

HREVDIS2 It seems like blacks, women, homosexuals and other groups don't want equal rights, they want special rights just for them.

HFEMININ Society as a whole has become too soft and feminine.

Page 7: Industrial Robots

Please consider this definition of industrial robots. An industrial robot is a programmable machine system capable of carrying out a complex series of actions. Industrial robots are automated, programmable and capable of movement on three or more axes.

Typical applications of robots include welding, painting, assembly, disassembly, pick and place for printed circuit boards, packaging and labelling, palletising, product inspection, and testing; all accomplished with high endurance, speed, and precision. They can also assist in material handling.

[Image: industrial robot photograph]

Incentivised questions (one randomly selected question earns a bonus of $0.50 if answered correctly):

- What is the number of robots per 1 000 workers in your country as of 2022? *(float)*

- What is your level of confidence in your answer?
  (Likert scale 1–7: 1 = low, 7 = high)

- From the list China, Germany, Italy, Japan, Republic of Korea, US – select the three countries with the <u>most</u> robots per worker and rank them from highest (1) to lowest (3).
  (Correct answer: 1 Republic of Korea, 2 Germany, 3 Japan)

- Which country installed the most industrial robots in the past decade (2012–2022)?
  *(**China**, US, France, Italy, Germany, UK, Russia, Japan, Republic of Korea)*

- In which industrial sector are the most robots installed worldwide as of 2022?
  *(Automotive, **Electrics/Electronics**, Metal and Machinery, Plastic and Chemical Products, Food)*

- In which industrial sector are the most robots installed in your country as of 2022?
  *(**Automotive** [US & Germany] / **Metal and Machinery** [Italy] / Electrics/Electronics / Plastic and Chemical Products / Food)*

- If a typical manufacturing firm buys an industrial robot, do you think the number of jobs at that firm will increase or decrease, and by how many workers? *(float)*

- If all manufacturing firms in the US buy industrial robots, do you think overall employment will increase or decrease?
  (Likert scale 1–7: 1 = decrease a lot, 7 = increase a lot)

- What is your level of confidence in these answers?
  (Likert scale 1–7: 1 = low, 7 = high)

Page 8: Artificial Intelligence

Now consider this definition of artificial intelligence (AI). AI is a collection of algorithms that act intelligently by recognising and responding to the environment to achieve specified goals. AI algorithms process, identify, and act on patterns in unstructured data (e.g., speech data, text, or images) to achieve specified goals. It has become quite proficient at translating text, creating

images, providing chatbot services, performing facial recognition, programming computer code, etc.

As with the previous screen, one of the following questions will be randomly selected for a bonus of $0.50 if answered correctly:

Do you know how current AIs like ChatGPT, Claude, Gemini, etc. work?

1. They are very large deep learning models that can predict patterns in texts, pictures and videos.

2. They are very large deep learning models that have developed a form of intelligence by replicating how the human brain works.

3. They are very large models that use an elaborated set of pre-defined rules to understand context and provide plausible answers.

- Do you think the number of jobs will increase or decrease because of AI in the next 5 years, and by how much (in percentage)? *(float)*

- What is your level of confidence in your answer?
  (Likert scale 1–7: 1 = low, 7 = high)

Page 9: Additional Questions on AI

Now think about workers with different qualifications.

- Do you think the number of jobs in **low-skilled occupations** will increase or decrease because of AI in the next 5 years, and by how much (in percentage)? *(float)*

- Do you think the number of jobs in **high-skilled occupations** will increase or decrease because of AI in the next 5 years, and by how much (in percentage)? *(float)*

- What is your level of confidence in these answers?
  (Likert scale 1–7: 1 = low, 7 = high)

Page 10: Open Question

Please briefly state (max. 100 words) your opinion on how automation and AI are shaping the present and future of jobs in terms of number of jobs, their quality, and average wages. *(open question)*

Page 11: Statement (not in the Baseline)

Do you think you have devoted your full attention to the questions so far? Do you believe, in your honest opinion, that we should use your response for the study? *(Yes / No)*

Automation and AI is a hot topic in the current political debate. We would like you to carefully read the following political statement.

Here there is one of the three statements.

Page 12: Control Questions (not in the Baseline)

Please answer the following question: what was the statement about? You will not be allowed to proceed until you have answered correctly. Select the **two** correct answers. You may go back to the statement at any time.

