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## Abstract

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JEL Classification: J68, J58, H24

Keywords: Automation, Information treatment, Political attitudes, Political preferences, Redistribution, Inequality, Populism, Unions



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# The Impact of Fear of Automation

Marta Golin and Christopher Rauh*

January 11, 2023

**Abstract**

In this paper, we establish a causal effect of workers' perceived probability of losing one's job due to automation on worker's policy preferences and workplace intentions. In a representative sample of the US workforce, we elicit the perceived fear of losing one's job to robots or artificial intelligence. We document a strong relationship between fear of automation and intentions to join a union, retrain and switch occupations, preferences for higher taxation, higher government handouts, populist attitudes, and voting intentions. We then show a causal effect of providing information about occupation-specific job loss probabilities on preferred levels of taxation and handouts. In contrast, the information treatment does not affect workers' intentions to self-insure by retraining or switching occupations, but it increases workers' self-reported likelihood of joining a union to seek more job protection. The treatment effects are mostly driven by workers who are informed about larger job loss probabilities than they perceived.

Keywords: Automation; Information treatment; Political attitudes; Political preferences; Redistribution; Inequality; Populism

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# 1 Introduction

Large shifts towards automation, robots, and artificial intelligence have been uprooting the labor market. Computing power has grown exponentially, thus leading to great advances in artificial intelligence, with applications that span diverse tasks, from self-driving cars to cancer detection. While these advances improve the working lives and leisure activities of some, they also pose a threat to the jobs of many workers.[1] Keynes (1931), Marx (1967) and Leontief (1952) already predicted that labor displacement through technological advancement would lead to social and political unrest and instability. Recent studies have provided systematic evidence for this hypothesis by looking at historical events such as the introduction of steam-powered textile mills, which made spinners and weavers redundant 200 years ago (Aidt and Franck 2015, Caprettini and Voth 2020). The threat posed by pending automation will impact today's society by shifting political preferences and, ultimately, politics and policies. This causal pathway is relatively understudied despite historical evidence suggesting potentially potent effects. Due to the difficulty of isolating exogenous variation in the individual perceived threat, we provide experimental evidence to fill this gap, and find some considerable effects in survey data from a representative sample of around 4,300 workers in the United States (US).

Two main sets of findings emerge from this paper. First, workers are on average concerned about the threat of automation to their jobs within the next 10 years. More specifically, we measure perceived automation threat by asking: "On a scale of 0-100%, how likely do you think it is that you might lose your job/not find a job due to automation, robots and artificial intelligence within the next 10 years?". Respondents to our survey fear displacement through technology with an average probability of 35%, and almost 40% of respondents believe they have a probability of being replaced by a machine, robot or algorithm that is higher than 50%. The average perceived automation risk is higher for less educated and younger respondents. Strikingly, we find age to play a very important role amongst high earning workers. Amongst workers younger than 40 in the top earnings decile, the perceived probability of displacement is nearly 50%, while for older workers in the top earnings decile this probability is

[1]For evidence, see, for instance, Brynjolfsson and McAfee (2014), Brynjolfsson et al. (2018), Acemoglu and Restrepo (2020), Blanas et al. (2019), Dauth et al. (2021), Hémous and Olsen (2022) or Boustan et al. (2022). Baldwin (2022) predicts large imminent increases in the automation of services. We focus on employment risk through substitution and ignore the complementary role , and therefore potentially beneficial for workers, technological advancements might bring for some professions.

less than 30%. We also document large differences across occupations. Workers in education community or social services and protective services on average fear to lose their jobs due to automation with a probability of less than one quarter. In contrast, the same probability is nearly one half for workers working in food preparation and serving related jobs, or in transportation and material moving.

Second, we look at how workers' preferences, attitudes, and intentions relate to this perceived automation threat in both a descriptive and causal manner. In response to a perceived threat of job loss because of automation, workers can, roughly speaking, respond along three margins. They can turn to the state and request more redistribution or welfare. They can differentiate themselves vertically by upskilling, or horizontally by changing occupations.[2] Or they can save to self-insure against the potential future shock. In this paper we study the first two margins, i.e. changes in political preferences and employment responses. We provide correlational evidence that perceived automation risk strongly relates to preferences for redistribution, employment responses, populist attitudes, and voting intentions. Focusing on participants assigned to the control group, we find that fear of losing one's job due to automation is positively related to intentions to retrain or switch occupations, as well as higher taxation and more redistribution. Many of these relationships are pronounced. For instance, workers without fear of being displaced by robots within the next ten years favor an average income tax rate below 15%. In contrast, those fearing displacement with certainty request one-third of income to be taxed, on average.

However, these correlations might be driven by other observed or unobserved factors and cannot be interpreted causally. Therefore, we provide evidence of a *causal* effect of fear of automation on workers' preferences, attitudes and behaviors using the results of our information experiment. To overcome endogeneity concerns related to the perceived automation threat, we design an information treatment that introduces exogenous variation in workers' beliefs about the automation risk. More precisely, we randomize participants into a control group that receives no information, and two treatment groups where participants are provided with information about the potential automation risk faced by workers in their occupation, and we compare this number to respondents' own perceived risk. Given that before treatment assignment we ask workers about their perceived automation risk, our treatment creates good news and bad news, as some workers are exposed to a job loss probability that is lower than the

[2] Innocenti and Golin (2022) provide correlational evidence that perceived automation risk is positively related to intentions to retrain.

probability they perceived, and others to one that is higher.

The information about automation risk that we provide to treated respondents relies on a previous data collection carried out in 2020 as part of the Covid Inequality Project. In the study, workers were asked how likely they thought it was that they might lose their job within the next ten years due to automation.[3] With responses to this question at hand, we compute average automation risks for different occupations. We then present treated participants to our survey with the number that corresponds to the automation threat in their own narrow occupation category. The aim of the paper is not to defend these measures of automation risk, which is extremely difficult to predict due to uncertainty and endogeneity surrounding future innovations.[4] Rather, our goal is to use this constructed measure of average perceived automation threat to introduce variation in workers' beliefs.

Our information experiment features one control group and two treatment groups. While all treated respondents receive information on the automation probability that comes from the Covid Inequality Project data, the two treatments differ in the stated source of the information. More precisely, some respondents are told that the information they see comes from a study conducted by expert economists from the University of Oxford (the 'experts' treatment) and others are told that the information refers to the opinion of people working in similar jobs as theirs (the 'people' treatment).[5] This allows us to study whether workers respond differently to information coming from experts, i.e., a socially distant group, or people that are similar to them.

Our experiment shows that information provision leads to significant treatment effects on preferences for redistribution. Treated respondents' preferred tax rate on income and their preferred level of universal basic income payments increases with the difference between the probability of job loss they are exposed to and their own prior. When looking at support for government-funded adult retraining programs, we find a symmetric response: workers exposed to good news reduce their support, while those

[3] See `covidinequalityproject.com` for the surveys and corresponding projects. For the information treatment, we use data from the May 2020 wave of the Covid Inequality Project, which contained a question on perceived automation risk. Note that the question on perceived automation threat from the survey used in this paper was kept identical to the question from the third wave of the Covid Inequality Project survey for comparability.

[4] As a comparison, Frey and Osborne (2017) use extrapolations of hand-labelled automation risk of occupations using answers to the question "Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment?".

[5] The reason we can do this is that information from the Covid Inequality Project on workers in the United States was analyzed by Economists at the University of Oxford. The flattering addition of the term 'experts' is for polarizing expositional purposes.

exposed to bad news increase it. However, we do not document a significant causal effect of the automation threat on employment responses as measured by propensity to participate in a retraining program and switch occupation. Instead, workers exposed to bad news intend to protect their job by joining a union.[6] This evidence is suggestive of the fact that the future automation trends will lead to more support for redistribution and a larger welfare state, but not to increased differentiation through upskilling or re-skilling. Moreover, workers exposed to bad news are more likely to consider their ideology to be left rather than right wing, while those exposed to good news report higher trust in politicians. These polarizing attitudes go hand in hand with a common problem of modern democracy, whereby good news increases the likelihood of wanting to vote in the next presidential elections, while bad news decreases it. Turning to whether workers react differently to information coming from different sources, we find mild differences in treatment effects depending on whether the information was phrased as coming from experts or other workers similar to the respondent, with the people treatment leading to a greater impact on preferences for redistribution.

Guiso et al. (2022) argue that automation threats are less important determinants of populism than financial crises as automation not only creates losers but also winners.[7] Our findings instead suggest that the impact of the automation threat on 'winners', those receiving good news, is rather muted, while 'losers', those exposed to bad news, adapt their attitudes significantly. Indeed, most of the treatment effects that we document are driven by workers exposed to a higher job loss probability than they perceived. Looking at magnitudes, some of the before-mentioned effects are considerable. Being exposed to a 50 to 100 percentage point higher job loss probability than perceived increases the preferred mean tax rate by 4 percentage points and increases the desired level of UBI by 77 log points.

This paper contributes to two main strands of literature. First, we build on and expand the growing body of work that has studied the link between automation and political preferences, as well as voting outcomes.[8] Findings suggest that populist vote

[6] Balcázar (2022) finds that for skilled workers unionization actually declined between 2004-2014 and attributes this to their skills being complementary to robots, which increases the opportunity cost of rent-seeking behavior via union activities.

[7] See Guriev and Papaioannou (2022) for an overview of the economics literature on populism.

[8] For instance, Dal Bó et al. (2018), Frey et al. (2018), Anelli et al. (2019) rely on regional or time variation in the exposure to automation to study aggregate outcomes. Busemeyer et al. (2022) look at correlations between individual and job characteristics and political preferences. Im et al. (2019) provide correlational evidence that fear of automation is related to voting for the radical right. Wu (2022) hypothesizes that workers misattribute blame for job losses stemming from automation

shares increase with automation and that the induced inequality worries people. Zhang (2019) finds that information provision leads workers to update their beliefs about automation, but the study remains inconclusive on potential effects on preferences for public policies. Arntz et al. (2022) find that information about overall zero net employment effects, on average, reduces concerns related to automation, and also find that treatment responses depend on prior beliefs. Ladreit (2022) finds that providing information about economy-wide effects does not alter preferences concerning public policies as the general information only alters perceived aggregate automation risk but not perceptions about respondents' own occupations. We contribute to this literature by providing causal evidence of the fear of own occupation-specific risk of automation using individual level data for preferences and attitudes amongst a representative sample of the US labor force.

Our work also contributes to the literature that uses survey experiments to study political preferences and attitudes.[9] Demand for public policy is studied in the context of beliefs about the gender wage gap (Settele 2022) and public debt (Roth et al. 2021). Preferences for redistribution using information treatments have also been studied in the context of inequality (Kuziemko et al. 2015; Hvidberg et al. 2020), intergenerational mobility (Alesina et al. 2018), efficiency (Stantcheva 2021), immigration (Alesina et al. 2022), and racial gaps (Alesina et al. 2021).[10] We contribute to this literature by studying the potential impact that one of the largest shifts in the labor market – the advancement of robots, algorithms and artificial intelligence – might have in the short and long run. Moreover, we study whether individuals are more likely to respond to the automation threat through their own actions by retraining or switching occupations, versus whether they are more likely to call for a bigger welfare state. Further, we contribute to our understanding of the importance of how information is conveyed. While Stantcheva (2020) shows that explanations have a greater impact than "cold" facts, we study heterogeneity in the responsiveness to different stated sources of the

toward immigrants and workers abroad, and provides descriptive evidence in support of the hypothesis. Chaudoin and Mangini (2022) suggest that this misattribution is driven by opportunistic politicians. In a survey experiment, Jeffrey (2021) finds that by heightening fairness concerns when talking about automation, preferences for redistribution increase. In an overview article, Colantone and Stanig (2019) stipulate that "[...] the counter-positioning of winners and losers from these forms of structural economic change has created a new political cleavage that might last a long time [...]". See Gallego and Kurer (2022) for an overview article in Political Science.

[9] In related work, Roth and Wohlfart (2020) study how survey respondents adapt their beliefs and behavior when confronted with expert forecasts about the macroeconomy.

[10] In a related study which is not a survey experiment, Galasso et al. (2022) run an experiment during a referendum in Italy to study how deconstructing a populist narrative affects populist votes.

same information and, similar to Bernard et al. (2022), do not find large differences. Finally, in contrast to some other studies (e.g. D'Acunto et al. 2021), we also do not find large differences in the responsiveness to the information treatment by demographic characteristics.

# 2 Survey and experimental design

Identifying a causal relationship between fear of automation and policy preferences, employment responses and political attitudes is difficult due to the endogenous nature of perceived automation risks. For instance, less adaptable workers might fear automation due to their flatter learning curve and, because of their lack of adaptability, they might also demand a greater welfare state. Therefore, in order to make causal inference on the role of fear of automation, one needs to identify a credible source of exogenous variation in perceived automation risk. In this paper, we exploit data from an online survey of 4,284 labor force participants in the United States to examine the relationship between perceived automation risk and a range of outcomes of interest (see Section 3 for a description of the data). We embed an information provision experiment in the survey in order to introduce exogenous variation in workers' beliefs about automation risk. This section describes the different modules of our survey, as well as our experimental design. The exact wording of all survey questions and response scales is provided in Appendix B.

## 2.1 Job characteristics

In our survey, we collect information on whether respondents are currently in work or unemployed but looking for new employment. Based on this information, we elicit detailed information on the characteristics of the respondents' main or last job. In particular, we use the Standard Occupational Classification (SOC) 2018 occupation taxonomy to elicit information on both the major and the minor occupation group in which respondents are employed or were last employed in. Broad and narrow occupation groups follow the 2018 SOC System covering 23 major groups, and 840 minor groups. We also collect information on the broad industry classification of the respondent's main or last job.

## 2.2 Perceptions about automation

Our goal is to elicit a quantitative and interpersonally comparable measure of perceived automation risk. To do so, we ask respondents to state what they think the probability is that, within the next 10 years, they will lose their job, or not find a new job in case they are unemployed, due to automation, robots and artificial intelligence. Answers are elicited on a 0-100 percent chance scale.

## 2.3 Information experiment

We embed an information provision experiment into our survey to introduce exogenous variation in respondents' perceptions about automation risk. In particular, treated participants receive information about the average expectation of job automation of other labor force members working in similar jobs as theirs. The information experiment exploits data collected as part of the Covid Inequality Project featuring information on perceived automation risk.[11] We use these data to calculate the average perceived likelihood that workers would lose their job because of robots, computers or algorithms within the next ten years for different occupational categories.

