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DISCUSSION PAPER

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The End of Work Is Near, Isn't It? Survey Evidence on Automation Angst

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The End of Work is Near, Isn't It? Survey Evidence on Automation Angst *

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Abstract

We study the extent of automation angst and its role for policy preferences, labor market choices and real donation decisions using a customized survey in Germany and the US. We first document that a majority perceives automation as a major threat to overall employment and as a cause of rising inequality, whereas less than a third is concerned about their own labor-market prospects. We find evidence that automation angst is strongly associated with people's trust in governments and general political beliefs, especially in the US. At the same time, automation angst is associated with preferences for more policy interventions and also relates to stated and actual behavior. Using randomized survey experiments, we find that scientific information about zero net employment effects of automation, on average, reduce related concerns. Yet, treatment responses are multidimensional and depend on prior beliefs about the future or work. This translates into heterogeneous and sometimes even opposing effects on policy preferences and individual behavior.

JEL Classification: C91, D83, J23, O33

Keywords: Automation Angst, Labor Market Concerns, Policy Preferences, Survey (Experiment)

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1 Introduction

Recent advances in digital technologies that allow for automating an increasingly wide range of human tasks have been widely debated in the academic literature. While Acemoglu and Restrepo (2020a) find negative employment effects from robot adoption in the US, most other studies find either no or even positive employment effects of robot adoption, automation expenditures of firms or computerization (see the review by Aghion et al., 2022 and further references below). Generally, such positive net employment effects may arise if the labor-creating effect of automation technologies dominates the labor-saving effect (Acemoglu and Restrepo, 2019).

Despite the existing empirical evidence, the public debate seems to be biased towards the labor-saving (replacement) rather than the labor-creating nature of these technologies.[1] This is fueled by studies estimating that almost 50% of US jobs and a similar share in other advanced countries are at a high risk of being automatable within 1-2 decades (Frey and Osborne, 2017). Although evidence to the contrary suggests that a much lower share of jobs is potentially automatable (Arntz et al., 2017; Nedelkoska and Quintini, 2018; Pouliakas, 2018), negative narratives surrounding automation and its fatal consequences for the value of human labor and unemployment are widespread in popular science (e.g., Precht, 2018), newspaper articles[2] and areas of the economic profession (see Shiller, 2019 for an overview) alike. Presumably driven by such one-sided debates, the general public is more pessimistic about the impact of automation than experts (Walsh, 2018). Shiller (2020) even argues that fears of automation are part of a historically recurring narrative which is subject to a long and vivid history of stories about mass job losses or degradation that recur in worries over the effects of modern robots and AI for the labor force (Shiller, 2019; Autor, 2015; Mokyr et al., 2015).

If such one-sided narratives entangle, people likely develop false negative perceptions about the (actual) labor market effects of automation. Such negative perceptions may then have real consequences: They can affect people's acceptance of new technologies, potentially slowing down innovation and related productivity gains (Eißer et al., 2020); they can reduce the willingness to prepare for changing demands and skill requirements (Rodriguez-Bustelo et al., 2020); and they may also increase people's propensity to vote for radical right parties (Anelli et al., 2021; Caselli et al., 2021; Im et al., 2019). Beyond this, the Luddite protest movements against new machinery in 19th century England even resulted in the destruction of newly installed machines (Caprettini and Voth, 2020).

[1] Kregel et al. (2021) show empirical estimates that the majority of news article circulation on robotic process automation was indeed dominantly negatively in the two years preceding our survey.

[2] Examples include New York Times (2016), New York Times (2020), BBC (2019), The Economist (2018), CNBC (2017), The Guardian (2017), BBC (2015), FAZ (2018), Spiegel (2018), and Die Zeit (2016).

This paper aims to develop a better and more nuanced understanding of concerns related to the perceived impact of automation on the labor market as well as on individual labor market prospects (i.e., different margins of *automation angst*). We do so in the context of two advanced economies, the US and Germany, which are both strongly affected by automation, but differ in terms of their welfare system and the political landscape. In particular, our paper has the following objectives. First, we document perceptions about the implications of automation along three dimensions: i) the overall labor-market situation (e.g., impact on aggregate employment), ii) the individual labor-market situation (e.g., fear of losing one's job), and iii) distributional aspects (e.g., impact on different skill groups). Second, we examine how these perceptions are associated with demographics, individual labor-market risks and political views, and how they relate to policy preferences and individual labor-market behavior. Third, we use randomized survey experiments to study whether perceptions are responsive to information. We particularly ask whether one can turn around the presumably negative narrative on automation on labor market outcomes by the provision of scientific information. Fourth, we shed light on related cross-country differences, which potentially occur because perceptions and related outcomes are affected by the generally lower level of redistribution towards the poor in the US (e.g. Alesina et al., 2001) and a high degree of political polarization in the US that is accompanied by polarized views on how economic and social issues should be addressed (Alesina et al., 2020).

We approach these objectives using comprehensive and representative web-based surveys with randomized components in the US and Germany (described in Section 2). Our final survey sample comprises 5,147 respondents, including about 3,000 respondents from the US and 2,000 respondents from Germany. Throughout the survey and the paper, we use a broad concept of automation that allows us to appeal to survey respondents from different countries, sectors and occupations.[3] In a first step (see Section 3.1), we introduce three main dimensions of automation angst in a brief conceptual framework and document the empirical patterns of automation angst. We find that people are strongly concerned about the impact of automation on the economy as a whole and on inequality, but less so regarding their personal economic situation. In fact, more than half of respondents in both countries expect aggregate unemployment to increase because of automation, while around 10% expect unemployment to decline. Around 90% of respondents in both countries further expect unequal effects of automation, where the labor market prospects of low-skilled workers are believed to suffer most severely. At the same time, less than 30% of respondents in both countries are concerned about their personal risk of becoming

[3] We refer to automation as *the technological progress currently taking place, especially in the field of robotics, big data, and artificial intelligence* and further express that *these developments enable a largely digitally controlled production of value, thus enabling workflows to be increasingly automated.* All survey respondents are transparently informed about our concept of automation.

unemployed. While such individual concerns are comparable between countries, general and distributional concerns regarding the impact of automation on the entire economy turn out to be more polarized in the US than in Germany with more replies on both extremes of the respective question scales.

Second (Section 3.2), we document that the perceived risk of becoming unemployed oneself due to automation is strongly correlated with job and employment characteristics in both countries, a finding that is consistent with an economic self-interest motive (Dekker et al., 2017). In addition, we see that, conditional on a broad set of covariates, general political preferences are strongly associated with all dimensions of automation fears in the US, but not in Germany, and that these views contribute to polarized perceptions of automation. For instance, for a left-wing proponent, concerns about rising unemployment and distributional concerns are 0.2 and 0.5 standard deviations higher than for a right-wing supporter (conditional on demographics, job and workplace characteristics, among others). This is consistent with previous US findings that political views matter for perceptions in the US (e.g., Alesina et al., 2020).

Third (Section 3.3), we explore how automation perceptions are linked with outcomes that potentially translate into real-world behavior. In particular, we study the correlation between perceptions with policy preferences, individual labor market behavior and donations to charities (as a proxy for prosocial behavior).[4] We find that all dimensions of automation fears are strongly associated with higher demand for policy support and interventions, even as we condition on political and economic views, demographics and work characteristics. The magnitude of these effects are similar to differences in policy preferences between, for instance, rich and poor households. Moreover, if automation is expected to raise aggregate unemployment or to increase inequality, people are more willing to switch occupation in case of unemployment and to invest in their own training, but they donate less to charities. We also observe that the perceived personal risk of being laid off due to automation is more strongly correlated with policy demand and the willingness to invest in training in the US than in Germany, potentially reflecting the less generous safety net in the US. These findings suggest that people perceive automation as a threat that needs to be addressed by more policy intervention and support, but that also necessitates an individual effort to cope with automation-induced changes, especially in the US.

Fourth (Section 4), our survey includes a randomized information experiment to investigate if automation fears reflect correctable misperceptions and whether communicating scientific information can change the negative narrative of automation effects on the labor market. We randomly provide respondents with information about some

[4]The donation decision is implemented as an actual incentivized decision, see Section 2.

of the findings of the recent cross-country study by Graetz and Michaels (2018).[5] Our first experimental group receives information about the study's finding that robots do not significantly decrease overall employment, and the second experimental group is informed about its finding that robots decrease the employment share of low-skilled workers. A neutral control group does not receive information about the study.[6] Given our previous findings, we expect the first information treatment ("no aggregate employment effects") to have a stronger corrective effect on perceptions of automation than the second information treatment ("distributional effects"). This is because the first treatment likely works against the prevalent perception that automation increases overall unemployment, while information about distributional effects (second treatment) is consistent with prior perceptions in the general public.

In line with these expectations, the first treatment ("no aggregate employment effects", see results in Section 4.2) reduces respondents' fears of higher aggregate unemployment (by about 0.15 standard deviations, on average) and also reduces concerns that skilled workers might suffer from automation. Induced shifts turn out to be somewhat stronger in the US, suggesting that the role of political and economic attitudes in the US provides more leverage for correcting views by providing objective information. Moreover, we find that treatment effects are not uniform and depend on people's prior attitudes towards technological change, which are themselves strongly predicted by political ideology, trust and general economic beliefs. Reduced concerns about rising unemployment are driven by individuals with pessimistic prior beliefs. Treatment-induced shifts of individual and distributional concerns, however, are more prevalent among those with less pessimistic views. On the one hand, these results hence support the notion of systematic misperceptions in the context of overall employment effects – possibly due to a one-sided public debate. On the other hand, the results stress that the same information triggers individual-specific and heterogeneous responses of perceptions. As regards the second treatment ("distributional effects", see results in Section 4.3), the corrective effect is small and works against concerns that workers with a college education might suffer from automation (-0.1 standard deviations), suggesting that the distributional impact of

[5] Specifically, Graetz and Michaels (2018) study the causal effects of modern industrial robots on employment and productivity. Due to the use of cross-country data (including the two countries in our survey, US and Germany) and its credible approach for causal inference, their study is a suitable source for providing subjects in our survey experiment with relevant scientific information about the labor-market effects of automation. In addition, the study allows us to randomly inform individuals about the effects of automation on both aggregate employment and distributional aspects (also see Section 2.3).

[6] Our previous documentation of perceptions and fears is based on control-group respondents (as they did not receive any information). A fourth group receives a different order of survey questions than all other groups where questions about policy preferences and individual labor market behavior come ahead of questions that relate to labor-market automation. For example in Alesina et al. (2022), Daniele et al. (2020a) and Daniele et al. (2020b), this alternative sequence of questions allows for testing priming effects. For brevity, we do not discuss the related results here, but refer to Section 2.3 and Appendix Section H for a detailed discussion.

automation was even considered to be worse than our intervention suggested.

Consistent with these previous findings, communicating scientific evidence on the lack of aggregate employment effects of automation (first treatment) also translates into a heterogeneous policy-demand response. While respondents with optimistic prior beliefs respond to the treatment by reducing the demand and support for policy interventions, we find somewhat weaker, opposite responses for previously neutral respondents and none for pessimists for whom fears regarding economy-wide future unemployment rates were alleviated most. This suggests that, even if the provision of scientific information reduces anxieties related to automation, this does not necessarily translate into uniform policy responses because the same information treatment shifts different dimensions of automation angst and results in different conclusions drawn depending on people's prior beliefs. This even results in partly opposing responses regarding policy preferences, labor market choices and donations to charities.[7]

Contribution to the Literature Our paper relates to several strands of the literature. First, we speak to a vibrant literature that uses non-survey data to investigate the employment effects in the context of labor-market automation and digitalization.[8] This literature strand typically finds distributional effects of automation (see also Acemoglu and Restrepo, 2020b, 2021), but generally no negative effects on aggregate employment (Acemoglu and Restrepo, 2020a being the exception). Mainly based on administrative data, these papers provide the empirical basis for our survey experiment.[9] Our paper complements this literature by providing novel evidence on the extent and role of perceptions in the context of automation. This is important even in light of robust evidence based on observational data, because labor-market behavior and the demand for policy are shaped by individual perceptions, rather than actual threats (Mueller et al., 2021). Our paper thus informs labor-market policy and can point to potential strategies that help to correct biased perceptions. Our findings underline the complexity of this task as addressing one dimension of automation angst does not necessarily mitigate other dimensions thereof and the same information may trigger opposite responses depending on heterogeneous prior beliefs.

[7]We also use a follow-up survey to assess the persistence of the treatment effects. We find no bouncing back of the perceptions among the treated respondents; see Section 4.4 for a more detailed discussion.

[8]This literature includes work on the labor-market effects of robot adoption (Dauth et al., 2021; Graetz and Michaels, 2018; Mann and Püttmann, 2018; Aghion et al., 2020; Acemoglu and Restrepo, 2020a; Koch et al., 2021; Humlum, 2019; Dixon et al., 2021; Hirvonen et al., 2022), cutting-edge 4.0 technologies including artificial intelligence (Genz et al., 2021; Acemoglu et al., 2022), automation expenditures of firms (Bessen et al., 2019) and computerization (Autor and Dorn, 2013; Gregory et al., 2022; Bessen et al., 2019).

[9]Based on an extensive review of the literature and own empirical work using French data, Aghion et al. (2022) find that automation has a positive effect on labor demand both at at the firm level and industry level.

Using a survey-based approach, we also relate to a small but evolving set of papers that survey aspects of automation concerns (e.g., Dekker et al., 2017; McClure, 2018; Mulas-Granados et al., 2019; Rodriguez-Bustelo et al., 2020; or Gallego et al., 2022) and the implications of occupational risk exposure to automation for policy preferences (e.g., Mulas-Granados et al., 2019; Zhang, 2019; Thewissen and Rueda, 2019; Jeffrey, 2021; or Gallego et al., 2022). Compared to our paper, these surveys do not consider different types of automation angst (economy-wide, personal and distributional), their respective determinants, and associations with policy attitudes and individual labor-market strategies to cope with automation. Yet, our findings suggest that different dimensions of automation angst show distinct patterns and that focusing on one proxy of automation angst omits relevant channels and effects of how perceptions shape preference formation and behavior. Furthermore, our paper is the first to run survey experiments to study whether scientific information about unemployment and distributional effects of automation shift labor-market perceptions and subjective fears of the general public, and whether and how exactly they translate into policy demand and personal labor market choices. The comprehensive nature of our survey allows us to study interesting and relevant treatment responses that depend on prior beliefs and attitudes towards automation.

More generally, we relate to a growing literature that uses customized large-scale surveys and survey experiments to shed light on perceptions in the context of particular fields and policies; see the overview paper by Haaland et al. (2022) and recent examples such as Stantcheva (2021) and Haaland and Roth (2021). There generally is only very little experimental survey evidence on societal (mis)perceptions of labor-market mega-trends – such as technological change (but also globalization, decarbonization and demographic change, as defined by Socialeurope, 2018) – and their influence on policy preferences. Our study advances the understanding in the context of a very important labor-market trend, i.e. the labor market repercussions of automation. Lastly, there is, of course, a long tradition in using surveys in labor economics; recent examples include Mueller et al. (2021) and Jäger et al. (2021). However, we are only aware of the papers referenced above that use surveys with a specific focus on automation.

2 Survey and Randomized Treatments

2.1 Data Collection and Sampling

Our data are obtained from a survey that we conducted in the US and Germany in February-March 2019. All respondents are residents of the respective country in which they were surveyed. We commissioned the commercial survey provider *YouGov* to implement the survey.[10] Invited survey participants[11] are not being told about the topic of the survey, only that their participation contributes to a scientific study. Upon the survey invitation, participants are asked to answer the survey questions carefully and are assured that their participation is voluntary. We inform them that the survey should take (on average) 15 minutes and that the compensation for completing the survey equals 1,000 (750) Yougov coins in the US (Germany) which is equivalent to about 1 USD (1.5 Euro). We also inform participants that participation in the survey automatically enrolls them in a lottery for 1,000 USD.

Since our study is on the labor-market implications of automation, we focus on individuals who are part of the active labor force and not close to retirement. To meet this objective, the survey provider only invited residents in the US and Germany between 18 and 55 years old. The resulting initial "gross" sample of 7,482 individuals is designed to be representative for the working-age population in terms of age, gender, education, regions as well as net household income in the US and Germany, respectively. In the initial part of the survey, we then used filter questions to screen out those individuals who are not in the active labor force such as i) unemployed and currently not looking for a job, ii) unemployed and currently in vocational training, iii) unemployed and have never been employed before, iv) pensioners and/or retirees, v) incapable of working, and/or vi) in general education (such as college students).

Those either currently employed or currently unemployed, but seeking employment, then participated in the full survey. The corresponding final ("net") sample then comprises 5,147 respondents (US: 3,066 and Germany: 2,081). A non-response analysis which regresses participation in the final sample (i.e., being in the net sample after applying restrictions and filters) on dummies of region and country of residence, education level, employment status, gender and age dummies suggests no systematic attrition patterns.[12] We nevertheless use sampling weights provided by the survey provider (which are based on census information for the target variables) in all subsequent analyses to ensure our sample is as representative as possible.[13] Appendix Table A.1 presents summary statistics for key demographics in our weighted survey sample and compares these to population statistics (separately by country). Our sample proves fairly comparable to the overall US and German population along these dimensions, respectively.

[10] This survey provider is commonly used for scholarly research (Haaland et al., 2022). More information about YouGov is available on the company's web appearance: `https://today.yougov.com/`.

[11] Participants enroll on the Yougov online panel. Yougov then invites online panelists to participate in our survey via email.

[12] Results are available upon request.

[13] All our results are very similar – both quantitatively as well as qualitatively – if we do not use survey weights (results are not reported for reasons of brevity, but are available upon request).

2.2 Structure of the Survey

In the following, we summarize the sequence of the survey. The full questionnaire is available in Appendix I.[14] The survey can be categorized into four blocks which we label **A**, **B**, **C**, and **D**. We describe those four blocks below. Four weeks after the initial survey, we ran a **follow-up survey** which we describe in Section 2.4.

Block A: Background Information. This block surveys standard demographic characteristics and respondents' labor-market history. We also survey political and economic beliefs (e.g., self-placement in left-right-spectrum and trust in government) in this survey block.

Block B: Perceptions about Automation (incl. randomized interventions). Block B begins by explaining that the subsequent part of the survey is about the implications of digital technologies and automation for the labor market. We define the concept to all survey participants as follows:

"The technological progress currently taking place, especially in the field of robotics, big data, and artificial intelligence. These developments enable a largely digitally controlled production of value, thus enabling work flows to be increasingly automated. Additionally, these digital production technologies form the foundation of new internet-based business models."

Our definition of digital technologies is thus not limited to production technologies, but also encompasses digital technologies that are relevant in the service sector as a means of automating and creating job tasks. After this introduction, block B contains the following elements:

B.1 – Prior beliefs. We first survey what we call prior beliefs, i.e. perceptions about the future of work that we ask prior to providing respondents with further information. We particularly survey prior beliefs regarding the past and future value of human work.

We use these questions to examine the extent to which such prior beliefs affect people's response to the information treatments. If strong prior beliefs reflect genuine misinformation, we would expect that people with extreme priors are more responsive to being exposed to scientific information. On the other hand, extreme prior beliefs might be more difficult to correct by objective information.

[14] The survey can also be viewed online via the following links: US version: `https://isurvey-us.yougov.com/refer/vsMGkxyS8MtZ4y`; Germany version `https://start.yougov.com/refer/vYL8nbPmSnnxz3`.

B.2 – Information Treatments. In a next step, we include a randomized survey experiment which we describe in Section 2.3.

B.3 – Perception Measures. We then survey perceptions regarding the impact of automation with respect to three main dimensions. For each of these main dimensions, we survey four perception measures:

- **General implications:** substitutability between digital technologies and the human workforce, effect on overall unemployment rate, effect on overall prosperity, and overalldesirability of digitalization.
- **Individual implications:** risk of becoming unemployed, salary implications, replaceability of own tasks by machines, being a loser or winner of digitalization.
- **Distributional implications:** inequality across social groups, assessment of impact on workers with and without high-school diploma and with college education.

These survey questions allow for a nuanced documentation of perceptions across different dimensions in the context of labor-market automation. Section 3.1 conceptualizes the three dimensions and discusses them in more detail.

Block C: Policy Preferences, Labor Market and Donation Decision. Question block C first surveys respondents' preferences for public policies. This includes their views on various types of government interventions such as redistributive actions and their desired allocation of government budget. We also survey the individual support of more specific labor-market policies and we collect stated labor-market choices on whether respondents would be willing to participate in vocational training, or to accept a job with a lower salary or switch occupation in case of unemployment.

Question block C also includes an **actual donation decision** (see Appendix Figure I.5 for a screenshot). The motivation to include a "real" donation decision is twofold. First, there are sometimes concerns that the responses in conventional survey questions are different from actual decisions. We therefore included a survey component that includes actual monetary stakes. Second, the donation decision provides the opportunity to shed light on the question of how perceived threats from automation are linked to pro-social behavior and solidarity. In addition, the choice between different recipients of the donation (see below) allows us to study what type of solidarity respondents consider most suitable.

Respondents were informed that upon survey completion, they are automatically entered in a lottery with a price of 1,000 USD (Euro). All respondents were then asked to decide in advance if they want to keep the price money for themselves or wish to donate all or a part of the price money to three different charities which differ with respect to their objectives.

The three charities were chosen to reflect different strategies to address the implications of digital technologies for the labor market. In both countries, the choice was between three types of NGOs that either aim at i) improving digital education, ii) supporting the poor with free food, or iii) raising equality of opportunity by assisting children from low-income backgrounds.[15] The donation decision can thus be related to perceptions of automation and sheds light on the respondent's solidarity in response to labor-market automation.

Block D: Workplace Characteristics, Household Income and Survey Quality. The questionnaire asks for a small set of workplace-related characteristics at the end of the survey. We decided to include these questions upon the end, rather than in block A, to avoid that these questions introduce a priming. The surveyed characteristics include questions regarding the daily work routine (e.g. share of routine or manual tasks), the job-related use of digital technologies and whether job requirements have been rather increasing or decreasing during the last three years.

We finally also survey household income and ask if the survey was perceived to be politically unbiased by participants. Reassuringly, the survey results show that 80% of all respondents do not find the survey to be politically biased and only 5% consider the survey to be strongly leaning either to the left or right.

Summary Statistics. For the median respondent, the survey took 18.9 minutes to complete. In order not to apply any arbitrary sample restrictions based on survey duration, the following analysis always uses the full sample.[16] For this sample, Table 2 contains summary statistics of the main variables from block A and D[17] for the US and German sample.[18] While most demographic characteristics are quite comparable across

[15]We chose the following NGOs (see their websites for more information): **Digital education:** NGOs that encourage high-school students to study computer science. US: *Code.org* (`https://code.org/`), Germany: *Digitale Bildung für Alle e.V.* (`https://digitalebildungfueralle.org/`); **Foodbank:** NGOs that organize food banks throughout the country. US: *Feeding America* (`https://www.feedingamerica.org/`), Germany: *Die Tafel e.V.* (`https://www.tafel.de/`); **Equal opportunity:** NGOs that help children from low-income backgrounds to graduate from high school and college. US: *iMentor* (`https://imentor.org/`), Germany: *ArbeiterKind* (`https://www.arbeiterkind.de/`).

[16]Reassuringly, we get almost identical results for the main analyses when excluding respondents with survey durations below the 1st or above the 99th percentile. Importantly, the assignment to the experimental group does not have any explanatory power for being an outlier, but younger respondents and US respondents are more likely to have extreme durations.

[17]Note that block D questions on workplace characteristics were asked at the end of the questionnaire after the information treatments. The later analyses hence treat these variables differently (although they should not be affected by our experimental treatments because they measure objective facts).

[18]For the subsequent analysis, we define categorical variables which are described in Appendix Table A.2.

countries, a much higher share of US respondents has a college education, reflecting that many workers in Germany receive an apprenticeship instead of tertiary education. Moreover, the share of rich households with more than twice of the median household income is larger in the US than in Germany, where a much higher share belongs to middle income households. The vast majority of respondents are currently employed, but half of them in Germany and almost 60% in the US have previously been unemployed at some point in time. In the US, twice as many respondents are self-employed, while a higher share in Germany report working in a precarious job. This latter finding likely reflects the high share of part time employment and minor jobs among women in Germany as compared to the US. The share of manual tasks on the job is quite comparable across both countries, while the share of routine tasks and, hence, the risk of being replaceable by machines, is somewhat higher in Germany (37.8%) than in the US (32.2%). US respondents also report a higher share of IT-based tasks. Despite these differences, however, a comparable 50% in both countries report increasing on-the-job skill requirements in the last 3 years, while less than 10% report any deskilling.

Finally, the share of respondents placing themselves at the extreme ends of the political spectrum is much higher in the US (50.9%) than in Germany (24.9%). Pro-market views are more widespread in the US, whereas anti-market views are shared by around a quarter of respondents in both countries. Further, the share of people with a high level of mistrust in the government exceeds 50 percent in both countries.

2.3 Randomized Treatments

People may be misinformed about the implications of automation and therefore potentially form incorrect perceptions and expectations. This, in turn, could lead to biased political demand and sub-optimal individual responses. In order to study how the provision of scientific information about the implications of automation affects respondents' perceptions of automation, their political preferences, charitable donation behavior and stated labor market choices, we implement randomized information treatments before measuring the relevant perception questions and outcomes in blocks B.3 and C. In particular, we have four randomized groups in a between-subjects design described below in detail. Table 1 provides an overview of the four groups and their corresponding sample size by country.

Information Treatment Groups ($ABCD_1$ and $ABCD_2$). Treatment groups $ABCD_1$ and $ABCD_2$ receive the standard order of question blocks (as indicated by $ABCD$) and are exposed to one of two information treatments (denoted by subscripts 1 and 2, respectively). The information treatments are based on the findings of the recent study by Graetz and Michaels (2018), see below for a discussion of the study choice. They provide credible cross-country evidence on the economic implications of modern industrial robots for 17 countries in the period 1993–2007. The paper finds that robots do not significantly decrease overall employment, but they decrease the employment share of low-skilled workers. The authors show that the lack of overall employment effects is due to the fact that an increased robot usage improves labor productivity and reduces output prices, thereby boosting international competitiveness. To underline its credibility, the treatment information in both treatment groups include the exact bibliographic reference of Graetz and Michaels (2018). We randomly elicit two types of information based on this study:

Information I_1 - "no aggregate employment losses". Respondents in treatment group $\mathbf{ABCD_1}$ receive information I_1 about the role of automation for aggregate employment levels. The information highlights the theoretical channel that automation does not necessarily lead to a decline in employment because automation induces an improvement of firms' competitiveness. The subsequent part of the treatment summarizes the empirical results of Graetz and Michaels (2018) in this context, namely that the number of hours worked has remained constant despite the use of digital technologies. . A screenshot of the treatment (including its exact wording) is displayed in Figure 2.

Information I_2 - "employment shifts from unskilled to skilled workers". The information I_2 displayed to respondents in treatment group $\mathbf{ABCD_2}$ focuses on the distributional implications of automation. In particular, the treatment highlights that automation may have heterogeneous effects on workers with different educational backgrounds. It subsequently summarizes the empirical findings by Graetz and Michaels (2018) that more qualified workers have displaced less qualified workers. A screenshot of the treatment (including its exact wording) is displayed in Figure 3. Recently, supporting evidence from Acemoglu and Restrepo (2021) found that task displacement by automation explained at least 65% of the rise in college wage premium as well as about 50% of changes in the overall wage structure in the US.

Control Group ($ABCD_0$). The control group, $ABCD_0$, did not receive any information treatments (indicated by subscript 0) and received the same 'standard' order of question blocks, A-B-C-D, as the two information-treatment groups. The control groups has two purposes. First, it serves as the comparison group in the randomized survey experiment (see below for a discussion of identification and balancedness across groups). Second, because respondents in the control group do not receive any information that could affect their perceptions, we use the control group for the plain documentation of perceptions about labor-market automation (see Section 3.1).

