The End of Work Feels Near. How Do People Perceive the Impact of Digital Technologies and Automation?*

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Abstract

Using customized survey data from the US and Germany, we study how respondents perceive the impact of recent technological advances on the labor market. We document that a majority views digital technologies and automation as a major threat to overall employment and as a cause of rising inequality, while a quarter is concerned about their own labor market prospects. Providing scientifically-grounded information on the likely labor market implications of automation in a randomized experiment reduces these concerns. Yet, treatment responses depend on prior beliefs about the future of work. This translates into heterogeneous and opposing treatment effects on policy demand.

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1 Introduction

Recent advances in digital technologies that allow for the automation of an increasingly wide range of human tasks have been widely debated in the academic literature. This literature generally acknowledges that digital technologies may have both a labor-saving and labor-creating effect, implying that the net employment effects remain an empirical question (Acemoglu and Restrepo, 2019). Although there is some evidence for negative employment effects, especially for specific technologies and country contexts (e.g., Acemoglu and Restrepo, 2020a), the general tendency in the literature is that digital technologies have either no or a slightly positive employment effect (see the review by Aghion et al., 2022 and further references below).

Despite this cautiously optimistic evidence, the public debate seems to lean 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 other academic evidence suggests that a much lower share of jobs is potentially automatable (Arntz et al., 2017; Nedelkoska and Quintini, 2018; Pouliakas, 2018), negative narratives surrounding digitalization 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. Most recently, the publication of ChatGPT at the end of 2022 again provoked a public debate focusing on the labor-saving effects of AI rather than it's potentially labor-creating impact.[3] A recurring narrative surrounding new technological breakthroughs is that while the technologies have not yet proven detrimental to human labor, they likely will in the future. Shiller (2020) even argues that such a narrative is subject to a long and vivid history of stories about mass job losses or degradation that recur in worries about the impact of modern robots and AI for the labor force (Shiller, 2019; Autor, 2015; Mokyr et al., 2015).

One-sided narratives in the public debate may thus be one reason why the general public tends to be more pessimistic about the impact of digital technologies than experts

[1]Kregel et al. (2021) show empirical estimates that the majority of news article circulation on robotic process automation was indeed dominantly negative 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).

[3]Examples include CNN (2023), Capital (2023) and New York Post (2023). Some reports, however, do not only emphasize replacement effects but also a complementary role of AI to human labor (Guardian, 2023; Neue Zürcher Zeitung, 2023).

(Walsh, 2018). This may have real consequences: It can affect people's acceptance of new technologies, potentially slowing down innovation and related productivity gains (Eißer et al., 2020); it can reduce the willingness to prepare for changing demands and skill requirements (Rodriguez-Bustelo et al., 2020); and it may 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).

This paper aims to develop a better and more nuanced understanding of how people perceive the impact of digital technologies and automation on the overall labor market and on their individual labor market prospects. In particular, our paper has the following objectives. First, we aim to improve our understanding about the nature and scope of perceptions and subjective concerns relating to digital technologies and automation. For this purpose, we document perceptions along three dimensions: i) the overall labor-market situation, ii) the individual labor-market situation, and iii) distributional aspects. Moreover, we examine the correlation of these perceptions with respondent characteristics. Second, we investigate whether such perceptions are relevant for real economic outcomes. For this, we relate perceptions to policy demand, stated labour market choices and actual donation decisions. Third, we use randomized survey experiments to test whether perceptions, related policy demand and labour market behavior are responsive to the provision of scientifically backed-up information about the likely impact of digital technologies. We conduct these analyses in the context of two advanced economies, the US and Germany, which are both strongly affected by digitalization processes, but that differ in terms of their welfare system and the political landscape. Hence, we also shed light on cross-country differences.

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,[4] which allows us to appeal to survey respondents from different countries, sectors and occupations, and which we transparently communicate to all respondents.

In a first step, we motivate our three dimensions of automation perceptions in a brief conceptual framework (Section 3.1) and document the empirical nature and patterns of these perceptions (Section 3.2). We find that the majority of respondents is concerned

[4]This concept (see Section 2.2) implies that we are interested in the perceived impact of digital technologies in general and of automation in particular. For reasons of brevity and to be consistent with the terminology and focus in much of the related literature, in the paper we sometimes use *automation* as an umbrella term for the recent general digitalization trends in the labor market.

about the aggregate and distributional impact of automation on the economy. More than half of respondents in both countries expect aggregate unemployment to increase because of digital technologies, while only around 10% expect unemployment to decline. Around 90% of respondents in both countries expect unequal effects of automation, where the labor market prospects of low-skilled workers are believed to suffer most severely. At the same time, more than one quarter of respondents in both countries is concerned about their personal risk of becoming unemployed within the next five years. This exceeds actual automation risk estimates which typically refer to the share of workers at a high risk of being potentially replaceable within the next 1-2 decades (Arntz et al., 2017; Nedelkoska and Quintini, 2018; Pouliakas, 2018). While the individual concerns are well comparable between countries, general and distributional concerns turn out to be more polarized in the US than in Germany.