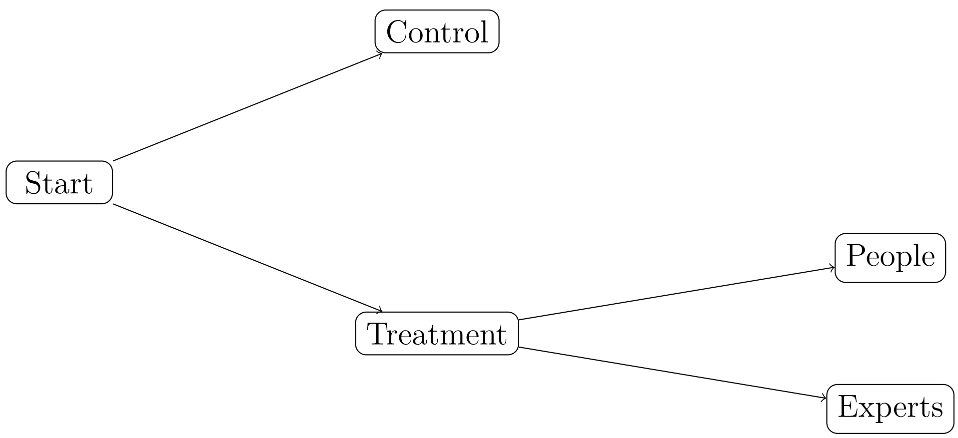
Our experimental design features one control group that receives no information, and two treatment groups. Motivated by the literature highlighting the ambiguous effect that 'expertise' may have on individual beliefs and behaviors (see, e.g., Sapienza and Zingales 2013; Alsan and Eichmeyer 2021), the two treatments vary along the stated source of the information provided (experts vs people treatment). More precisely, we follow a two-step approach for our randomization. In a first step, after eliciting respondents' perceptions about the probability of losing their job because of automation, participants to the study are randomly assigned to either the control or the treatment group. Within the treatment group, a first group receives information on average automation risk, where the stated source information is said to be a study by expert economists from the University of Oxford (the experts treatment). A second treatment group receives the same information in terms of job loss probabilities, but for this

[11] The Covid Inequality Project had the goal of documenting the labor market impacts of the Covid-19 pandemic. It is a collection of rapid response online surveys of members of the labor force conducted over March-May 2020 across three large economies - the United States, the United Kingdom and Germany. We use data from the survey wave that was run in in May 2020, and which contained a question on the perceived probability of losing one's job due to automation, to construct our measure of perceived automation risk for the information provision experiment. More information about the Covid Inequality Project can be found at: www.covidinequalityproject.com.

group the information is phrased to be reflecting the opinion of people 'like you' in the United States working in similar jobs as the respondent's (the people treatment). This exogenous variation in the source of the information provided allows us to evaluate whether workers respond differently to information coming from socially distant groups (the experts in this case) than they would to information coming from people closer to them.

Randomization is performed at the individual level, and study participants had a 50% chance of being assigned to either the control or treatment group and, conditional on being in the treatment group, a 50% chance of being in the people or expert treatment. Figure 1 graphically represents our randomization procedure.

Figure 1: Randomization procedure

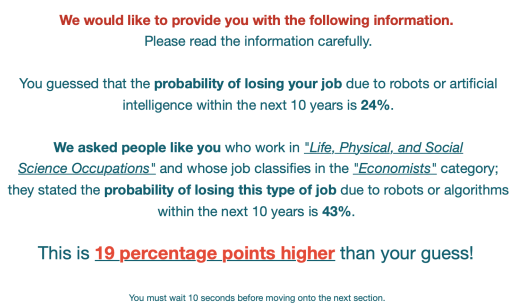



*Notes*: The figure displays the in-survey randomization procedure for the information provision experiment. Participants had an *ex-ante* 50% chance of being assigned to the control group, and 25% to the experts or people groups.

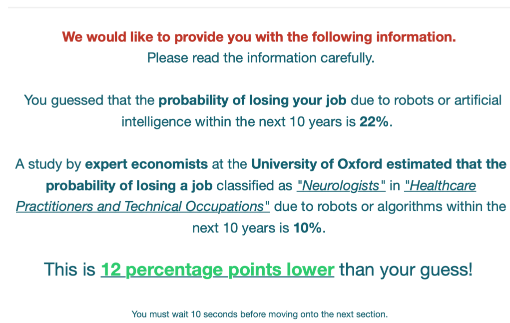
To make the information provided in the information treatments more salient, treated participants were also told how the average automation risk they saw compared with their own automation expectations, which we elicit before treatment assignment. Panel (a) in Figure 2 provides an illustrative example of the information provided to a participant assigned to the people treatment, whose expectation is below the average guess of participants to the Covid Inequality Project working in the same broad occupation. Panel (b) shows an example of the information provided to a respondent assigned to the experts treatment and whose perceived probability of losing their job because of automation is above the average expectation. As can be seen from the figure, we always compare respondents' own expectation to the average expectation of participants to the Covid Inequality Project, and use the red or green color to highlight whether the difference between the received information and the respondent's prior is positive (i.e. a bad news treatment) or negative (i.e. a good news treatment).

Figure 2: Examples of information treatments

(a) 'People' treatment




(b) 'Experts' treatment




*Notes*: Panels (a) and (b) provide a visual example of the information provided to participants in the people and experts treatment, respectively.

## 2.4 Policy preferences, employment responses and attitudes

We are interested in how perceived automation risks affect workers' policy preferences, their employment responses, voting intentions and populist attitudes. Below we describe how we elicit information on each of the outcomes of interest in turn, and in Section 2.5 we describe how we aggregate the various outcomes of interest that we elicit into different composite measures of preferences, attitudes and intentions.

**Redistribution** We elicit respondents' preferences about a number of redistributive policies, from tax preferences to preferences about universal basic income (UBI) and other public policies. With regards to tax preferences, we elicit preferences for capital and income taxes, and for a so-called 'robot' tax, i.e. a tax on the income generated by robots. In particular, we inform respondents of the tax rate on capital gains in the United States (20%) and ask them what they think the tax rate should be for income generated by robots. Furthermore, respondents are informed that the highest federal marginal tax rate on income is 37% in the United States. Thereafter, we elicit their preferences with regards to the preferred average labor income tax rate.

We also ask a number of questions to elicit respondents' preferences about other public policies. We ask respondents what the amount should be that everyone should receive if all transfer programs were to be replaced universal basic income (UBI), whether a worker should be able to retire early when being replaced by a robot, what they think the replacement rate should be for unemployment benefits, and for how long after losing their job they think people should be entitled to receive unemployment benefits.

**Support** We ask respondents to state the extent to which they agree or disagree with statements about increasing government spending towards adult training programs and income support programs for the poor. When presenting these two government support programs, we specify that other government expenditures would have to be scaled down to compensate.

**Employment responses** We elicit respondents' intended responses to automation risk by asking survey participants how likely they think they are to retrain using an adult training program or switch occupation within the next 10 years. For in-work participants, we also elicit respondents' likelihood to remain part of a labor union, if they already belong to one, or join a labor union, if they have not done so already. For respondents who are out-of-work at the time of data collection, we ask what they think the likelihood would have been that they would have remained part of a labor union or joined one in their last main job.

**Populist attitudes** Respondents are asked to classify themselves ranging from -10 (left) to +10 (right) in terms of political ideology. Further, we collect information on respondents' level of agreement with several statements about having had enough of experts, whether robots steal jobs, whether they trust politicians to do the right thing, and the extent to which they agree with the statement 'I am anti-elite'. Answers to these questions are elicited using five-point Likert scales. Finally, we also ask respondents the extent to which they think that inequality is a problem in the United States.

**Voting intentions** We ask respondents for which party's candidate they think they will vote in the next presidential election, allowing for the option of not voting at all. We construct indicators for whether respondents will likely vote for a Republican or Democratic candidate, or whether they plan not to vote at all.

## 2.5 Construction of outcome variables

We group the outcome variables into four aggregate indices for preferences for redistribution, government support policies, employment responses, and populist attitudes. All indices and their components are summarized in Table 1. For voting intentions we do not construct an index, but rather use the three binary indicators for voting Democrat, Republican, and not voting at all in our regressions because all three responses are mutually exclusive. We now describe how we construct our main indices.

First, we construct an index of preferences for redistribution from all answers to the questions on tax preferences as well as preferences about other public policies, including UBI (index "*(1) Redistribution*"). We do so by extracting the first factor of all relevant answers using principal component analysis. The index has mean zero and a standard deviation of one for the sample of analysis.[12] All components load positively on the index. Higher values of the policy preference index correspond to preferences for more redistributive policies (higher income taxes and taxes on robots) and more social security (e.g., higher unemployment benefits). We further construct an index for policies in support of workers affected by automation by combining answers to our questions on whether respondents would support more government funding towards adult training programs and income support for the poor. Again, we extract the first factor from these two variables. The support index loads positively on both of the support programs.

Turning to our questions on employment responses, we construct an index that summarizes workers' intentions to join a union, participate in a retraining program or switch occupation. Higher values of the index indicate a higher propensity to take any of the above actions, and thus insure one's self against the threat of automation.

Additionally, we construct an index of populist attitudes by extracting the first factor of respondents' reported agreement with statements about experts and being anti-elite, the threat that robots pose to the labor market and problems that society currently faces. Agreement with the statement about having had enough of experts loads positively on the populist attitude index, and so does agreement with statements about robots stealing jobs and being anti-elite. Conversely, beliefs about inequality being an important problems in today's society loads negatively on the populist attitude index. Overall, higher values of the index can be interpreted as respondents having stronger populist attitudes and a political orientation skewed to the right. In Appendix

[12]See Section 3 for details on our sample restrictions.

Tables A.1-A.4 we present the full breakdown of all our indices, with the factor loadings of each component.[13]

Table 1: Construction of outcome variables

| **Index** | **Components** |
|---|---|
| *(1) Redistribution* | Average income tax |
| | Tax on robot income |
| | Duration unemployment benefits |
| | Replacement rate unemployment benefits |
| | Permission to retire early |
| | Monthly UBI |
| *(2) Government support* | Favor funding adult training |
| | Favor income support for poor |
| *(3) Employment responses* | Intention to join union |
| | Intention to retrain |
| | Intention to switch occupation |
| *(4) Populist attitudes* | Left-right ideology |
| | Enough of experts |
| | Robots steal jobs |
| | Anti elite |
| | Inequality is a problem |
| | Trust in politicians |
| *Voting intentions*[(a)] | Will vote Democrat |
| | Will vote Republican |
| | Will not vote |

*Notes*: All indices are constructed by extracting the first factor using principal component analysis. Indices have mean zero and standard deviation of one for the analysis sample, as defined in Section 3. [(a)] Voting intention variables are not grouped into an index but used as individual outcomes instead. This is because the variables are close to being mutually exclusive.

[13]Note that for questions elicited on a Likert scale, we include the full scale as a continuous variable since principal component analysis is meant to deal with variables that have no scale or location. However, when we look at the outcomes individually, we transform them into binary indicators taking the value one when respondents agree or strongly agree with the statements.

# 3 Data

We collect survey data from a sample of 4,284 labor force participants in the United States. The data was collected in March-April 2022 through an online survey, and participants were recruited from the panel members of a professional survey company. To participate in our study, respondents had to be aged between 24 and 54, resident in the US and either be in paid work or have had some work experience in the past and be actively looking for a new job.[14] We use quota-based sampling to target the joint representativeness of our sample in terms of gender, age, educational attainment, occupation groups, and broad regions.[15] Table A.5 in the Appendix shows a fairly close match of the background characteristics of our sample to the population statistics from the CPS.

Participants to our study are randomized into either one control group, which is made up of roughly half of the sample, or one of two treatment groups, each made up of approximately 25% of the sample. Appendix Table A.6 shows descriptive statistics for the background characteristics of our analysis sample by treatment status. The sample is well balanced across the control and treatment groups.

# 4 Who fears automation and how does it correlate with responses?

Are workers afraid of losing their job to robots, automation, or algorithms within the next ten years? In panel (a) of Figure 3, we plot the binned distribution of respondents' perceived likelihood of losing their job within the next ten years due to automation. There is a large dispersion in fear of automation among our survey participants: 18% of workers are not worried at all about losing their job, whereas 3% of them are sure that they will lose their job in the near future because of automation. 38% of the sample

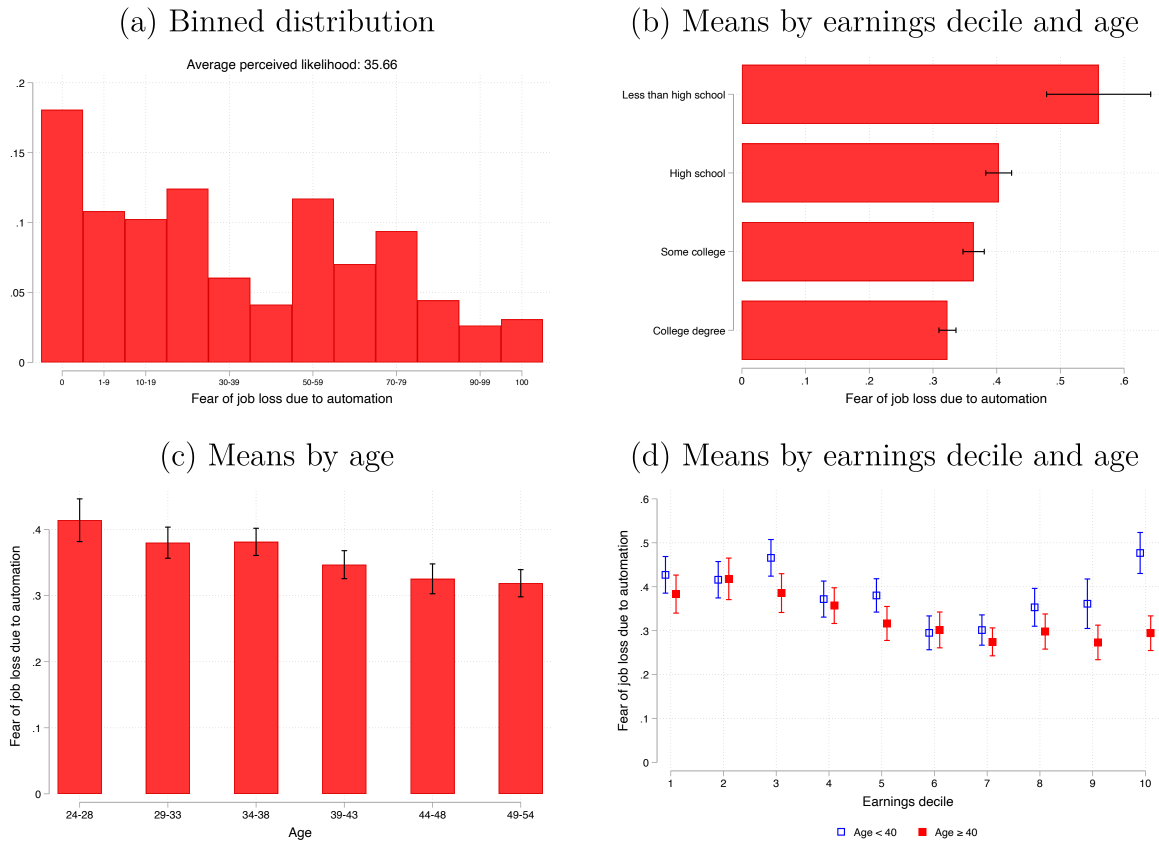
[14] The survey was scripted in the software Qualtrics, and the randomization for the information provision experiment was performed on the same software. Participants received incentives to participate in the survey that approximately correspond to the pro-rata minimum wage in the United States. The median time to complete the survey was 14 minutes. We screen out participants who fail an attention check, who do not provide information on their narrow occupation category, or whose completion time was below three minutes.

[15] More precisely, we target the joint distributions of gender (female / male), age categories (below 40 / aged 40 or above), educational attainment (has university degree / does not have university degree), occupational categories (blue- / white-collar workers) and regions (Northeast, Midwest, South, West). Population statistics were taken from the IPUMS CPS March supplement 2021 (Flood et al. 2021).

reports a perceived probability of losing their job above 50%, and workers' average perceived probability of job loss is 35%.