Priming Group ($ACBD_0$). Respondents in this group receive the survey questions in different order. In particular, they receive question block B about automation in the labor market after answering questions from block C. In other words, respondents in this group were not exposed to questions related to automation before being asked about preferred policy measures, stated labor market choices and donation decisions. Just as the control group, however, this group did not receive an information treatment and we denote this treatment group as $ACBD_0$. A comparison of control group $ABCD_0$ with priming group $ACBD_0$ hence allows for examining differential outcomes due to priming the respondents with the automation topic and making the topic salient to them (similar as e.g., Alesina et al., 2022).

Motivation for Information Provided. We chose Graetz and Michaels (2018) to be the basis for our survey experiment in the two information treatments I_1 and I_2 for several reasons. First, their paper offers credible causal identification (using an instrumental variable strategy) and offers external validity based on a cross-country sample with 17 advanced economies, including our survey countries Germany and the US. Other related studies only cover either the US or Germany and hence do not provide findings that can be applied easily to both countries. Second, using their study allows us to provide information on both the aggregate employment effect and distributional consequences that come from the same unified empirical approach. Third, the results in Graetz and Michaels (2018) mirror the majority of findings in the empirical literature on the effects of automation on employment and equity (see the review paper by Aghion et al., 2022 and recall the papers referenced in the Introduction). However, we acknowledge that the literature is not yet settled with regard to automation effects. For example, the effects of automation on labor markets may be different across countries, as might be concluded from the recent results by Acemoglu and Restrepo (2020a) for the US and by Dauth et al. (2021) for Germany. Yet, these papers had not been published when our survey was in the field and do not cover both countries within a unified approach. Hence, to underline the credibility of information provided in the treatments, we also required the chosen research paper to be published in a prestigious journal after having gone through full peer review.

Discussion of Identification and Experimenter Demand Effects. The identification of causal effects of our information treatments rests on random assignment to control group and treatment groups. In order to test whether the randomization led to a balanced sample of respondents across the control group and the treatment groups, Appendix Table A.3 runs a multinomial logit to explain the group assignment with the characteristics from block A. Although there are a few characteristics with significant relations to the treatment groups, the overall F-test of the model implies that the model has no explanatory power. The number of significant point estimates among personal background characteristics is also well in line with the margin of random error. Hence, the respondents are, on average, balanced across groups, allowing us to identify causal treatment effects with our data.

To identify the effect of the information treatments, we compare the two information-treatment groups, $ABCD_1$ and $ABCD_2$, to the control group, $ABCD_0$. All three groups face the same order of survey questions ($ABCD$) and our survey is designed such that the automation topic is equally salient to respondents in all three groups. For example, as we describe above in Section 2.2, all three groups are exposed to an opening statement at the beginning of question block B in which we introduce the general topic of the survey and where we provide our definition of automation. In addition, all three groups receive prior-belief questions (for example about the future of work and the value of human work; see question block B.1) which potentially raise the salience of the topic. As a result, the three groups are only different with respect to the information that they are exposed to. The results from our priming experiment (i.e., comparing the control group, $ABCD_0$, to the priming group, $ACBD_0$) show that the mere exposure to the topic of automation does not trigger any notable effects (see Appendix Section H). This supports the idea that the control group and the information-treatment groups are only different with respect to the information level, because aspects of priming and salience do not seem to play a decisive role.

To gain insights as to whether respondents find the provided information trustworthy and helpful, we asked respondents at the end of the survey for a corresponding assessment. These questions were answered by about 90% of all treatment-group respondents and, among them, 87% consider the treatment information to be trustworthy and 82% consider it to be helpful. Reassuringly, this suggests that a high share of treatment-group respondents paid attention to the information treatments and found them relevant and reliable.

A potential concern with most (survey) experiments is that experimenter effects could drive some of the findings. As we show below, we find pronounced heterogeneities in our treatment effects. Such heterogeneity is strongly indicative that experimenter demand effects do not drive our results as it is implausible that experimenter demand effects are exactly aligned with the type of heterogeneities that we find. This is also consistent with two recent papers by de Quidt et al. (2018) and Mummolo and Peterson (2019) that explicitly study experimenter effects in survey experiments. They provide evidence that experimenter demand is apparently not much of a concern in survey experiments.[19]

[19]For example, Mummolo and Peterson (2019) run online survey experiments with more than 12,000 participants and randomly assign information about experimenter intent. They find that providing this information does not affect treatment effects; even financial incentives to respond in line with experimenters' intent did not trigger any demand effects.

2.4 Follow-up Survey

Four weeks after the main survey, we re-contacted survey participants in the US in a follow-up survey to test the persistence of the randomized information treatments in the main survey. This is a common procedure in identifying the effect of information campaigns on policy preferences in the context of survey experiments (for a review, see Haaland et al., 2022; recent applications are Alesina et al., 2018, Haaland and Roth, 2021 and Haaland and Roth, 2020). 2,225 participants (∼75%) completed the short follow-up-questionnaire. A non-response analysis, depicted in Appendix Table A.4, suggests that there is no systematic evidence for selective attrition.[20] The follow-up survey is available in Appendix J.[21]

When inviting participants to the follow-up questionnaire, we again do not inform them about the topic of the survey. After a neutral opening screen, all participants read a statement which highlights that there is a discussion on the future of work due to the increased importance of digital technologies in many occupations. Subjects are again asked to read the questions carefully and to answer honestly. Similar to the initial survey, we then survey beliefs regarding the impact of digital technologies on the general labor market situation and related distributional aspects. We also survey how the respondents see their perceived personal unemployment prospects in the context of automation as well as whether they view an increasing use of digital technologies desirable. We hence repeat some of the core questions from the initial survey on perceptions of automation.

3 Perceptions of Labor-Market Automation

We start our analysis with a detailed discussion of perceptions related to automation in both the US and Germany. At this stage, we do not yet leverage the experimental setting which we leave to Section 4. Our objective here is to shed light on the different dimensions of automation angst, its anatomy and correlates. The analysis is largely descriptive and does not make any claims of causality. Nevertheless, regression analyses in this section condition on a rich set of covariates, and we document major patterns relating to automation angst and shed light on the relevance of (different margins of) automation angst for individual policy support and stated labor market choices.

[20] As an exception, very young respondents (i.e., 18–25 years old) from the main survey are less likely to participate in the follow-up survey, while self-employed individuals are more likely to be surveyed twice. Most importantly, there is no selectivity regarding the experimental group assignment.

[21] It can also be accessed online via the following weblink: `https://isurvey-us.yougov.com/refer/vYXvbxtmPhQg93`.

3.1 Dimensions of Automation Angst

Before we present our empirical findings on automation angst, we present a brief conceptual framework to provide guidance on how we think of automation angst and its different dimensions in the context of our survey.

Conceptual Framework of Automation Angst. In line with previous studies (see references in the Introduction), we focus on concerns related to the replacement effect of automation technologies. While some studies refer to these concerns as 'automation fears' or 'automation anxiety', we use the term 'automation angst' which was popularized by The Economist (2015). Replacement risks are typically being conveyed for a specific workplace or task, but they are often also part of an overall narrative which emphasizes the substitution risk, either for the labor force as a whole or for certain workforce segments. Fears of replacement are thus multi-layered and have different dimensions and aspects to it. The objective in the context of our survey was to capture such distinct dimensions in our survey.

To meet this objective, we surveyed three dimensions of automation angst: I) *general implications* for the aggregate labor-market situation, the overall economy and society as a whole, II) *individual implications* for a respondent's own situation, and III) *distributional implications* of automation. *Dimension I* captures general fears about the aggregate level of 'available' work or levels of employment in the economy. Implicitly, this dimension surveys the overall sensitivity/elasticity of human-labor substitution with respect to automation processes. These fears are likely to be affected by misperceptions related to a one-sided public debate of the automation risk. We conjecture that these 'abstract' fears at the aggregate level are driven by political beliefs (i.e. ideology or government trust) and perceptions of the economy as a whole, and less by respondents' individual characteristics and their workplace tasks.

Dimension II captures the specific fears that workers have for their own labor market prospects, e.g., the fear of losing one's own job. Compared to the general fears in Dimension I, these fears are more likely determined by individual task structures and workplace characteristics as well as past labor market experiences and demographic features of respondents.

Workers may not only be concerned about the aggregate or individual impact of automation. In light of robust evidence that many people are averse to inequality (e.g., Kerschbamer and Mueller, 2020 for Germany), our respondents may also be concerned that automation impacts different parts of the (income) distribution differently. *Dimension III* thus captures fears related to automation-induced inequality. This dimension is likely to be shaped by economic beliefs about automation impacts and political attitudes (such as redistribution preferences and trust that policy can or wishes to mitigate automation-induced inequality).

Our survey includes several questions relating to each dimension of automation angst. An overview of questions belonging to each of the three dimensions is provided in Table 3. This table also features summary statistics by country for all relevant perceptions, labeled with P_1 to P_{12} (based on respondents that were assigned to the control group $ABCD_0$). Note that higher values for all measures always denote higher concerns or more negative perceptions. For brevity, the subsequent analysis focuses on one survey question of key interest for each dimension of automation angst, while we report more detailed results for all remaining perceptions in the Appendix.

Results. The following descriptive results are based on the sample of those respondents who were randomly assigned to the control group of our survey experiment to ensure that the results are not driven by any information provided in the experiments. Subsequent regression analyses further below include all respondents, but condition on the experimental group.

For the **general implications** of automation, we focus on the perceived effects of automation on the overall unemployment rate (P_1) because the discussion about net employment effects is at the core of the public debate in the context of automation effects. The distribution of survey replies in the US and Germany is shown in Figure 1(a). We find that workers in both countries, on average, expect the unemployment rate to increase due to automation. In light of the empirical evidence during the time of the survey, this finding indeed suggests that people have false perceptions about the aggregate effects of automation.

Interestingly, the pattern in the US tends to be more polarized with fewer shares of the population reporting a moderate view on the impact of automation.[22] This result appears consistent with observed political polarization in a number of recent papers (Alesina et al., 2020; Canen et al., 2021; Boxell et al., 2020; Coibion et al., 2020).

With respect to **individual implications**, we focus on the perceived own unemployment risk (P_5) as this measure provides an interesting comparison to P_1 and has also been used before in other studies on automation angst (Morikawa, 2017; McClure, 2018; Coupe, 2019) and similarly on perceived job security (e.g. Dominitz and Manski, 1997 and Manski and Straub, 2000). Figure 1(b) shows that a little more than a quarter of respondents in both countries are at least somewhat concerned to become unemployed themselves due to automation within the next five years. The patterns are quite comparable between Germany and the US and differences are not significant (see also related cross-country tests in Table 3). The share of respondents reporting a high automatability

[22]The remaining perception measures regarding general impacts show a largely similar pattern with more polarized answers in the US also regarding perceived implications for overall prosperity and the relevance of the human workforce (see Figure B.1 in Appendix B).

of job tasks or expecting automation-induced salary losses is even smaller and only a minority considers themselves losers of automation (see Figure B.2 in Appendix B). Related concerns are slightly more moderate in Germany, but as a main take away, individual concerns in both countries appear to be less widespread than automation fears for the economy and the society as a whole.

Regarding **distributional implications** of automation, we focus on the perceived impact of automation on inequality across social groups (P_9). We do so because it is the most general indicator for distributional concerns, while $P_{10} - P_{12}$ are more specific and capture whether people expect different skill groups to rather benefit or suffer from automation.[23] Figure 1(c) suggests that overall distributional concerns are widespread. Almost 90% in both countries rather or absolutely agree that automation will have an unequal impact on social groups. Moreover, these concerns are insignificantly more pronounced in the US. Perceived threats for specific skill groups in the US significantly exceed related concerns in Germany (see Appendix Figure B.3) and cross-country differences are statistically significant (see Table 3). Roughly 50% of US respondents expect uneducated workers to substantially suffer from automation while the corresponding share among German counterparts is around 30%. The difference for workers with a high-school diploma is even stronger, with almost 20% of US respondents expecting this group to substantially suffer from automation, while only 4% of Germans expect this. Hence, institutional differences seem to translate into stronger distributional concerns in the US.

Take-Away. We find strong concerns related to the impact of automation on the economy as a whole and inequality. Nevertheless, most people are fairly optimistic with regard to their own chances related to automation. This rather weak link between general perceptions and expected consequences for oneself is also reflected in limited correlations between these measures, see Appendix Table B.1. In fact, the correlation between general and distributional concerns, i.e. between P_1 and P_9, is 0.3, while the correlation of both of these measures with perceived individual risks P_5 is less than 0.1. This suggests that these indicators indeed capture distinct dimensions of automation angst.[24]

Moreover, attitudes towards automation for the US tends to be more polarized than in Germany, but only when it comes to automation fears regarding the whole economy. US workers tend to have more polarized perceptions of the general impact of automation and are more concerned with the unequal impact that automation may have. Despite these differences in aggregated automation angst, individual unemployment risks are

[23]We decided to ask for perceived threats for different skill groups rather than other social groups because education and skills are at the core of the debate of rising skill requirements related to new technologies.

[24]A factor analysis for these three measures finds no relevant common factor and a uniqueness of each measure of around 0.8 and above.

perceived to be quite similar across both countries. This indicates that the process of forming these perceptions differs from the rather general concerns and that welfare and political differences between both countries might be less important for the formation of these individual perceptions. This is what we turn to next.

3.2 Anatomy of Automation Angst

In a next step, we explore to what extent the three dimensions of automation angst are correlated with individual characteristics of the respondents. In particular, we study how actual risk factors of being adversely affected by automation (as measured by demographic as well as job and workplace characteristics) and factors such as political and economic beliefs (i.e. political ideology, views on market economy and trust in government) are linked to different margins of automation fears. The latter set of factors may indicate to what extent perceptions of automation are related to someone's general (i.e. political or economic) beliefs and attitudes rather than specific knowledge on the labor market consequences of automation. Hence, if perceptions relate strongly to these general beliefs, this might either indicate a lack of knowledge or denote a biased processing of such information.

Empirical Approach. We estimate separate individual-level regressions for the three main indicators of interest, P_{ji} with $j = 1, 5, 9$ (each representing a distinct dimension of automation angst; see above) and run simple OLS regressions of the following form based on the whole sample of respondents:

$$P_{ji} = \alpha + \beta \text{ Demography}_i + \gamma \text{ Job and Workplace}_i + \delta \text{ Political and Economic Views}_i + u_i \quad (1)$$

where P_{ji} refers to perception j of respondent i. The outcome variables are overall unemployment concerns (P_1), individual concern to become unemployed due to automation (P_5) and the expected effect of automation on inequality (P_9). We use standardized (z-score) versions of the outcome variables to make the results more comparable across variables.[25] As mentioned before, higher values always indicate more pessimistic attitudes. We run separate regressions for the US and Germany to shed light on cross-country differences.

We regress these outcome variables on different sets of control variables, including basic demographics, education levels and household income (Demography_i) and further factors that constitute potential correlates with automation angst; in particular, we include respondents' job and workplace characteristics (referred to as $\text{Job and Workplace}_i$) such as the share of routine and manual tasks, IT exposure at the workplace, the re-

[25] Standardized scores are derived by subtracting individual outcome realizations by their mean μ and dividing by the respective standard deviation σ for each outcome (i.e., $z = \frac{P_i - \mu}{\sigma}$), respectively.

cent up- or deskilling of workplace-related skill requirements, and someone's current and past job status.[26] All together, this set of variables to some extent captures the actual risks of being affected by automation. In addition, our right-hand-side variables contain a respondent's political and economic beliefs and the level of government trust (Political and Economic Views$_i$). We also control for the experimental group an individual has been assigned to (not reported in the respective tables below). At this stage, this variable serves as a pure control as we analyze the impact of the randomized interventions below in Section 4 and use the full sample of all respondents for the estimations.[27]

Results. Table 4 shows estimation results for each of the main perception measures (P_1, P_5, P_9) by country. One of the key messages is that the correlates differ notably between the three dimensions of automation angst, but also to some extent between countries. Moreover, the overall explanatory power of the model is much lower for perceptions regarding aggregate unemployment (P_1) and distributional concerns (P_9) than for automation angst related to oneself (P_5). All in all, the correlates indicate that perceptions about individual risks and general concerns about automation are distinct dimensions that do not necessarily relate to the same factors.

As expected, job and workplace related characteristics, for instance, matter most for concerns about one's own unemployment risk, reflecting that individual labor market experience and actual risk factors shape perceived future labor market prospects. Previously and currently unemployed individuals in both countries are more concerned about losing their job due to automation. People with routine-intensive job, jobs which are more exposed to IT and changing job requirements are more concerned and pessimistic, especially in the US. Such cross-country differences might be linked to differences in how labor market institutions support workers and aim at preserving jobs during structural change. We also find cross-country differences in individual job concerns regarding demographic characteristics. For example, in the US, the polarization between poor and rich households is much more pronounced than in Germany, where, by contrast, formal education gives rise to polarized concerns.[28] Regarding political and economic views, we generally find for both countries that these factors correlate strongly with distributional concerns (P_9) and somewhat less so with general concerns (P_1). Distributional concerns are particularly high for respondents mistrusting the government, people with anti-liberal market views (Germany only) and left-wing political views (US only). We further find that political ideology and trust in government matter for individual concerns (P_5) in

[26]Since the survey data contain some missing values for most of the characteristics, we add dummies for missing observations.

[27]We find very similar coefficients when excluding respondents that received an information treatment.

[28]Additionally, we also some find significant effects for age groups (US only), household structure, race and migration background.

the US, but not in Germany. Both political beliefs and trust in government seem to be a major source of polarized perceptions about the implications of automation for the economy as a whole. For instance, right-wing (left-wing) proponents are significantly less (more) concerned compared to workers who support neither left- nor right-leaning ideologies. Specifically, for a left-wing proponent, concerns about rising unemployment and distributional concerns are 0.2 and 0.5 standard deviations higher than for a right-wing supporter (conditional on demographics, job and workplace characteristics, among others). This is consistent with previous US findings that political views matter strongly for perceptions (see, for instance Alesina et al., 2020 and Stantcheva, 2021).

On the one hand, there may thus be more scope for correcting such perceptions in the US if polarized perceptions result from a lack of information. On the other hand, polarized perceptions may also reflect the biased nature of collecting and processing information and a general resistance to scientific information, potentially reducing the responsiveness of perceptions to the provision of scientific information (Alesina et al., 2020). Section 4 will shed light on related treatment effects of information about automation.

3.3 Policy Preferences, Stated Labor Market Choices, and Donations

Before moving on to the information treatments in Section 4, we examine whether actual and stated behavior as well as policy preferences are associated with different margins of automation angst. For this, we describe how the three main perception indicators are correlated with a number of outcomes that we describe below in more detail: policy preferences, stated labor market behavior, and actual donation decisions.

Outcome Measures. For the analysis of **policy preferences**, the survey contains 15 questions that capture a wide range of different policies. These can be grouped into four types of policies: i) redistribution policies, ii) anti-poverty policies, iii) passive labor market policies and iv) active labor market policies (see Appendix C for details). For each type of policy, we select the survey questions belonging to the respective policy type and calculate a standardized total z-score[29] (for a similar procedure see e.g. Kling et al., 2007 and Alesina et al., 2022). As a result of this procedure, we obtain one standardized measure for each type of policy which is based on several survey questions. We compared this approach to running a factor analysis instead and find very similar results, see Appendix C for details.

For outcomes related to **stated labor market behavior**, the survey contains information on whether respondents would be generally willing to participate in further

[29]This is calculated by dividing the composite z-score by its standard deviation as the mean value of the total z-score equals zero.

training, and whether they would be willing to accept a lower salary or switch occupations in case of unemployment. We use all three measures in the subsequent analysis, but also derive a standardized total z-score for these measures that captures an individual's overall willingness to make an effort to stay employed and invest in one's own human capital.

Finally, for the **donation decisions** related to the lottery that we described in Section 2, we examine to what extent perceptions of automation are related to whether people donate any prize money of the lottery, the share of the prize money they donate and the related structure of the respective beneficiaries. Table C.2 in Appendix C shows summary statistics of all outcome measures.

Empirical Approach. In order to examine to what extent perceptions of automation risks relate to these outcomes, we estimate conditional correlations of the following form:

$$Y_{ji} = \alpha + \lambda_1 P_1 + \lambda_2 P_5 + \lambda_3 P_9 + \beta X_i + [\gamma Country_i] + u_i \tag{2}$$

where Y_{ji} refers to the various outcomes described above. λ_k, with $k = 1, 2, 3$, capture the impact of concerns regarding general unemployment (P_1), individual unemployment concerns (P_5), and the perceived unequal impact of automation on social groups (P_9) related to automation (i.e., the three main perception variables as above). X_i is a composite vector of controls that comprises demographic features, job and workplace characteristics as well as political and economic views as defined before in Section 3.2. We include all perception measures simultaneously because the previous analysis suggests that these main dimensions of automation angst are related, but still measure distinct aspects. Hence, not including all dimensions at once may give rise to omitted variable bias and previous studies focusing on only one dimension likely suffer from this. Our approach thus allows us to disentangle which dimension of automation angst is most strongly related to the outcomes of interest. This is important to keep in mind for the interpretation of the results: the coefficient for one perception measure will always be conditional on the respective other two perception measures.

The analysis here, again, does not make any claims of causality, but regressions always condition on a rich set of covariates X_i. More precisely, as we condition on many job- and workplace-related characteristics as well as differences in individual employment careers, and general economic and political views, any significant marginal effect of perceived threats from automation tentatively confirms the role of perceptions in affecting individual behavior and preferences. We again also always control for the assigned experimental group[30] and add a country dummy whenever we pool both countries.

[30]The main findings are robust to excluding respondents who received a treatment information.

Results. The results of this approach are summarized in Tables 5 (policy preferences)[31], 6 (labor market choices) and 7 (real donation behavior).

We generally find that all dimensions of automation angst positively (and significantly) relate to demand for policy interventions (i.e., redistribution and antipoverty measures as well as active and passive labor market policies), even after controlling for job and workplace characteristics that are related to actual risks of automation, the respective other dimensions of angst as well as political and economic views. Moreover, distributional concerns as well as own unemployment concerns relate more strongly to a higher demand for all types of policies in the US than in Germany. These estimates are not only significant, but also suggest a relevant magnitude. As an example, an increase in the perceived risk of becoming unemployed by one standard deviation in the US, is accompanied by a +0.14 standard deviation increase in the demand for redistributive policies. The difference in policy demand between Germany and the US likely reflects that Germans feel better protected from automation-related threats than US respondents. The less extensive welfare system and lower redistribution level in the US thus seems to make policy demands more responsive to perceived threats from automation.

Regarding the link between dimensions of automation angst and stated labor market choices turns out to be much less strong than for the previously discussed policy preferences. This suggests that, even in the US with a strong tradition of self-responsibility, automation fears only weakly translate into behavioral responses. As an exception, US workers are more inclined to switch occupation and be flexible if they are concerned about threatening labor market conditions, but are not willing to give up on their salary level. German workers are willing to switch jobs more often if they fear more unequal effects of automation. The willingness to participate in training, on the other hand, is higher among US respondents who feel threatened by unemployment, and slightly higher among Germans who fear rising inequality, the latter potentially reflecting some form of last-place aversion.

Finally, different margins of automation angst only affects generosity of donation behavior but not the specific beneficiaries thereof. Being concerned about one's own employment prospects comes with increased generosity in donation behavior, while heightened general and distributional concerns (Germany only) reduce donation generosity. The former result speaks in favor of increased sensibility and solidarity with those who are

[31]Table D.1 in Appendix D shows further coefficient estimates for joint estimations suggesting mostly plausible relationships between other individual characteristics and the demand for policy interventions. For instance, respondents from rich households report lower demands for policy interventions that they likely perceive to potentially raise their tax burden, while people with past unemployment experience demand more government intervention. Being currently employed comes with lower demands for passive labor market policies and anti-poverty measures. Most strikingly, political and economic beliefs are strongly and plausibly related to policy preferences: Leftwing voters and people with anti-liberal market views have a strong preference for any type of government support, while the opposite holds for rightwing voters and people with liberal market views.

already in a disadvantaged position, as has been argued before in the donation-economics literature such as in Lange et al. (2022). The latter finding, by contrast, suggests that, conditional on perceived own risks, concerns that the society as a whole might suffer from automation tends to erode rather than foster prosocial behavior.

Taken together, these findings suggest that people in both countries, on average, perceive automation as a threat that needs to be addressed by more policy intervention and support, but that also necessitates an individual effort to cope with automation-induced changes. Moreover, in both countries, individual unemployment concerns seem to raise solidarity with those potentially suffering from automation in terms of increasing people's charitable donations, while general and distributional come with reduced donations. This could be an indicator that automation fears can harm social cohesion.

4 The Role of Information

We now exploit the experimental setup of the survey in order to examine to what extent perceptions of automation are responsive to scientific information (for details see Section 2.3).

4.1 Empirical Strategy

In what follows, we focus on the causal impact of providing information on either "no aggregate employment losses" (Treatment I_1) or "employment shifts from unskilled to skilled worker" (Treatment I_2) on two sets of outcomes: i) the perception measures, P_j with $j = 1, \ldots, 12$ (as summarized in Table 3) and ii) policy demands, stated labor market choices and donations (all summarized in Appendix C). Note that we do not restrict the perception measures to the three main indicators that we examined before. Instead, we look at all 12 perception measures because there is no reason to believe that only the main perception indicators that we focused on so far respond to the treatment interventions.

To estimate the treatment effects for information I_k (with $k = 1, 2$) on outcome Y_i, we compare the treated sub-group $ABCD_k$ with the control group $ABCD_0$ who received the same ordering of the question blocks (see section 2.3 for more on identification). For the intention-to-treat (ITT) effect,[32] we then estimate the following regression jointly for both countries:

$$Y_i \quad = \quad \alpha + \beta_1 ABCD_{ki} + \beta_2 \, US_i + u_i \tag{3}$$

[32] All survey respondents in the treatment groups were exposed to the treatment information. Although it is plausible that survey participants read the information, we naturally cannot tell whether actually did. Hence, we consider our treatment effects to reflect an ITT rather than an average treatment effect on the treated.

where Y_i refers to different outcomes of survey participant i (as discussed above). $ABCD_{ki}$ is a dummy indicating whether a person received information treatment I_k or instead belongs to the control group. Due to random assignment,[33] β_1 captures the ITT of information treatment k. We tested extended versions of the specification and, reassuringly, found results to be extremely robust to including or excluding control variables from question block A. Hence, all subsequent results are based on estimations without further covariates (except for the country dummy indicating US respondents).

We also consider treatment effects for different subgroups. First, we allow the ITT to differ between the US and Germany by extending the above equation to

$$Y_i = \alpha + \beta_1 ABCD_{ki} \times Ger_i + \beta_2 \, ABCD_{ki} \times US_i + \beta_3 \, US_i + u_i \tag{4}$$

where β_1 and β_2 capture the ITTs for German and US respondents, respectively.[34]

Second, we allow treatment effects to vary with beliefs on automation that respondents stated prior to receiving the information treatments (at the beginning of question block B) as is typically done in the literature (see the review of Haaland et al., 2022). In particular, we allow treatment effects to vary depending on whether respondents expect technological progress to rather decrease the value of human work (called *pessimists*), to increase the value of human work (called *optimists*) or to leave the value of human work largely unaffected (called *neutrals*).[35] We do so because the information treatment might be processed differently depending on whether the scientific information contradicts or confirms prior beliefs. As shown in Appendix E, most people expect the value of human labor in the future to decline rather than increase. Specifically, multivariate analyses in Appendix Table E.1 reveal that this prior belief is strongly related to a similar set of factors as the perception measures discussed in Section 3.2, especially with regard to political and economic views of respondents. It is mainly leftwing voters, people with low government trust and anti-market views who expect the value of human labor to decrease, while the opposite holds for market proponents and people with a high trust in the government. In order to allow for related heterogeneities, we run the following

[33]See Appendix Table A.3 for tests of balance across treatment groups.

[34]We use this model with different effects for each sub-group rather than an interaction model, because the sample size of the survey leaves limited possibilities in establishing significant treatment differences between sub-groups. As noted by Haaland et al. (2022), a minimum of 700 respondents per treatment arm is necessary to detect a treatment effect of 15 percent of a standard deviation with a statistical power of 80 percent. While our pooled treatment groups that we look at in equation 3 satisfy this condition with a statistical power of 97 percent, this is usually not the case when looking at a sub-group level. For US and German respondents (see Table 1), for example, we get a statistical power of 75% to detect a differential treatment effect of 15% of a standard deviation.