Optimistic version

1. How AI and automation enhance productivity.

2. US financial help to Ukraine in the war between Russia and Ukraine.

3. The potential of new technology to improve the quality of jobs.

4. What would have happened if the FED had not raised interest rates.

5. Future developments in medicines to fight tumours.

Pessimistic version

1. How AI and automation reduce employment opportunities.

2. US financial help to Ukraine in the war between Russia and Ukraine.

3. The potential of new technology to exacerbate economic inequalities.

4. What would have happened if the FED had not raised interest rates.

5. Future developments in medicines to fight tumours.

Balanced version

1. The potential of new technology to enhance productivity and improve the quality of jobs.

2. US financial help to Ukraine in the war between Russia and Ukraine.

3. How AI and automation reduce employment opportunities and exacerbate economic inequalities.

4. What would have happened if the FED had not raised interest rates.

5. Future developments in medicines to fight tumours.

Page 13: Policy

- Now, do you think that policy-makers should intervene on automation and AI? *(Yes / No)*

- Please write down two arguments (one per field) as to why, in your opinion, policy-makers should or should not intervene on automation and AI. *(two open-answer fields)*

Page 14: Policy Proposals

We would like to ask you about your preferred policies among the following. There is no minimum or maximum limit on the number of policies you can select. Choose the options that best represent your opinions. *(radio buttons, presented in random order)*

- **Minimum wage** – a minimum level of hourly wages set by law that applies to all jobs.

- **Stronger regulations on AI and social media** – to strengthen user privacy, prevent massive data collection, avoid mass face recognition, and limit spreading information without consent.

- **Universal income** – a social welfare provision guaranteeing all citizens or families an income sufficient to live on.

- **Breaking up big tech monopolies** – splitting the big tech companies currently dominating the AI revolution (Microsoft, Amazon, Facebook, Google, etc.).

- **Education policies and workplace training** – adapting the educational system and retraining current workers with skills complementary to machines.

- **Lower taxes on labour** – reducing payroll taxes on income related to human labour.

- **Tax credits and subsidies for innovation** – reductions in taxes or additional support for firms investing in innovation.

- **Robot tax** – directly taxing firms that use robots, treating them similarly to a type of labour.

- **More generous unemployment benefits** – increasing benefits associated with job loss beyond current levels.

Page 15: Public Support

We would like to give you the opportunity to express support for a political statement on AI/automation by signing a related petition. The petitions are hosted on Change.org and will be sent to all members of Congress and the President of the United States once the survey is completed. If you choose to sign a petition, you will be redirected to its Change.org webpage at the end of the survey.

Would you like to express your support publicly by signing a petition? *(select one)*

- No, I decline to express support for a statement publicly.

- Yes, I will sign the petition **"Let's promote policies that favour technological change!"** on Change.org.

- Yes, I will sign the petition **"Let's promote policies that protect workers from technological change!"** on Change.org.

- Yes, I will sign the petition **"Let's promote policies that take a balanced approach to technological change!"** on Change.org.

Page 16: Additional Question (if currently working)

Based on your assessment, what are the chances that you will lose your job because of automation or artificial intelligence in the next 5 years? *(slider, 0–100)*

Page 17: Final Questionnaire (Part 1)

Finally, before ending the survey, we would like to ask for some information about you. Please answer all questions honestly and accurately. Your answers will remain anonymous.

- Please indicate the postal (zip) code of your current place of residence.   *(string)*

- What is your civil status?

  (Married / Divorced / Separated / Widowed / In a civil union / Single)

- In total, how many children (0–17), adults (18–64), and elderly (65+) live in your household? *(one field each)*

- What was your annual gross household income from all sources last year (round to nearest $100)? *(integer)*

- *Conditional on high school:* Which type of high school did you graduate from? *(list)*

- *Conditional on university:* What was your university major?

- *Conditional on employed:* Is your firm using robots and/or AI in its production activities? *(Robots / AI / Both / None / Not applicable)*

- Were you born in the US? *(Yes / No)*

- Do you belong to a religious community? If yes, which one?

  (None / Protestant / Catholic / Christian Orthodox / Islamic / Jewish / Other)

Page 18: Final Questionnaire (Part 2)

Please tell me, on a scale of 0–10, how much you personally trust each of the following. (0 = do not trust at all; 10 = complete trust.)

- Federal Government *(0–10)*

- Political parties *(0–10)*

- Trade unions *(0–10)*

- Tech tycoons *(0–10)*

Page 19: Final Questionnaire (Part 3)

- Please tell me, in general, how willing or unwilling you are to take risks.