Fear of automation also significantly varies across workers with different background characteristics. In Panel (b) we see that the perceived fear of job loss is, on average, decreasing in education. While for respondents who did not complete high school the average perceived fear is 56%, for those with a college degree it is 32%. Panel (c) displays the mean perceived fear of losing one's job by age summarized in intervals of 5 years. The young, i.e. those aged 24-28, are particularly afraid, with an average perceived probability of job loss of 41%. This fear declines nearly linearly in age, reaching an average of 32% for the oldest age group in our sample, i.e. workers aged 49-54 years. In Panel (d) we summarize the perceived likelihood of job loss by earnings decile while separating perceptions about automation risk for those aged below 40 and for those aged 40 or above within each decile. For older respondents, perceived fear of automation seems flat for the bottom three income deciles, decreasing for deciles 4-7 and then again flat for the top earners. For younger respondents, this pattern is tracked very closely for all but the top two earnings deciles. Here, perceived fear of automation increases and spikes amongst the very top earners, who display the highest perceived automation risk of all groups.

Figure 3: Distribution of fear of automation overall and by education, age and income




*Notes*: Panel (a) shows the binned distribution of perceived probability of job loss due to robots, automation, or algorithms within the next 10 years across different groups. Panels (b)-(d) show the average perceived probability of job loss. The thin lines correspond to the 95% confidence intervals.

Panel (a) of Figure A.1 shows the binned distribution of the perceived likelihood of job loss due to automation, separately for the 23 major occupation groups. Respondents working in food preparation and serving related jobs are most in fear of losing their job, with an average perceived probability of job loss of 47%. They are closely followed by those working in occupations related to production as well as transportation and material moving, while workers working in community and social service or in protective services are the least worried, with an average perceived probability of job loss of just above 20%. Similarly, in Panel (b) we can see the large heterogeneity in perceived automation risk across industries, with workers in information and communication displaying the highest perceived fear of automation, and workers employed in public administration, defence or social security displaying the lowest. In Figure

A.2 we compare the average responses by occupation to the information used for the treatment. Across narrow (broad) occupation categories the correlation between mean responses between this project's survey and the Covid Inequality Project is 0.35 (0.52).

## 4.1 Fear of automation and preferences, intentions, and attitudes

For the descriptive analysis, we restrict our sample to the control group in order to document cross-sectional evidence on the relationship between workers' perceived fear of automation and their employment response, attitudes, and preferences. Respondents in this sub-sample received no information about the likelihood of their job being automated in the future.[16] In Figure 4, we graphically represent the relationship between perceived automation risk and workers' preferences, intentions and attitudes: in each panel, we plot bins of the individual perceived likelihood of losing one's job within the next ten years due to automation on the x-axis against the average of a range of intentions, preferences, and opinions on the y-axis, while adding the 95% confidence interval as black caps for each bin of the perceived fear of automation. Appendix Figure A.6 similarly plots the relationship between perceived automation threat and voting intentions.

**Preferences for redistribution** The top left panel of Figure 4 plots the relationship between fear of automation and preferences for redistribution. In our sample, we find an overall strong positive gradient in the relationship between perceived automation risk and policy preferences, with workers who are least worried about the threat of automation to their own job being the least likely to support higher income taxes, or larger unemployment benefits. Appendix Figure A.3 shows the relationship between perceived automation risk and each individual component of the preference for redistribution index. We find that fear of automation exhibits a strong positive correlation with preferred top marginal tax rates, average income tax rates, tax rates on robots, duration of unemployment benefits, the unemployment benefit replacement rate and the amount of UBI. In summary, workers who worry the most about automation are significantly more likely to express preferences for higher redistribution through income and robot taxes.

[16] Appendix Table A.7 reports the average responses of the control group for all the outcome variables of interest.

**Support programs** In the top right panel of Figure 4 we plot the relationship between perceived automation risk and preferences for spending on social security programs. We find a relatively flat relationship between the perceived threat of automation and being in favor of more government funding towards training and income support programs. Looking at the different components of the index, Appendix Figure A.3 shows that people who are more worried about automation also support higher spending towards income support for the poor, but that the relationship between perceived automation risk and support for funding towards adult training programs is not steep.

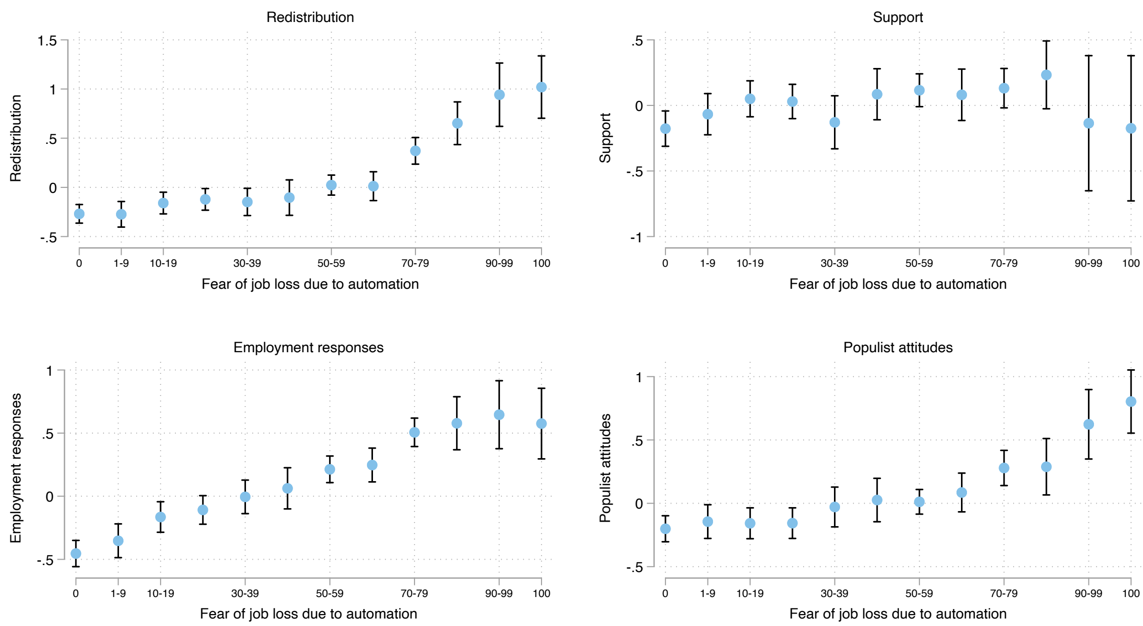
**Employment responses** In the bottom left panel of Figure 4 we document a strong positive relationship between workers' perceived automation risk and their intended employment responses: individuals who are not concerned at all about the automation threat score around one standard deviation lower on the employment response index than individuals who are most concerned about automation. In Figure A.4 we contrast workers' fear of automation with our three measures of intended employment responses. We see a strong positive relationship between automation fears and intentions of becoming part (or remaining part) of a labor union, retraining, and switching occupations.

**Populist attitudes** The bottom right panel of Figure 4 and Appendix Figure A.5 document a positive correlation between workers' perceived likelihood of losing their job because of automation and the extent to which they agree with different populist statements. Having had enough of experts is strongly related to workers' fear of automation. Further, those most in fear of automation are more likely to agree that robots steal jobs, and these respondents are also more likely to claim to be anti elite. Finally, workers who most worry about the automation threat to their job are also more likely to agree with the statements that inequality is a problem.

**Voting intentions** Finally, in Figure A.6 we look at how the perceived automation risk relates to voting intentions. Those in fear of automation are less likely to intend to vote Republican. While voting Democrat exhibits no clear relationship with workers' perceived automation risk, the positive relation between fear of automation and intentions of not voting at all is more pronounced.

To summarize, the patterns we document paint a consistent picture: workers' fear of losing one's job because of automation is strongly related to stronger preferences for redistributive policies, labor market behavior that would insure workers against the threat of automation, heightened populist attitudes, and voting abstention. In the next section, we analyze whether we can detect a causal relationship between perceived automation risk and workers' preferences, intentions and attitudes.

Figure 4: Fear of automation and preferences, intentions, and attitudes




*Notes*: The x-axis shows the binned perceived probability of losing ones job due to automation within the next 10 years versus the average outcome indicated in the title on the y-axis. The sample is restricted to the control group. Thin lines represent 95% confidence intervals.

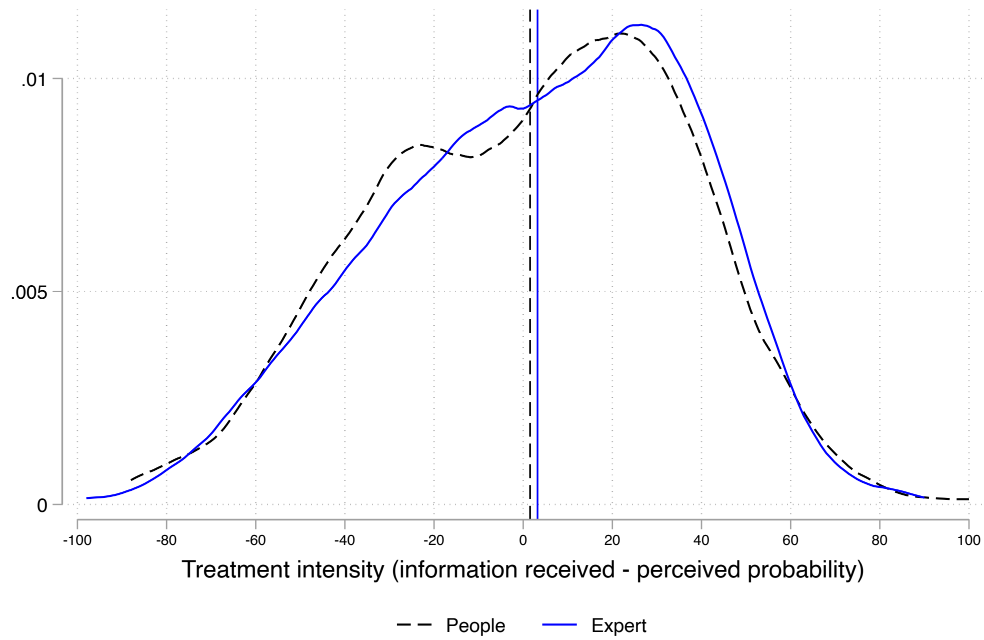
# 5 Causal evidence

We begin by documenting the exogenous variation in beliefs about automation risk that we intend to induce with our information treatments. In Figure 5 we present the distribution of the net treatment intensity for treated participants, separately by treatment group. Net treatment intensity is calculated as the information about the job loss probability that we provide to treated respondents minus respondents' self-reported perceived likelihood of losing their job within the next ten years due to automation, which we elicit before treatment assignment. The larger the provided job loss probability, and the smaller the respondents' perceived job loss probability, the greater the net treatment intensity. Overall, the net treatment intensity can vary between -100 percentage points and +100 percentage points. Positive (negative) numbers for the net treatment intensity indicate that respondents' own views about the automation threat are more (less) optimistic than the information they were provided with. In other words, positive numbers for the net treatment intensity indicate 'bad news', whereas negative numbers indicate that treated participants received 'good news' compared to their prior.[17] As we can see from the figure, the distribution of net treatment intensity is close to normal, similar across all treatment groups and centred around zero, as shown by the vertical bars in Figure 5 representing the average treatment intensity. In each of the four treatment groups, around 55% of respondents were exposed to job loss probabilities that were higher than they feared and on average, across both treatments, the net treatment intensity was 2.44 percentage points. This is reassuring of the fact that the perceptions about automation risk from the Covid Inequality Project that we use for our information treatment are on average similar to the perceptions of participants to this study. However, Figure 5 also shows that realized net treatment intensities span almost the entire support of the distribution.[18]

[17]In Appendix Figure A.7 we plot the distribution of the net treatment intensity by broad occupation categories.

[18]The minimum and maximum values of treatment intensity, pooling together all treatments, are -98 and +100, respectively.

Figure 5: Distribution of fear of automation and treatment intensity




*Notes*: The figure shows the kernel density of the treatment intensity in terms of difference between the information about the job loss probability we provide minus the self-reported perceived likelihood of losing one's job within the next ten years due to automation for the for different categories. The vertical lines indicate the respective means.

## 5.1 Empirical framework

In the previous section we established strong correlations between fear of automation and intentions, attitudes, and preferences. In the following, we focus on whether the information provision leads to a causal effect of fear of automation. Our identification strategy testing whether outcome $y_i$ is influenced by treatment indicator $t$ with intensity $\Delta_i$ can be written as:

$$y_i = \alpha + \beta t + \gamma p_i + \omega \Delta_i + \phi X_i + \nu + \lambda + \rho + \varepsilon \tag{1}$$

where $p_i$ is the prior, individual perceived probability of job loss due to robots within the next 10 years. The treatment intensity $\Delta_i$ is the probability of job loss the participant is informed about minus the prior $p_i$. $\Delta_i$ takes the value zero for all non-treated participants. $X_i$ are a comprehensive set of individual characteristics, $\nu$ are occupation fixed effects, $\lambda$ are industry fixed effects, $\rho$ are region fixed effects, and $\varepsilon$ are errors clustered at the occupation level. The individual characteristics included across all regressions are one measure for each of the Big 5 personality traits, risk preferences, patience, whether the respondent has a university degree, union membership, unemployment, gender, age, and the logarithm of earnings.

We run different model specifications to examine the causal impact of information provision on preferences, attitudes and intentions. First, we pool together the two treatment groups and create a single indicator $t$ for having received any information versus none at all. Second, we test whether the effect of information provision varies depending on the presented source of information, i.e. whether the information received is reported as originating from experts or people in similar jobs as the respondent's. The main coefficients of interest are $\omega$, which correspond to the effect of the treatment intensity. In Section 5.3 we further analyze whether the treatment effect varies depending on the direction of treatment - namely, if respondents who receive information that is more optimistic than their own prior react differently than respondents whose beliefs are shocked with a higher probability of job loss than their prior. Within occupation the identification comes from two people with the same job and same prior of which one receives information and the other does not (different information, different intensity) and from two people with the same job and different priors of which one receives bad news and the other good news (same information, different intensity). Between occupation identification comes from the fact that in some occupations people tend to receive worse news and in others better news (different information, different intensity).

## 5.2 Results

In the following Table 2 and Figure 6 we test whether the information treatment changed attitudes, preferences, and intentions.[19] More specifically, in Table 2, we look at the effect of the treatment in two different manners. In panel A, we include a pooled treatment indicator and the net treatment intensity, i.e. the difference between the provided information and the prior self-reported perceived job loss probability. In panel B, we break down the treatment by whether the source of the information was said to be experts or people. Moreover, we include the net treatment intensities separately for each of the treatment categories.

In terms of outcomes, in Table 2 we report results on the effect of fear of automation on the extracted first factor with mean zero and a standard deviation of one from

[19]The corresponding tables to Figure 6 can be found in Appendix A.

responses to questions related to redistributive policies (column (1)), preferences for government spending on support programs (column (2)), employment responses (column (3)), and populist attitudes (column (4)).[20]

Controlling for treatment intensity, simply receiving information on automation probabilities increases preferences for redistribution slightly by 0.06 standard deviations (sd). However, treatment intensity matters even more. Looking at the index of redistributive preferences in clumn (1) and for government support in column (2), we find that an increase of 100 percentage points in the reported job loss probability relative to the respondent's prior leads to an increase of 0.22 sd in preferences for redistribution and government support programs. By contrast, the aggregate employment and populism indices in columns (3) and (4) show no significant movement with the treatment.