[35]We use this measure because it reflects the most general belief about the future impact of technological progress on the labor market. Note that we surveyed also other prior beliefs that are, however, more specific (e.g. the importance of higher education for future labor market chances).

regressions jointly for both countries:

$$Y_i = \alpha + \beta_1\, optimist_i + \beta_2\, pessimist_i + \beta_3 ABCD_k \times\ optimist_i + \beta_4 ABCD_k \times\ neutral_i + \beta_5 ABCD_k \times\ pessimist_i + \beta_6 US_i + u_i \quad (5)$$

where β_3 captures the ITT of information treatment k for respondents with optimistic prior beliefs regarding the future value of human work, while β_4 and β_5 capture the ITT for respondents with neutral and pessimistic prior beliefs, respectively.[36]

Third, for treatment I_2, we also allow the ITT to differ along the skills distribution because the distributional message of the treatment may have different implications for workers with a high-school degree or less, some college or college education and beyond.[37] Due to a large set of potential outcome variables and multiple treatments, we check the robustness of all our findings to adjusting standard errors to multiple hypothesis testing by the Westfall-Young multiple testing procedure (Young, 2018).[38]

4.2 Information Treatment I_1 - no aggregate employment losses

Expected Effects. The first information treatment of a zero aggregate employment effect (I_1) likely works against predominant existing fears of rising unemployment due to automation. This is mainly captured by P_1, but might also affect other perceptions related to aggregate effects of automation ($P_2 - P_4$) as well as individual or distributional concerns related to automation. As perceptions concerning the impact of automation on the economy as a whole are more negative in the US (see Section 3.1), the corrective effect of the treatment might particularly strong in the US, unless extreme views reflect a general resistance to accepting scientific information.

The findings in the previous section 3.3 should only be considered as a broad indicator of what to expect from the information treatments though. This is because shifts in perceptions are unlikely to be limited to the three main indicators[39] and because previous results correspond to correlates rather than causal effects. Still, we expect lower policy demands if the treatment information generally reduces automation angst. For stated labor market choices as well as charitable donations, by contrast, deriving hypotheses is, however, already complicated by the fact that general, individual and distributional

[36]Since the majority of respondents have pessimistic prior beliefs, the sub-groups are rather imbalanced in terms of sample size, resulting in a statistical power of 53-56 percent to detect a differential treatment effect of 15 percent of a standard deviation between pessimists and the two other groups of respondents.

[37]Those without a high-school degree are too few to estimate any separate treatment effects which is why we define the least skilled group to have up to a high-school degree, see also Table A.2.

[38]We use the Stata module RANDCMD to compute randomization inference p-values (Statistical Software Components S458774, Boston College Department of Economics).

[39]We did not include all 12 perception measures in the analysis in section 3.3 because of multicollinearity.

concerns seem to be related differently (and generally more loosely) to these outcomes. Hence, corresponding treatment effects are not clear a priori and may go in both directions depending on how different dimensions of automation angst respond to the treatment.

Effects on Perceptions. The left-hand side of Figure 4 shows mean treatment effects of treatment information I_1 for all 12 perception outcomes. First of all, note that all significant treatment effects are shifted to the left, suggesting that the information treatment reduced fears and concerns related to automation. Moreover, a Westfall-Young joint significance test for all 12 perception outcomes is significant at the 5% significance level (see Table 8). The treatment thus had a significant impact on the perceptions of treated individuals.

In particular, people are now significantly less concerned about rising unemployment (P_1), and are less afraid about the substitution of humans by machines (P_2). The magnitude of these shifts with about -0.15 standard deviations is small, but not negligible. It is comparable to the difference in the fears of higher unemployment (P_1) for someone in the US who mistrusts the government compared to someone who trusts the government (see Table 4). Interestingly, the treatment also significantly reduces concerns that skilled workers and graduates might suffer from automation, while perceptions remain unchanged for unskilled workers. Concerns related to one's own employment prospects also seem to be reduced slightly due to the treatment information, but these shifts remain insignificant.

These results imply that, on average, people had misinformed perceptions mainly about the impact of automation on aggregate employment and the implications that this has for better skilled workers. This might reflect that automation fears for the aggregate economy have been found to be more at both ends of the Likert-scale and linked more closely to general beliefs and attitudes, suggesting that they are more responsive to scientific information (see section 3).

Consistent with this, we also find some evidence that information falls on a more fertile ground in the US than in Germany when it comes to correcting economy-wide concerns. As shown in the top panel of Figure 5, much of the shifts in perceptions that we discuss above is driven by US rather than German respondents.[40] Although we cannot pin down the statistical significance of the cross-country difference for most perception measures due to lack of statistical power (with P_2 being an exception), these findings tentatively suggest that US respondents are more responsive to the treatment information.

We also observe differences depending on people's prior beliefs about technological

[40]A Westfall-Young joint significance test for all 12 perception outcomes suggests significance of the sub-group analysis by country as well as by prior beliefs, see Table 9.

change (bottom Panel (b) of Figure 5). In particular, the treatment significantly reduces concerns about rising unemployment (P_1) only among those with previously neutral or pessimistic views regarding technological change. Pessimists are also less concerned about the substitutability of the human workforce (P_2) in response to the treatment. Hence, it is especially those with negative prior beliefs that update their perceptions in response to the scientific information. For optimists, there is no shift in P_1 as the treatment probably confirms their perceptions about the role of technology for unemployment. Instead, the reassuring character of the treatment raises the desirability of digitalization (P_4) among optimists, but also comes with reduced concerns for skilled workers and graduates.

To sum up the, we find that exposing people to recent academic results on the lack of aggregate employment losses reduces automation angst related to aggregate unemployment and to the potential obsolescence of the human workforce. It also affects other dimensions of automation angst such as concerns that skilled workers or graduates might suffer from automation. Such effects tend to be more pronounced in the US. This is in line with the notion that the (polarized) views in the US are more responsive to scientific information because concerns in the US are more closely related to political views, including political ideology or government trust. Moreover, prior beliefs about the future role of human labor turn out to be an important source of heterogeneity in the treatment response pattern. For example, subjects with pessimistic attitudes tend to be more responsive to the treatment in terms of reducing general concerns, while for those with more optimistic views the treatment decreases concerns that skilled workers and graduates may suffer from automation, but leaves overall concerns rather unchanged. These heterogeneous response patterns are likely to also translate into treatment heterogeneity for other outcome measures that we will consider next.

Effects on Further Outcome Variables. The effects of the treatment on policy demand, stated labor market choices and donations are presented in panels (a), (b) and (c) of Figure 6, respectively. In the following, we summarize the main findings in this context and leave a more detailed discussion to Appendix F.

We find largely insignificant *average* treatment effects on policy demands, stated labor market choices and donations, both among US and German respondents. However, these insignificant average effects mask some heterogeneous and opposing effects along the distribution of prior beliefs. For example, the treatment reduces policy demands among people with optimistic prior beliefs, while pessimists do not respond to the treatments at all and people with neutral beliefs even somewhat increase policy demand. The counterintuitive zero or positive effects on policy demand might actually reflect that perceptions shift differently depending on prior beliefs. Among neutral respondents, I_1 also (insignificantly) raises inequality concerns which may translate into higher policy demand despite the zero aggregate employment loss information. Among pessimists, the strongly reduced concerns about the substitutability of humans by machines (P_2) may actually counteract the effect of reduced concerns about rising unemployment (P_1). This is because a lower perceived substitutability of humans by machines might increase confidence in the usefulness of policy interventions to address related challenges by labor market policies, thereby increasing policy demand.[41]

With respect to donation decisions, we also find heterogeneities along the distribution of prior beliefs. Optimists, for instance, not only consider less need for policy interventions, but also feel less inclined to donate to charities, while the higher policy demand for neutral respondents is accompanied also by somewhat higher donations. Stated labor market choices, by contrast, turn out to be largely unresponsive to the treatment information even along the distribution of prior beliefs.[42]

As a major take-away, these results suggest that even if the provision of scientific information generally reduces concerns related to automation, this does not need to translate into uniform policy or behavioral responses. This is because induced shifts in perceptions are multidimensional and depend on people's prior beliefs, resulting also in heterogeneous response patterns for other outcomes. We discuss the implications of this observation in more detail below in the Conclusion (section 5).

4.3 Information Treatment I_2 - employment shifts from unskilled to skilled workers

Expected Effects. With regard to the information treatment of employment shifts from unskilled to skilled labor (I_2), the corrective effect on perceptions is potentially more limited because the existing perceived threats for unskilled workers and the expected unequal impact of automation seem to be largely in line with the treatment information. If relevant misperceptions exist, we would mainly expect distributional concerns to respond to the treatment information. However, the general public in both countries seems to be aware of the skill-biased nature of recent labor market trends due to automation (see Section 3.1 for details on this). We thus neither expect substantial effects from this information on individual perceptions, policy demands nor for behavioral responses.

Perception Measures and Other Outcome Variables. In line with these expectations, shifts in perceptions about automation are mainly limited to distributional concerns (see Figure 4) and the multiple hypothesis test for relevance of the treatment for all per-

[41]Indeed, when adding P_2 to equation 2, we find negative partial effects for related concerns on active and passive labor market policies as well as anti-poverty policies. Results are available upon request.

[42]As an exception, there is weakly significant evidence that optimists are more willing to accept lower salaries in response to the treatment. This might reflect that optimists are now more confident that any low-paying job would only be a temporary state to terminate unemployment.

ception measures narrowly misses the 10% significance level (see Table 8). In particular, perceived risks for unskilled workers remain unchanged in response to the treatment, suggesting that the already extremely pessimistic view on automation-related effects on unskilled workers (see Section 3) is in line with the treatment information. Still, the treatment further raises concerns about an unequal impact of automation (P_9) as the perceived risks for skilled workers and graduates are corrected downward after receiving the treatment (P_{11}, P_{12}). For perceptions on the general and individual implications of automation, the treatment mainly tends to insignificantly reduce related concerns. As an exception, respondents are now significantly less concerned that they might face lower salaries in the future (P_7). These latter shifts are driven mainly by German respondents though, see Figure 7(a). The same holds for concerns about skilled workers' fate during digitalization. Hence, distributional concerns in the US appear to be more in line with the information treatment, thus resulting in somewhat weaker corrections of related perceptions.[43]

We also find some heterogeneity by prior belief in Figure 7(b) and by skill group in Appendix Figure G.1, albeit the corresponding multiple hypothesis tests cannot reject the joint irrelevance of the treatment for all outcomes by both skill level or prior beliefs (see Table 10). Still, the results suggest that it is mainly optimists who are now less concerned about declining salaries. Lower concerns about skilled or unskilled workers can be found to a varying extent in all sub-groups, albeit increased concerns about an unequal impact of automation (P_9) is significant only for skilled workers.

To conclude, our treatment triggers some expected effects regarding better labor market chances of skilled workers, but does not raise concerns about the plight of unskilled workers. However, related effects are limited and not robust to multiple hypothesis testing. Not surprisingly, we thus do not find much effects of I_2 on policy demands, stated labor market choices or real-world charitable giving (see Appendix Figures G.2, G.3, and G.4) and multiple hypotheses tests cannot reject the null that there is no significant effect on these outcomes in most cases (see Table 10). The only exception is policy demand where college graduates show significantly higher demands for active labor market policies and anti-poverty measures in response to the treatment, see Appendix Figure G.4. As the treatment raises distributional concerns in this privileged group, this seems to raise their demand for supportive measures. Consistent with this, graduates also donate more. Interestingly, no notable effects can be found for unskilled workers who are most exposed to suffering from automation according to the treatment information. Treatment heterogeneity by prior belief or country (see Appendix Figures G.2 and G.3) seems to be largely irrelevant.[44]

[43]The multiple hypothesis test for the overall relevance of the treatment with country-specific effects is significant at the 5% level, see Table 10.

[44]As an exception, responses differ somewhat along the distribution of prior beliefs with more generous

4.4 Follow-up Survey

As we have seen, the information treatments significantly shifted various dimensions of automation angst. We now test the persistence of these corrective effects by analyzing whether these effects prevail in a follow-up survey fielded one month after the main survey (see Section 2.4 for more details). The follow-up survey is only available for US respondents and re-elicits different dimensions of automation fears from the main survey's Block B.3 using the exact same wording of questions (for $P_1, P_2, P_4, P_5, P_9, P_{10}, P_{11}, P_{12}$).

To test for persistent treatment effects, we estimate a difference-in-differences type of estimation based on the sample of respondents that we observe in both surveys, limited to those assigned in the main survey to either the control group $ABCD_0$ or one of the two treatment groups $ABCD_1$ and $ABCD_2$:

$$P_{kti} = \alpha + \beta_1 ABCD_{1i} + \beta_2 ABCD_{2i} + \beta_3 FU_{it} + \beta_4 ABCD_{1i} \times FU_t + \beta_5 ABCD_{2i} \times FU_t + u_{it} \tag{6}$$

where P_{kti} are the k perception measures of respondent i reported in one of the two surveys ($t = 1$ for follow-up survey, $t = 0$ for main survey). $ABCD_{ji}$ is a dummy indicator variable for the treatment group receiving information treatment I_j (with $j = 1, 2$) in the initial main survey, and FU_{it} refers to a dummy indicating the follow-up survey. Based on this specification, we compute the perception levels for the control and treatment groups in the main and follow-up survey.

Figure 8(a) provides corresponding results for perception measures capturing general and individual concerns. The Figure reports perception levels separately for each group (control, $ABCD_1$, $ABCD_2$) and "time period" (main survey, follow-up survey) – see the Notes to Figure 8 for more details. For P_1 and P_2 in the main survey, we again find reduced concerns for those treated with the "zero aggregate employment loss"-information compared to the controls (see Figure 4). These reduced concerns in the treatment group remain quite persistent between the main and the follow-up survey with only slightly smaller but nevertheless still significant effects for P_2.

Surprisingly, respondents in the control group reduced their concerns significantly between the two surveys, especially for P_1. As a result, differences between the control group and those treated with I_1 are no longer significant in the follow-up survey. This convergence in perceptions is driven mainly by reduced concerns over time for respondents from the control group rather than a bouncing back of the perceptions among those in the first treatment group (I_1).

One potential explanation for this finding is that respondents have been exposed to some information between the main and follow-up survey that had quite similar corrective

donations only among optimists and some shifts to charities targeted at equal opportunity at the expense of donations for anti-poverty measures among neutral respondents.

effects as our treatment information I_1 and that did not induce any further corrections of perceptions among the first treatment group. Though we can of course only speculate about such confounding events, we did some research about events that could potentially have had an effect. One potential event that we could identify was an episode of the popular late night show "Last Week Tonight with John Oliver" which discussed automation and it's link to job loss extensively and conveyed a message very similar to our first information treatment (I_1, "zero aggregate employment loss"). This episode was first broadcasted on March 4, 2019, which is around two weeks after the main survey and one week prior to the follow-up survey.[45]

The John Oliver Show is widely considered to have an influence on the public debate in the US. This influence is regarded to be so relevant that it even coined a commonly used name: the "John Oliver Effect".[46] Aside from the show being generally popular and influential, there is also evidence that this particular episode of the John Oliver Show was publicly resembled and received substantial attention during the time between our two surveys: several newspapers and websites refer to this episode and report on its labor-market-automation content during this time period.[47]

Given its well-known influence on public debates in the US and the public reception of this particular episode, the coincidence of having this show being broadcasted in between our surveys may have contaminated our control group in the follow-up. If that was true, we would actually expect our second treatment group ($ABCD_2$ that received information I_2 on the distributional effects) to be contaminated by the same effect as this group had not been treated with the "zero aggregate employment loss"- information and had not shown any shifts in P_1 and P_2 in the main survey. According to our results in Figure 8(a), this is indeed the case: related concerns are similarly reduced for respondents in the second treatment group as for those participants in the control group. Unfortunately, we do not possess information on individual news-consumption from our follow-up subjects, implying that we cannot directly link viewership of that particular show to our survey respondents and their respective treatment status.

Altogether, there is no evidence against persistent effects of our treatment information. The corrections induced by our treatment information I_1 did not disappear and our results either point to persistent effects of our treatment or the exposure to the same information that contaminated the control group. However, no major control group shifts

[45]The video can be seen here: `https://youtu.be/_h1ooyyFkF0`.

[46]For example, the *TIME* magazine has examined "How the 'John Oliver Effect' Is Having a Real-Life Impact" (TIME, 2015). John Oliver's *Wikipedia* page states: "He has received widespread critical and popular recognition for his work on the series, whose influence over US culture, legislation, and policymaking has been dubbed the 'John Oliver effect'." (`https://en.wikipedia.org/wiki/John_Oliver`).

[47]For example, TIME (2019), Inverse (2019), Entertainment Weekly (2019) and Alliance for American Manufacturing (2019).

between the main and the follow-up survey can be found for distributional concerns (see Figure 8(b)) and shifts in these perceptions in the main survey for both treatment groups tend to bounce back at least partially. This is in line with various experiments in the literature. For example, Coppock (2016) and Druckman and Nelson (2003) find that information and framing effects quickly decrease over time. It is also consistent with Haaland et al. (2022) who summarize previous information experiments and find that follow-up effects shrink over time. Hence, the persistence of reduced automation fears that we find for our first treatment group in Figure 8(a) may in part be driven by repeated exposure to information similar to the "zero aggregate employment loss"-treatment (for instance, in the John Oliver show broadcast before the follow-up).

5 Conclusion

Automation technologies reshape labor markets and career prospects for large shares of the workforce. The effects and implications of this automation trend depend, at least to some extent, on the labor-market and policy-demand responses of workers. These responses are likely driven by the perceived, rather than actual, threats from automation. Relying on customized large-scale surveys in the US and Germany, this paper studies perceptions of the labor force in the context of labor-market automation.

We show that people tend to have very negative perceptions of labor market automation. Compared to the more optimistic scientific evidence, this suggests systematic misperceptions likely due to a one-sided narrative of automation in the public debate. Our results further show that, especially in the US, general economic and political preferences are strongly associated with all dimensions of automation fears, suggesting that threats of automation are perceived through an individual lens that are shaped by pre-existing attitudes.

Our survey also indicates that automation perceptions matter: we find different dimensions of automation angst to be strongly associated with demand for policy interventions, stated labor market behavior and actual donation decisions, even conditional on a large set of controls. This then implies that biases in people's perceptions can translate into sub-optimal individual decisions and misguided demand for policy interventions.

Can information mitigate the biases in people's perceptions? Our randomized information experiments show that providing scientific and objective evidence to inform perceptions mitigates automation angst. This supports the notion that perceptions are indeed systematically biased. However, we also detect multidimensional and heterogeneous treatment-induced shifts in perceptions that depend on people's prior beliefs about the impact of technological change on jobs. Hence, the same information is digested differently depending on people's prior beliefs, which are, in turn, deeply rooted in political and economic beliefs. This heterogeneity also translates into differential treatment effects on policy demand, labor market behavior and charitable donations. As these induced shifts even occur in opposite directions for different groups, we find no significant average shifts in these outcomes.

In summary, our results indicate the presence of systematic biases in people's perceptions of automation that can be mitigated with the provision of scientific information. In fact, our follow-up survey does not show evidence of a bouncing back of the perceptions among the treated respondents to the untreated counterfactual, potentially due to an unintended repetition of our information in between the main and the follow-up survey. We thus speculate that information campaigns, especially when reinforced through repetition, may have a lasting effect on people's perception of automation. Nevertheless, our results also imply that different groups of people draw different and even opposing conclusions from the same campaign. This puts doubt on the usefulness of such campaigns for moving behavior and policy preferences in a particular direction if people have strong prior beliefs (that are rooted in political and economic views). These findings potentially have implications for other (similarly polarized) debates. For example, deeply rooted political views might explain why some groups of the population are inaccessible to objective information about the pros and cons of getting vaccinated against Covid-19.

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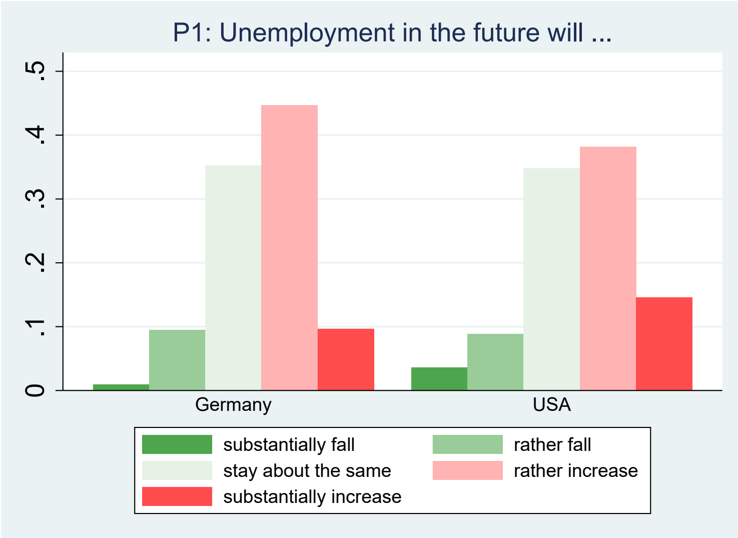
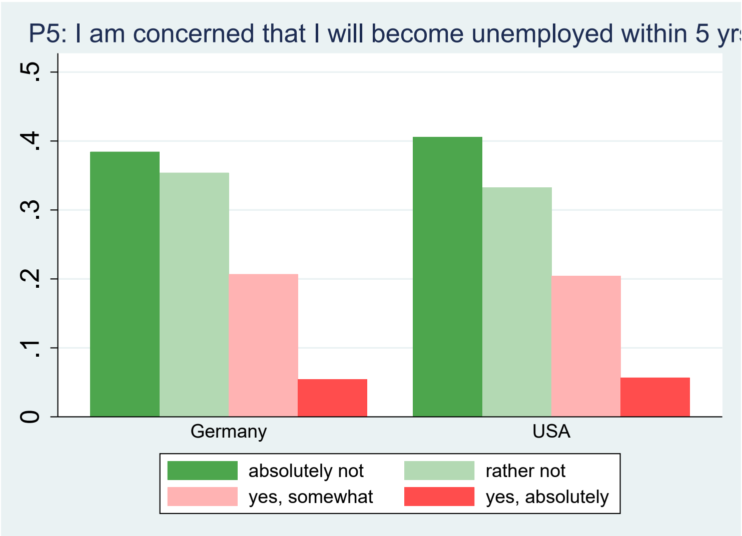
Figures

Figure 1: Main perception indicators in the US and Germany

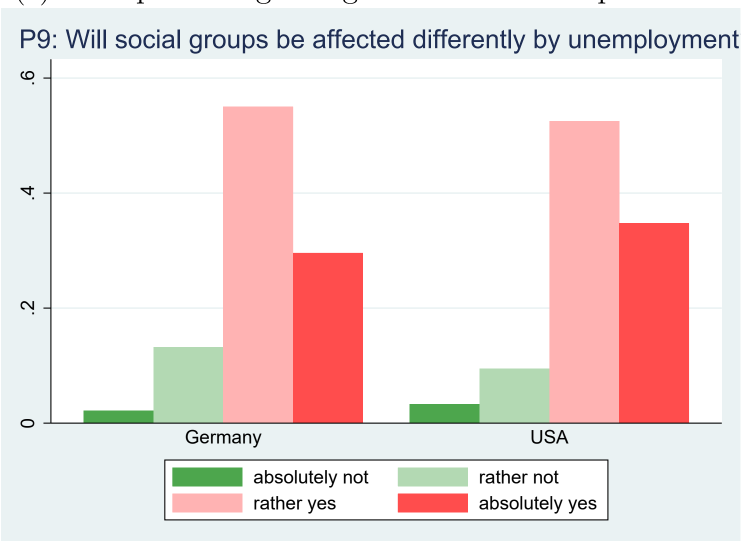
(a) Perceptions regarding general implications



(b) Perceptions regarding individual implications



(c) Perceptions regarding distributional implications



Notes: Sample only consists of respondents assigned to the control group $ABCD_0$. For detailed statistics see Table 3.

Figure 2: First Information Treatment (I_1)

YouGov

As technological progress continues, new possibilities arise to replace human labor with machines. However, **the use of the latest digital production technologies does not necessarily lead to a decline in employment,** because the use of these technologies can improve the competitiveness of firms. This allows firms to sell more products, which in turn increases employment.

This is also confirmed by a recent study* which analyzed comprehensive technology and labor market data for 17 industrialized countries. The study examines the relationship between the actual use of the latest digital production technologies and the resulting development of employment.

The study shows that **the number of hours worked has remained the same despite the increasing use of digital technologies.** Thus, there is **no evidence that the use of the latest digital production technologies contributed to an overall decline in employment.**

*Graetz, Georg, and Guy Michaels. "Robots at work." *Review of Economics and Statistics* (2018).

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Figure 3: Second Information Treatment (I_2)

YouGov

As technological progress continues, new possibilities arise to replace human labor with machines. An occasionally expressed concern is that the **impact of the use of latest digital production technologies** on workers differs between different worker types and **depends on the educational background of the affected workers.**

This is also confirmed by a recent study* which analyzed comprehensive technology and labor market data for 17 industrialized countries. The study examines the relationship between the actual use of the latest digital production technologies and the resulting development of employment.

The study shows that with the increasing use of digital technologies, **more qualified workers have displaced less qualified workers.** For example, **the share of hours worked by people without high school degree decreased,** while **the share of hours worked by people with a high school degree, a professional degree as well as with a college or a university degree increased.**

*Graetz, Georg, and Guy Michaels. "Robots at work." *Review of Economics and Statistics* (2018).