  (Likert scale 0–10: 0 = completely unwilling, 10 = very willing)

- How do you feel about the use of technology in your daily life?

  (Likert scale 0–10: 0 = negative, 10 = positive)

- What is the operating system of your smartphone?   *(iPhone / Android / Other)*

- How many hours do you use a computer per day for work?   *(float)*

- Are you active on social media?   *(Yes / No)*

- Which ones?

  (Facebook / X (Twitter) / Instagram / TikTok / LinkedIn / Other)

- How many minutes per day do you approximately use them?   *(integer)*

- How often do you use AI tools such as ChatGPT, Gemini, Claude, etc.?

  (Never / Occasionally / Most weeks / Almost daily / Daily)

- Do you have any general comments on this survey?   *(open question)*

- Do you feel that this survey was biased?

  (Yes, left-wing bias / Yes, right-wing bias / No, it did not feel biased)

- Recall that you were given a statement to read: did you find the statement informative?

  (Likert scale 0–10)

Page 20: Completion Screen

Thank you. We are really grateful for your participation in this survey.

[If signed petition:] You have decided to express support for a statement by signing a corresponding petition on Change.org. Here is the link to the petition you chose: Link to the petition.

Follow-Up Questionnaire

Page 1: Informed Consent

Dear participant, our names are Federico Boffa, Steven Stillman and Eugenio Levi. We are researchers at the Free University of Bozen-Bolzano in Italy and this is a follow-up on a study you have taken in October or November on topics such as technological change, automation, and Artificial Intelligence. We would just like to ask you a few additional questions. The survey will take approximately 5 minutes, and you will be paid according to the standard rate of compensation for this time.

Your participation in this study is purely voluntary and your data will be treated confidentially by our research team. The questionnaire is fully anonymous and we have implemented all necessary technical and organisational security measures to guarantee the anonymity of participants. Except for the initial questions, you are free not to answer some of the questions, but we would really be grateful if you answered all of them. Your opinion matters to us and remember, the questionnaire is fully anonymous. You are free to opt out of the survey at any time you wish, but in this case you will forfeit your payment. The results of the study may be published or presented at professional meetings, but only group characteristics will be discussed. All payments are managed through the company that contacted you and we will never contact you directly.

We will be happy to answer any questions you have about the study. You may contact us by phone: xxxxxxxxxxxx or by e-mail at xxxxxxxxxxxxx. Thank you for your consideration. If you would like to participate, please click on the button below. When you are done, simply click *Finish* to complete the survey.

Page 2: Additional Questions

- Do you think that policy-makers should intervene on automation and AI?   *(Yes / No)*

Page 3: Policy Proposals

Now, we would like to ask you about your preferred policies among the following. There is no minimum or maximum limit on the number of policies you can select. Choose the options that best represent your opinions. *(radio buttons, presented in random order)*

- **Minimum wage** – a minimum level of hourly wages set by law that applies to all jobs.

- **Stronger regulations on AI and social media** – to strengthen the protection of user privacy, prevent massive data collection from users, avoid mass face recognition, help achieve data ownership and limit spreading information on the web without consent.

- **Universal income** – a social welfare provision that guarantees all citizens or families an income sufficient to live on.

- **Breaking up big tech monopolies** – splitting the big tech monopolists of the digital markets that are currently dominating the AI revolution (Microsoft, Amazon, Facebook, Google, etc.).

- **Education policies and workplace training** – adapting the educational system to provide the workers with the necessary skills for an automation/AI labour market and retraining current workers with skills that are complementary to the machines.

- **Lower taxes on labour** – reducing payroll taxes on income related to human labour.

- **Tax credits and subsidies for innovation** – a reduction in taxes or additional support for firms willing to invest in innovation.

- **Robot tax** – directly taxing firms that use robots, treating them similarly to a type of labour.

- **More generous unemployment benefits** – an increase in benefits associated with losing the job compared to current levels.

Page 4: Additional Questions

- Do you know how current AIs like ChatGPT, Claude, Gemini, etc. work?

  (a) They are very large deep learning models that can predict patterns in texts, pictures and videos.

  (b) They are very large models that use an elaborated set of pre-defined rules to understand context and provide plausible answers.

  (c) They are very large deep learning models that have developed a form of intelligence by replicating how the human brain works.

- Did you read any news articles or blog posts on automation and Artificial Intelligence in the last month after completing the previous survey?