When looking at the coefficients of the breakdown of the treatment by stated source of information in panel B, there is no clearly discernible pattern in whether the people or the experts information shocks respondents more. For redistributive preferences, the impact of the intensity of the people treatment is stronger (0.31 sd vs. 0.14 sd), albeit to a statistically insignificant extent as the p-value when testing the equality of coefficients is 0.18. For the other outcomes the relationship is reversed, with the intensity of the expert treatment having a mildly larger, but again insignificantly different impact than the people treatment.

[20]Appendix Table A.8 displays the coefficients of the included controls.

Table 2: Treatment effect of fear of automation on summary indices

| | (1) Redistribution | (2) Support | (3) Employment | (4) Attitudes |
|---|---|---|---|---|
| *Panel A*: Baseline | | | | |
| Treatment dummy | 0.0586* | 0.0328 | 0.0036 | 0.0157 |
| | (0.0317) | (0.0389) | (0.0301) | (0.0307) |
| Treatment intensity | 0.2212** | 0.2194* | -0.0028 | -0.1352 |
| | (0.1061) | (0.1228) | (0.0890) | (0.0914) |
| Perceived job loss to robot | 0.8669*** | 0.1574 | 0.8660*** | 0.3995*** |
| | (0.0728) | (0.0964) | (0.0741) | (0.0737) |
| Control group mean | -0.03 | -0.01 | -0.01 | -0.01 |
| Observations | 4041 | 2843 | 4045 | 4052 |
| R-squared | 0.26 | 0.17 | 0.31 | 0.19 |
| *Panel B*: Source of information | | | | |
| People dummy | 0.0560 | 0.0268 | -0.0261 | 0.0083 |
| | (0.0407) | (0.0455) | (0.0378) | (0.0428) |
| Expert dummy | 0.0625* | 0.0380 | 0.0318 | 0.0221 |
| | (0.0365) | (0.0524) | (0.0341) | (0.0350) |
| People intensity | 0.3073** | 0.1939 | -0.0710 | -0.2033* |
| | (0.1259) | (0.1402) | (0.1121) | (0.1154) |
| Expert intensity | 0.1350 | 0.2427 | 0.0592 | -0.0689 |
| | (0.1252) | (0.1585) | (0.1072) | (0.1120) |
| Controls | Yes | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes | Yes |
| Occupation FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |

*Notes*: The dependent variables are indicated in the column headers. The tax policies index includes preferred top marginal income tax rates, average income tax rates, and tax rates on income generated by robots, the other policies index includes duration of unemployment benefits, the replacement rate of unemployment benefits, permission to retire early, favoring UBI, the preferred log amount of UBI + 1, favoring public funding for adult training, and favoring public funding for income support for the poor, the employment index includes intentions to join a union, to retrain and to switch occupations, and the index includes all of the before mentioned together. Each of the indices has a mean of zero and standard deviation of one for the analysis sample, and is derived by extracting the first factor. Standard errors clustered at the occupation level are in parenthesis with stars indicating *** p< 0.01, ** p< 0.05, * p< 0.1.

Taken together, the indices show a causal effect of the information provided on preferences for redistribution, but not on employment responses or populist attitudes. In the following, we will look at which particular responses are affected most.

In Figure 6, we plot the $\omega$ coefficients from Equation (1) for each of the individual outcomes for baseline regressions that have the same empirical specification as in panel A of Table 2 (see the top graph in Figure 6), as well as broken down by source of information as in panel B of Table 2 (middle and bottom graphs in Figure 6).[21] The plotted coefficients can be interpreted as the extent to which a response shifted for a

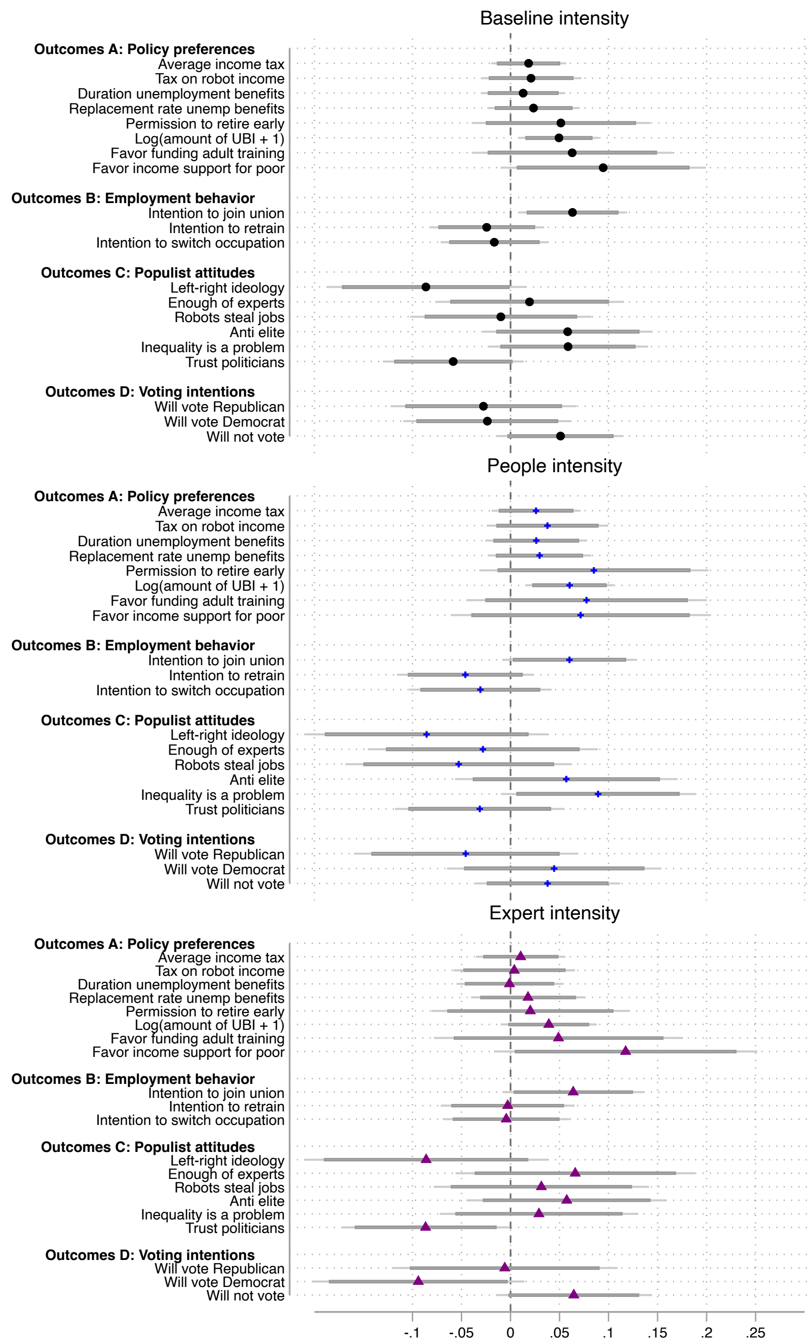
[21] See Appendix Figure A.8 for a direct comparison of the plotted coefficients of the intensity of the expert vs. the people treatment.

100 percentage points higher net intensity of the treatment, i.e. the difference between the provided information about job loss probability and the respondent's prior.

For the baseline specification, the net treatment intensity does not shift many responses significantly. The preferred average tax rate increases by 1.9 percentage points (pp) when the information provided is 100 percentage points higher than the prior. The preferred tax rate on income generated by robots is also 2.1 pp higher. The other policies responding to the treatment are an increase in approval of early retirement for those displaced by automation (+5.2 pp), the provision of income support for the poor (+9.5 pp), and the amount of UBI provided.

While respondents overall show a clear shift towards higher preferred levels of redistribution, they appear less inclined to be willing to respond in terms of retraining or switching occupations (see outcome group B in Figure 6). In contrast, we find evidence that intentions to join a union increase (+6.6 pp) with the intensity of the treatment. For populist attitudes reported in outcome group C, we see a noisy increase in the share of respondents agreeing that inequality is problem (+5.9 pp). Finally, in outcome group D we look at voting intentions where the intensity of the treatment shifted people towards not wanting to vote in the next elections (+5.1 pp).

Figure 6: Treatment effect of fear of automation




*Notes*: The top figure shows the coefficients of the treatment intensity as in panel A of Table 2, while the middle and bottom figures show the coefficients of the intensity when separating the intensity by source of information as in panel B of Table 2. Log(Amount UBI + 1) is divided by 10 and unemployment benefit duration is expressed in terms of 5 years, i.e. divided by 60. Controls include the individual perceived probability of job loss due to robots within the next 10 years, one measure for each of the Big 5, risk preferences, patience, whether the respondent has a university degree, is unemployed, union membership, sex, age, log(earnings), occupation fixed effects, industry fixed effects, and region fixed effects. Standard errors are clustered at the occupation level. Thick lines indicate the 90% and thin lines the 95% confidence intervals.

## 5.3 Heterogeneity by direction of treatment

The previous section documented significant shifts in preferences and intended behaviors in response to the provided information, in particular for policy preferences concerning redistribution. In the following, we will investigate whether the impact is symmetric for respondents exposed to good news, i.e. a lower job loss probability than their prior, and those exposed to bad news, i.e. a higher job loss probability compared to their prior. In other words, we test whether outcome $y_i$ is influenced by the treatment indicator $t$, and indicators capturing the range in which $\Delta_i$ falls. The four intensity indicators are one for large negative intensity (very good news $\Delta_i^{[-100,-50]}$), mildly negative intensity (good news $\Delta_i^{(-50,1]}$), mildly positive intensity (bad news $\Delta_i^{[1,50)}$) and large positive intensity (very bad news $\Delta_i^{[50,100]}$), given the respondent's prior $p_i$. Our empirical specification can be written as:

$$y_i = \alpha + \beta t + \gamma l_i + \omega_{vg}\Delta_i^{[-100,-50]} + \omega_g \Delta_i^{(-50,1]} + \omega_b \Delta_i^{[1,50)} + \omega_{vb}\Delta_i^{[50,100]} + \phi X_i + \nu + \lambda + \rho + \varepsilon. \tag{2}$$

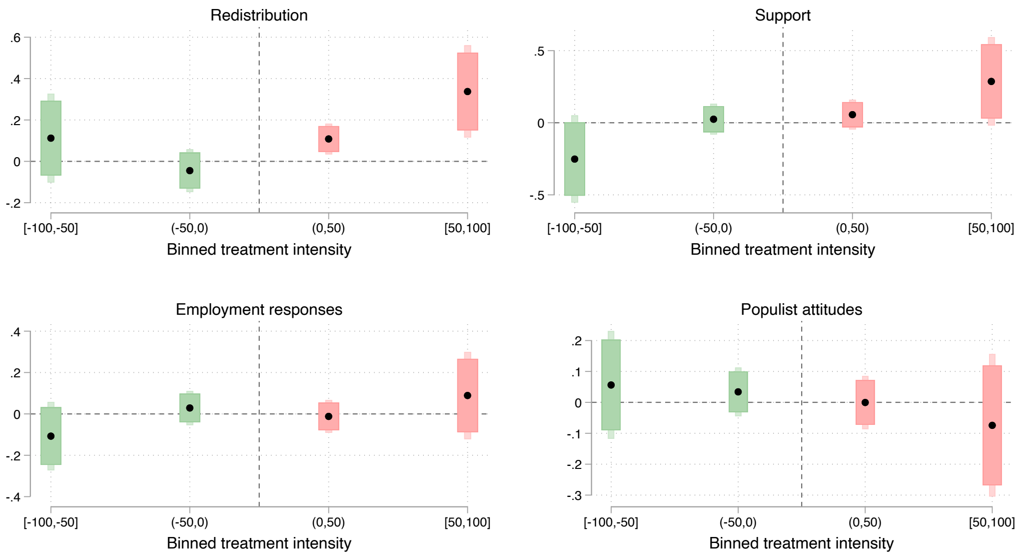
In Figure 7, we display the treatment effects for exposure to lower and higher probabilities of job loss on the aggregate indices.[22] More specifically, we plot the aggregate effect $\beta + \omega_j$ for each intensity range $j \in \{vg, g, b, vb\}$ with the impact of (very) good news plotted to the left in green and of (very) bad news to the right in red.

It stands out that for the policy index capturing preferences for redistribution, the exposure to a higher job loss probability than one's prior increases preferred levels of redistribution, while receiving good news appears to have no systematic effect. Moreover, the impact for bad news is convex, with an increase of 0.12 sd for intensities falling in the range of $[1, 50)$ and 0.34 sd in the range of $[50, 100]$. For preferences for government support programs, in contrast, we find a symmetric effect. While receiving very good news reduces preferred support by 0.25 sd, for very bad news it increases it by 0.29 sd. For the indices capturing employment responses and populist attitudes we find no significant effect, irrespective of the level of net treatment intensity.

In Figure 8 we plot the estimated impact of the binned intensities for each of the questions related to preferences for redistribution. Summarizing the main findings, we find that very bad news increases the preferred mean tax rate by 4 pp. For taxes on income generated by robots, the duration and replacement rate of unemployment

[22] We do not separately test the effect of having one's prior confirmed, as this is only the case for 17 respondents. This category is covered by the coefficient $\beta$ estimated on the treatment indicator.

Figure 7: Treatment effect of fear of automation depending on direction of intensities



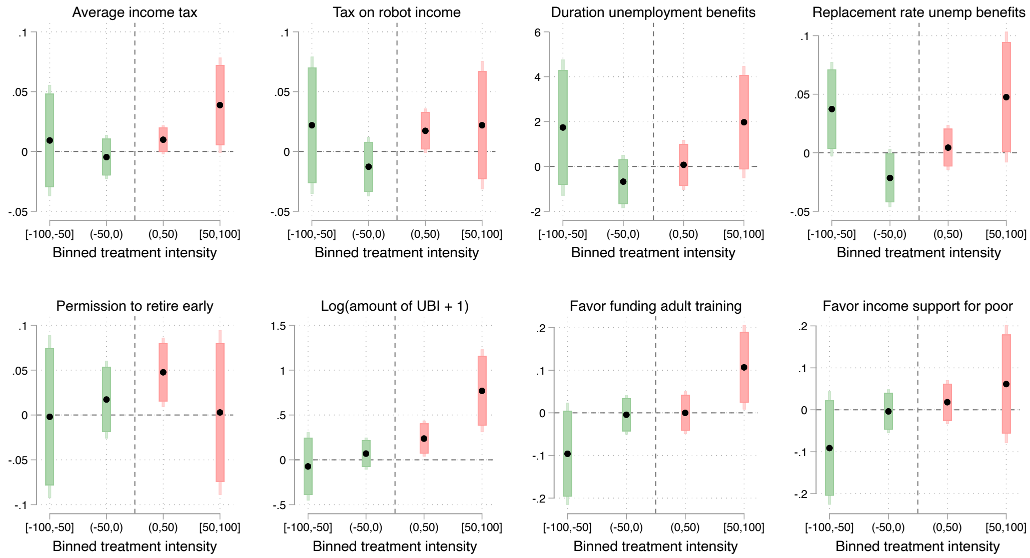

*Notes*: The figures plot the sum of the coefficient on the treatment dummy and the dummy capturing the intensity range indicated on the x-axis (see $\beta + \omega_j$ in Equation (2)). The outcomes on the y-axis are the indices captured by the first factors summarized in Appendix Tables A.1-A.4. Thick lines indicate the 90% and thin lines the 95% confidence intervals.

benefits, and the permission to retire early the patterns are not conclusive. For UBI we find that bad news increases the preferred level by 24 log points and very bad news by 77 log points. In contrast, good news does not appear to reduce the preferred levels. For both the funding of government programs related to adult training and income support for the poor, we find symmetric negligible effects for mildly good or bad news. However, the decrease (increase) for each support program is close to 10 pp for very good (bad) news, though the effect is not always significant at conventional levels.