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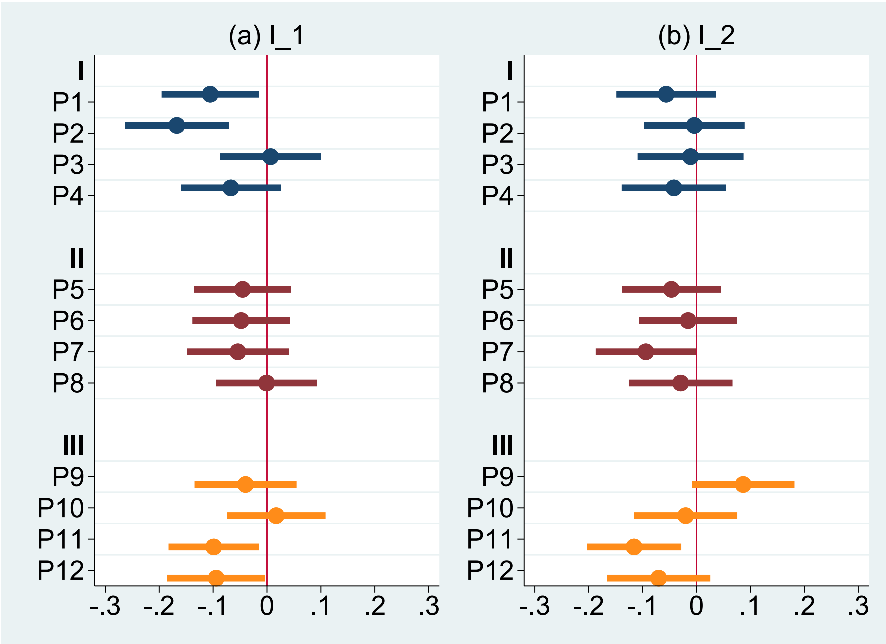
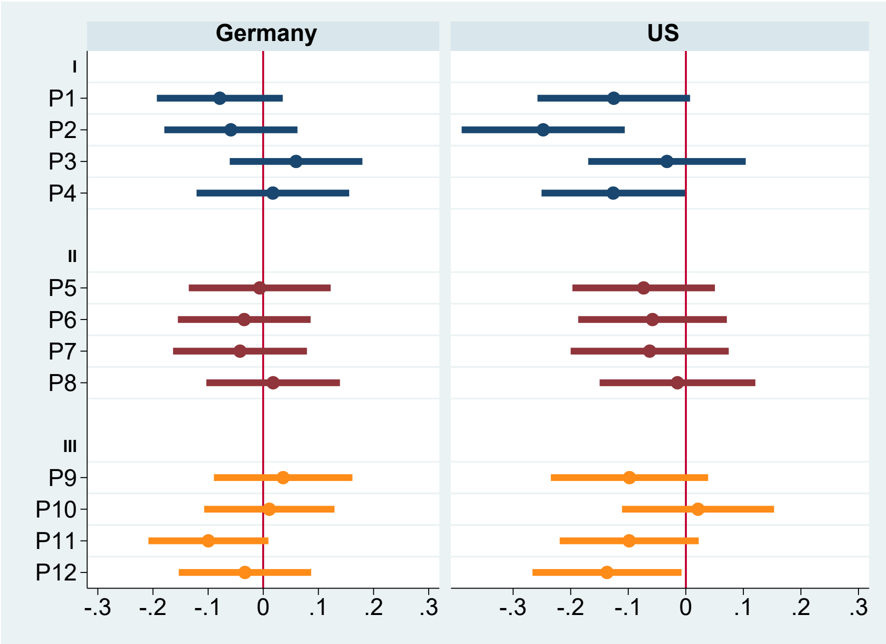
Figure 4: ITT of information treatment I_1 and I_2 on perceptions of automation ($\alpha = 0.05$)



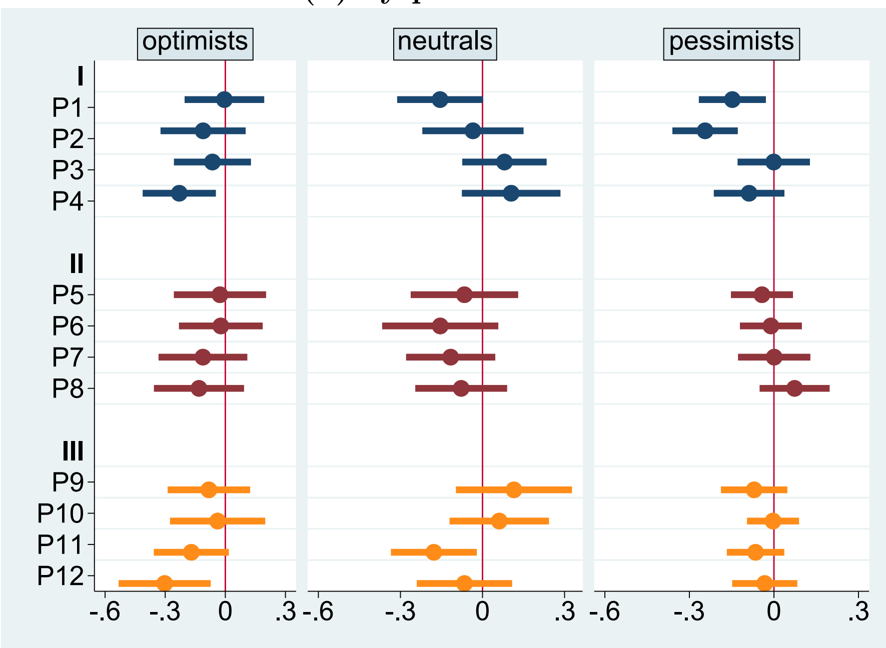
Notes: Pooled estimations for US and Germany, for information treatment regarding (a) no aggregate employment losses (I_1) and (b) employment shifts from unskilled to skilled labor (I_2), see equation 3. Perception measures (estimated separately) refer to (I) General concerns: unemployment rate (P_1), human substitutability (P_2), overall prosperity (P_3), desirability of digitalization (P_4)); ((II) Individual concerns: own unemployment (P_5), automatable job tasks (P_6), own salary (P_7), being a loser or winner (P_8)), and (III) Distributional concerns: inequality across workers (P_9), risks for workers w/o high-school/with high-school/with college ($P_{10} - P_{12}$), see Table 3 for details.

Figure 5: ITT effect of "No aggregate employment losses"-information (I_1) on perceptions of automation ($\alpha = 0.05$)

(a) by country



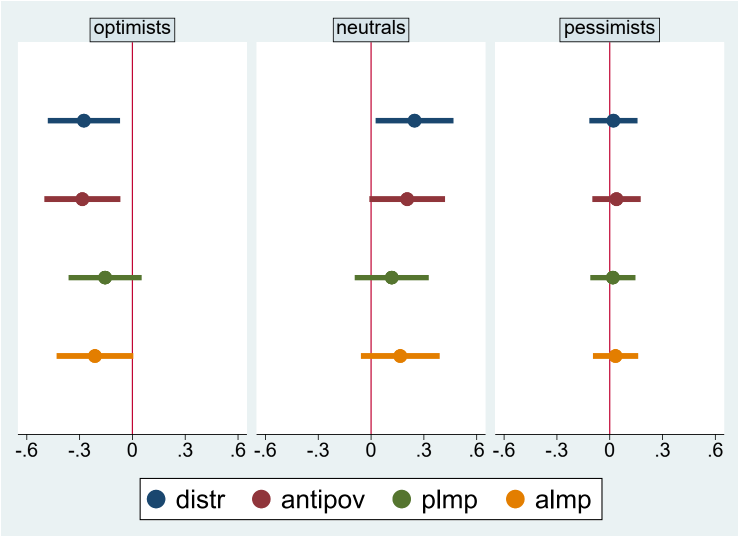
(b) by prior belief



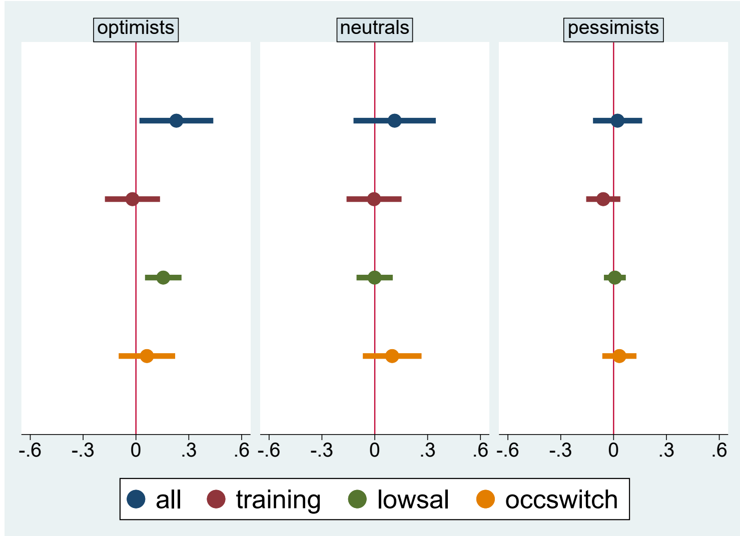
Notes: Pooled estimations for US and Germany showing (a) ITT for Germany (β_1) and the US (β_2), see equation (4), and (b) ITT for "optimists" (β_3), "neutrals" (β_4) and "pessimists" (β_5) regarding the future value of human work, see equation (5). Perception measures (estimated separately) refer to (I) General concerns: unemployment rate (P_1), human substitutability (P_2), overall prosperity (P_3), desirability of digitalization (P_4)); ((II) Individual concerns: own unemployment (P_5), automatable job tasks (P_6), own salary (P_7), being a loser or winner (P_8)), and (III) Distributional concerns: inequality across workers (P_9), risks for workers w/o high-school/with high-school/with college ($P_{10} - P_{12}$), see Table 3 for details.

Figure 6: ITT effect of "No aggregate employment losses"-information (I_1) on set of outcomes by prior belief ($\alpha = 0.05$)

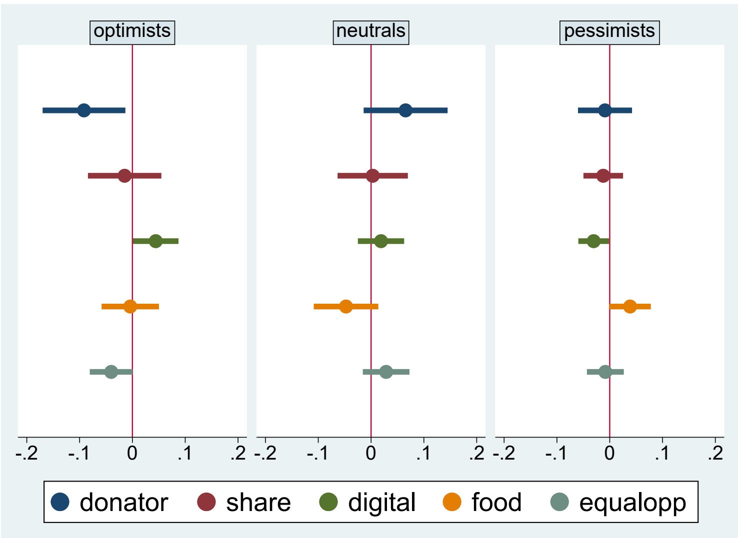
(a) Policy Demands



(b) Stated Labor Market Choices

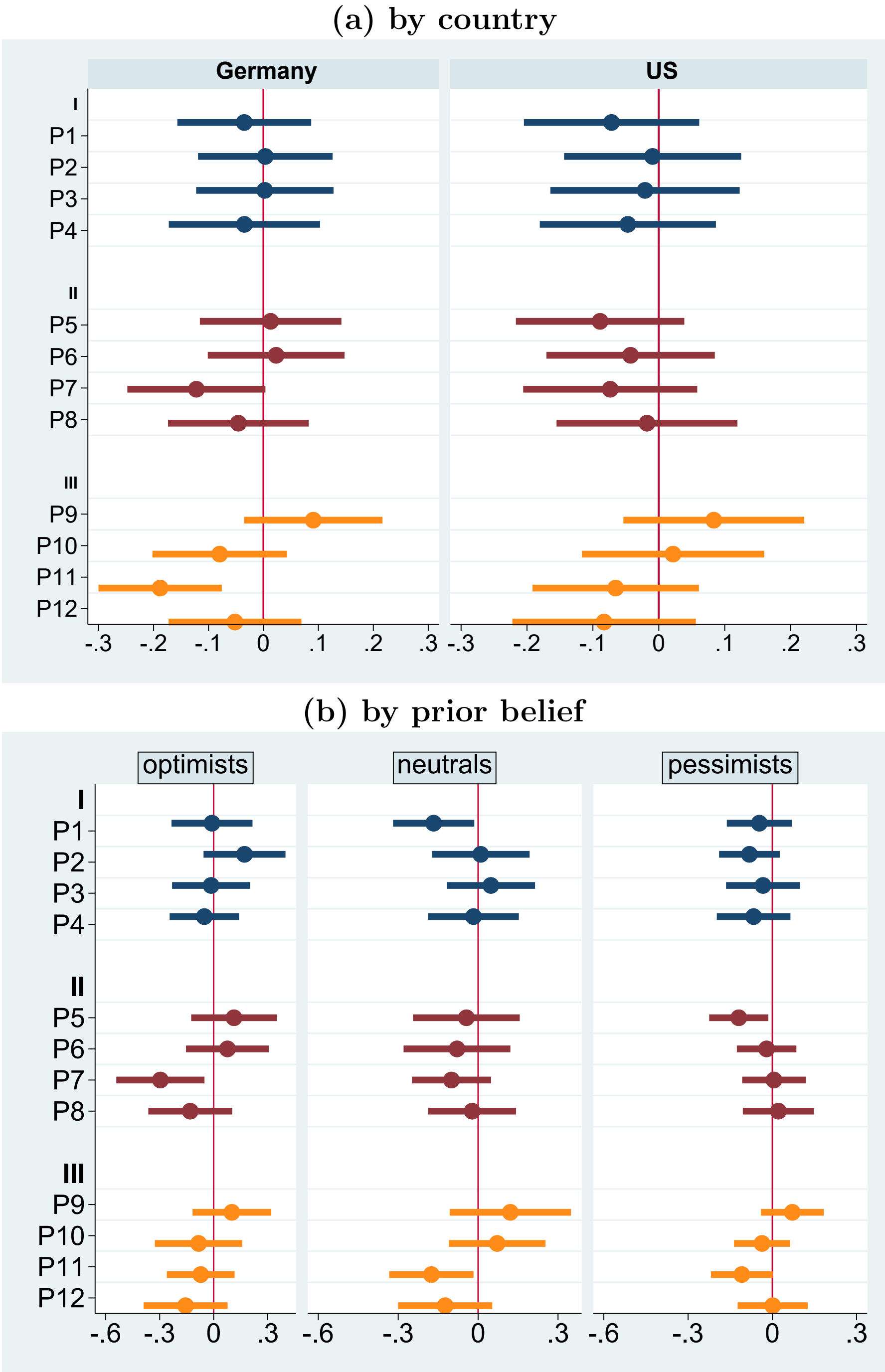


(c) Donations to Charities



Notes: ITT by prior belief, i.e. for "optimists" (β_3), "neutrals" (β_4) and "pessimists" (β_5) regarding the future value of human work, see equation (5). Separate estimations for each outcome. Policy Demand captures redistributive policies (*distr*), anti-poverty measures (*antipov*), passive labor market policies (*plmp*) and active labor market policies (*almp*); Stated Labor Market Choices refers to participating in training (*training*), accepting lower salaries (*lowsal*) and switching occupations (*occswitch*); Donations to Charities refer to whether someone donates at all (*donator*), the share donated (*share*) and the relative share donated for digital education (*digital*), for feeding the poor (*food*) or equal opportunity (*equalopp*), see Appendix C for details.

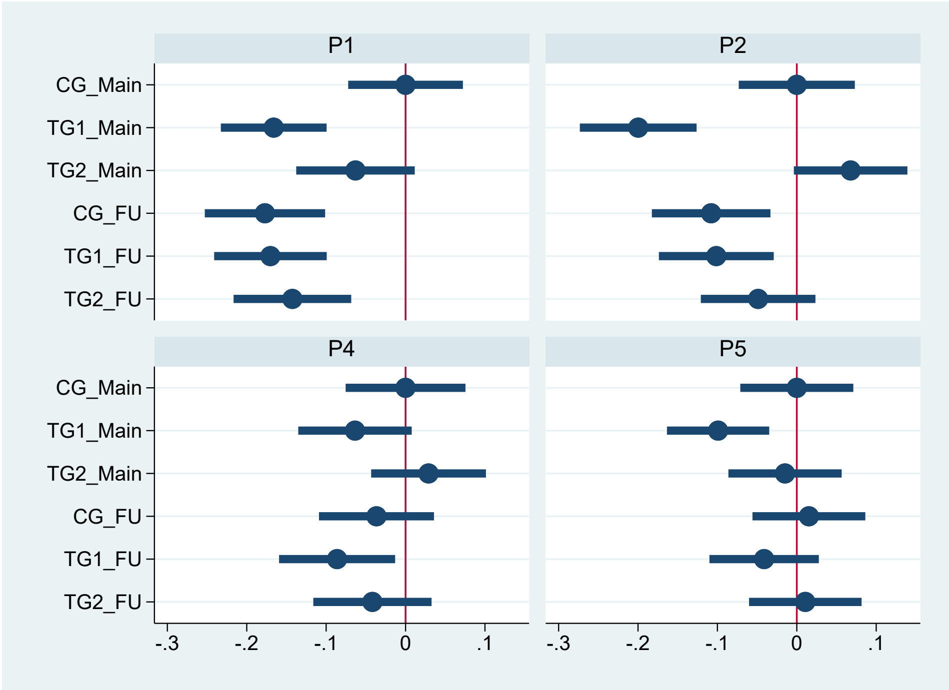
Figure 7: ITT effect of "Employment shifts from unskilled to skilled workers"-information (I_2) on perceptions of automation ($\alpha = 0.05$)



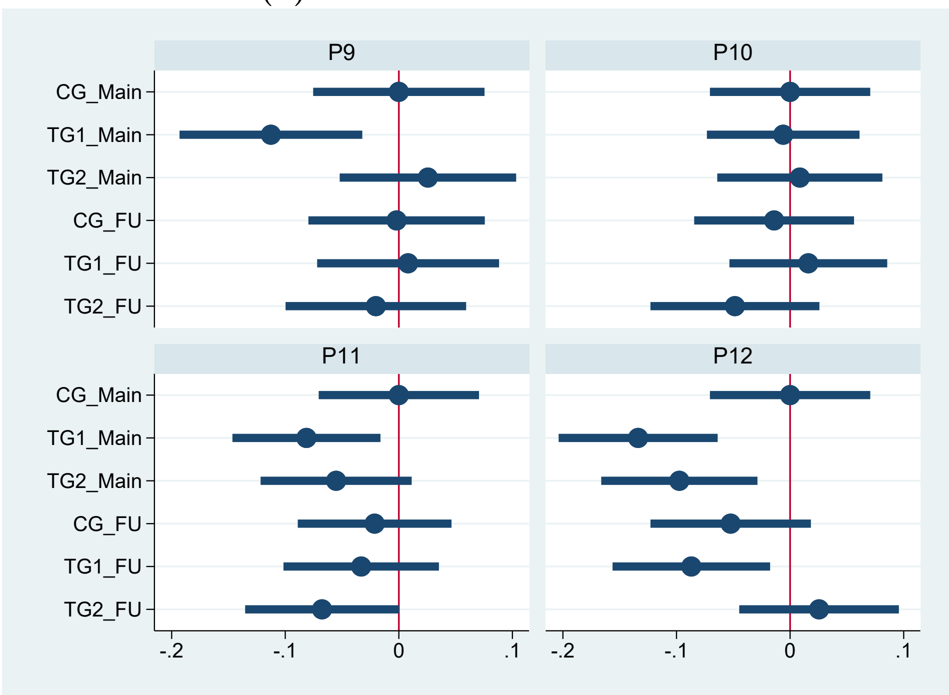
Notes: Pooled estimations for US and Germany showing (a) ITT for Germany (β_1) and the US (β_2), see equation (4), and (b) ITT by prior belief, i.e. for "optimists" (β_3), "neutrals" (β_4) and "pessimists" (β_5) regarding the future value of human work, see equation (5). Perception measures (estimated separately) refer to (I) General concerns: unemployment rate (P_1), human substitutability (P_2), overall prosperity (P_3), desirability of digitalization (P_4)); ((II) Individual concerns: own unemployment (P_5), automatable job tasks (P_6), own salary (P_7), being a loser or winner (P_8)), and (III) Distributional concerns: inequality across workers (P_9), risks for workers w/o high-school/with high-school/with college ($P_{10}-P_{12}$), see Table 3 for details.

Figure 8: Difference-in-Differences Estimates for Perception Measure in Control and Treatment Groups in the Main and the Follow-Up Survey, US only ($\alpha = 0.10$)

(a) General and Individual Concerns



(b) Distributional Concerns



Notes: Estimates based on equation 6 for general concerns: unemployment rate (P_1), human substitutability (P_2), overall prosperity (P_3), desirability of digitalization (P_4); individual concerns: own unemployment (P_5), and distributional concerns: inequality across workers (P_9), risks for workers w/o high-school/with high-school/with college ($P_{10} - P_{12}$), see Table 3 for details. Figures show estimated perception levels for control group in main survey (CG_Main= α) and follow-up survey (CG_FU=$\alpha+\beta_3$), for treatment group 1 (TG1_Main=$\alpha+\beta1$, TG1_FU=$\alpha+\beta1+\beta3+\beta4$), and treatment group 2 (TG2_Main= $\alpha+\beta2$, TG2_FU= $\alpha+\beta2+\beta3+\beta5$).

Tables

Table 1: Experimental Groups and Sample Size by Country

Group Assignment	Ordering of questions	Information Treatment	Sample size US	D	All
$ACBD_0$	A-C-B-D	No	766	512	1,278
$ABCD_0$	A-B-C-D	No	779	536	1,315
$ABCD_1$	A-B-C-D	I_1, see Fig. 2	763	523	1,286
$ABCD_2$	A-B-C-D	I_2, see Fig. 3	758	510	1,268

Notes: A, B, C and D refer to the respective survey blocks as described in section 2.2.

Table 2: Summary statistics (mean and sd) of control variables by country

	Germany		USA		Total	
Demographics						
Female	0.470	(0.499)	0.450	(0.498)	0.458	(0.498)
Migration background	0.197	(0.398)	0.164	(0.370)	0.178	(0.382)
Race: nonwhite	n/a	–	0.261	(0.439)	0.261	(0.439)
Cohabiting	0.607	(0.488)	0.619	(0.486)	0.614	(0.487)
Children in hh yes/no	0.405	(0.491)	0.440	(0.496)	0.425	(0.494)
Number of hh members	2.243	(1.135)	2.418	(1.315)	2.346	(1.247)
Age 18-25	0.130	(0.336)	0.181	(0.385)	0.160	(0.367)
Age 26-35	0.261	(0.439)	0.249	(0.433)	0.254	(0.435)
Age 36-45‡	0.273	(0.446)	0.260	(0.439)	0.266	(0.442)
Age 46-55	0.336	(0.472)	0.309	(0.462)	0.320	(0.467)
No high-school	0.270	(0.444)	0.307	(0.461)	0.292	(0.455)
High-school‡	0.491	(0.500)	0.338	(0.473)	0.401	(0.490)
College degree	0.238	(0.426)	0.355	(0.478)	0.307	(0.461)
Poor household	0.181	(0.385)	0.200	(0.400)	0.192	(0.394)
Mid inc. household‡	0.594	(0.491)	0.437	(0.496)	0.501	(0.500)
Rich household	0.169	(0.375)	0.250	(0.433)	0.217	(0.412)
Job and workplace characteristics						
Currently employed: yes	0.967	(0.179)	0.984	(0.124)	0.977	(0.150)
Precarious job: yes	0.253	(0.435)	0.213	(0.410)	0.230	(0.421)
Self-employed: yes	0.058	(0.234)	0.108	(0.311)	0.088	(0.283)
Ever unemployed: Yes	0.495	(0.500)	0.576	(0.494)	0.543	(0.498)
Share of routine tasks	0.378	(0.283)	0.322	(0.287)	0.345	(0.287)
Share of manual tasks	0.283	(0.291)	0.295	(0.297)	0.290	(0.294)
Incr. job requirements	0.500	(0.500)	0.470	(0.499)	0.482	(0.500)
Stable job requirements‡	0.351	(0.477)	0.384	(0.486)	0.370	(0.483)
Decr. job requirements	0.079	(0.270)	0.070	(0.255)	0.074	(0.261)
Share of IT-based tasks	0.400	(0.377)	0.451	(0.403)	0.430	(0.393)
Political and Economic Views						
Pol. view: left	0.164	(0.370)	0.272	(0.445)	0.227	(0.419)
Pol. view: moderate‡	0.653	(0.476)	0.404	(0.491)	0.506	(0.500)
Pol. view: right	0.085	(0.278)	0.237	(0.425)	0.174	(0.379)
Econ. view: liberal	0.295	(0.456)	0.357	(0.479)	0.332	(0.471)
Econ. view: moderate‡	0.356	(0.479)	0.280	(0.449)	0.311	(0.463)
Econ. view: anti-liberal	0.254	(0.436)	0.281	(0.450)	0.270	(0.444)
Gov. trust: high	0.238	(0.426)	0.224	(0.417)	0.230	(0.421)
Gov. trust: moderate‡	0.212	(0.408)	0.215	(0.411)	0.214	(0.410)
Gov. trust: low	0.511	(0.500)	0.528	(0.499)	0.521	(0.500)
N	2,081		3,066		5,147	

Notes: ‡ denotes reference category for non-binary categorical variables, see also Table A.2. Categories do not necessarily add up to 100% due to missing values. Table A.2 includes number of missings for each variable. All subsequent regression analyses always includes a dummy for missings in each variable.

Table 3: Descriptive Statistics of Perception Measures related to Automation in Germany and the US

	cat1 ... cat6	country	mean	cat1	cat2	cat3	cat4	cat5	cat6	N	*pval*
(I) Perceptions regarding general implications											
P_1 - Unemployment rate	subst. fall ... subst. rise	D	3.53	.9	9.5	35.3	44.7	9.7	n/a	536	.0071
		US	3.51	3.6	8.8	34.8	38.1	14.6	n/a	779	
P_2 - Relev. of human workforce	mainly supplement ... mainly substitute	D	3.45	2.3	15.6	31.1	36.5	14.5	n/a	536	.0013
		US	3.46	4.8	13.8	33.3	26.6	21.5	n/a	779	
P_3 - Overall prosperity	increase strongly ... decrease strongly	D	3.17	1.6	22.5	38.8	31.3	5.8	n/a	536	.0003
		US	3	5.5	28.8	33.8	23.6	8.3	n/a	779	
P_4 - Desirability of digitaliz.	abs. yes... abs. not	D	2.27	10.6	56.5	27.6	5.3	n/a	n/a	536	.5939
		US	2.25	13.3	54.2	26.4	6.1	n/a	n/a	779	
(II) Perceptions regarding individual implications											
P_5 - Own unemployment risk	abs. not ... abs. yes	D	1.93	38.5	35.4	20.7	5.4	n/a	n/a	536	.8877
		US	1.91	40.6	33.2	20.5	5.7	n/a	n/a	779	
P_6 - Share of automatable tasks	$0-10 \ldots 91-100$	D	2.16	33.6	33.8	19.6	10	1.9	1.1	536	.0986
		US	2.19	37.7	29.9	15	12.7	2.8	1.9	779	
P_7 - Expe. change in own salary	increase strongly ... decrease strongly	D	2.94	.9	24.1	57.9	14.9	2.3	n/a	536	0002
		US	2.83	5.9	20.8	60.1	10.4	2.8	n/a	779	
P_8 - Loser of digitalization	def. winner... def. looser	D	2.79	4.8	25.9	56.9	10.3	2.1	n/a	536	.0064
		US	2.65	9.7	29.8	49.5	7.6	3.5	n/a	779	
(III) Perceptions regarding distributional implications											
P_9 - Inequ. across social groups	abs. not ... abs. yes	D	3.12	2.2	13.2	55	29.6	n/a	n/a	536	.1411
		US	3.19	3.3	9.5	52.5	34.8	n/a	n/a	779	
P_{10} - Workers w/o high-school	subst. benefit ... subst. suffer	D	3.81	1.8	7.6	28.9	31	30.6	n/a	536	.0000
		US	4.02	4.6	6.5	20.1	19.7	49.1	n/a	779	
P_{11} - Workers with high-school	subst. benefit ... subst. suffer	D	2.64	12.2	27.6	48.6	7.6	4	n/a	536	.0000
		US	3.41	6.7	8.5	41.1	24.4	19.3	n/a	779	
P_{12} - Workers with tertiary ed.	subst. benefit ... subst. suffer	D	2.36	20.6	32.5	39.4	5.3	2.2	n/a	536	.0008
		US	2.6	17.2	24.2	45	8.4	5.3	n/a	779	

Notes: Sample only contains respondents assigned to the control group $ABCD_0$, D refers to Germany, US to United States. *pval* denotes the pvalue for a Pearson-Chi^2 test of cross-country differences.