  (No, I have not read anything / Yes, 1 article or post / Yes, between 2 and 5 articles or posts / Yes, between 5 and 10 articles or posts / More than 10 articles or posts)

- Did you go looking for any information on the opinion of each Presidential candidate on these topics in the last month after completing the previous survey?

  (Yes / Yes, but only of one candidate / No)

- Where did you search for such information?

  (Twitter (now X) / On the web / Podcasts / Other social media / Blogs / TV news / Facebook / Radio / Instagram / Newspapers / Candidates' speeches / Verbal communication with friends or colleagues / The candidates' websites / TikTok)

- In your opinion, how much should automation and AI become a policy priority?

  (Likert scale 1–10)

Page 5: Additional Questions

Have you decided to become more politically active on the topic of automation and AI, for instance by starting to talk about them more in your family, at work, in your community, etc.?

(Yes, I have become more active on these topics / Yes, I will become more active on these topics in the near future / No, I will not become more active on these topics)

In which context? *(With my community / On social media / At work and/or with work colleagues / In my neighbourhood / With friends / With my family)*

- With your community

  (I was already active on these topics before the initial survey / Yes, I have become more active on these topics / Yes, I will become more active on these topics in the near future)

- In your neighbourhood

  (I was already active on these topics before the initial survey / Yes, I have become more active on these topics / Yes, I will become more active on these topics in the near future)

- At work and/or with work colleagues

  (I was already active on these topics before the initial survey / Yes, I have become more active on these topics / Yes, I will become more active on these topics in the near future)

- With friends

  (I was already active on these topics before the initial survey / Yes, I have become more active on these topics / Yes, I will become more active on these topics in the near future)

- On social media

  (I was already active on these topics before the initial survey / Yes, I have become more active on these topics / Yes, I will become more active on these topics in the near future)

- With your family

  (I was already active on these topics before the initial survey / Yes, I have become more active on these topics / Yes, I will become more active on these topics in the near future)

- Which candidate did you vote for in the last Presidential elections?

- Which party do you think can best help foster the development of AI/Automation?

- Which party do you think can best protect workers against the negative impact of AI/Automation?

Page 6: Chances of Losing Job

[Content carried over from the main survey – see Page 16 of the pre-registration questionnaire.]

Page 7: Additional Questions

Some of you were shown a political statement in the previous survey before being given the possibility to sign a petition in the subsequent screens. What was the political statement about? *(Note: there may be more than one correct answer; answers randomised.)*

1. How AI and automation enhance productivity.

2. US financial help to Ukraine in the war between Russia and Ukraine.

3. The potential of new technology to improve the quality of jobs.

4. What would have happened if the FED had not raised interest rates.

5. Future developments in medicines to fight tumours.

6. How AI and automation reduce employment opportunities.

7. The potential of new technology to exacerbate economic inequalities.

8. I do not remember seeing any political statement before the petitions.

Page 8: Beliefs Elicitation

Consider again the three petitions you saw in the previous survey, among which there is the petition you may have chosen a couple of months ago. They are reproduced below for your convenience.

You will receive a bonus if you answer the questions in this box correctly. More specifically, one of the following questions will be randomly selected. If your answer is correct you will be paid an additional bonus of $0.50.

- Which petition do you think was selected by most people?

  (names of the petitions, randomised)

- Out of 100 participants who signed a petition, how many do you think selected petition XXXXXXX (in percentages)? *(open question)*

- Out of 100 participants who signed a petition, how many do you think selected petition XXXXXXX (in percentages)? *(open question)*

- Out of 100 participants who signed a petition, how many do you think selected petition XXXXXXX (in percentages)? *(open question)*

Note: answers for each petition must sum to 100; order of petitions randomised.

Page 9: Emotions Elicitation

Please tell us how you feel about the following political statement. *(For each item, 7-point scale: Strongly disagree – Disagree – Slightly disagree – Indifferent – Slightly agree – Agree – Strongly agree)*

- This statement makes me happy.

- This statement makes me angry.

- This statement makes me fearful.

- This statement is politically correct.

Page 10: Final Questionnaire

- Where do you usually get your news information?

  (TV news / Google feed / Radio / Blogs / Podcasts / Newspapers / X (Twitter) / Facebook / TikTok / Instagram / Verbal communication with friends or other people)

- How much time do you daily devote to acquiring and consuming news information? *(open question)*

- Which is the main media outlet you consume? *(open question)*

Page 11: Final Screen

Thank you. We are really grateful for your participation in this survey.

[Button: Finish the survey]