In Figure 9 we analyze the impact on the intended employment responses. On the one hand, it again appears that neither intentions to retrain nor to switch occupations seem to have been shifted by the treatment. On the other hand, intentions to join a union show a convex effect with the level of bad news, with mildly bad news increasing intentions by 2.8 pp and very bad news by 9.3 pp. Good news does not affect intentions to join a union.

In Figure 10 we show how different treatment intensities affect populist attitudes. In the first panel we see that for very bad news respondents shift to the left by -0.1 on a scale ranging from -1 (left) to 1 (right), a shift equivalent to 0.2 sd. The patterns for

Figure 8: Treatment effect of fear of automation depending on direction of intensities

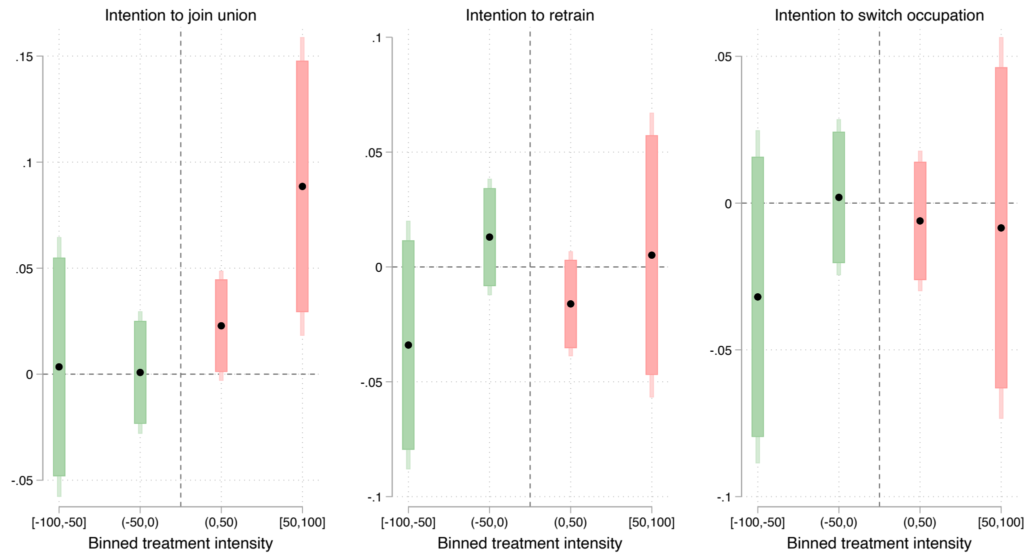



*Notes*: The figures plot the sum of the coefficient on the treatment dummy and the dummy capturing the intensity range indicated on the x-axis (see $\beta + \omega_j$ in Equation (2)). ‘Duration unemployment benefits’ are measured in weeks and ‘permission to retire early’, 'favor adult funding', and ‘favor income support for poor’ are binary indicators equal to one if respondents ‘agree’ or ‘strongly agree’ to the corresponding statements. Thick lines indicate the 90% and thin lines the 95% confidence intervals.

whether one has enough of experts and whether one considers oneself anti elite appear to have symmetric linearly increasing from very good to very bad news. However, none of the coefficients are significant at conventional levels. For whether respondents consider inequality a problem, very bad news increases this likelihood by 10 pp. Finally, trust in politicians is not affected by bad news. However, good news leads to a mild increase in trust in politicians.

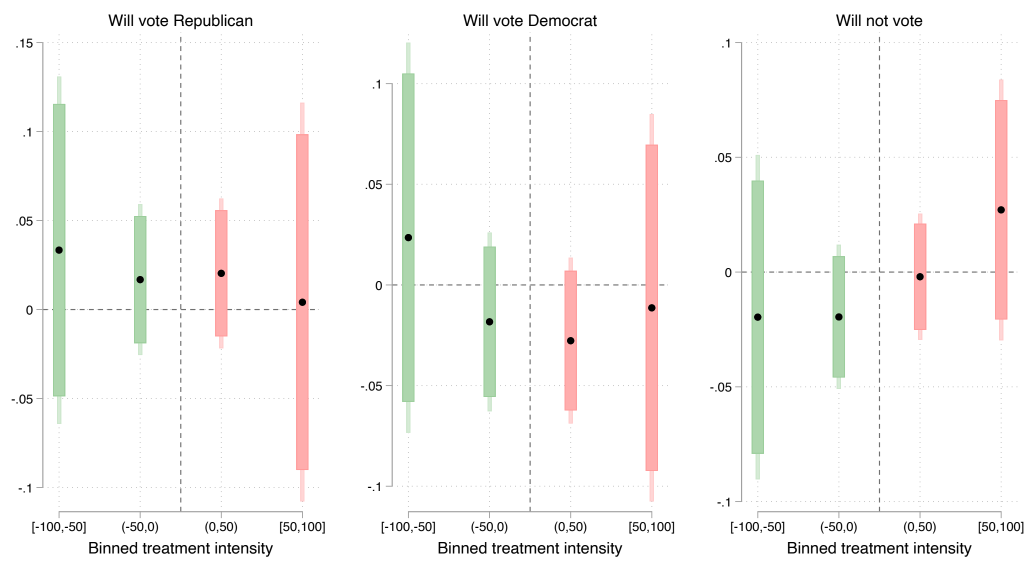
Finally, we plot the heterogenous impacts on voting intentions in the next federal elections in Figure 11. For partisan voting intentions, no clear patterns can be detected. For whether or not to vote at all, there appears to be a symmetric linear impact on abstention from very good to very bad news. However, none of the coefficients individually are significant at conventional levels.

Figure 9: Treatment effect of fear of automation depending on direction of intensities



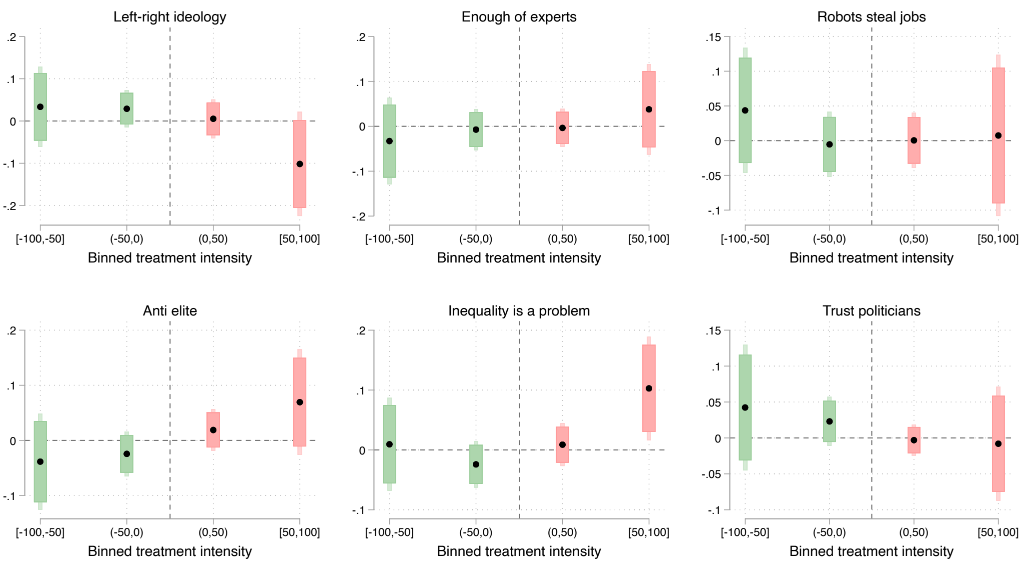

*Notes*: The figures plot the sum of the coefficient on the treatment dummy and the dummy capturing the intensity range indicated on the x-axis (see $\beta + \omega_j$ in Equation (1)). All three outcomes are elicited in terms of probabilities and enter the regressions as shares between 0-1. Thick lines indicate the 90% and thin lines the 95% confidence intervals.

Figure 11: Treatment effect of fear of automation depending on direction of intensities




*Notes*: The figures plot the sum of the coefficient on the treatment dummy and the dummy capturing the intensity range indicated on the x-axis (see $\beta + \omega_j$ in Equation (2)). All three outcomes are binary indicators. Thick lines indicate the 90% and thin lines the 95% confidence intervals.

Figure 10: Treatment effect of fear of automation depending on direction of intensities




*Notes*: The figures plot the sum of the coefficient on the treatment dummy and the dummy capturing the intensity range indicated on the x-axis (see $\beta + \omega_j$ in Equation (2)). 'Left-right ideology' was elicited on a scale from -10 (left) to +10 (right) but enters the regression scaled between -1 and +1. All other outcomes are binary indicators equal to one if respondents 'agree' or 'strongly agree' to the corresponding statements. Thick lines indicate the 90% and thin lines the 95% confidence intervals.

# 6 Conclusion

One of the starkest trends in the changing landscape of work has been, and will be, automation through technological advancement. The threat of robots, algorithms, and artificial intelligence replacing workers has been studied extensively. In this paper, we exploit a representative sample of the prime aged US working population to look at how workers perceive the automation threat to their jobs and the impact of perceived automation risk on policy preferences, employment responses, populist attitudes, and voting intentions.

We document that self-reported fear of automation strongly correlates with requests for more redistribution and taxation, populist attitudes, and intentions to retrain or switch occupations. We then exploit a randomized information treatment to document the causal impact of perceived automation risk on these outcomes. We find that being exposed to higher job loss probabilities than perceived has a significant causal effect on a range of policy preferences and populist attitudes. In particular, workers exposed to higher job loss probabilities request higher levels of taxation, universal basic income, and income support for the poor. They are also more likely to consider themselves politically left leaning. In contrast, on average workers are not planning to respond to the automation threat by retraining or switching occupations. The only causal employment response is a much higher likelihood to intend to join a union.

Our findings provide insights into how the spread of automation might continue to alter the political landscape. 'Winners' of automation, in our case those exposed to lower job loss probabilities than perceived, tend to respond less, while 'losers', i.e. those facing a higher automation risk than they believe, tend to turn to the state rather than responding through upskilling or reskilling. This asymmetric response might put pressures on public budgets that are already characterized by high levels of debt and shrinking tax bases. Combined with high levels of political polarization and low civic engagement through voting, future technological developments might pose challenges to democracies. How policymakers can respond to these threats is an important question left for future research.

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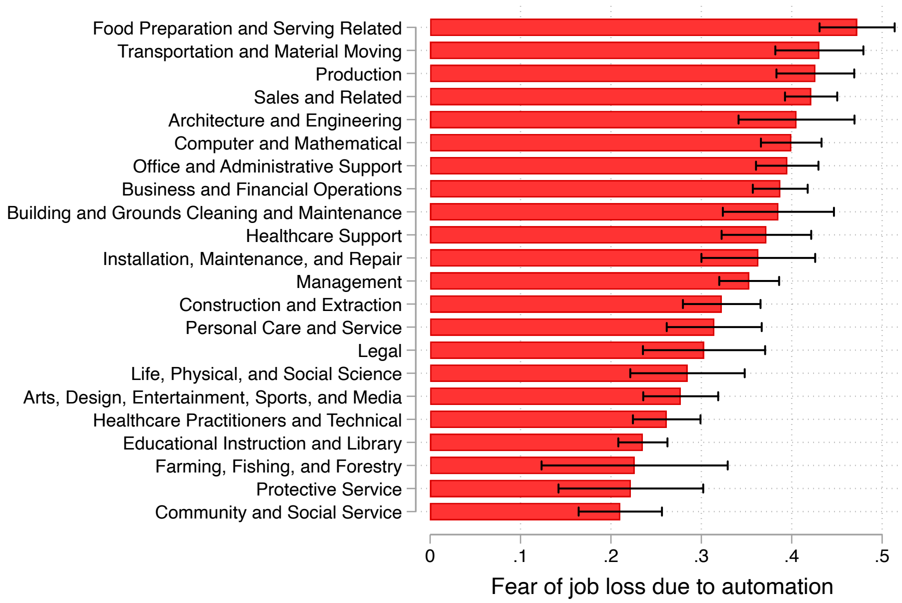
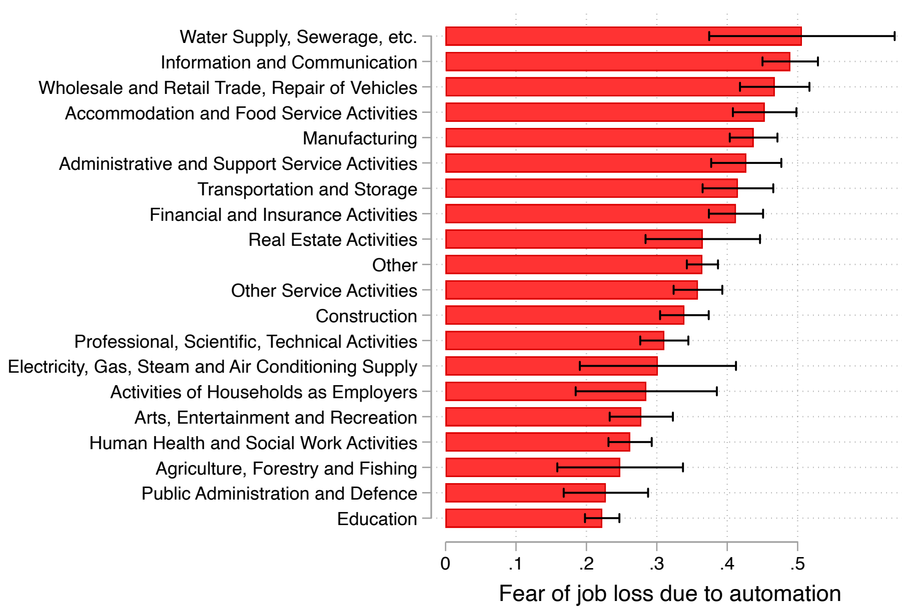
# A Additional tables and figures