Table 4: LPM Estimations for Main Perception Indicators by Country

	Germany			United States		
	(P_1)	(P_5)	(P_9)	(P_1)	(P_5)	(P_9)
Demographics						
Female	0.046	0.037	0.029	-0.066	-0.037	0.025
Migration background	0.029	0.143**	0.062	0.152**	-0.026	-0.139*
Nonwhite	n/a	n/a	n/a	-0.153**	0.178***	-0.076
Cohabiting spouse/partner	-0.007	-0.203***	-0.094	0.142**	0.029	0.057
Children in hh	-0.099	-0.105	-0.042	0.001	-0.045	0.050
Number of hh members	0.084*	0.116**	0.008	-0.057	-0.037	-0.025
Age 18-25	-0.039	0.021	-0.055	-0.164*	-0.183**	-0.065
Age 26-35	-0.074	0.090	0.004	-0.185***	0.005	-0.117*
Age 46-55	0.057	-0.081	0.083	-0.172***	-0.109**	-0.051
High-school or less	-0.030	0.147***	-0.045	-0.108	0.084	-0.050
Tertiary degree	-0.098*	-0.129**	0.090	-0.038	0.025	0.164***
Poor household	-0.027	0.113	-0.022	-0.029	0.289***	0.044
Rich household	-0.097	-0.112*	-0.071	-0.021	-0.236***	0.030
Job and workplace characteristics						
Currently employed	-0.270**	-0.475***	0.003	0.225	-0.316	0.181
Precarious job	0.013	0.047	0.074	-0.134**	0.071	-0.044
Self-employed	0.028	-0.154*	0.073	-0.025	0.000	0.077
Ever unemployed: Yes	-0.006	0.177***	0.054	0.003	0.168***	0.105**
Share of routine tasks	0.192**	0.102	0.032	0.282***	0.194**	0.067
Share of manual tasks	0.067	0.135	-0.049	-0.138	0.056	0.052
Incr. job requirements	0.063	-0.053	0.140***	0.089*	0.103**	0.094*
Decr. job requirements	-0.015	0.145*	-0.047	-0.001	0.464***	0.084
Share of IT-based tasks	-0.179**	0.151*	0.001	-0.192**	0.209***	0.090
Political and Economic Views						
Political view: left	-0.009	-0.069	0.049	0.072	-0.113**	0.237***
Political view: right	-0.013	0.024	0.109	-0.186***	-0.122**	-0.310***
Economic view: liberal	-0.009	-0.031	0.060	0.041	-0.075	-0.039
Economic view: not liberal	0.024	-0.096*	0.203***	0.085	-0.082	0.077
Trust in government	0.039	-0.005	0.062	-0.028	0.235***	0.146**
Mistrust in government	0.343***	-0.054	0.286***	0.140**	-0.139***	0.152***
Constant	-0.035	0.077	-0.450**	0.082	0.029	-0.416*
N	1,985	2,011	1,905	2,824	2,893	2,633
R-squared	0.073	0.136	0.060	0.070	0.180	0.085

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Notes: Regressions based on equation (1), including dummies for experimental groups and dummies for missing categories. Perception measures P_1 (unemployment rate), P_5 (unemployment risk), and P_9 (unequal impact) as defined in Table 3.

Table 5: OLS regressions of Policy Preferences on Main Perception Indicators by Country

	(1) redistr	(2) antipov	(3) plmp	(4) almp
United States				
Estimates related to concerns regarding ...				
P_1 - higher unemployment rate	0.035	0.065**	0.048*	0.071**
P_5 - own unemployment risk	0.164***	0.099***	0.129***	0.056*
P_9 - unequal impact of automation	0.137***	0.105***	0.133***	0.078***
N	2096	1691	2141	1871
adj. R^2	0.450	0.384	0.289	0.190
Germany				
Estimates related to concerns regarding ...				
P_1 - higher unemployment rate	0.100***	0.103***	0.055*	0.053*
P_5 - own unemployment risk	0.001	0.061**	0.014	0.058**
P_9 - unequal impact of automation	0.053**	0.027	0.074**	-0.011
N	1450	1635	1622	1611
adj. R^2	0.145	0.112	0.093	0.050

*** p<0.01, ** p<0.05, * p<0.1

Notes: Regressions based on equation (2), including controls for demographics, job and workplace characteristics, political and economic beliefs, dummies for the experimental group, and dummies for missing categories. Outcomes refer to preferences for redistributive policies (distr), anti-poverty measures (antipov), passive labor market policies (plmp) and active labor market policies (almp), see Appendix C for details. Perception measures P_1, P_5, and P_9 as defined in Table 3.

Table 6: OLS Regressions of Stated Labor Market Outcomes on Main Perception Measures by Country

	(1) all	(2) training	(3) lowsal	(4) occswitch
United States				
Estimates related to concerns regarding ...				
P_1 - higher unemployment rate	0.0328	0.0108	-0.0128	0.0724***
P_5 - own unemployment risk	0.0303	0.0749***	-0.0199	-0.0140
P_9 - unequal impact of automation	0.0201	0.0427	-0.00688	0.00296
N	2026	2286	2197	2402
adj. R^2	0.101	0.052	0.124	0.052
Germany				
Estimates related to concerns regarding ...				
P_1 - higher unemployment rate	0.0403	0.0370	0.0224	0.00446
P_5 - own unemployment risk	-0.00159	-0.0275	-0.0112	0.0473*
P_9 - unequal impact of automation	0.0760**	0.0641**	0.0119	0.0852***
N	1605	1819	1663	1802
adj. R^2	0.120	0.123	0.077	0.022

*** p<0.01, ** p<0.05, * p<0.1

Notes: Regressions based on equation (2), including controls for demographics, job and workplace characteristics, political and economic beliefs, dummies for the experimental group, and dummies for missing categories. Outcomes refer to willingness to participate in training (training), accepting lower salaries (lowsal) and switching occupations (occswitch), see Appendix C for details. Perception measures P_1, P_5, and P_9 as defined in Table 3.

Table 7: OLS regressions of Donation Outcomes on Main Perception Measures by Country

	(1) donator	(2) share don.	(3) digital	(4) food bank	(5) equal opp.
United States					
Estimates related to concerns regarding ...					
P_1 - higher unemp. rate	-0.00911	-0.0320***	-0.00624	0.0141*	-0.00786
P_5 - own unemp. risk	0.0349***	0.0356***	0.00503	-0.00862	0.00358
P_9 - unequal impact	0.0143	0.0142*	0.00241	-0.0139	0.0115
N	2474	1912	1912	1912	1912
adj. R^2	0.059	0.064	0.028	0.038	0.013
Germany					
Estimates related to concerns regarding ...					
P_1 - higher unemp. rate	-0.00408	-0.0232**	-0.00218	-0.00527	0.00744
P_5 - own unemp. risk	0.0208*	0.0212**	0.00252	-0.00944	0.00692
P_9 - unequal impact	-0.0265**	-0.0102	0.00343	-0.00872	0.00528
N	1857	1443	1443	1443	1443
adj. R^2	0.036	0.068	0.021	0.022	0.011

*** p<0.01, ** p<0.05, * p<0.1

Notes: Regressions based on equation (2), including controls for demographics, job and workplace characteristics, political and economic beliefs, dummies for the experimental group, and dummies for missing categories. Outcomes refer to whether someone donates at all (donator), the share donated (share) and the relative share donated for digital education (digital), for feeding the poor (food) or equal opportunity (equalopp), see Appendix C for details. Perception measures P_1, P_5, and P_9 as defined in Table 3.

Table 8: Multiple Hypothesis Testing for Treatment Effects in Figure 4 (p-values)

	I_1 "no agg. emp. loss"	I_2 "emp. shifts"
P_1 - unemployment rate	.0248	.2432
P_2 - relevance of human work	.0016	.9270
P_3 - overall prosperity	.8903	.8215
P_4 - desirability of digitalization	.1615	.4051
P_5 - own unemployment risk	.3240	.3231
P_6 - automatable job tasks	.2946	.7556
P_7 - own salary change	.2488	.0469
P_8 - being loser or winner	.9899	.5654
P_9 - inequality across workers	.4106	.0702
P_{10} - risks for workers w/o high-school	.7078	.6996
P_{11} - risks for workers w high-school	.0182	.0131
P_{12} - risks for college graduates	.0458	.1514
Overall	.0154	.1321

Notes: P-values based on re-sampling (with 1,000 repetitions) from a distribution of t-statistics using Stata command randcmd, see Young (2019) for details. Overall p-value tests null hypothesis of irrelevance of treatment for all perception measures using Westfall-Young multiple hypothesis testing.

Table 9: Multiple Hypothesis Testing for Heterogeneous Treatment Effects of "No Aggregate Employment Losses"-Information I_1 (p-values)

	by country			*by prior belief*			
	Germany	US	*jointly*	*optimists*	*neutrals*	*pessimists*	*jointly*
Perception Measures, see Figure 5							
P_1	.1667	.0655	.1257	.9522	.0444	.0198	.0575
P_2	.3398	.0007	.0016	.2995	.7180	.0008	.0008
P_3	.3290	.6372	.5553	.5281	.3318	.9894	.7082
P_4	.7942	.0509	.1003	.0154	.2737	.1733	.0470
P_5	.9241	.2552	.4407	.8066	.4805	.4544	.8369
P_6	.5826	.3845	.6220	.8271	.1586	.8433	.4058
P_7	.4797	.3611	.5945	.3303	.1874	.9838	.4673
P_8	.7754	.8403	.9525	.2515	.4023	.2470	.5746
P_9	.5881	.1571	.2865	.4484	.2943	.2487	.5643
P_{10}	.8478	.7635	.9415	.7654	.5021	.9455	.8749
P_{11}	.0806	.1024	.1551	.0849	.0274	.2150	.0799
P_{12}	.5955	.0349	.0681	.0092	.4718	.5906	.0297
Overall			.0125				.0300
Policy Preferences, see Figure 6							
distr	.9052	.6825	.8983	.0078	.0366	.7639	.0213
antipov	.8987	.9459	.9873	.0131	.0567	.5830	.0393
plmp	.9654	.8223	.9653	.1286	.2784	.7935	.3342
almp	.7327	.8120	.9220	.0578	.1553	.5891	.1604
Overall			.9999				.07624
Stated Labor Market Choices, see Figure 6							
training	.8786	.1351	.2533	.7934	.9549	.2467	.5839
lowsal	.5510	.3026	.5170	.0098	.9871	.8275	.0275
occswitch	.1540	.3189	.2818	.4450	.2423	.4898	.5615
Overall			.60719				.09486
Donation Choices, see Figure 6							
donator	.6093	.3462	.5599	.0178	.1134	.7155	.0515
shdon	.2070	.2414	.3640	.6544	.9396	.5081	.8898
digital	.8904	.7141	.9141	.0497	.4085	.0373	.1071
foodbank	.8973	.8869	.9793	.8807	.1303	.0573	.1634
equalopp	.0193	.2331	.0377	.0467	.2268	.6416	.1365
Overall			.15197				.2004

Notes: Randomized-t p-values for single coefficients and Westfall-Young multiple hypothesis testing for each equation and for all equations jointly (iterations: 1,000). Perceptions as defined in Table 3, further outcomes as defined in Appendix C.

Table 10: Multiple Hypothesis Testing for Heterogeneous Treatment Effects of "Employment Shifts from Unskilled to Skilled Labor"-Information I_2 (p-values)

	by skill group				*by prior belief*			
	low	middle	high	*jointly*	*optimists*	*neutrals*	*pessimists*	*jointly*
Perception Measures, see Figure 7								
P_1	.6108	.5733	.2221	.5246	.9370	.0393	.4111	.1149
P_2	.1414	.1003	.7207	.2585	.1782	.9035	.1387	.3602
P_3	.1128	.9270	.5448	.2917	.9090	.5726	.6306	.9240
P_4	.0212	.9162	.9456	.0644	.6060	.8597	.3374	.7055
P_5	.5975	.7451	.6970	.9342	.3540	.6514	.0264	.0794
P_6	.7482	.6413	.2485	.5671	.4914	.4590	.7512	.8478
P_7	.0197	.7775	.3730	.0579	.0147	.2063	.9072	.0416
P_8	.2294	.7567	.5745	.5378	.2724	.7798	.7542	.6159
P_9	.5713	.0285	.9736	.0838	.4050	.3177	.2131	.5162
P_{10}	.2371	.3156	.4861	.5515	.4757	.4350	.4622	.8236
P_{11}	.1254	.4134	.0125	.0383	.4430	.0280	.0471	.0831
P_{12}	.0086	.6163	.1352	.0247	.2056	.1814	.9933	.4447
Overall				.26465				.4039
Policy Preferences, see Figure G.4 and G.2								
distr	.9743	.7550	.1298	.3408	.9841	.5746	.6979	.9227
antipov	.3207	.9708	.0618	.1740	.9158	.9041	.6824	.9672
plmp	.7841	.9150	.2311	.5471	.3929	.7513	.9707	.7562
almp	.3960	.5289	.0085	.0256	.3994	.2056	.4265	.4983
Overall				.09104				.9010
Stated Labour Market Choices, see Figure G.4 and G.2								
training	.3651	.1856	.8562	.47406	.0821	.9183	.2957	.2292
lowsal	.6210	.9677	.6318	.94966	.3805	.3387	.2991	.6603
occswitch	.7976	.4055	.5238	.79063	.5929	.1447	.8070	.3661
Overall				.8423				.5533
Donation Choices, see Figure G.4 and G.2								
donator	.1314	.7257	.5072	.3369	.8412	.6717	.4479	.8306
shdon	.6483	.2575	.0233	.0679	.0864	.9130	.3380	.2372
digital	.4468	.1945	.5884	.4776	.3422	.2008	.3640	.4896
foodbank	.4378	.9943	.6290	.8119	.4568	.0233	.2535	.0664
equalopp	.9748	.2250	.9758	.5434	.9296	.0878	.7724	.2380
Overall				.26823				.2724

Notes: Randomized-t p-values for single coefficients and Westfall-Young multiple hypothesis testing for each equation and for all equations jointly (iterations: 1,000). Perceptions as defined in Table 3, further outcomes as defined in Appendix C.

Appendix

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A Data Descriptives and Balancing Test

Table A.1: Representativeness of Sample Characteristics

	Germany		USA	
	Sample	Population	Sample	Population
female	0.470	0.468	0.450	0.474
age 18-25	0.130	0.114	0.181	0.190
age 26-35	0.261	0.255	0.249	0.291
age 36-45	0.273	0.280	0.260	0.264
age 46-55	0.336	0.351	0.309	0.254
high educ	0.238	0.293	0.355	0.355
poor	0.191	0.103	0.226	0.253
middle	0.630	0.744	0.492	0.536
rich	0.179	0.153	0.282	0.211
foreign born	0.078	0.175	0.076	0.194
married	0.433	0.630	0.513	0.448
household size	2.243	2.718	2.418	3.113
sample size	2,081	13,037	3,066	1,171,369

Notes: This table presents summary statistics for the overall population in Germany and the USA, and compares it to the characteristics in our German and US surveys, respectively. American population statistics are from the American Community Survey (ACS), survey wave 2019 (retrieved from IPUMS USA, `https://usa.ipums.org/usa/`). German population statistics are from the German Socio-Economic Panel (SOEP), survey wave 2019 (`https://www.diw.de/en/diw_01.c.615551.en/research_infrastructure__socio-economic_panel__soep.html`). To be comparable with our survey sample, the population data are restricted to individuals in the labor force who are between 18 and 55 years old. Data are weighted to represent population statistics. Income categories *poor*, *middle*, *rich* are based on net household income (adjusted by household size) and constructed relative to the median in this variable (where *poor* indicates less than 60% of median and *rich* indicates more than twice the median). Variable *high educ* indicates the share of respondents with education level *college or more*.

Table A.2: Definition and Reference Categories of Categorical Variables

Variable name	Description (= 1 if)	Reference	Missing
Demographics			
female	female gender	male gender	0
migrant	migration background	both parents born in US/DE	45
partner	cohabiting spouse or partner	other marital status	26
children	≥ 1 child below age 18 in hh	no child below age 18 in hh	17
age	age1: 18-25; age2: 25-35; age4: 45-55; age5: 55-65	age3: 35-45	0
poor	HHinc/head $<$ 0.6 median HHinc/head	HHinc/head $>$ 0.6 & $<$ 2 median hh inc/head	402
rich	HHinc/head $>$ 2 median HHinc/head		
Job and Workplace Characteristics			
unskilled	high-school diploma or less	some college or 2yr-college	0
college	4-yr college or above		
employed	currently employed or on sick leave	currently unemployed and looking for job	0
precemp	temp./marg. empl. or $<$ 30 hours/week	unlimited contract with $\geq$ 30 hours/week	324
selfemp	self-employed or freelancer	dependent employment	324
everunemp	ever been unemployed	never been unemployed	58
upskill	increasing skill requirements (4-5 out of 5)	stable job requirements (3 out of 5)	402
downskill	decreasing skill requirements (1-2 out of 5)		
Political and Economic Beliefs			
leftwing	political view left (1-3 out of 1-10)	moderate view (4-7 out of 10)	539
rightwing	political view left (8-10 out of 1-10)		
liberal	economic view liberal (4-5 out of 5)	moderate view (3 out of 5)	497
not liberal	economic view liberal (1-2 out of 5)		
govtrust	trust in government (4-5 out of 5)	moderate view (3 out of 5)	203
govmistrust	mistrust in government (1-2 out of 5)		

Notes: In all regressions, we add additional controls for observations with missings whenever the specifications include the respective variable.

Table A.3: Balancing Test, multinomial logit ($ABCD_0$ as base category)

	ACBD_0	ABCD_1	ABCD_2
Demographics			
US resident	0.0392	-0.0228	-0.0565
Female	0.0043	0.0331	0.1060
Migration background	-0.0987	-0.0933	-0.2060*
Cohabiting spouse/partner	-0.1830	-0.0836	-0.3190**
Children in hh	0.0697	0.1730	-0.0426
Number of hh members	0.0075	-0.0140	0.0480
Age 18-25	-0.0716	-0.0104	0.0107
Age 26-35	-0.0579	-0.0373	-0.0122
Age 46-55	-0.0872	-0.0935	-0.0420
High-school or less	0.0751	0.0362	0.1080
Tertiary degree	0.0627	0.0875	0.0745
Poor household	-0.1250	-0.2210*	-0.0391
Rich household	0.1730	0.1150	0.0522
Job and Workplace Characteristics			
Currently employed	0.5240*	-0.0489	0.0871
Precarious job	-0.0081	0.0392	-0.2260*
Self-employed	-0.1790	-0.164	0.0402
Ever unemployed: Yes	0.2490***	0.1830*	0.2340**
Political and Economic Views			
Political view: left	-0.1890	-0.0052	0.0973
Political view: right	-0.3570**	-0.0380	0.1180
Economic view: liberal	0.0621	-0.0225	0.1080
Economic view: not liberal	0.0390	0.0256	0.0855
Trust in government	-0.0225	-0.0663	-0.0195
Mistrust in government	-0.0861	-0.1000	-0.2810**
_cons	-0.4680	0.0591	-0.0437
N		5147	
adj R-squared		0.00773	
p-value for model test		0.659	

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

Notes: Regressions for group assignment status, see section 2.3 - $ABCD_0$: control group; $ABCD_1$: information treatment 1, $ABCD_2$: information treatment 2; $ACBD_0$: different ordering. Regressions include dummies for missing categories of variables.

Table A.4: LPM for Participation in Follow-Up Survey, US Respondents only

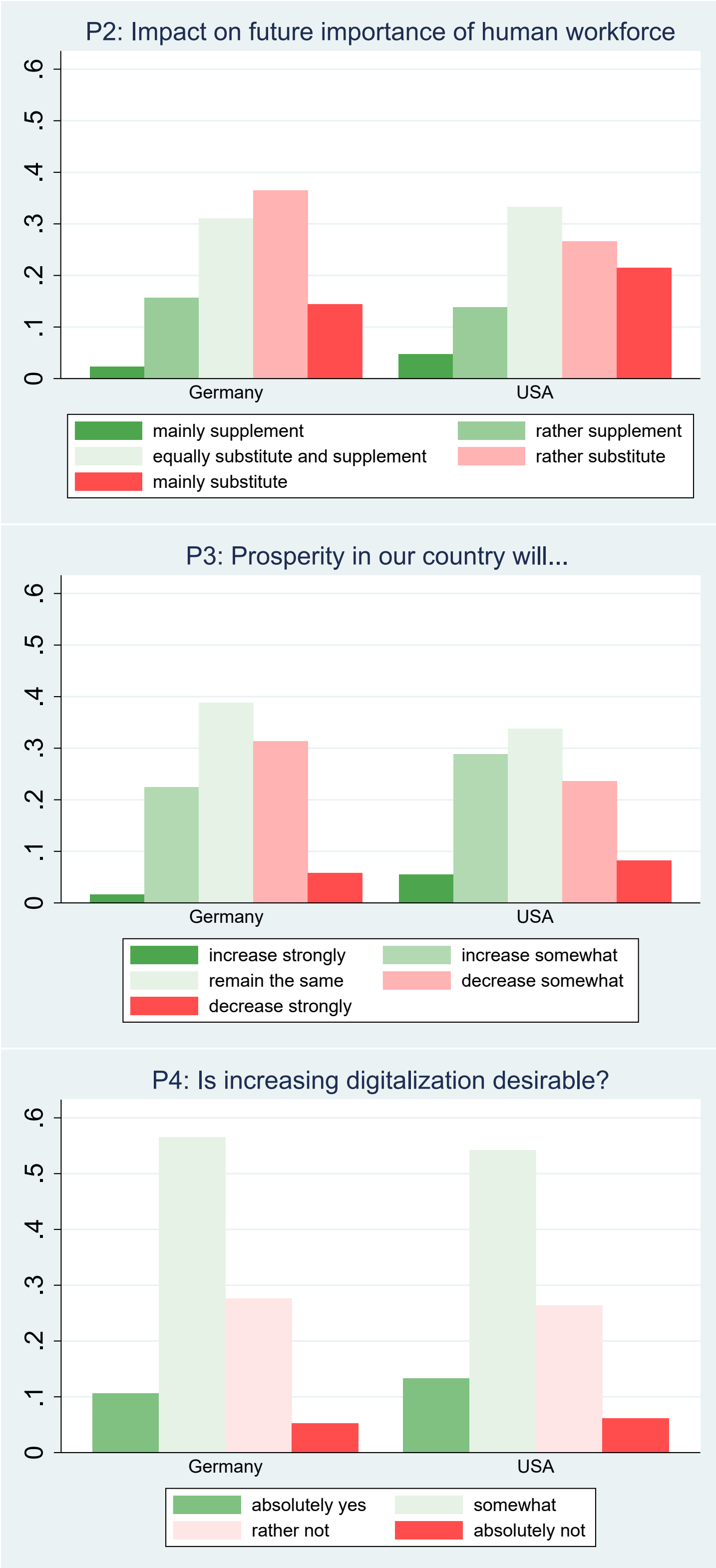
	(1)	(2)	(3)
Group assignment main Survey (ref.: $ABCD_0$)			
$ACBD_0$	-0.0074	-0.0055	-0.0090
$ABCD_1$	-0.0316	-0.0308	-0.0297
$ABCD_2$	-0.0417	-0.0411	-0.0404
Demographics			
Female	-0.0016	0.0048	0.0088
Migration background	-0.0118	-0.0083	-0.0075
Cohabiting spouse/partner	-0.0307	-0.0329	-0.0348
Children in hh	-0.0441	-0.0452	-0.0481
Number of hh members	0.0165	0.0159	0.0182
Age 18-25	-0.1540***	-0.154***	-0.152***
Age 26-35	-0.0147	-0.0127	-0.0113
Age 46-55	0.0101	0.0041	0.00677
High-school or less	0.0066	0.0069	0.0011
Tertiary degree	0.0169	0.0190	0.0284
Poor household	0.0200	0.0187	0.00569
Rich household	0.0002	0.0027	0.0068
Job and workplace characteristics			
Currently employed	0.0143	0.0111	0.0104
Precarious job	-0.0218	-0.0218	-0.0300
Self-employed	0.0669**	0.0639**	0.0551*
Ever unemployed: Yes	0.0098	0.0129	0.0166
Share of routine tasks			-0.0044
Share of manual tasks			0.0108
Incr. job requirements			-0.0206
Decr. job requirements			-0.0596
Share of IT-based tasks			-0.0734*
Political and Economic Views			
Political view: left		-0.0313	-0.0227
Political view: right		0.0235	0.0212
Economic view: liberal		-0.0000	0.0045
Economic view: not liberal		-0.0030	0.0068
Trust in government		-0.0485	-0.0433
Mistrust in government		-0.0388	-0.0347
Constant	0.726***	0.767***	0.800***
adj. R^2	0.018	0.021	0.026

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

Notes: Regression further controls for missings in all categorical variables, see Table A.2; $N = 3,066$ for all specifications. For group assignment see section 2.3 - $ABCD_0$: control group; $ABCD_1$: information treatment 1, $ABCD_2$: information treatment 2; $ACBD_0$: different ordering

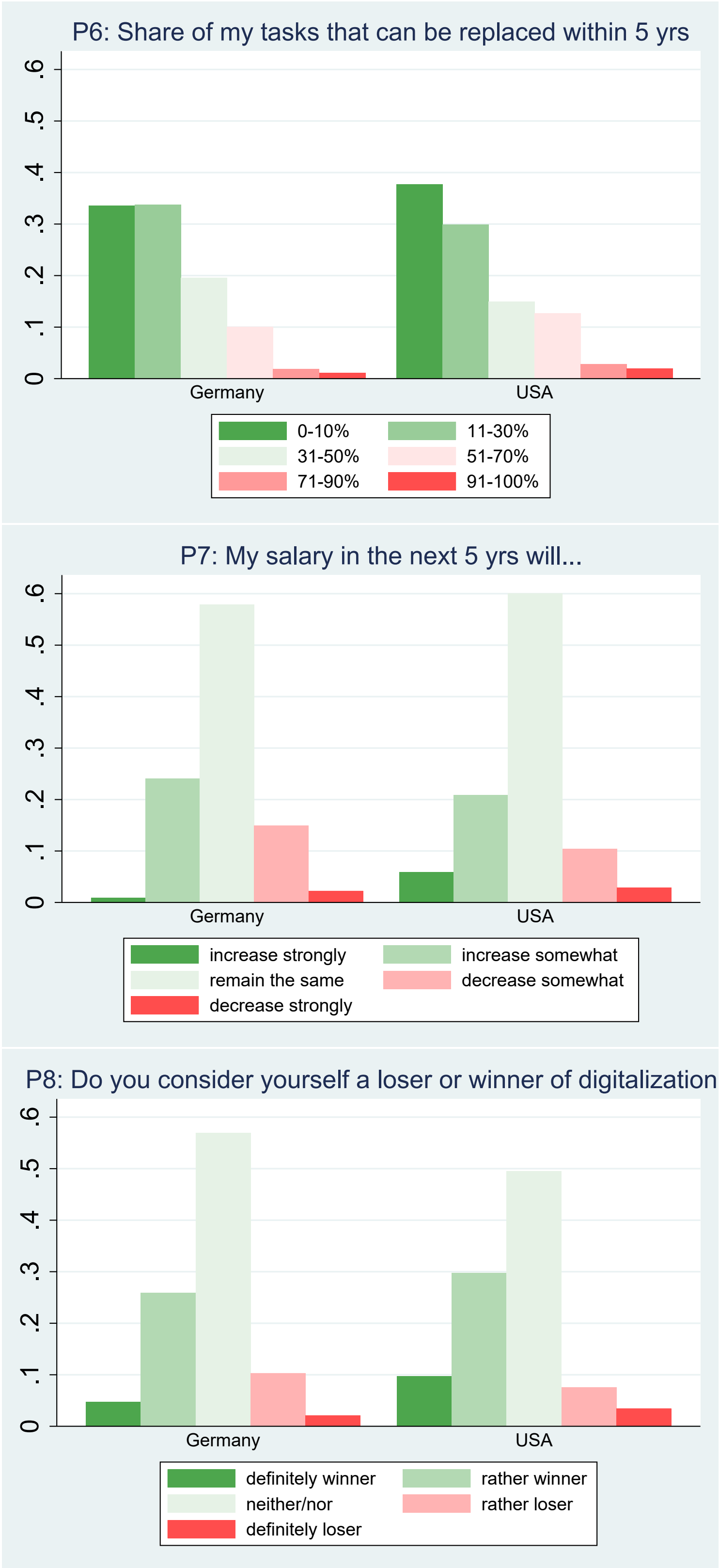
B Perception Measures: Further Results

Figure B.1: Perceptions of General Implications by Country



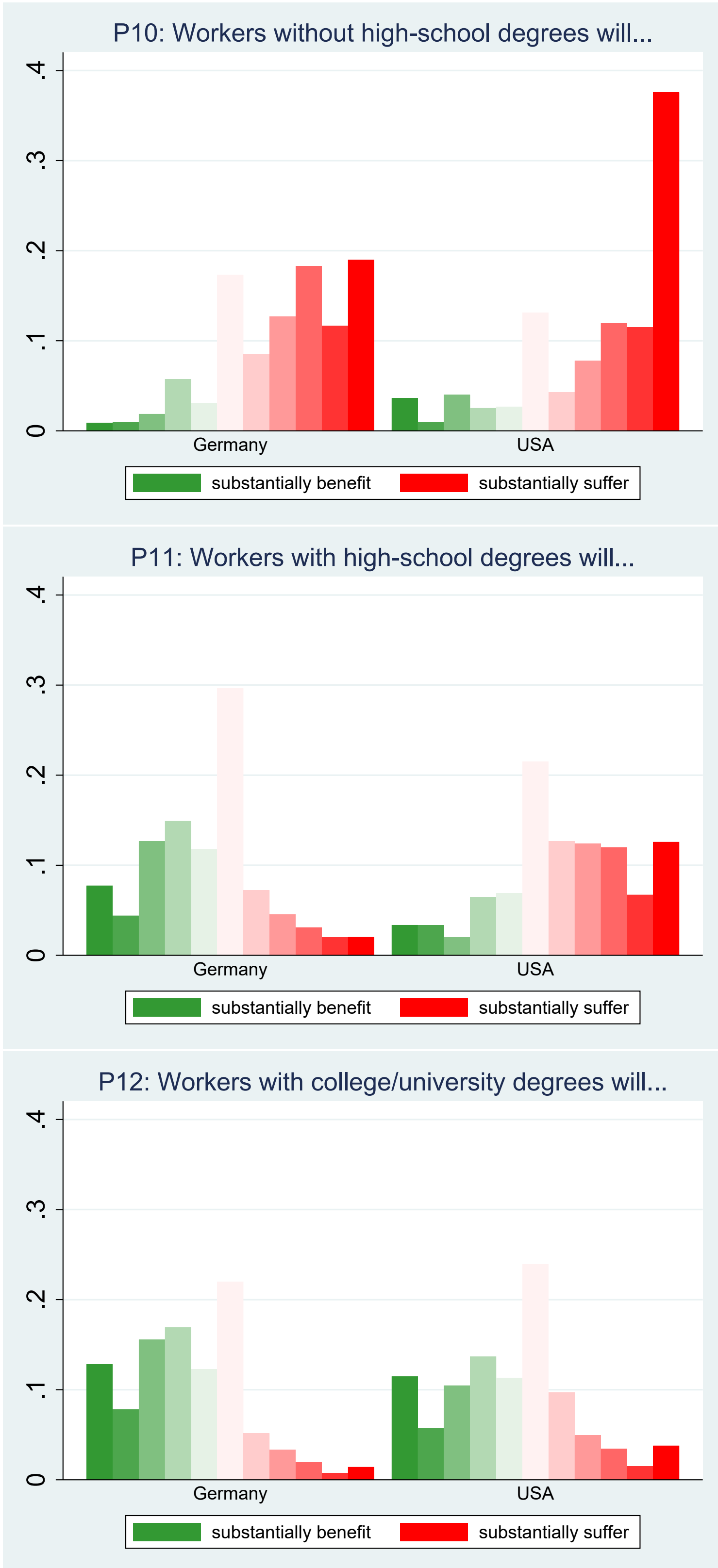
Notes: Sample only consists of respondents assigned to the control group $ABCD_0$. Detailed statistics of perception measures in Table 3.