Figure A.1: Distribution of means fear of automation by occupation and industry

(a) By occupation

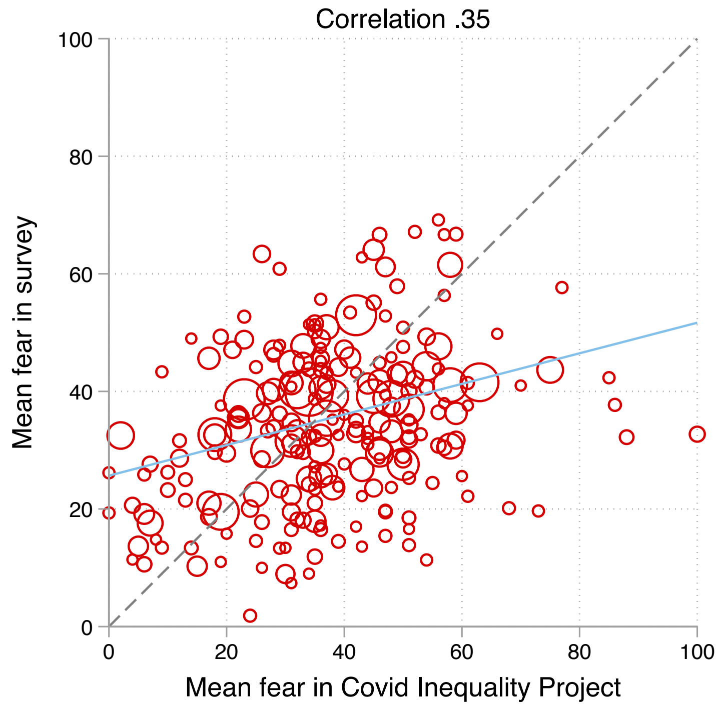



(b) By industry



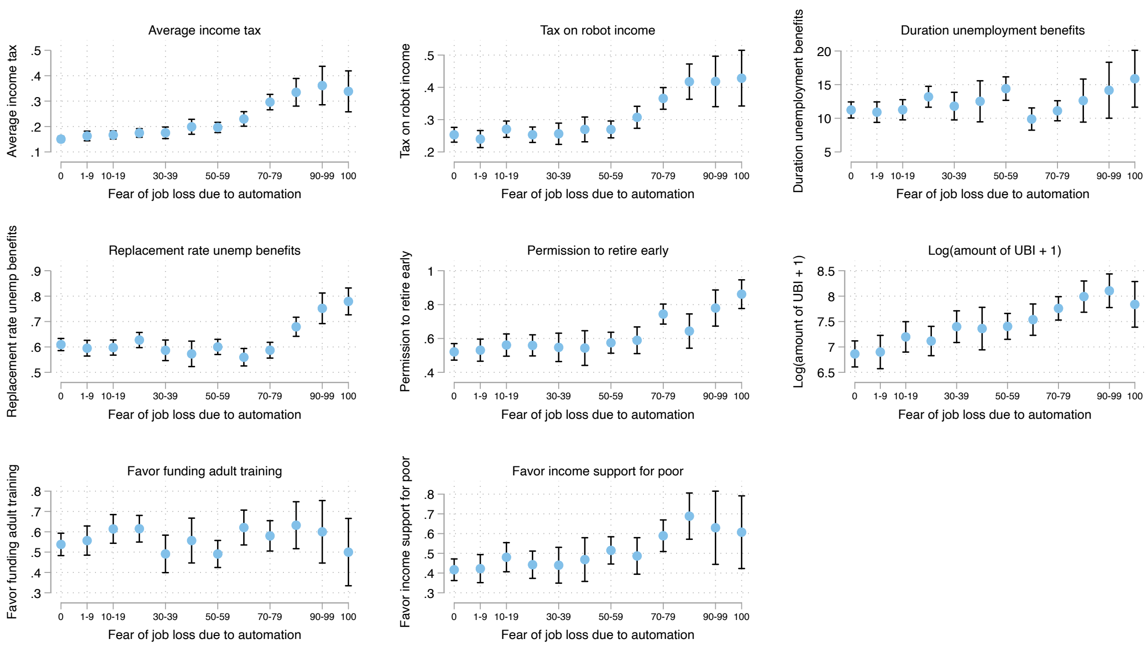

*Notes*: The two panels show the average perceived probability of job loss due to robots, automation, or algorithms within the next 10 years across different groups. The thin lines correspond to the 95% confidence intervals.

Figure A.2: Distribution of mean fear of automation by occupation in survey vs Covid Inequality Project



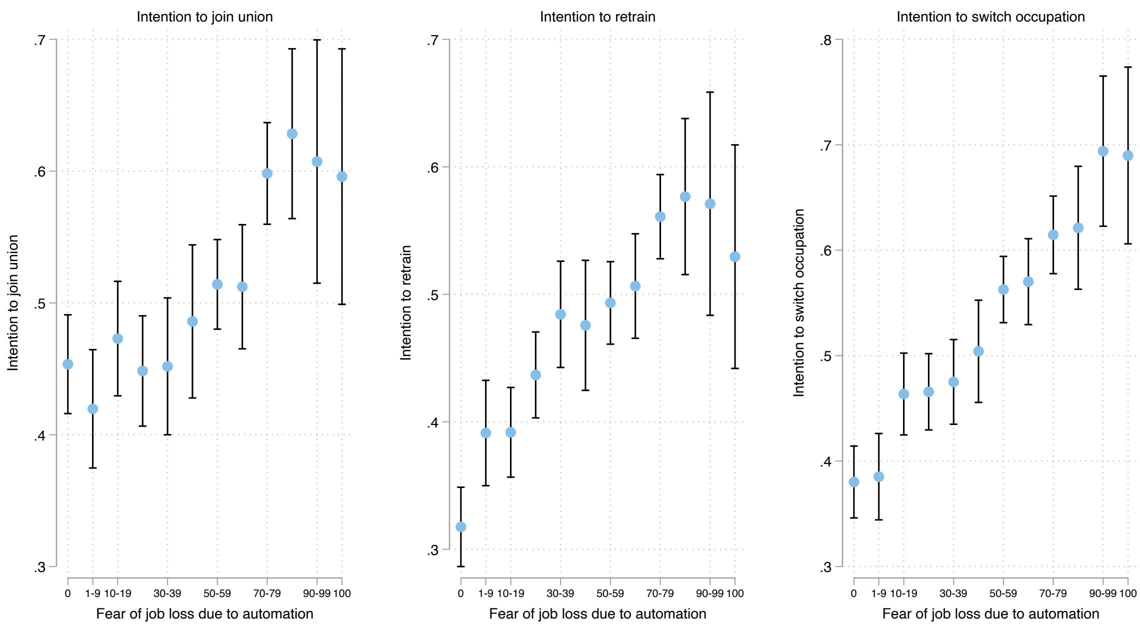

*Notes*: The figure shows the average perceived probability of job loss due to robots, automation, or algorithms within the next 10 years across different groups in the survey compared to in the Covid Inequality Project, which is used for the sake of treatment. Occupations with less than five observations are excluded from the plot and the size is proportional to the number of observations in the survey.

Figure A.3: Fear of automation and policy preferences



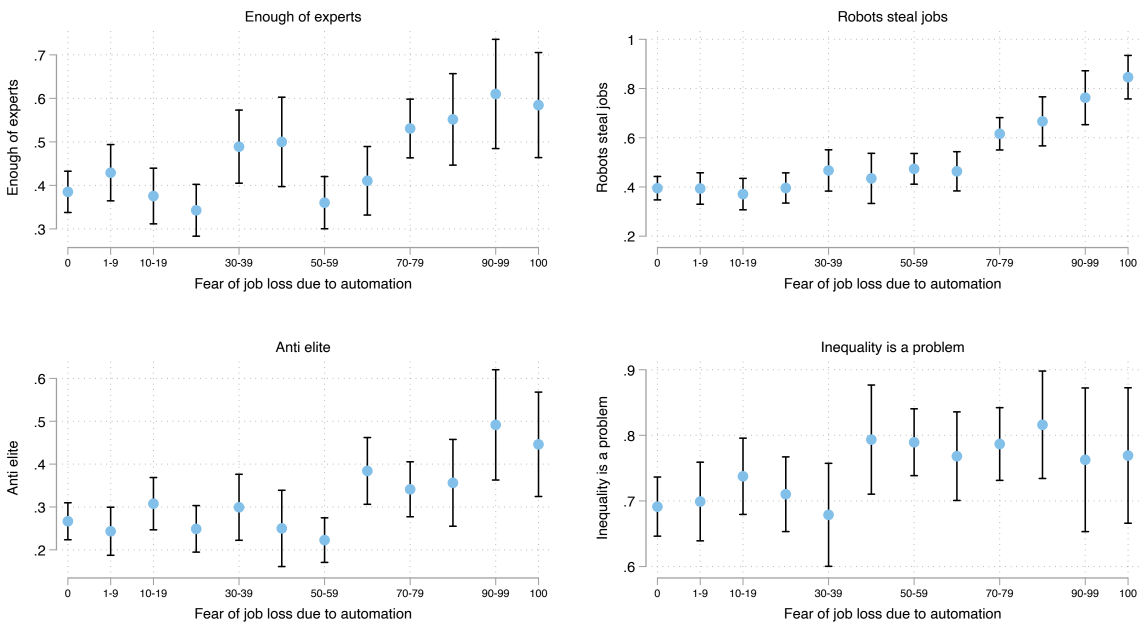

*Notes*: The x-axis shows the binned perceived probability of losing ones job due to automation within the next 10 years versus the average outcome indicated in the title on the y-axis. The sample is restricted to the control group. Thin lines represent 95% confidence intervals.

Figure A.4: Fear of automation and employment responses



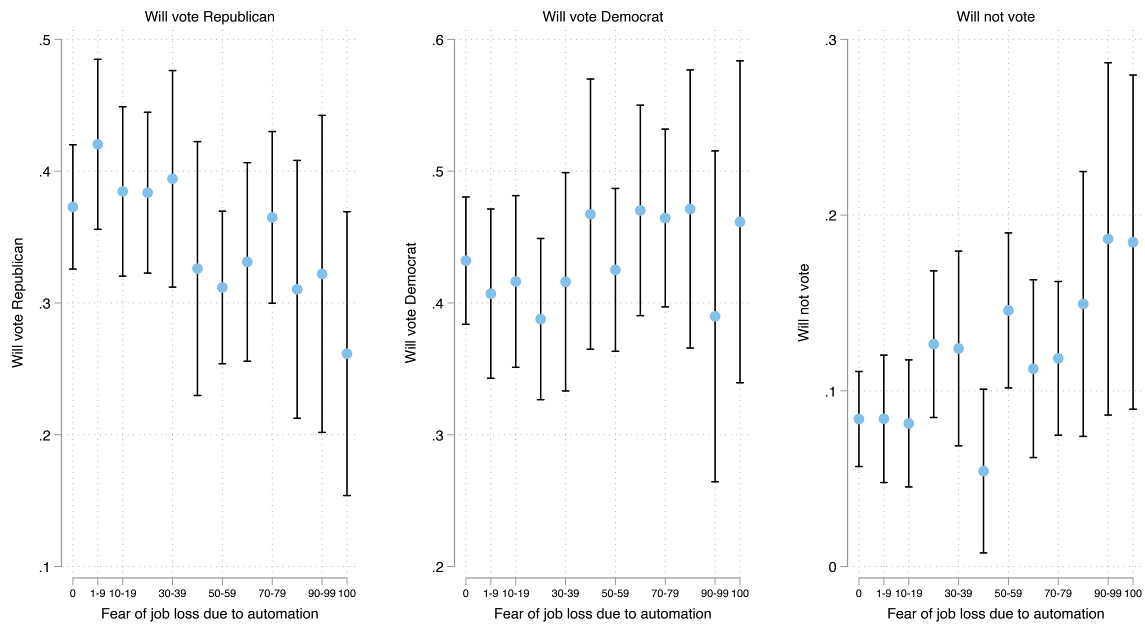

*Notes*: The x-axis shows the binned perceived probability of losing ones job due to automation within the next 10 years versus the average outcome indicated in the title on the y-axis. The sample is restricted to the control group. Thin lines represent 95% confidence intervals.

Figure A.5: Fear of automation and populist attitudes



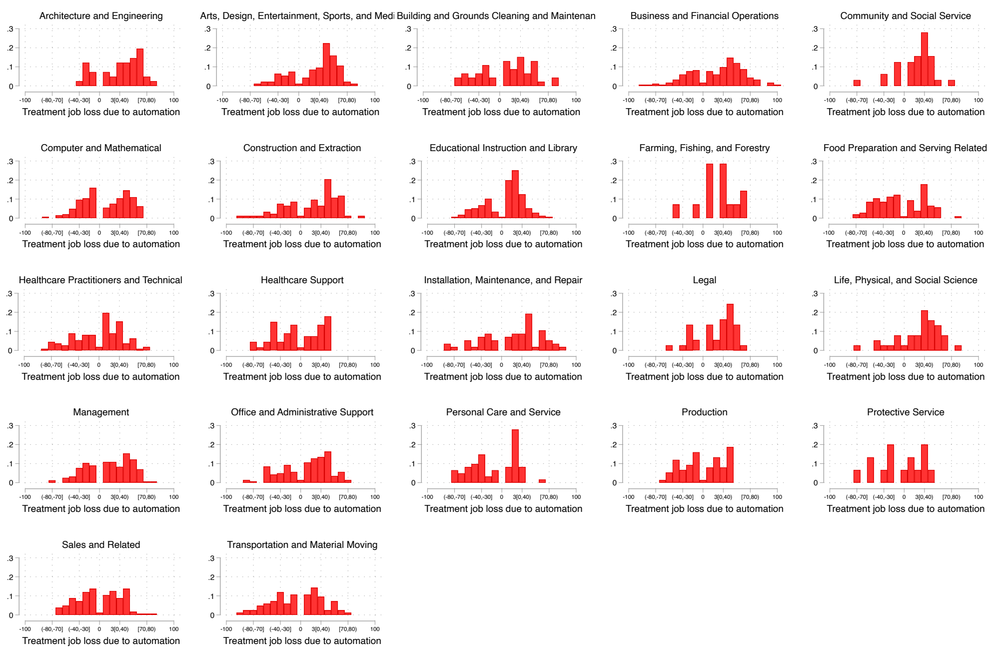

*Notes*: The x-axis shows the binned perceived probability of losing ones job due to automation within the next 10 years versus the average outcome indicated in the title on the y-axis. The sample is restricted to the control group. Thin lines represent 95% confidence intervals.

Figure A.6: Fear of automation and voting intentions




*Notes*: The x-axis shows the binned perceived probability of losing ones job due to automation within the next 10 years versus the average outcome indicated in the title on the y-axis. The sample is restricted to the control group. Thin lines represent 95% confidence intervals.

Figure A.7: Binned distribution of net treatment intensity by occupation




*Notes*: The figures show the binned distribution of net treatment intensities across occupations.

Table A.1: Factor loadings of redistribution index

| | L[1] |
|---|---|
| Average income tax | 0.644 |
| Tax on robot income | 0.654 |
| Duration unemployment benefits | 0.434 |
| Replacement rate unemp benefits | 0.551 |
| Permission to retire early | 0.513 |
| Log(amount of UBI + 1) | 0.552 |

*Notes*: The factor captures 32% of the variation.

Table A.2: Factor loadings of support index

| | L[1] |
|---|---|
| Favor funding adult training | 0.847 |
| Favor income support for poor | 0.847 |

*Notes*: The factor captures 72% of the variation.

Table A.3: Factor loadings of employment response index

| | L[1] |
|---|---|
| Intention to join union | 0.557 |
| Intention to retrain | 0.811 |
| Intention to switch occupation | 0.783 |

*Notes*: The factor captures 53% of the variation.

Table A.4: Factor loadings of populist attitudes index

| | L[1] |
|---|---|
| Enough of experts | 0.731 |
| Robots steal jobs | 0.517 |
| Anti elite | 0.274 |
| Inequality is a problem | -0.579 |
| Trust politicians | -0.049 |
| Left-right ideology | 0.730 |

*Notes*: The factor captures 29% of the variation.