Figure B.2: Perceptions of Individual Implications by Country



Notes: Sample only consists of respondents assigned to the control group $ABCD_0$. Detailed statistics of perception measures in Table 3.

Figure B.3: Perceptions of Distributional Implications by Country



Notes: Sample only consists of respondents assigned to the control group $ABCD_0$. Detailed statistics of perception measures in Table 3.

Table B.1: Correlation Matrix between Perception Measures (see Table 3 for details)

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}
General implications											
P_1 - Unemployment rate	1										
P_2 - Relev. of human workforce	0.221***	1									
P_3 - Overall prosperity	0.214***	0.317***	1								
P_4 - Desirability of digitaliz.	0.181***	0.270***	0.402***	1							
Individual implications											
P_5 - Own unemployment risk	0.0906***	0.112***	0.109***	0.0300*	1						
P_6 - Share of automatable tasks	0.00974	0.0697***	0.00974	-0.0786***	0.540***	1					
P_7 - Expe. change in own salary	0.125***	0.158***	0.340***	0.289***	0.164***	0.0623***	1				
P_8 - Loser of digitalization	0.193***	0.212***	0.367***	0.421***	0.165***	0.0649***	0.483***	1			
Distributional Implications											
P_9 - Inequ. across social groups	0.297***	0.186***	0.108***	0.0698***	0.0883***	0.0446**	0.0537***	0.0661***	1		
P_{10} - Risks w/o high-school	0.250***	0.176***	0.190***	0.191***	-0.195***	-0.236***	0.145***	0.173***	0.239***	1	
P_{11} - Risks with high-school	0.181***	0.175***	0.201***	0.222***	-0.0628***	-0.0700***	0.156***	0.167***	0.141***	0.394***	1
P_{12} - Risks with tertiary ed.	0.0928***	0.134***	0.235***	0.227***	0.0695***	0.0727***	0.164***	0.196***	-0.0350*	-0.000273	0.395***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Details on definition of perception measures in Table 3.

C Outcome Measures

Policy Preferences. Several indicators measure closely related types of policies. In order to reduce the number of dimensions, we group measures according to four types of policies. A separate factor analysis for each of these sub-groups finds only one relevant factor loading (see table) while other allocations of indicators across policy fields result in several factor loadings. Note that the scale of all policy measures included in block C increase with the preference for more governmental support and redistribution.

Table C.1: Policy Measures by Type of Policy

	q	f	N
Redistributive Policies (*redistr*)			
Support for gov. measures to reduce income differences	Cq42	0.71	4,955
Support for higher inc. taxes for high-inc. people	Cq43	0.74	4,988
Preferred top personal income tax rate	Cq44	0.48	3,998
Policies preventing poverty (*antipov*)			
Support for EITC (US)	Cq51	0.59	2,147
Support for food stamps (US)	C-q50	0.71	
Support for unemp. assistance ALG II (Germany)	Cq50	0.59	4,829
Support for unconditional basic income in US/Germany	Cq54	0.15/0.49	4,528
Support for higher minimum wage in US/Germany	C-q52	0.72/0.47	4,963
Passive labor market policies (*plmp*)			
Support for higher unemployment benefits	Cq48	0.79	4,788
Support for longer unemployment benefit duration	Cq49	0.79	4,719
Support for solidary basic income	Cq55	0.28	4,516
Active labor Market Policies (*almp*)			
Support for job creation schemes	Cq53_a	0.57	4,420
Support for voc. training and qualification	Cq53_b	0.57	4,733
Support for improved job search assistance	Cq53_c	0.65	4,523
Support for income subsidies for reintegration	Cq53_d	0.63	4,481
Support for measures to increase job mobility	Cq53_e	0.67	4,372

Notes: q refers to questionnaire number, f denotes the factor loading of the factor analysis run separately for each policy field but jointly for both countries (except for anti-poverty policies). N denotes number of non-missing observations out of 5,147 total observations (US: 3,066; Germany: 2,081).

For each policy field, we then calculate the composite z-score as the standardized sum of the z-scores for each indicator (see Kling et al., 2007 and Alesina et al., 2022 for a similar procedure). Note that we also compared these measures to directly using the factor loadings instead, but these measures are highly correlated with the z-scores ($\rho > 0.9$) and gave very similar results in robustness checks.

Stated Labor Market Choices. In order to capture stated labor market behavior, we use the following three indicators: the general willingness to participate in training (*training*, C-q56), and the willingness to accept a job with lower salary (*lowsal*, C-q58), or switch occupation (*occswitch*, C-q59) in case of unemployment. For the empirical analyses, we use standardized (z-score) values for each indicator and an aggregate measure, *all*, which is the sum of these z-scores. This approach is supported by the fact that in a factor analysis, all three indicators load on one factor loading only.

Donation Choices. For the analysis of the donation choices, we use five outcomes based on the lottery in C-q46. In particular, we use an indicator of whether someone donated anything to an NGO (*donator*), the share of the total amount that was donated to some NGO (*share*), as well as the share of the total donation spent on charities that aim for digital education (*digital*), feeding the poor (*foodbank*), or promoting equal opportunity (*equalopp*), see Section 2 for details on the charities.

Table C.2: Summary Statistics of Outcome Variables by Country

	Germany		US		All	
	mean	sd	mean	sd	mean	sd
Policy Preferences for ...						
all types ‡	0.0681	(0.839)	-0.0423	(1.100)	0.00411	(1.000)
redistribution ‡	0.0974	(0.762)	-0.0844	(1.120)	-0.0135	(1.000)
social assistance ‡	0.195	(0.957)	-0.117	(1.016)	0.0326	(1.000)
passive labor market policies ‡	0.119	(0.935)	-0.118	(1.032)	-0.0202	(1.000)
active labor market policies ‡	-0.0154	(0.860)	-0.0171	(1.101)	-0.0163	(1.000)
Personal willingness for ...						
any personal accomodation ‡	-0.0537	(0.953)	0.0785	(1.030)	0.0220	(1.000)
participating in training †	0.179	(0.921)	-0.132	(1.035)	-1.22e-08	(1.000)
accepting lower salary †	-0.215	(0.928)	0.150	(1.021)	-2.75e-08	(1.000)
switching occupation †	-0.0895	(0.974)	0.0615	(1.013)	-4.49e-09	(1.000)
Donation Behavior						
donator (yes=1)	0.775	(0.418)	0.771	(0.420)	0.772	(0.419)
total share donated	0.371	(0.324)	0.401	(0.348)	0.389	(0.339)
of which donated for ...						
digital education	0.258	(0.193)	0.252	(0.216)	0.254	(0.207)
food bank	0.406	(0.262)	0.477	(0.289)	0.448	(0.280)
equal opportunity	0.336	(0.227)	0.271	(0.214)	0.297	(0.221)

Notes: †-variables: standardized to z-scores, ‡-variables: standardized composite z-scores

D Policy Preferences: Further Results

Table D.1: Perceptions of Automation and Policy Preferences

	(1) distr	(2) socass	(3) plmp	(4) almp
Perceptions of Automation				
P_1 - general unemp. risks	0.0628***	0.0898***	0.0508**	0.0713***
P_5 - individual unemp. risks	0.0990***	0.0847***	0.0800***	0.0585***
P_9 - distributional risks	0.117***	0.0891***	0.126***	0.0579***
Demographics - selected				
Poor household	0.122***	0.121**	0.0564	-0.0893*
Rich household	-0.0813*	-0.214***	-0.152***	-0.125**
Job and Workplace Characteristics				
Currently employed	0.0647	-0.300***	-0.224**	0.0224
Precarious job	-0.0509	-0.0454	-0.0275	-0.142***
Self-employed	-0.0475	-0.0261	-0.0919	-0.144**
Ever unemployed: Yes	0.108***	0.141***	0.224***	0.0167
Share of routine tasks	-0.0972	-0.0974	0.0344	0.0780
Share of manual tasks	0.0172	0.0703	0.00726	0.206**
Incr. job requirements	-0.0312	-0.0464	0.0507	0.0205
Decr. job requirements	0.0691	-0.162**	-0.0272	0.100
Share of IT-based tasks	-0.0204	-0.0379	-0.0247	0.0854
Political and Economic Beliefs				
Political view: left	0.633***	0.583***	0.430***	0.236***
Political view: right	-0.493***	-0.309***	-0.255***	-0.263***
Economic view: liberal	-0.265***	-0.266***	-0.238***	-0.186***
Economic view: not liberal	0.231***	0.0807*	0.105**	0.0704
Trust in government	0.230***	0.230***	0.185***	0.0989*
Mistrust in government	-0.114***	0.0141	-0.0561	-0.116***
Constant	0.0575	0.499***	0.282**	-0.157
N	3546	3326	3763	3482
adj. R-squared	0.332	0.237	0.194	0.103

Notes: Regressions based on equation (2), pooled for both countries. Control variables also include other demographics (see Table 2), dummies for the experimental group assignment, and missing categories. Perception measures P_1, P_5, and P_9 as defined in Table 3.

E Prior Beliefs

Prior beliefs were surveyed prior to the information treatments at the beginning of survey block B (see Section 2). For the analysis, we use respondents' answer to the question "What do you think about the future of work given the increasing use of digital technologies?", as shown in Figure E.1, to define three distinct groups: Respondents who assess the value of human labor to decrease in the future (green shades) are called *pessimists*, while those expecting the value to decline (red shades) are called *pessimists*. Respondents in between (grey shade) are considered *neutral.*:

Figure E.1: Distribution of prior beliefs by country

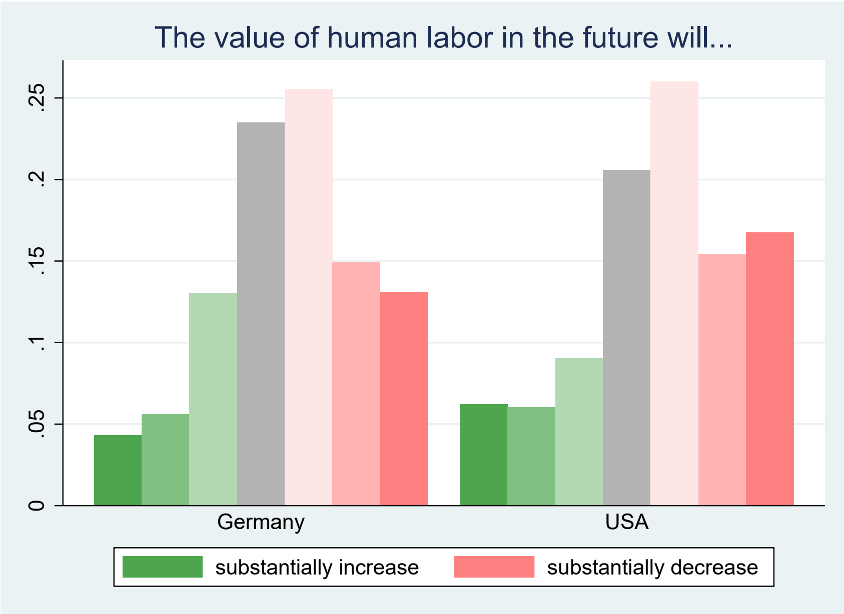


Table E.1 shows separate regressions for Germany and the US to examine which factors correlate with these prior beliefs. Prior beliefs about the future value of human work are related closely to general political and economic views as well as someone's trust in the government in both countries.

Table E.1: Prior perceptions on value of human labor by country

	US	Germany
Demographics		
Female	0.0361	0.109**
Migration background	-0.0644	-0.0196
Nonwhite	-0.140**	
Cohabiting spouse/partner	-0.0249	0.0225
Children in hh	0.0823	-0.0348
Number of hh members	-0.0492	-0.0412
Age 18-25	-0.0614	-0.0456
Age 26-35	-0.0994*	-0.0986
Age 46-55	0.0757	0.0107
High-school or less	-0.0376	-0.0318
Tertiary degree	-0.104**	-0.110*
Poor household	-0.144**	0.177***
Rich household	0.179***	-0.123*
Job and workplace characteristics		
Currently employed	0.221	0.0303
Precarious job	-0.0720	-0.0388
Self-employed	0.0535	0.00952
Ever unemployed: Yes	-0.00118	0.0382
Political and Economic Views		
Political view: left	0.0850	0.148**
Political view: right	-0.209***	-0.0898
Economic view: liberal	0.0039	-0.123**
Economic view: not liberal	0.292***	0.137**
Trust in government	-0.351***	-0.174***
Mistrust in government	0.145***	0.408***
Constant	-0.0808	-0.196
N	2958	1997
adj R-squared	0.0890	0.0939

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Notes: Regressions use z-scores of prior beliefs as dependent variables. Regressions are similar to equation (1), but only include covariates that have been surveyed in block A prior to the information treatment.

F Information Treatment I_1: More Detailed Discussion and Further Results

Section 4.2 in the main body of the text presents and discusses the main results in the context of the first information treatment. In the following, we discuss some additional results for the outcome variables relating to policy demand, stated labor market choices and donations (while the discussion regarding the effects on the perception variables is fully included in 4.2).

Policy Demand. Looking at the estimates for the treatment effect on policy preferences, we find no significant effect for the average German respondent, nor for the average US individual (see Figure F.1(a)).[48] However, this masks an interesting heterogeneity along the distribution of prior beliefs, see Figure 6(a). In particular, optimists demand significantly less redistributive policies, anti-poverty measures and active labor market policies in response to the treatment. Hence, for people with optimistic prior beliefs, the treatment, as expected, reduces policy demands. These effects are significant at the 5% level and inference is robust to multiple hypothesis testing (see Table 9). In contrast, people with neutral beliefs about the future value of human work even increase demand for redistributive and anti-poverty measures (significant at the 5% level) as well as active labor market policies (significant at the 10% level). This is perhaps a surprising finding given that policy demand relates positively to automation-related concerns in Section 3.3. However, neutral respondents are not only concerned less regarding automation-induced unemployment in response to the treatment, but are also the only group of respondents with (insignificantly) increased inequality concerns in response to the treatment (see Figure 5(b)), thereby raising rather than reducing the demand for redistribution and anti-poverty measures.

Pessimists' policy demand, on the other hand, does not respond at all to the information treatment at significant levels despite strong reductions in fears related to unemployment (P_1) and the substitutability of human tasks (P_2). One explanation could be that these shifts have opposing effects on policy demand. Indeed, this seems to be the case. When adding P_2 to equation 2, we find negative partial effects for related concerns on active and passive labor market policies as well as anti-poverty policies.[49] One reason for this could be that, conditional on expected effects of automation on overall unemployment, a lower perceived substitutability of humans by machines in response to the treatment information increases confidence in the usefulness of policy interventions

[48] Average treatment effects across respondents of both countries also turn out to be insignificant. Results are available upon request.

[49] Results are available upon request.

to address related challenges by labor market policies, thereby increasing policy demand. Hence, policy demand effects induced via shifts in P_1 and P_2 may cancel out for pessimists.

We can thus conclude that despite overall plausible shifts in the perceptions of automation in response to the treatment, there is no average effect on policy demand. This seems to be driven by the fact that induced shifts in perceptions differ between individuals with different prior beliefs, and that these shifts translate into partly opposing policy demand effects.

Stated Labor Market Choices. From the descriptive analysis in Section 3.3, we know that concerns related to the aggregate economy and economic inequality both tend to increase the willingness to get further training or to make concessions in case of unemployment, while individual unemployment risk raised the willingness to participate in training in the US, but not in Germany. Since the treatment mainly reduces concerns related to the aggregate economy, but also, depending on prior beliefs, slightly affected other dimensions of automation angst, different channels might be at work again.

However, even along the distribution of prior beliefs, the information treatment does not have considerable effects on labor market choices (see Figure 6(b)). However, the multiple hypothesis tests suggests that treatment effects are weakly significant at the 10%-level for the whole set of labor market related outcomes (see Table 9).[50] This is driven by an increased willingness to accept lower salaries among workers with optimistic prior beliefs. One reason for this counterintuitive finding could be that given the reassuring evidence on the lack of negative impacts of automation, optimists expect a low-paying job to be only a temporary state to terminate unemployment. For other labor market outcomes such as training participation and the willingness to switch occupations, we find no significant effects for any of the sub-groups. Hence, the findings suggest that individual intentions for labor market behavior are rather unresponsive to receiving information about a zero employment effect related to automation on the overall economy.

Donations. Previous descriptive evidence on the relationship between the main perception measures and donations to charities suggests that different dimensions of automation correlate quite differently with whether and what share people donate and, to a lesser extent, which type of charity they choose as a recipient. The fact that we do not find any significant average effects of the treatment may thus, again, reflect that induced shifts in perceptions have opposing effects and cancel out. However, we find some heterogeneities along the distribution of prior beliefs[51], see Figure 6(c), albeit the overall significance of the treatment experiment for these outcomes is rejected (see Table 9). Still, there is

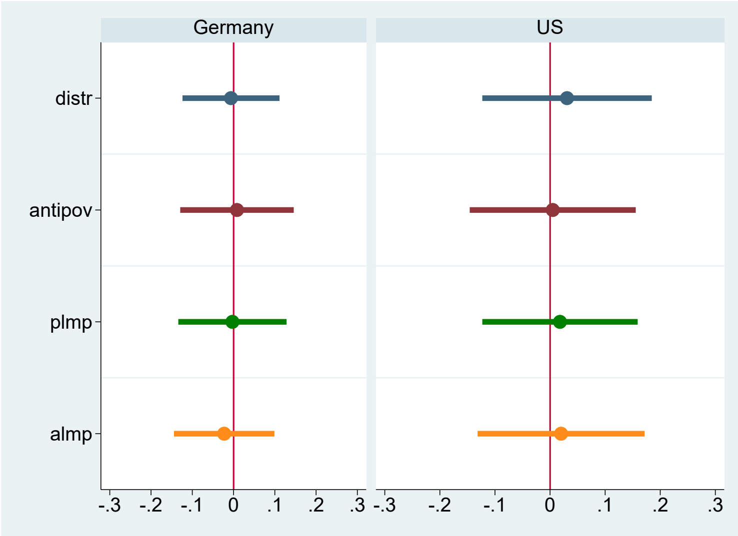
[50]Note that average treatment effects across both countries as well as cross-country differences are insignificant, see Appendix Figure F.1(b).

[51]Cross-country differences turn out to be insignificant, see Appendix Table F.1(c).

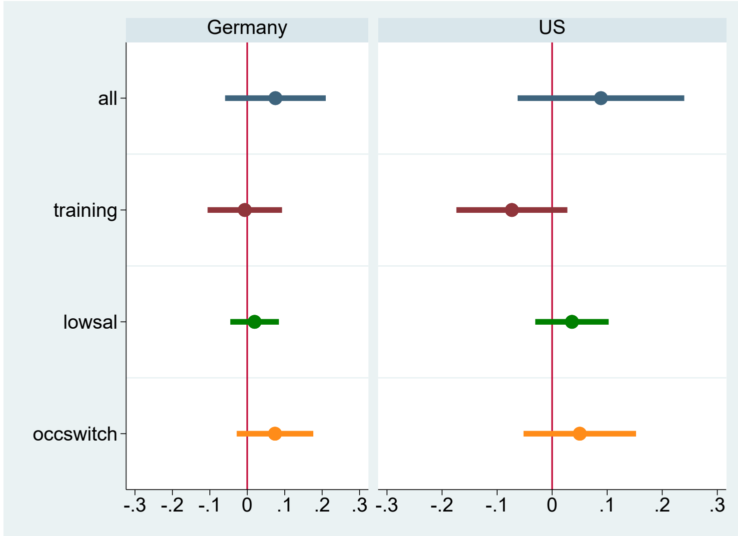
evidence that optimists do not only consider less need for policy interventions (due to the confirmation received through the treatment information, as discussed before), but also feel less inclined to donate to charities, while shifting donations from charities for equal opportunity to those targeted at digital education. Neutral respondents, by contrast, are now more likely to donate (significant at 10% level) with some tentative evidence that this is accompanied by shifting donations to digital education and equal opportunity at the expense of donations for feeding the poor. Among pessimists, we only see a shift of donations from charities for digital education to feeding the poor. Hence, the response patterns for donations again reveal a stark heterogeneity along the distribution of prior beliefs. For instance, while pessimists take the information on zero employment effects as evidence that digital education is less relevant, the opposite holds for optimists for whom the same piece of evidence seems to suggest that digital education is even more useful.

Figure F.1: ITT of “No aggregate employment losses”-Information I_1 on Set of Outcomes by Country ($\alpha = 0.05$)

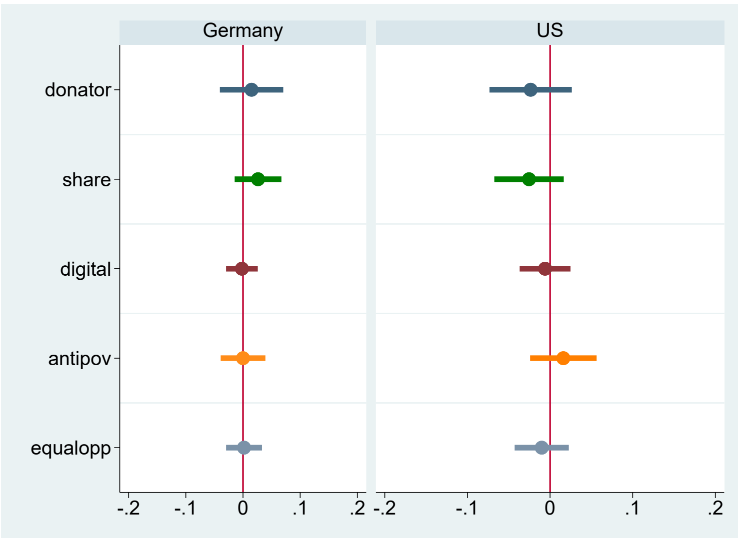
(a) Policy Demands



(b) Stated Labor Market Choices



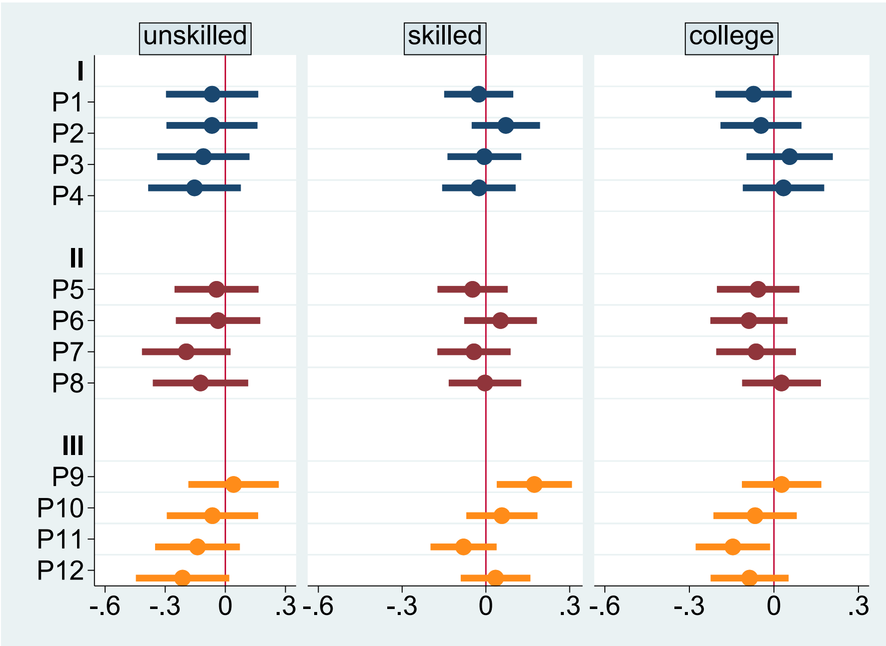
(c) Donations to Charities



Notes: ITT for German respondents (β_1) and US respondents (β_2), see equation (4). Policy Demand captures redistributive policies (*distr*), anti-poverty measures (*antipov*), passive labor market policies (*plmp*) and active labor market policies (*almp*); Stated Labor Market Choices refers to participating in training (*training*), accepting lower salaries (*lowsal*) and switching occupations (*occswitch*); Donations to Charities refers to whether someone donates at all (*donator*), the share donated (*share*) and the relative share donated for digital education (*digital*), for feeding the poor (*food*) or equal opportunity (*equalopp*), see Appendix C for details.

G Information Treatment I_2: Further Results

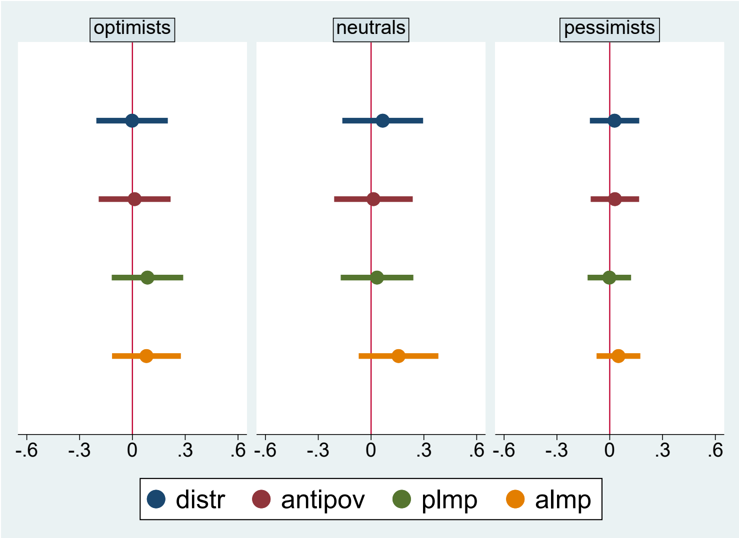
Figure G.1: ITT of "Employment Shifts from Unskilled to Skilled Labor"-Information I_2 on Perceptions of Automation by Skill Group($\alpha = 0.05$)



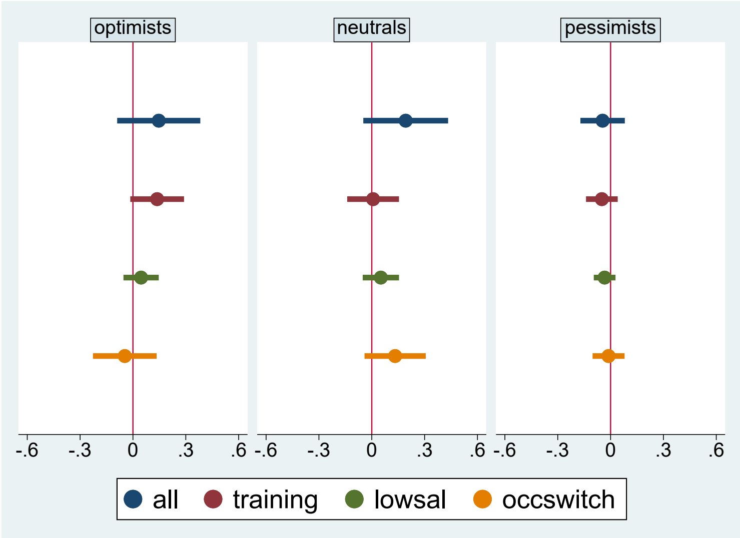
Notes: ITT by skill group, i.e. for "unskilled" (high-school or below), "skilled" (up to 2-yr college) and "college" (more than 2-yr college), see section 4.1. Perception measures refer to (I) General concerns: unemployment rate (P_1), human substitutability (P_2), overall prosperity (P_3), desirability of digitalization (P_4)); ((II) Individual concerns: own unemployment (P_5), automatable job tasks (P_6), own salary (P_7), being a loser or winner (P_8)), and (III) Distributional concerns: inequality across workers (P_9), risks for workers w/o high-school/with high-school/with college ($P_{10} - P_{12}$), see Table 3 for details.

Figure G.2: ITT of "Employment Shifts from Unskilled to Skilled Labor"-Information I_2 on Set of Outcomes by Prior Belief ($\alpha = 0.05$)

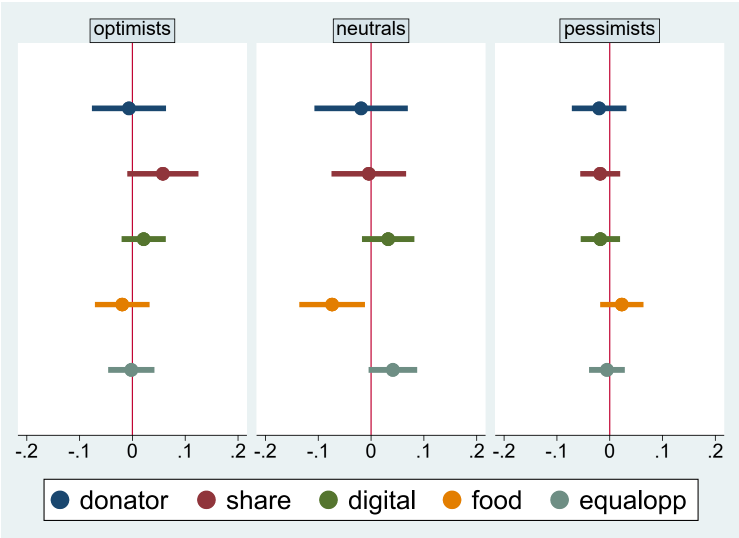
(a) Policy Demands



(b) Stated Labor Market Choices



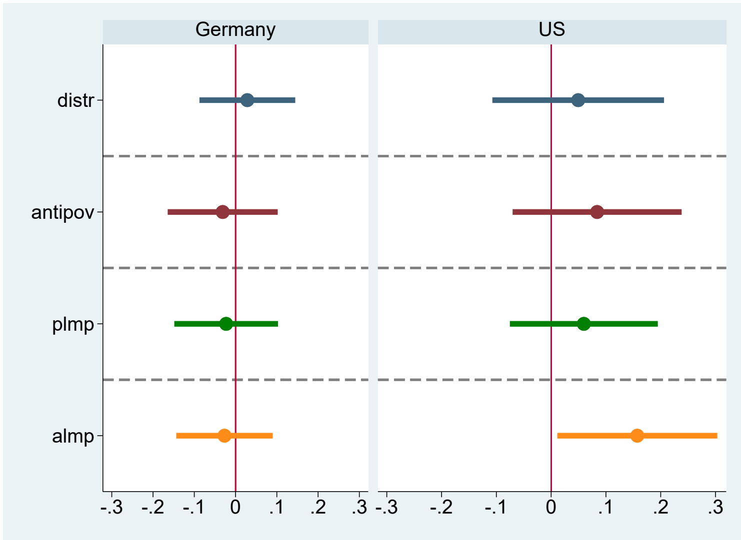
(c) Donations to Charities



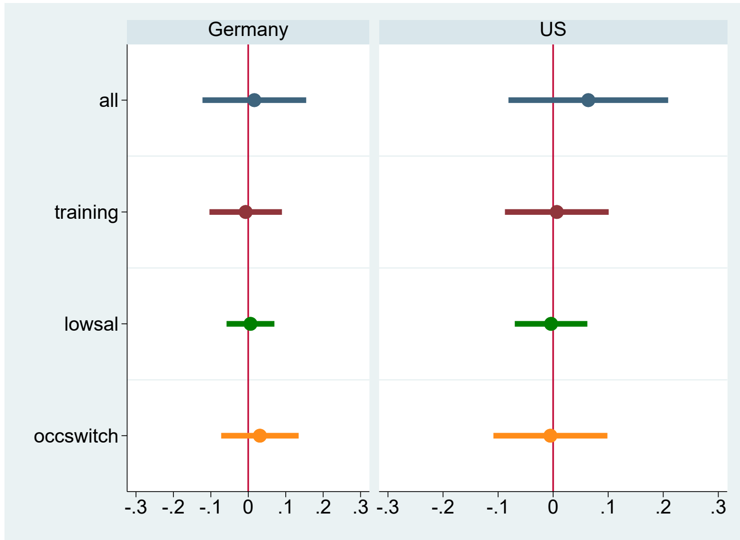
Notes: ITT for "optimists" (β_3), "neutrals" (β_4) and "pessimists" (β_5) regarding the future value of human work, see equation (5). Policy Demand captures redistributive policies (*distr*), anti-poverty measures (*antipov*), passive labor market policies (*plmp*) and active labor market policies (*almp*); Stated Labor Market Choices refers to participating in training (*training*), accepting lower salaries (*lowsal*) and switching occupations (*occswitch*); Donations to Charities refers to whether someone donates at all (*donator*), the share donated (*share*) and the relative share donated for digital education (*digital*), for feeding the poor (*food*) or equal opportunity (*equalopp*), see Appendix C for details.

Figure G.3: ITT of "Employment Shifts from Unskilled to Skilled Labor"-Information I_2 on Further Outcomes by Country ($\alpha = 0.05$)

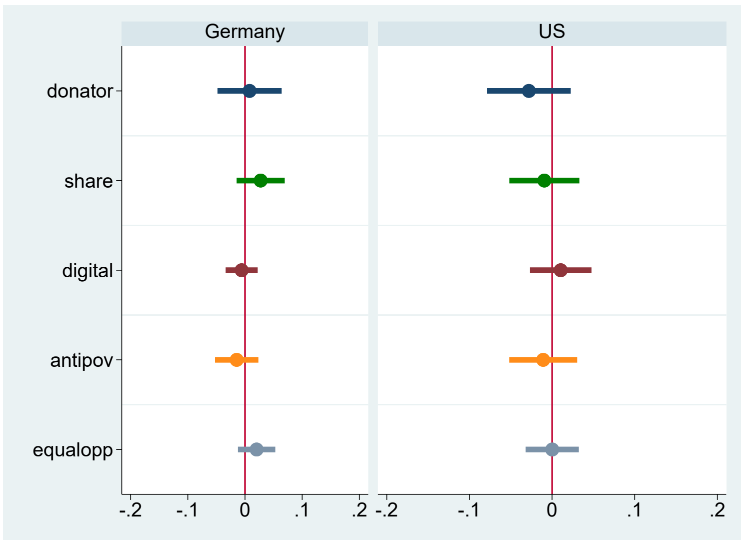
(a) Policy Demands



(b) Stated Labor Market Choices



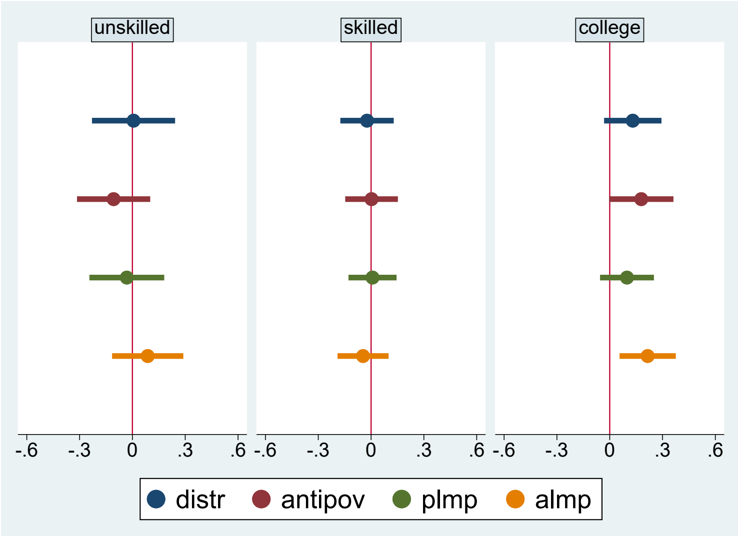
(c) Donations to Charities



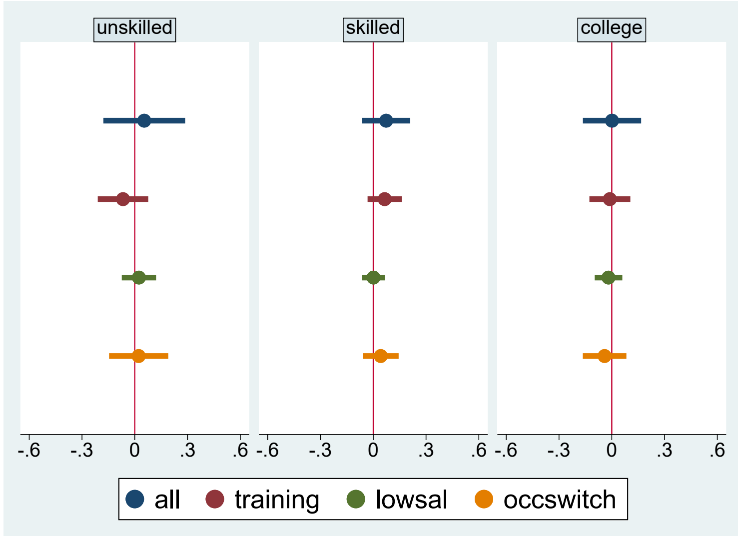
Notes: ITT for Germany (β_1) and the US (β_2), see equation (4). Policy Demand captures redistributive policies (*distr*), anti-poverty measures (*antipov*), passive labor market policies (*plmp*) and active labor market policies (*almp*); Stated Labor Market Choices refers to participating in training (*training*), accepting lower salaries (*lowsal*) and switching occupations (*occswitch*); Donations to Charities refers to whether someone donates at all (*donator*), the share donated (*share*) and the relative share donated for digital education (*digital*), for feeding the poor (*food*) or equal opportunity (*equalopp*), see Appendix C for details.

Figure G.4: ITT for I_2 on Set of Outcomes by Skill Group ($\alpha = 0.05$)

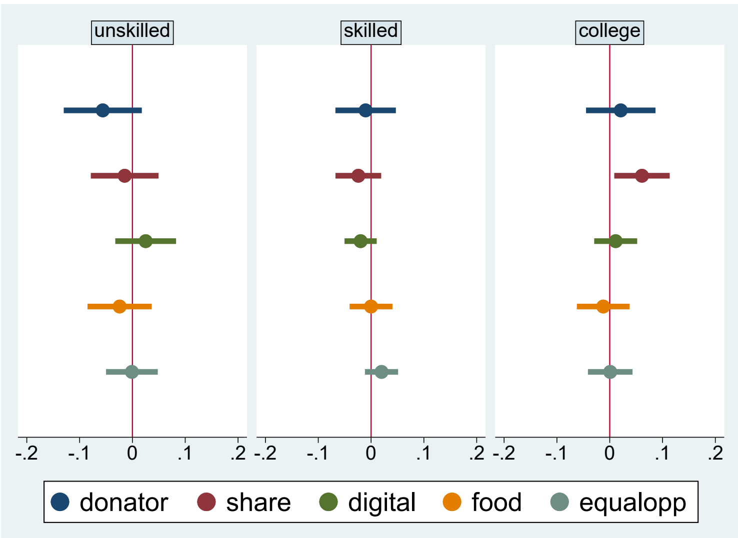
(a) Policy Demands



(b) Stated Labor Market Choices



(c) Donations to Charities



Notes: ITT for "optimists" (β_3), "neutrals" (β_4) and "pessimists" (β_5) regarding the future value of human work, see equation (5). Policy Demand captures redistributive policies (*distr*), anti-poverty measures (*antipov*), passive labor market policies (*plmp*) and active labor market policies (*almp*); Stated Labor Market Choices refers to participating in training (*training*), accepting lower salaries (*lowsal*) and switching occupations (*occswitch*); Donations to Charities refers to whether someone donates at all (*donator*), the share donated (*share*) and the relative share donated for digital education (*digital*), for feeding the poor (*food*) or equal opportunity (*equalopp*), see Appendix C for details.

H Priming Treatment

In addition to the information treatments above, we also consider the effect of priming, i.e. of changing the order of the question blocks. While the standard order asks about automation-related perceptions prior to block C on policy preferences and own labor market behavior, the priming group received the reversed order. That is, subjects in this treatment group are forced to think about available policy tools in modern welfare states and own coping strategies on the labor market prior to reporting their perceptions of automation. Specifically, we now use all individuals from sub-groups $ACBD_0$ and $ABCD_0$, who did not receive any information treatment but differ in the sequence of the question blocks B and C, and estimate

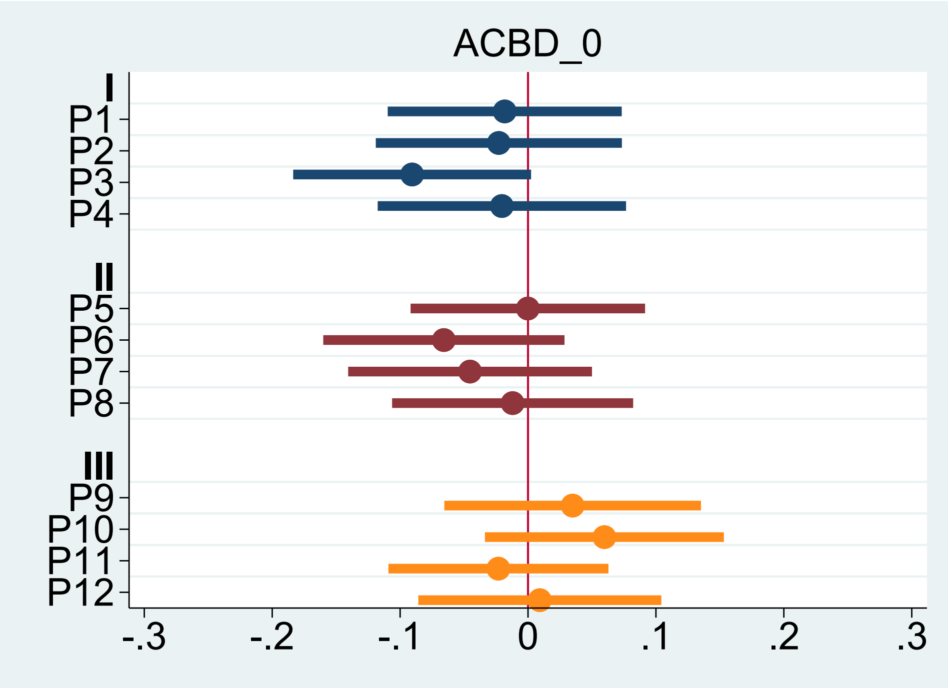
$$Y_i = \alpha + \beta ACBD_{0i} + u_i \tag{7}$$

where β reflects the effect of receiving block C including policy preferences and stated labor market choices first relative to the control group $ABCD_0$ that received the standard order of question blocks.[52]

As we do not find any notable cross-country differences, Figure H.1 shows the average treatment effects for respondents of both countries. The corresponding multiple hypothesis test for all outcome equations has a p-value of 0.46 and thus cannot reject the hypothesis that the ordering of the question blocks is irrelevant for reported perceptions of automation. However, respondents treated with the alternative question order are less concerned that automation might reduce overall prosperity (P_3). Hence, thinking about the policy instruments (and own personal adjustments) that are potentially available to cushion the effects of automation, slightly reduces some concerns. However, the effect is small and marginally misses the 5% significance level. Moreover, priming does not have any significant effect on policy preferences and donation choices, see Figure H.2 (a) and (c). As regards stated labor market choices, see Figure H.2(b) of the Appendix, respondents of the priming group show a higher willingness to accept a job with lower salary in case of unemployment, a finding that is robust to multiple hypothesis testing. This might indicate that being confronted with available tools of the welfare state or personal strategies to cope with automation in the labor market makes people more willing to accept lower wages, possibly due to a higher salience of ways to receive top-up benefits from the government.

[52]Note that we do not extend this model with any prior beliefs as prior beliefs depend on the sequence of question blocks. Including them would have required these prior beliefs to be surveyed at the end of block A rather than the beginning of block B. However, this would have introduced some priming also for the group $ACBD_0$ such that no pure priming effect would have been identifiable.

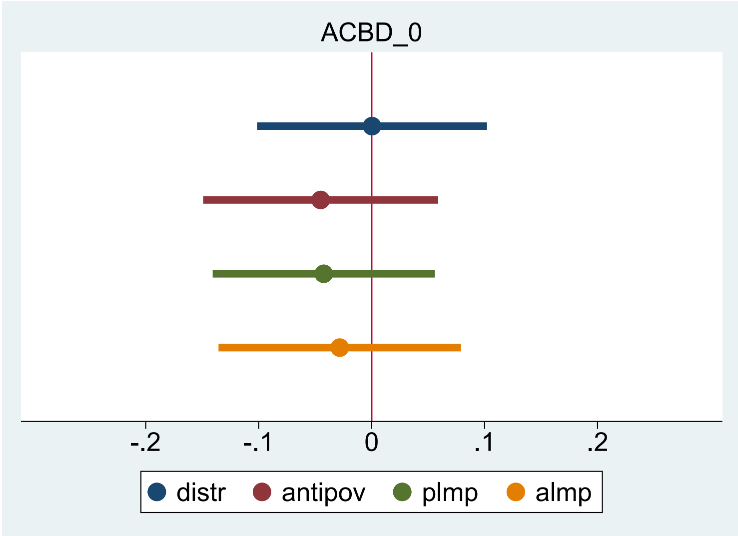
Figure H.1: Treatment Effect of receiving block C prior to automation block B ($ACBD_0$) on perceptions of automation ($\alpha = 0.05$)



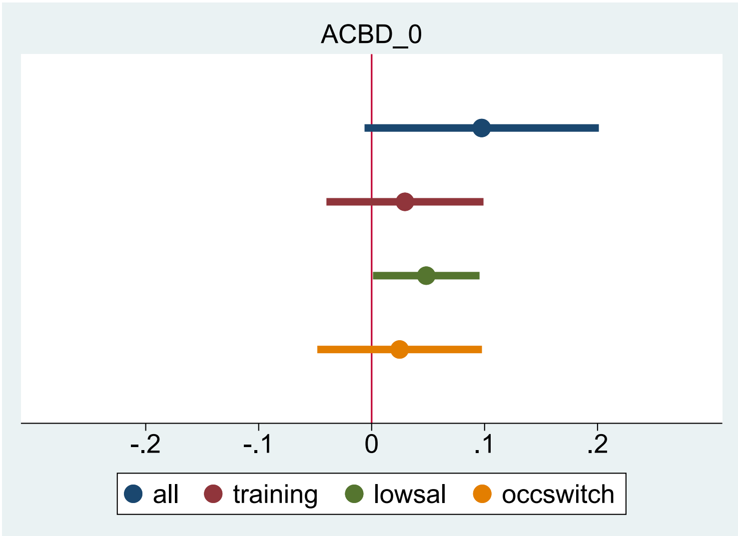
Notes: Separate regressions for all perception measures based on equation (7). Perception measures I refer to general concerns regarding unemployment rate (P_1), substitutability of human workforce (P_2), overall prosperity (P_3), and desirability of digitalization (P_4)). Perception measures II refer to individual concerns regarding own unemployment (P_5), automatable job tasks (P_6), own salary (P_7), and being a loser of digitalization (P_8)), while type III measures capture concerns regarding inequality across worker groups (P_9), as well as perceived risks for workers w/o high-school (P_{10}), for workers with high-school (P_{11}), and for college graduates (P_{12})), see Table 3 for details.

Figure H.2: Treatment Effect of receiving block C prior to automation block B ($ACBD_0$) on various outcomes

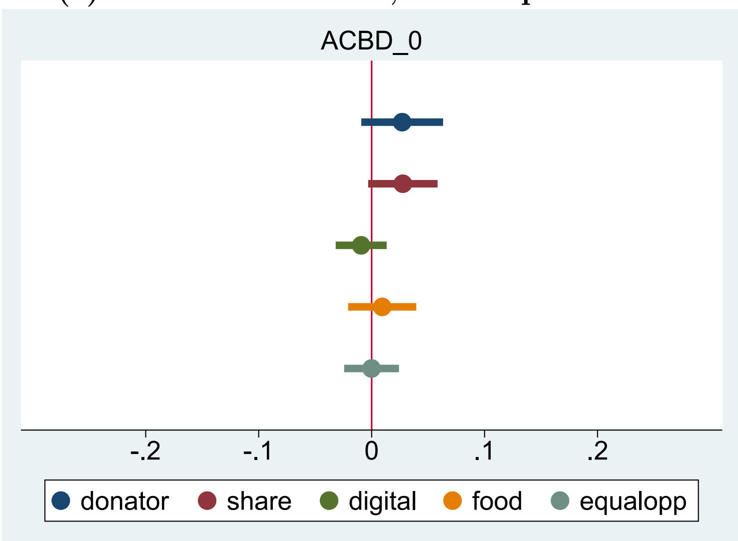
(a) Policy Preferences, MHT‡ p-val: 0.84



(b) Stated Labor Market Choices, MHT‡ p-val: 0.09



(c) Donation Choices, MHT‡ p-val: 0.28



Notes: Outcome measures as defined in Appendix C. ‡P-values refer to Westfall-Young multiple hypothesis test of all outcome equations jointly for each set of outcomes.

I Questionnaire of Main Survey

The following questionnaire presents the 'standard order' $ABCD$ of questions.

Block A: Background Information

1. Are you...?

   Male; *Female*

2. In what year were you born? *(only first-time panelists)*

3. In which month were you born? *(only first-time panelists)*

4. What day of the month were you born on? *(only first-time panelists)*

5. What is your state of residence? *(only first-time panelists)*

   List of all states; *Not in the US*

6. In which census division do you live? *(only first-time panelists)*

7. Which category best describes your highest level of education?

   Eighth Grade or less; *Some High School*; *High School Degree / GED*; *Some College*; *2-year College Degree*; *4-year College Degree*; *Master's Degree*; *Doctoral Degree*; *Professional Degree (JD, MD, MBA)*; *Other, namely [insert text]*; *do not know/ no answer*

8. Thinking back over the last year, what was your family's annual income?

   Less than $10,000; *$10,000 - $19,999*; *$20,000 - $29,999*; *$30,000 - $39,999*; *$40,000 - $49,999*; *$50,000 - $59,999*; *$60,000 - $69,999*; *$70,000 - $79,999*; *$80,000 - $99,999*; *$100,000 - $119,999*; *$120,000 - $149,999*; *$150,000 - $199,999*; *$200,000 - $249,999*; *$250,000 - $349,999*; *$350,000 - $499,999*; *$500,000 or more*; *Prefer not to say*

9. Which of the following descriptions best fits your current situation?

   I am currently employed.; *I am currently in dormant employment (for example, on long-term sick leave).*; *I am currently unemployed and looking for work.*; *I am currently unemployed and not looking for work.*; *I do not know/I refuse to answer*

10. Which of the following descriptions best fits your current job?

    Unlimited employment; *Temporary employment*; *Marginal employment*; *Civil servant*; *Self-employed or freelancer*; *I do not know/I refuse to answer*

11. When did your last employment contract end? (only if unemployed)

    [MM,YYYY]; *I have never worked.*; *I do not know/I refuse to answer*

12. Which of the following descriptions best fits your current situation? (only if unemployed)

    Student at a general education school; *Student at a college/university*; *In a vocational education/apprenticeship*; *In vocational retraining*; *Receive unemployment benefits*; *Unable to work due to disability*; *Pensioner, retiree, in early retirement*; *Voluntary activities*; *Other, [insert text]*; *I do not know/No answer*

13. Introduction: see Figure I.1 below.

14. Please indicate your marital status. *(only first-time panelists)*

    Single; *Married*; *Registered Partnership*; *Living together with partner*; *Legally separated*; *Divorced*; *Widowed*; *I do not know/I refuse to answer*

15. How many children younger than 18 do you have that live in your household?

    No children; *1*; *2*; *3*; *4 or more children*; *I do not know/I refuse to answer*

16. Were you born in the United States?

    Yes; *No*; *I do not know/I refuse to answer*

17. What racial or ethnic group best describes you? (US only)

    White; *Black or African American*; *Hispanic or Latino*; *Asian or Asian American*; *Native American*; *Middle Eastern*; *Two or more races*; *Other [insert text]*

18. Were both of your parents born in the United States?

    Yes; *No*; *I do not know/I refuse to answer*

19. Recalling your own educational and professional experience, all in all, how easy was it for you to achieve your professional and educational goals?

    Very hard; *Hard*; *Rather hard*; *Rather easy*; *Easy*; *Very easy*; *I do not know/I refuse to answer*

20. Have you ever been unemployed during your work life? Note that we <u>do not</u> mean temporarily dormant employments (e.g. longer periods of sickness).

    Yes; *No*; *I do not know/I refuse to answer*

21. What is your current job? Note: In case of multiple jobs, we refer to the job you spend most your time with. Please type in your job in the text field. After entering the first letters, suggestions will be displayed. Please select the job applies best to your current occupation.

    [Insert text]: comprehensive list of jobs; *Other, namely [insert text]*; *I do not know/I refuse to answer*

22. Below is a detailed list of business sectors. We would like to ask you to classify yourself here as well. In which of the following sectors do you currently work? If you carry out several activities, please mark which sectors applies to your main activity.