Table A.5: Background characteristics and comparison with CPS data

| | Survey | CPS |
|---|---|---|
| Female | 0.490 | 0.470 |
| Age < 40 | 0.504 | 0.528 |
| University degree | 0.538 | 0.450 |
| White collar | 0.501 | 0.452 |
| Midwest | 0.211 | 0.205 |
| Northeast | 0.189 | 0.170 |
| South | 0.376 | 0.379 |
| West | 0.225 | 0.246 |
| Observations | 4284 | |

Table A.6: Balance table

| Variable | Control | People | Experts | All treated | Differences | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1)−(2) | (1)−(3) | (1)−(4) |
| Woman | 0.487 | 0.491 | 0.496 | 0.493 | 0.004 | 0.008 | 0.006 |
| | [0.500] | [0.500] | [0.500] | [0.500] | (0.844) | (0.655) | (0.693) |
| Age < 40 | 0.501 | 0.506 | 0.509 | 0.507 | 0.005 | 0.008 | 0.007 |
| | [0.500] | [0.500] | [0.500] | [0.500] | (0.783) | (0.671) | (0.668) |
| College graduate | 0.543 | 0.529 | 0.535 | 0.532 | -0.014 | -0.008 | -0.011 |
| | [0.498] | [0.499] | [0.499] | [0.499] | (0.458) | (0.658) | (0.468) |
| Married | 0.466 | 0.463 | 0.482 | 0.473 | -0.003 | 0.016 | 0.006 |
| | [0.499] | [0.499] | [0.500] | [0.499] | (0.856) | (0.399) | (0.686) |
| Number of kids | 0.762 | 0.728 | 0.745 | 0.736 | -0.034 | -0.017 | -0.026 |
| | [1.018] | [0.952] | [1.020] | [0.986] | (0.361) | (0.651) | (0.402) |
| White collar | 0.487 | 0.499 | 0.532 | 0.515 | 0.012 | 0.045** | 0.028* |
| | [0.500] | [0.500] | [0.499] | [0.500] | (0.534) | (0.015) | (0.062) |
| Midwest | 0.212 | 0.190 | 0.230 | 0.210 | -0.022 | 0.018 | -0.002 |
| | [0.409] | [0.392] | [0.421] | [0.407] | (0.143) | (0.242) | (0.872) |
| Northeast | 0.186 | 0.191 | 0.191 | 0.191 | 0.004 | 0.004 | 0.004 |
| | [0.390] | [0.393] | [0.393] | [0.393] | (0.762) | (0.762) | (0.710) |
| South | 0.376 | 0.386 | 0.365 | 0.376 | 0.010 | -0.011 | -0.000 |
| | [0.485] | [0.487] | [0.482] | [0.484] | (0.571) | (0.535) | (0.975) |
| West | 0.226 | 0.233 | 0.214 | 0.224 | 0.007 | -0.011 | -0.002 |
| | [0.418] | [0.423] | [0.410] | [0.417] | (0.638) | (0.467) | (0.878) |
| Observations | 2,146 | 1,069 | 1,069 | 2,138 | | | |

*Notes*: The first three columns show the mean and standard deviations of respondents' background characteristics, separately by treatment group. Standard deviations are reported in square brackets. The last two columns show differences in means between the control group and each of the two treatment groups. P-values for a test of differences in means between two groups are reported in parentheses. * p<0.1, * p<0.05, *** p<0.01.

Table A.7: Mean preferences, attitudes, and intentions amongst control group

| | | | |
|---|---|---|---|
| *Policy preferences* | | *Populist attitudes* | |
| Average income tax | .20 | Left-right ideology | .03 |
| Tax on robot income | .29 | Robots steal jobs | .47 |
| Duration unemployment benefits | 12.24 | Anti elite | .29 |
| Replacement rate unemp benefits | .61 | Inequality is a problem | .74 |
| Permission to retire early | .58 | Trust politicians | .13 |
| Monthly UBI in US$ | 3191.47 | Enough of experts | .43 |
| Favor funding adult training | .56 | | |
| Favor income support for poor | .47 | | |
| *Employment responses* | | *Vote intentions* | |
| Intention to join union | .49 | Will vote Republican | .36 |
| Intention to retrain | .45 | Will vote Democrat | .43 |
| Intention to switch occupation | .50 | Will not vote | .11 |

*Notes*: Average responses of the control group to outcomes evaluated.

Table A.8: Treatment effect of fear of automation on summary indices

| | (1) Redistribution | (2) Support | (3) Employment | (4) Attitudes |
|---|---|---|---|---|
| Treatment dummy | 0.0586* | 0.0328 | 0.0036 | 0.0157 |
| | (0.0317) | (0.0389) | (0.0301) | (0.0307) |
| Treatment intensity | 0.2212** | 0.2194* | -0.0028 | -0.1352 |
| | (0.1061) | (0.1228) | (0.0890) | (0.0914) |
| Perceived job loss to robot | 0.8669*** | 0.1574 | 0.8660*** | 0.3995*** |
| | (0.0728) | (0.0964) | (0.0741) | (0.0737) |
| Age | 0.0005 | -0.0020 | -0.0140*** | 0.0136*** |
| | (0.0020) | (0.0026) | (0.0020) | (0.0020) |
| Woman | -0.0225 | -0.0055 | -0.0164 | -0.0599 |
| | (0.0405) | (0.0451) | (0.0357) | (0.0406) |
| College graduate | -0.1171*** | 0.0488 | 0.0160 | -0.0543 |
| | (0.0433) | (0.0479) | (0.0349) | (0.0450) |
| Risk Taking | 0.0240*** | 0.0094 | 0.0351*** | 0.0277*** |
| | (0.0085) | (0.0108) | (0.0077) | (0.0086) |
| Patience | 0.0273*** | 0.0183** | 0.0174*** | -0.0031 |
| | (0.0065) | (0.0077) | (0.0059) | (0.0060) |
| Try new activities | 0.0436** | 0.0403 | 0.0994*** | -0.0162 |
| | (0.0181) | (0.0271) | (0.0161) | (0.0182) |
| Organized | -0.0489*** | -0.0224 | -0.0400** | 0.0417** |
| | (0.0168) | (0.0234) | (0.0180) | (0.0192) |
| Center of attention | 0.0230 | -0.0067 | 0.0062 | 0.0011 |
| | (0.0142) | (0.0185) | (0.0145) | (0.0139) |
| Comforting | 0.0588*** | 0.0547** | 0.0442** | -0.0649*** |
| | (0.0175) | (0.0241) | (0.0201) | (0.0181) |
| Worrier | 0.0664*** | 0.0284 | 0.0611*** | 0.0039 |
| | (0.0132) | (0.0187) | (0.0123) | (0.0138) |
| log(Earnings) | -0.0105 | -0.0007 | -0.0361** | -0.0172 |
| | (0.0167) | (0.0196) | (0.0156) | (0.0160) |
| unemployed | 0.1122** | 0.1365** | 0.2581*** | -0.1121** |
| | (0.0512) | (0.0544) | (0.0468) | (0.0536) |
| Union member | 0.3582*** | 0.0715 | 0.3551*** | 0.1814*** |
| | (0.0542) | (0.0687) | (0.0386) | (0.0461) |
| Constant | -1.0536*** | -0.5266** | -0.4319** | -0.5219** |
| | (0.1898) | (0.2414) | (0.1745) | (0.2063) |
| Control group mean | -0.03 | -0.01 | -0.01 | -0.01 |
| Observations | 4041 | 2843 | 4045 | 4052 |
| R-squared | 0.26 | 0.17 | 0.31 | 0.19 |
| Region FE | Yes | Yes | Yes | Yes |
| Occupation FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |

*Notes*: The dependent variables are indicated in the column headers. The redistribution index includes preferred average income tax rate , the tax rates on income generated by robots, duration of unemployment benefits, the replacement rate of unemployment benefits, permission to retire early, and the preferred log amount of UBI + 1. The support index includes favoring public funding for adult training and favoring public funding for income support for the poor. The employment index includes intentions to join a union, to retrain and to switch occupations. The populist attitudes index includes whether the respondent agrees with people having enough of experts, robots steal jobs, being anti-elite, inequality is a problem, and trusting politicians and left-right ideology. Each of the indices has a mean of zero and standard deviation of one, and is derived by extracting the first factor. Standard errors clustered at the occupation level are in parenthesis with stars indicating *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

Table A.9: Treatment effect of fear of automation on policy preferences

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Tax | | Unemployment benefits | | Retire | UBI | Government funding for | |
| | mean | robot | length | rate | early | Log(amount) | Adult training | Income support |
| *Panel A*: Baseline | | | | | | | | |
| Treatment dummy | 0.0058 | 0.0059 | -0.0014 | -0.0019 | 0.0291* | 0.1744** | -0.0034 | 0.0030 |
| | (0.0060) | (0.0083) | (0.4541) | (0.0081) | (0.0158) | (0.0700) | (0.0178) | (0.0209) |
| Treatment intensity | 0.0185 | 0.0209 | 0.7733 | 0.0235 | 0.0514 | 0.4946** | 0.0629 | 0.0945* |
| | (0.0195) | (0.0261) | (1.3130) | (0.0240) | (0.0464) | (0.2070) | (0.0523) | (0.0534) |
| Perceived job loss to robot | 0.1628*** | 0.1414*** | 1.4879 | 0.0414*** | 0.1975*** | 1.0232*** | -0.0067 | 0.1467*** |
| | (0.0151) | (0.0181) | (0.9186) | (0.0159) | (0.0358) | (0.1530) | (0.0396) | (0.0414) |
| Control group mean | 0.20 | 0.29 | 12.09 | 0.61 | 0.59 | 7.30 | 0.56 | 0.48 |
| Observations | 4054 | 4055 | 4056 | 4059 | 4059 | 4050 | 3318 | 3120 |
| R-squared | 0.28 | 0.19 | 0.15 | 0.18 | 0.17 | 0.16 | 0.18 | 0.18 |
| *Panel B*: Source of information | | | | | | | | |
| People dummy | 0.0027 | 0.0048 | -0.2178 | 0.0010 | 0.0404** | 0.1906** | -0.0040 | 0.0022 |
| | (0.0074) | (0.0091) | (0.5593) | (0.0100) | (0.0203) | (0.0866) | (0.0216) | (0.0241) |
| Expert dummy | 0.0089 | 0.0073 | 0.2230 | -0.0046 | 0.0185 | 0.1600* | -0.0027 | 0.0033 |
| | (0.0068) | (0.0100) | (0.5324) | (0.0098) | (0.0190) | (0.0827) | (0.0227) | (0.0250) |
| People intensity | 0.0260 | 0.0377 | 1.5767 | 0.0297 | 0.0850 | 0.6026*** | 0.0776 | 0.0715 |
| | (0.0231) | (0.0316) | (1.5903) | (0.0269) | (0.0596) | (0.2300) | (0.0626) | (0.0675) |
| Expert intensity | 0.0104 | 0.0039 | -0.0646 | 0.0179 | 0.0202 | 0.3909 | 0.0489 | 0.1175* |
| | (0.0232) | (0.0316) | (1.6529) | (0.0296) | (0.0514) | (0.2494) | (0.0648) | (0.0685) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Occupation FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: The dependent variables are indicated in the column headers. Columns 1 and 2 report results for regressions where the dependent variable is the preferred length in months and replacement rate of unemployment benefits, respectively. 'Retire early' indicates agreement with the statement that one should be allowed to retire early if their job is replaced by a machine. The 'UBI - Favor' takes value one if respondents report being in favor of UBI and zero otherwise. 'UBI - Log(amount)' is the logarithm of the amount that respondents think people should receive per month. 'Adult training' and 'Support poor' are binary indicators for agreement with increasing government funding towards adult training programs and income support programs for the poor. Standard errors clustered at the occupation level are in parenthesis with stars indicating *** p< 0.01, ** p< 0.05, * p< 0.1.

Table A.10: Treatment effect of fear of automation on employment behavior

| | (1) Join union | (2) Retrain | (3) Switch occupation |
|---|---|---|---|
| *Panel A*: Baseline | | | |
| Treatment dummy | 0.0156 | -0.0045 | -0.0042 |
| | (0.0095) | (0.0090) | (0.0091) |
| Treatment intensity | 0.0632** | -0.0243 | -0.0165 |
| | (0.0283) | (0.0298) | (0.0279) |
| Perceived job loss to robot | 0.1354*** | 0.1917*** | 0.2428*** |
| | (0.0229) | (0.0250) | (0.0232) |
| Control group mean | 0.49 | 0.44 | 0.49 |
| Observations | 4051 | 4053 | 4056 |
| R-squared | 0.26 | 0.27 | 0.27 |
| *Panel B*: Source of information | | | |
| People dummy | 0.0036 | -0.0059 | -0.0136 |
| | (0.0120) | (0.0107) | (0.0115) |
| Expert dummy | 0.0273** | -0.0035 | 0.0050 |
| | (0.0111) | (0.0107) | (0.0111) |
| People intensity | 0.0602* | -0.0461 | -0.0307 |
| | (0.0350) | (0.0355) | (0.0370) |
| Expert intensity | 0.0640* | -0.0029 | -0.0043 |
| | (0.0368) | (0.0348) | (0.0329) |
| Controls | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes |
| Occupation FE | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes |

*Notes*: The dependent variables are indicated in the column headers. 'Join union', 'Retrain' and 'Switch occupation' are measured as percent probabilities from 0-100 and correspond to the self-reported likelihood that the respondent will join (or stay part of) a union, retrain and switch occupation in the future. Standard errors clustered at the occupation level are in parenthesis with stars indicating *** p< 0.01, ** p< 0.05, * p< 0.1.