    Agriculture, forestry and fishing; *Mining and quarrying*; *Manufacturing*; *Electricity*; *Water supply and waste industry*; *Construction*; *Wholesale and retail trade; repair of motor vehicles and motorcycles*; *Transport and storage*; *Accommodation and food service activities*; *Information and communication*; *Financial and insurance activities*; *Real estate activities*; *Professional, scientific and technical activities*; *Administrative and support service activities*; *Public administration, defence and social insurance*; *Education*; *Human health and social work activities*; *Arts, entertainment and recreation*; *Other service activities*; *Private households as employers*; *Activities of extraterritorial organizations and bodies*; *Other, namely [insert text]*; *I do not know/I refuse to answer*

23. My last employment contract was

    unlimited; *temporary*; *I do not know/I refuse to answer*

24. How many hours is your contractual working time per week? *[Insert number] hours/week*; *I do not know/I refuse to answer*

25. Generally speaking, do you think of yourself as a ...? *(only first-time panelists)*

    Democrat; *Republican*; *Independent*; *Other Party, namely: ...*; *Not sure*

26. In political matters people talk of "the left" and "the right". How would you place your views on this scale if 1 is "left" and 10 is "right"?

    1 left; *2*; *3*; *4*; *5*; *6*; *7*; *8*; *9*; *10 right*; *I do not know/I refuse to answer*

27. To what extent do you agree with the following statement? The government should keep out of market economic processes as far as possible.

    Totally disagree; *Rather disagree*; *Neither disagree nor agree*; *Rather agree*; *Totally agree*; *I do not know/I refuse to answer*

28. Do you trust the federal government to make the right decisions in the interests of the citizens?

    1 Not at all; *2*; *3*; *4*; *5*; *6*; *7 Completely*; *I do not know/I refuse to answer*

Block B: Perceptions about Automation

Recently, there has been a growing debate in the media and politics about the ***effects of digitalization on the labor market****. By* ***digitalization*** *we mean the technological progress currently taking place, especially in the field of robotics, big data, and artificial intelligence. These developments enable a largely digitally controlled production of value, thus enabling workflows to be increasingly automated. Additionally, these* ***digital production technologies*** *form the foundation of new internet-based business models.*

1. When you think about the technological progress in the recent past, what would you rather say? The value of human labor ...

    1 substantially decreased; *2*; *3*; *4 neither decreased, nor increased*; *5*; *6*; *7 substantially increased*; *I do not know/I refuse to answer*

2. What do you think about the future of work given the increasing use of digital technologies? The value of human labor in the future will ...

   1 substantially decrease; *2*; *3*; *4 neither decrease, nor increase*; *5*; *6*; *7 substantially increase*; *I do not know/I refuse to answer*

3. For future labor market chances, the importance of attaining a high level of education will ...

   1 substantially decrease; *2*; *3*; *4 neither decrease, nor increase*; *5*; *6*; *7 substantially increase*; *I do not know/I refuse to answer*

4. Do you think that digitalization will increase income inequalities on the labor market?

   No, definitely not; *Rather not*; *Yes, somewhat*; *Yes, definitely*; *I do not know/I refuse to answer*

Randomized Information Experiment: Random Assignment to either Control Group, Information Treatment 1 (see Figure I.2) or Information Treatment 2 (see Figure I.3)

In the following, we will ask you a few questions on how digitalization has changed your workplace at your last occupation and how you think digitalization is affecting your personal employment and income situation.

5. In your opinion, what impact will the use of the latest digital technologies have on the future importance of human workforce in general?
   Modern digital technologies will...

   substitute human workforce to a large extent.; *rather substitute than supplement human workforce.*; *substitute and supplement human workforce to the same extent.*; *rather supplement than substitute human workforce.*; *supplement human workforce to a large extent.*; *I do not know/I refuse to answer*

6. In your opinion, how will unemployment in the US be affected by the use of digital technologies in the future? Unemployment will...

   …substantially fall; *…rather fall*; *…stay about the same*; *…rather increase*; *…substantially increase*; *I do not know/I refuse to answer*

7. Will the use of digital technologies in the future affect certain social groups more than others in terms of unemployment?

   No, absolutely not; *Rather not*; *Rather yes*; *Yes, absolutely*; *I do not know/I refuse to answer*

8. In your opinion, will the following groups rather suffer or benefit from the progressing digitalization in terms of future labor market prospects? (order of items randomized)

   (a) Workers without high school degree

   (b) Workers with high school degree

   (c) Workers with completed college/university education

   1 Substantially suffer; *2*; *3*; *4*; *5*; *6 Neither suffer, nor benefit*; *7*; *8*; *9*; *10*; *11 Substantially benefit*; *I do not know/I refuse to answer*

9. In your opinion, how will the overall prosperity in the U.S., i.e. the sum of all incomes of US citizens, change in the future through the increasing use of the latest digital production technologies?

   decrease strongly; *decrease somewhat*; *remain roughly the same*; *increase somewhat*; *increase strongly*; *I do not know/I refuse to answer*

   In the following, we will ask you a few questions on how digitalization is changing your workplace and how you think digitalization is affecting your personal employment and income situation.

10. Are you personally concerned that you will become unemployed in the next five years in light of the increased use of new digital technologies?

    No, absolutely not; *No, rather not*; *Yes, somewhat*; *Yes, absolutely*; *I do not know/I refuse to answer*

11. Considering all the tasks you currently perform at your workplace, what proportion of these tasks do you think could be replaced by machines within the next ten years?

    0-10 %; *11-30 %*; *31-50 %*; *51-70 %*; *71-90 %*; *91-100 %*; *I do not know/I refuse to answer*

12. In your opinion, how will your salary change as a result of the introduction of digital technologies over the next five years? My salary ...

    decrease strongly; *decrease somewhat*; *remain the same*; *increase somewhat*; *increase strongly*; *I do not know/I refuse to answer*

13. Would you consider yourself a rather a winner or a loser of digitalization?

    definitely a loser; *rather a loser*; *neither winner, nor loser*; *rather a winner*; *definitely a winner*; *I do not know/I refuse to answer*

14. Do you think that the increasing digitalization on the labor market is desirable?

    no, absolutely not; *no, rather not*; *yes, somewhat*; *yes, absolutely*; *I do not know/I refuse to answer*

Block C: Policy Preferences, Labor Market and Donation Decision

There are just a few questions remaining until you have successfully completed the survey! In the following, we will ask you a few questions about the distribution of income, government spending, and labor market and social policies in the United States.

1. Do you agree with the following statement? The government should take measures to reduce income differences in the United States.

   Totally disagree; *Rather disagree*; *Neither disagree nor agree*; *Rather agree*; *Totally agree*; *I do not know/I refuse to answer*

2. Do you agree with the following statement? Higher-income persons should pay higher tax rates on their earned income than those with lower incomes.

Totally disagree; *Rather disagree*; *Neither disagree nor agree*; *Rather agree*; *Totally agree*; *I do not know/I refuse to answer*

3. What do you think the top personal income tax rate should be? Note: Please indicate how much % of the taxable income should be paid in taxes as a number between 0 and 100.

   [Insert number] percent; *I do not know/I refuse to answer*

4. Allocation of Government Budget: see Figure I.4 below (with order of items randomized)

5. See Figure I.5: Lottery and Donation (order of items randomized)

6. In your opinion, how important are the following tasks of the government in dealing with unemployment? Please rank the tasks in that order which you feel is most appropriate, starting with the most important one. (order of items randomized)

   Job search assistance (placement, mobility assistance, application training); *Ensuring an adequate livelihood (for example unemployment benefits)*; *Increase of employability (qualification measures, foster re-integration into labor market)*; *I do not know/I refuse to answer*

7. Do you think that unemployment benefits should be rather decreased or increased?

   Strongly decreased; *Somewhat decreased*; *Neither increased nor decreased*; *Somewhat increased*; *Substantially increased*; *I do not know/I refuse to answer*

8. Do you think that unemployment benefit duration should be rather decreased or increased?

   Strongly decreased; *Somewhat decreased*; *Neither increased nor decreased*; *Somewhat increased*; *Substantially increased*; *I do not know/I refuse to answer*

9. Do you oppose or support the Earned Income Tax Credit (EITC) program? (US only, for Germany Hartz IV)

   Strongly oppose; *Rather oppose*; *Rather support*; *Strongly support* ; *I do not know/I refuse to answer*

10. Do you oppose or support the Food Stamps program? (US only)

    Strongly oppose; *Rather oppose*; *Rather support*; *Strongly support*; *I do not know/I refuse to answer*

11. Do you think the minimum wage should be rather decreased or increased?
    Strongly decreased; *Somewhat decreased*; *Neither increased nor decreased*; *Somewhat increased*; *Substantially increased*; *I do not know/I refuse to answer*

12. Do you think the following labor market policies are appropriate to address labor market problems?

    (a) Job creation schemes of the government
    (b) Vocational training and qualification programs
    (c) Improved assistance of authorities with job search
    (d) Income subsidies for reintegration of unemployed into labor market
    (e) Interventions to increase job mobility

    Absolutely inappropriate; *Rather inappropriate*; *Somewhat appropriate*; *Absolutely appropriate*; *I do not know/I refuse to answer*

13. Recently, the idea of a universal basic income has often been discussed. This concept proposes that all citizens, regardless of their economic situation and need, receive a monthly income financed by the government, which is not linked to any service in turn. Therefore, there is no need to work or actively search for a job in order to receive that benefit. On the other hand, all other social and transfer benefits (such as subsidized public housing) are eliminated.

    Are you in favor of introducing such an unconditional basic income in the United States?

    No; *Indifferent*; *Yes*; *I do not know/I refuse to answer*

14. Consider the following proposal: Long-term unemployed who are able to work are eligible to work in jobs created and paid by the government and receive a wage at least equal to the minimum wage. Thus, the resulting income is not unconditional, but linked to the willingness to work.

Should there be such a government-financed labor market for the long-term unemployed?

No; *Indifferent*; *Yes*; *I do not know/I refuse to answer*

Now, we would like to ask you a few questions regarding your personal opinion on job search, professional reorientation, and your attitudes towards vocational training.

15. Would you be willing to participate in vocational training?

    Absolutely not; *Rather not*; *Rather yes*; *Yes, absolutely*; *I do not know/I refuse to answer*

16. Which further training contents would you rate as most important/useful for your professional development? (only if respondent (rather) wants to participate in vocational training)

    General IT know-how/knowledge/expertise; *Job-specific knowledge/expertise*; *Advanced programming skills*; *Interdisciplinary thinking*; *Management, intercultural and social skills*; *I do not know/I refuse to answer*

17. If you lost your current job, would you be willing to accept a new job with the same number of working hours per week but with a lower salary?

    No; *Yes, I would be willing to earn X % less.*; *I do not know/I refuse to answer*

18. In case of unemployment, would you be willing to look for a job in a different occupation than you have been working in so far?

    Absolutely not; *Rather not*; *Rather yes*; *Yes, definitely*; *I do not know/I refuse to answer*

Block D: Workplace Characteristics, Household Income and Survey Quality

1. Typical Working Day (order of items randomized): See Figure I.6

2. As to what extent of your professional activity are you supported by computers or other digital technologies?

   Not at all; *[Insert number] %*; *I do not know/I refuse to answer*

3. In your opinion, did the share of computer-based activities in your working time decline, increase or remain roughly the same in the last years?

   Declined strongly; *Declined somewhat*; *Neither declined nor increased*; *Increased somewhat*; *Increased strongly*; *I do not know/I refuse to answer*

4. Does your job require more or less skills and competencies than some years ago? My job requires ...

   noticeably fewer skills and competencies.; *somewhat fewer skills and competencies.*; *about the same skills and competencies.*; *somewhat more skills and competencies.*; *noticeably more skills and competencies.*; *I do not know/I refuse to answer*

5. What was your monthly household income, after taxes, last year? This includes the sum of wages, salaries, self-employment incomes, pensions, income from public subsidies, income from rents, leasing, housing benefits, child benefits and other income after deduction of taxes and social security contributions. *less than 1100 $*; *1100-1500 $*; *1501-2000 $*; *2001-2600 $*; *2601-4000 $*; *4001-7000 $*; *more than 7000 $*; *I do not know/I refuse to answer*

   Now you have reached the end of the questionnaire! However, we would be happy to get a short feedback about the survey from you.

6. Earlier in the survey, we provided you with information about the results from recent research on the labor market consequences of digitalization. Did you find the information we provided you with trustworthy or untrustworthy? (only for groups information treatment 1 and 2)

   very trustworthy; *somewhat trustworthy*; *somewhat untrustworthy*; *very untrustworthy*; *I do not know/I refuse to answer*

7. To what extent do you think that information was helpful for you to better understand the impact of digital technologies on the labor market? (only for information treatment 1 and 2)

Absolutely not helpful; *Rather not helpful*; *Somewhat helpful*; *Very helpful*; *I do not know/I refuse to answer*

8. Do you feel this survey was politically biased?

   Yes, very left-wing biased; *Yes, rather left-wing biased*; *No, neither left-wing nor right-wing biased*; *Yes, rather right-wing biased*; *Yes, very right-wing biased*; *I do not know/I refuse to answer*

   Thank you for participating in our survey!
   In about two weeks we will be able to tell you whether you have won in the prize game of this survey. Feel free to share your thoughts or any remaining questions about this survey with us.
   [Insert text]

Figure I.1: Introduction

YouGov

This survey is conducted as part of an independent (non-partisan) research project of the Centre for European Economic Research (ZEW) Mannheim and the University of Mannheim.

Our objective is to understand how information that we perceive in the media influence our views on policies. Thus, by participating in the survey, you are contributing to a better understanding of our society. You might not agree with all the information presented, and that is, of course, perfectly fine. You can also skip a question if you do not feel comfortable with it. However, it would be helpful if you would answer the questions in the survey as carefully as possible. The survey should take (on average) about **15 minutes** and gives you the opportunity to express your own opinion on various issues of societal relevance. You will receive **1000 points** for completing this survey.

In addition, by participating in this survey, you automatically enter into a prize lottery with a prize money of $ 1,000.

Please note: Your participation in this study is entirely voluntary. To participate in this study you must be at least 18 years old. You are not allowed to participate in this study more than once. If you have a technical problem or a question regarding the survey, please do not start the survey anew or try to re-take the survey after termination.

In case of questions about the survey, please contact help.us@yougov.com.

Have you understood the explanations above and do you want to participate in the survey?

- Yes
- No

Have fun with answering the survey!

Figure I.2: First information treatment (I_1)

YouGov

As technological progress continues, new possibilities arise to replace human labor with machines. However, **the use of the latest digital production technologies does not necessarily lead to a decline in employment,** because the use of these technologies can improve the competitiveness of firms. This allows firms to sell more products, which in turn increases employment.

This is also confirmed by a recent study* which analyzed comprehensive technology and labor market data for 17 industrialized countries. The study examines the relationship between the actual use of the latest digital production technologies and the resulting development of employment.

The study shows that **the number of hours worked has remained the same despite the increasing use of digital technologies.** Thus, there is **no evidence that the use of the latest digital production technologies contributed to an overall decline in employment.**

*Graetz, Georg, and Guy Michaels. "Robots at work." *Review of Economics and Statistics* (2018).

Figure I.3: Second information treatment (I_2)

YouGov

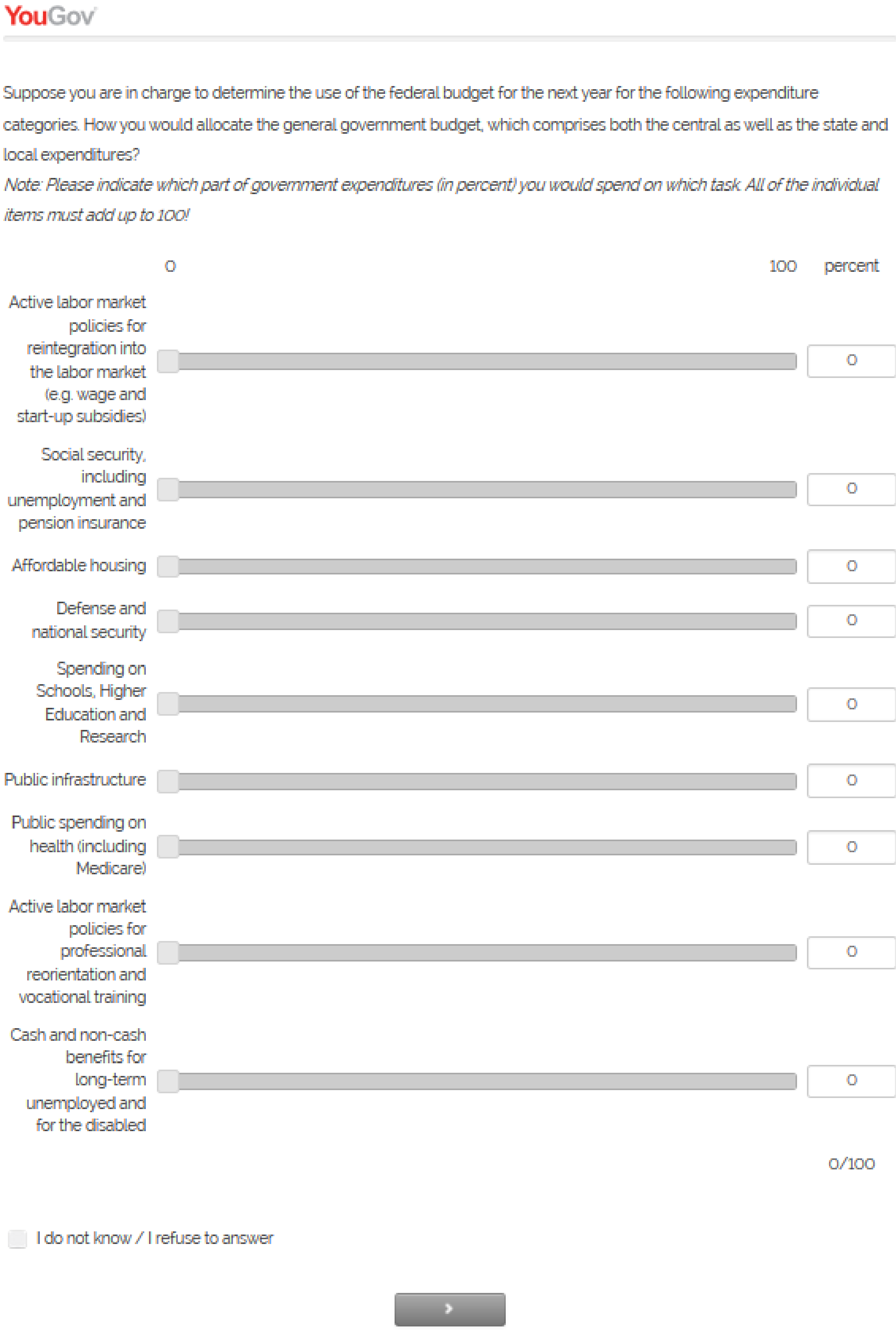
As technological progress continues, new possibilities arise to replace human labor with machines. An occasionally expressed concern is that the **impact of the use of latest digital production technologies** on workers differs between different worker types and **depends on the educational background of the affected workers.**

This is also confirmed by a recent study* which analyzed comprehensive technology and labor market data for 17 industrialized countries. The study examines the relationship between the actual use of the latest digital production technologies and the resulting development of employment.

The study shows that with the increasing use of digital technologies, **more qualified workers have displaced less qualified workers.** For example, **the share of hours worked by people without high school degree decreased,** while **the share of hours worked by people with a high school degree, a professional degree as well as with a college or a university degree increased.**

*Graetz, Georg, and Guy Michaels. "Robots at work." *Review of Economics and Statistics* (2018).

Figure I.4: Allocation of Government Budget (order of items randomized)



YouGov

Suppose you are in charge to determine the use of the federal budget for the next year for the following expenditure categories. How you would allocate the general government budget, which comprises both the central as well as the state and local expenditures?

Note: Please indicate which part of government expenditures (in percent) you would spend on which task. All of the individual items must add up to 100!

	0	100	percent
Active labor market policies for reintegration into the labor market (e.g. wage and start-up subsidies)			0
Social security, including unemployment and pension insurance			0
Affordable housing			0
Defense and national security			0
Spending on Schools, Higher Education and Research			0
Public infrastructure			0
Public spending on health (including Medicare)			0
Active labor market policies for professional reorientation and vocational training			0
Cash and non-cash benefits for long-term unemployed and for the disabled			0

0/100

I do not know / I refuse to answer

Figure I.5: Lottery and Donation (order of items randomized)

YouGov

By completing this survey you automatically take part in our lottery and have the chance to win $1000 price money. The lottery will take place approx. 2 weeks after the end of this study. The winner will be randomly drawn. In case of a win, you will be contacted by the YouGov team. Therefore, no further inconveniences arise for you as a result of receiving the prize money.

If you were to win the $1,000 prize money, you have the opportunity to donate all or a part of your prize money to one of the following three charity organizations.

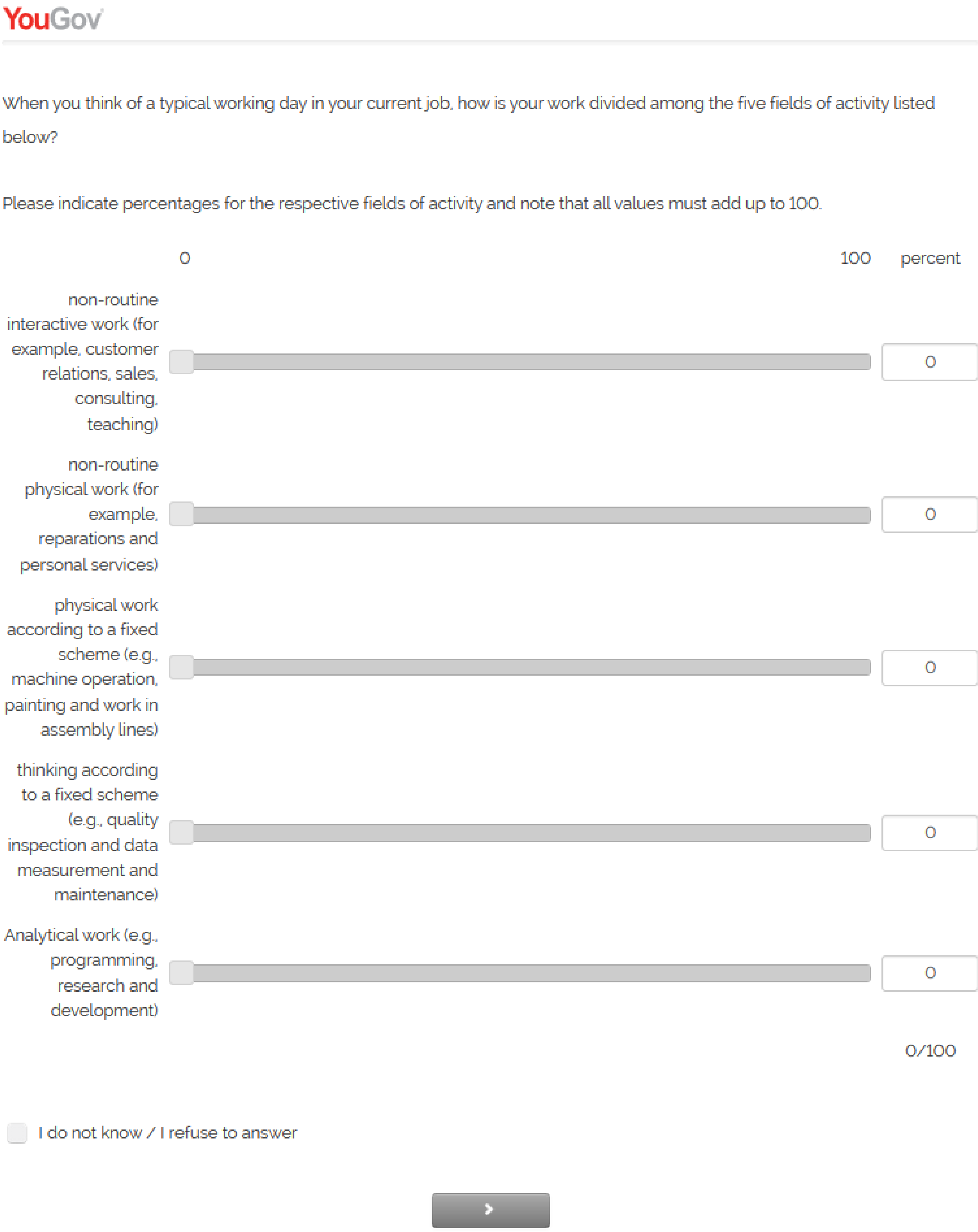
- **Code.org** is a non-profit organization that aims to **encourage** people, **particularly school students** in the United States, to **learn computer science.** The website includes **free coding lessons** and the initiative also targets schools in an attempt to encourage them to include **more computer science classes in the curriculum.** Particularly, the initiative wants to bring computer science classes to every K–12 school in the United States, especially in urban and rural neighbourhoods. More information you find under: https://code.org/
- **Feeding America** is a United States-based nonprofit organization that is a nationwide network of more than 200 **food banks** that feed more than 46 million people through food pantries, soup kitchens, shelters, and other community-based agencies. More information you find under: https://www.feedingamerica.org
- **iMentor** is a non-profit **organization** in the United States **that matches students from low-income communities to mentors** in order **to empower the student to graduate high school, attend and graduate college,** and achieve their goals. Students work with their mentor one-on-one, both in person and online, to develop a strong relationship, encourage college interest, and navigate the application process. Mentor-mentee matches can be connected for three to four years, or beyond into their first year at college, with the option of sticking with the program till college graduation. Learn more about iMentor under: https://imentor.org/

Please indicate how much of your prize money you would give to the three organizations. In the case you win, YouGov will transfer the amounts you have chosen to donate to the respective organization(s). You will automatically receive the remaining prize money in turn.

	$
Code.org:	
Feeding America:	
iMentor:	
My prize money:	
Total	0

Note: The sum of all four items must add up to $1000!

Figure I.6: Typical Working Day (order of items randomized)



YouGov

When you think of a typical working day in your current job, how is your work divided among the five fields of activity listed below?

Please indicate percentages for the respective fields of activity and note that all values must add up to 100.

	0 … 100	percent
non-routine interactive work (for example, customer relations, sales, consulting, teaching)		0
non-routine physical work (for example, reparations and personal services)		0
physical work according to a fixed scheme (e.g., machine operation, painting and work in assembly lines)		0
thinking according to a fixed scheme (e.g., quality inspection and data measurement and maintenance)		0
Analytical work (e.g., programming, research and development)		0

0/100

I do not know / I refuse to answer

J Questionnaire of Follow-Up Survey

1. Introduction Follow-up:

   The future of work has been a popular subject of discussion against the background of ongoing digitalization at the work place. Companies increasingly use modern digital technologies, which are becoming more and more important in many occupations. Please read the following questions carefully and answer as carefully and honestly as possible!

2. In your opinion, what impact will the use of the latest digital technologies have on the future importance of human workforce in general? Modern digital technologies will...

   ... substitute human workforce to a large extent.; *... rather substitute than supplement human workforce.*; *... substitute and supplement human workforce to the same extent.*; *... rather supplement than substitute human workforce.*; *... supplement human workforce to a large extent.*; *I do not know/I refuse to answer*

3. In your opinion, how will unemployment in the US be affected by the use of digital technologies in the future? Unemployment will...

   ... substantially fall; *... rather fall*; *... stay about the same*; *... rather increase*; *... substantially increase*; *I do not know/I refuse to answer*

4. Will the use of digital technologies in the future affect certain social groups more than others in terms of unemployment?

   No, absolutely not; *Rather not*; *Rather yes*; *Yes, absolutely*; *I do not know/I refuse to answer*

5. In your opinion, will the following groups rather suffer or benefit from the progressing digitalization in terms of future labor market prospects? (displayed in randomized order)

   (a) Workers without high school degree

   (b) Workers with high school degree

   (c) Workers with completed college/university education

1 Substantially suffer; *2*; *3*; *4*; *5*; *6 Neither suffer, nor benefit*; *7*; *8*; *9*; *10*; *11 Substantially benefit*; *I do not know/I refuse to answer*

6. Are you personally concerned that you will become unemployed in the next five years in light of the increased use of new digital technologies?

   No, absolutely not; *No, rather not*; *Yes, somewhat*; *Yes, absolutely*; *I do not know/I refuse to answer*

7. Do you think that the increasing digitalization on the labor market is desirable?

   No, absolutely not; *No, rather not*; *Yes, somewhat*; *Yes, absolutely*; *I do not know/I refuse to answer*

You arrived at the end of the questionnaire. We would like to thank you! We wish you a nice day!

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