Table A.11: Treatment effect of fear of automation on populist attitudes

| | (1) Left-right ideology | (2) Enough of experts | (3) Robots steal jobs | (4) Anti elite | (5) Inequality problem | (6) Trust politicians |
|---|---|---|---|---|---|---|
| *Panel A*: Baseline | | | | | | |
| Treatment dummy | 0.0128 | -0.0053 | 0.0015 | -0.0007 | 0.0004 | 0.0116 |
| | (0.0173) | (0.0164) | (0.0155) | (0.0151) | (0.0135) | (0.0105) |
| Treatment intensity | -0.0863* | 0.0194 | -0.0099 | 0.0583 | 0.0587 | -0.0584 |
| | (0.0518) | (0.0491) | (0.0471) | (0.0442) | (0.0417) | (0.0366) |
| Perceived job loss to robot | 0.1105** | 0.1312*** | 0.2902*** | 0.1068*** | 0.1226*** | 0.1938*** |
| | (0.0434) | (0.0377) | (0.0362) | (0.0354) | (0.0363) | (0.0264) |
| Control group mean | 0.03 | 0.43 | 0.47 | 0.29 | 0.74 | 0.13 |
| Observations | 4055 | 4059 | 4058 | 4058 | 4059 | 4058 |
| R-squared | 0.20 | 0.15 | 0.18 | 0.16 | 0.16 | 0.30 |
| *Panel B*: Source of information | | | | | | |
| People dummy | 0.0178 | -0.0089 | -0.0052 | -0.0127 | 0.0043 | 0.0053 |
| | (0.0227) | (0.0211) | (0.0207) | (0.0184) | (0.0186) | (0.0129) |
| Expert dummy | 0.0078 | -0.0024 | 0.0074 | 0.0111 | -0.0030 | 0.0182 |
| | (0.0184) | (0.0191) | (0.0174) | (0.0170) | (0.0163) | (0.0128) |
| People intensity | -0.0856 | -0.0282 | -0.0529 | 0.0569 | 0.0893* | -0.0313 |
| | (0.0630) | (0.0598) | (0.0590) | (0.0579) | (0.0505) | (0.0441) |
| Expert intensity | -0.0860 | 0.0660 | 0.0315 | 0.0574 | 0.0290 | -0.0866** |
| | (0.0632) | (0.0622) | (0.0560) | (0.0518) | (0.0516) | (0.0438) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Occupation FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |

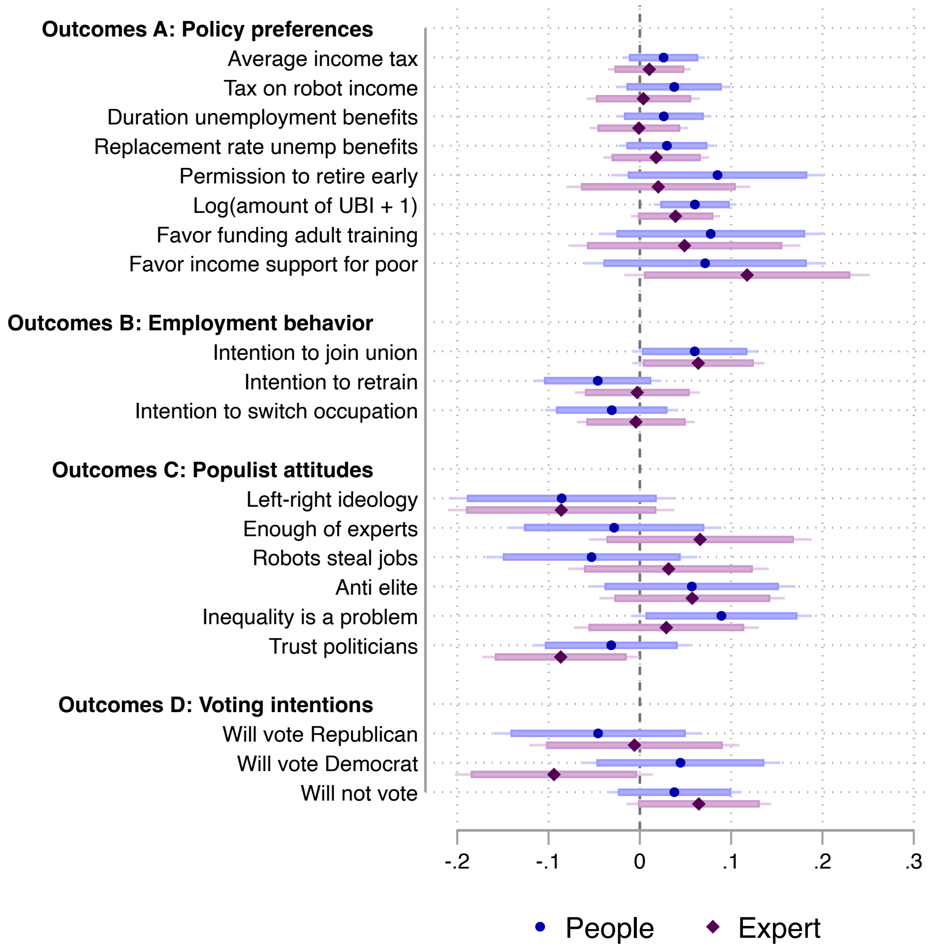
*Notes*: The dependent variables are indicated in the column headers. 'Left-right ideology' was elicited on a scale from -10 (left) to +10 (right) but enters the regression scaled between -1 and +1. All other outcomes are binary indicators equal to one if respondents 'agree' or 'strongly agree' to the corresponding statements. Standard errors clustered at the occupation level are in parenthesis with stars indicating *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

Table A.12: Treatment effect of fear of automation on voting intentions in next federal election

| | (1)<br>Vote<br>Republican | (2)<br>Vote<br>Democrat | (3)<br>Not<br>vote |
|---|---|---|---|
| *Panel A*: Baseline | | | |
| Treatment dummy | 0.0200 | -0.0187 | -0.0102 |
| | (0.0157) | (0.0154) | (0.0109) |
| Treatment intensity | -0.0276 | -0.0236 | 0.0510 |
| | (0.0484) | (0.0438) | (0.0328) |
| Perceived job loss to robot | -0.0668* | 0.0234 | 0.0599** |
| | (0.0365) | (0.0344) | (0.0244) |
| Control group mean | 0.36 | 0.43 | 0.11 |
| Observations | 4059 | 4059 | 4059 |
| R-squared | 0.15 | 0.17 | 0.17 |
| *Panel B*: Source of information | | | |
| People dummy | 0.0383** | -0.0322* | -0.0079 |
| | (0.0191) | (0.0181) | (0.0119) |
| Expert dummy | 0.0017 | -0.0044 | -0.0127 |
| | (0.0190) | (0.0185) | (0.0138) |
| People intensity | -0.0457 | 0.0445 | 0.0378 |
| | (0.0581) | (0.0557) | (0.0376) |
| Expert intensity | -0.0059 | -0.0940* | 0.0646 |
| | (0.0587) | (0.0553) | (0.0404) |
| Controls | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes |
| Occupation FE | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes |

*Notes*: The dependent variables are indicated in the column headers and are binary transformation to the answer of who the respondent is intending to vote for in the next federal election. 'Other candidate' is the missing category. Standard errors clustered at the occupation level are in parenthesis with stars indicating *** p< 0.01, ** p< 0.05, * p< 0.1.

Figure A.8: Effect of treatment intensity of fear of automation – Heterogeneity by source of information




*Notes*: Log(Amount UBI + 1) is divided by 10 and unemployment benefit duration is expressed in terms of 5 years, i.e. divided by 60. Controls include the individual perceived probability of job loss due to robots within the next 10 years, one measure for each of the Big 5, risk preferences, patience, whether the respondent has a university degree, is unemployed, sex, age, log(earnings), occupation fixed effects, industry fixed effects, and region fixed effects. Standard errors are clustered at the occupation level. Thick lines indicate the 90% and thin lines the 95% confidence intervals.

## A.1 Without controls

Table A.13: Treatment effect of fear of automation on summary indices

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Policies | | | |
| | Redistribution | Support | Employment | Attitudes |
| *Panel A*: Baseline | | | | |
| Treatment dummy | 0.0658** | 0.0306 | 0.0098 | 0.0191 |
| | (0.0313) | (0.0398) | (0.0308) | (0.0323) |
| Treatment intensity | 0.1882** | 0.2116* | -0.0344 | -0.1390 |
| | (0.0941) | (0.1260) | (0.0925) | (0.0971) |
| Perceived job loss to robot | 1.0079*** | 0.2229** | 1.0963*** | 0.4105*** |
| | (0.0705) | (0.0970) | (0.0695) | (0.0728) |
| Control group mean | -0.03 | -0.01 | -0.01 | -0.01 |
| Observations | 4046 | 2846 | 4050 | 4057 |
| R-squared | 0.22 | 0.16 | 0.24 | 0.17 |
| *Panel B*: Source of information | | | | |
| People dummy | 0.0592 | 0.0234 | -0.0233 | 0.0155 |
| | (0.0384) | (0.0489) | (0.0378) | (0.0397) |
| Expert dummy | 0.0733* | 0.0371 | 0.0411 | 0.0218 |
| | (0.0382) | (0.0484) | (0.0376) | (0.0395) |
| People intensity | 0.2609** | 0.1945 | -0.1146 | -0.1985* |
| | (0.1151) | (0.1534) | (0.1131) | (0.1188) |
| Expert intensity | 0.1144 | 0.2265 | 0.0388 | -0.0804 |
| | (0.1151) | (0.1526) | (0.1132) | (0.1187) |
| Controls | No | No | No | No |
| Region FE | No | No | No | No |
| Occupation FE | No | No | No | No |
| Industry FE | No | No | No | No |

*Notes*: The dependent variables are indicated in the column headers. The tax policies index includes preferred top marginal income tax rates, average income tax rates, and tax rates on income generated by robots, the other policies index includes duration of unemployment benefits, the replacement rate of unemployment benefits, permission to retire early, the preferred log amount of UBI + 1, favoring public funding for adult training, and favoring public funding for income support for the poor, the employment index includes intentions to join a union, to retrain and to switch occupations, and the aggregate index includes all of the before mentioned together. Each of the indices has a mean of zero and standard deviation of one for the analysis sample, and is derived by extracting the first factor. Robust standard errors clustered at the occupation level are in parenthesis with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

# B Questionnaire

### Background

1. What is your age in years?
   *Dropdown menu with years. Only 24-55 accepted.*

2. Please indicate your gender.
   *Male; Female; Other/Prefer not to say*

3. Race
   *White; Black or African American; American Indian or Alaska Native; Asian; Native Hawaiian or Pacific Islander; Two or More Races; Hispanic or Latino; Other*

4. Were you born in the United States
   *Yes; No*

5. Marital status
   *Married, spouse present; Married, spouse absent; Separated; Divorced; Widowed; Never married/single*

6. How many children under the age of 18 do you have living in your household?
   *0; 1; 2; 3; 4; 5; More than 5*

7. Are you currently doing any paid work, either as an employee or self-employed?
   *Yes; No*

8. When was the last time you did paid work, either as an employee or self-employed?
   *Never; Less than 2 years ago; Between 2-3 years ago; Between 3-4 years ago; Between 4-5 years ago; More than 5 years ago*

9. Are you actively searching for a job?
   *Yes; No*

### Education

1. Highest level of education
   *Less than high school degree; High school graduate (high school diploma or equivalent including GED); Some college but no degree; Associate degree in college*

*(2-year); Bachelor's degree in college (4-year); Master's degree; Doctoral degree; Professional degree (JD, MD)*

**Employment**

1. How many jobs are (were) you currently doing paid work for? Either as an employee or self-employed
   *1; 2; 3; 4; 5; More than 5*

2. Please think about your earning from your (last) main job. After tax, how much did you approximately earn per month?

**Industry and occupation**

1. What sort of occupation best describes this job?
   *Dropdown menu of occupations listed in CPS records: Management Occupations; Business and Financial Operations Occupations; Computer and Mathematical Occupations; Architecture and Engineering Occupations; Life, Physical, and Social Science Occupations etc.*

2. Which of the following categories best describes this job?
   *Dropdown list of occupation Categories listed in CPS records.*

3. What category best describes the industry of this job?
   *Dropdown list of industries listed in CPS records.*

4. Which of the following best describes the specific industry of this job?
   *Dropdown list of industries listed in CPS records.*

**Attention check**

1. Now, we would like to ask you a question about the following problem. In surveys such as this one, it is sometimes the case that participants rush through the questions without carefully reading them. Not only can this compromise the results of research studies, but it can also potentially lower the research quality of the answers. To show that you are reading the survey carefully, please select both "Very interested" and "Not at all interested" as answers to the following:

   Given the above how interested are you in politics?
   *Very interested; Somewhat interested; A little bit interested; Not very interested; Not at all interested*

**Personality traits**

1. In general, how willing or unwilling are you to take risks? Please tick a box on the scale from 0 to 10, where 0 means you are "Completely unwilling to take risks" and 10 means you are "Very willing to take risks."
   *0-10*

2. Are you generally an impatient person or someone who always shows great patience? Please tick a box on the scale from 0 to 10, where 0 means "Very impatient" and 10 means "Very patient."
   *0-10*

3. To what extent do you agree with the following statements about yourself? Please tick a box on the scale from 1 to 5, where 1 means "Completely Disagree" and 5 means "Completely Agree."
   - I am the first to try new activities.
   - I am very organized and always come prepared.
   - I don't mind being the center of attention.
   - I like to make other people feel at ease.
   - I am a worrier.

**Views on automation**

1. On a scale of 0-100%, how likely do you think it is that you might lose your job/not find a job due to automation, robots and artificial intelligence within the next 10 years?

**Treatment** One of the following treatments appear for the treatment group, and the participant is directed to the following questions without being shown the treatment for the control group.

1. We would like to provide you with the following information.
   Please read the information carefully.
   You guessed that the probability of losing your job due to robots or artificial intelligence within the next 10 years is [PIPED PROB LOSING JOB].
   We asked people like you who work in "[PIPED OCCUPATION] Occupations" and whose job classifies in the "[PIPED OCCUPATION CATEGORY]" category;

they stated the probability of losing this type of job due to robots or algorithms within the next 10 years is [PIPED AUTOMATION]%.
This is [PIPED DIFFERENCE] percentage points lower (higher) than your guess!
You must wait 10 seconds before moving onto the next section.

2. We would like to provide you with the following information.
   Please read the information carefully.
   You guessed that the probability of losing your job due to robots or artificial intelligence within the next 10 years is [PIPED PROB LOSING JOB].
   A study by expert economists at the University of Oxford estimated that the probability of losing a job classified as "[PIPED OCCUPATION CATEGORY]" in "[PIPED OCCUPATION] Occupations" due to robots or algorithms within the next 10 years is [PIPED AUTOMATION]%.
   This is [PIPED DIFFERENCE] percentage points lower (higher) than your guess!
   You must wait 10 seconds before moving onto the next section.

**Taxes**

1. There is a discussion about the introduction of universal basic income. Universal basic income is a concept where everybody, irrespective of whether they work or not, receive the same amount of money every month from the government, while all other benefit programs, such as food stamps or housing assistance, are removed. If universal basic income were to be introduced, how much should everybody receive per month?
   *Slider from 0-10,000*

2. In your opinion, what should the tax rate for income generated by robots be?
   *Slider from 0-100.*

3. How high do you think the average labor income tax rate should be?
   *Slider from 0-100.*

4. To what extent do you agree with the following statements?
   *Strongly disagree; Disagree; Neither Disagree nor Agree; Agree; Strongly agree*

   - People of this country have ad enough of experts
   - Robots steal jobs

- If someone's job is replaced by a robot they should be allowed to retire early and receive their public pension
- I trust politicians to do the right thing

5. On a scale of 0-100%, how likely do you think it is that you will do the following within the next 10 years?
   *Slider from 0-100*
   - You will retrain using an adult training program
   - You will switch occupations

**Political preferences**

1. We will now ask you whether you would be in favor of increasing government funds towards adult training programs and income support programs.

   Please keep in mind that an expansion of funds directed towards the programs below would mean cutting funds currently allocated towards other programs (e.g. affordable housing, defence, education, etc.).

   Would you say that you strongly favor, favor, neither favor nor oppose, oppose or strongly oppose increasing government spending towards the following:
   *strongly favor; favor; neither favor nor oppose; oppose; strongly oppose*
   - Adult training programs
   - Income support programs for the poor

2. Do you think inequality is serious problems in the United States?
   *Not a problem at all; A small problem; A problem; A serious problem; A very serious problem*

3. Unemployment benefits are payments made by authorized bodies to unemployed people.

   What percentage of their previous wage do you think people should receive as unemployment benefits every month?
   *Slider from 0-100*

4. How long after becoming unemployed should the unemployment benefits last for, if the worker does not find a new job despite searching?
   *Dropdown menu listing 1 month-5 years.*

5. On a scale of 0-100%, how likely do you think it is that you will stay a part of the labor union?
   *Slider for 0-100*

6. For which party's candidate do you think you will vote in the next presidential election?
   *Democrat candidate; Republican candidate; Other candidate; I will not vote*

**Outro**

1. Thank you for taking part in this study!
   Please continue to the following page for your responses to be recorded.