Second (Section 3.3), 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 perceptions 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 findings that political views matter for perceptions in the US (e.g., Alesina et al., 2020).

Third (Section 3.4), we explore how perceptions are linked with outcomes that potentially translate into real-world behavior. We find that all dimensions of automation perceptions are strongly associated with higher demand for policy support and interventions, even as we condition on a broad range of 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 (measured as an actual donation decision). This latter finding suggests that general concerns about the impact of automation may erode pro-social behavior. 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 US safety net. These findings suggest that people perceive automation as a threat that needs to be addressed by more policy action, 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 whether the provision of scientifically backed-up information about the impact of digital technologies affects perceptions of automation. For this, we randomly provide respondents with either of two information treatments. Our first experimental group receives information that digital technologies do not necessarily lead to labor displacement, because labor-creating effects may counteract the labor-saving effect of these technologies. As supportive scientific evidence, we refer to the cross-country study by Graetz and Michaels (2018) who find no net employment effects from robot adoption. The second experimental group is informed about the potentially unequal impact of digital technologies on different groups of workers, and provides supportive findings from the same study that robots decrease the employment share of low-skilled workers. The treatment groups are thus exposed to two distinct findings regarding the impact of digital technologies that are consistent with much of the literature and for which we provide a concrete study example to increase the credibility of the described mechanism.[5] A neutral control group does not receive any information about the potential impact of digital technologies.[6] We expect the first information treatment ("no net employment effects") to have a stronger effect on perceptions than the second information treatment ("distributional effects"). This is because the first treatment likely works against the prevalent perception that automation increases unemployment, while the second treatment is consistent with prior perceptions in the general public.

In line with these expectations, the second treatment ("distributional effects", see Section 4.3) indeed causes little effects. By contrast, the first treatment ("no net employment effects", see Section 4.2) significantly reduces respondents' concerns about higher aggregate unemployment (average effect size: 0.15 standard deviations). This supports the notion that, compared to the predominant empirical evidence, the public debate leans towards the view that automation reduces aggregate employment. Treatment effects 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 impacting views through information. Moreover, we find that treatment effects 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 technological pessimists, while treatment-induced shifts of individual and distributional

[5]We discuss the literature further below and in Section 2.3. The choice of the study that we use (Graetz and Michaels, 2018) is discussed in more detail in Section 2.3.

[6]Our previous documentation of perceptions and concerns is based on control-group respondents (as they did not receive any information). A fourth randomized group receives a different order of survey questions than all other groups to test for priming effects (along the lines of Alesina et al., 2022; Daniele et al., 2020a; and Daniele et al., 2020b). For brevity, we do not discuss the related results here, but refer to Section 2.3 and Appendix Section D for a detailed discussion.

concerns are more prevalent among those with less pessimistic views. This then triggers heterogeneous effects on policy demand. Technological optimists respond to the treatment by reducing the demand and support for policy interventions, whereas we find somewhat weaker, opposite responses for neutral respondents and none for pessimists. This suggests that the same information cause individual-specific shifts in different dimensions of automation concerns and results in different conclusions drawn depending on people's prior beliefs.[7]

Contribution to the Literature. Our paper relates to several strands of literature. First, we speak to a vibrant literature that uses non-survey data to investigate the employment effects of labor-market automation.

While some studies such as Acemoglu and Restrepo (2020a) or Bessen et al. (2019) find negative employment effects from automation, the tendency in the majority of the existing literature is that net employment is either not or slightly positively affected by the adoption of automation technologies, be it the spread of CNC (Computer Numerical Control) machinery in manufacturing (e.g., Boustan et al., 2022), robot adoption (e.g., Graetz and Michaels, 2018; Mann and Püttmann, 2018; Aghion et al., 2020; Acemoglu and Restrepo, 2020a; Dauth et al., 2021; Koch et al., 2021; Dixon et al., 2021; Anton et al., 2022; Bachman et al., 2022; Hirvonen et al., 2022), computerization (e.g., Gregory et al., 2022), or the adoption of most cutting-edge 4.0 technologies including artificial intelligence (e.g., Genz et al., 2021; Felten et al., 2019; Georgieff and Hyee, 2021; Acemoglu et al., 2022). Based on an extensive review of the literature and own empirical work, Aghion et al. (2022) find that automation has a positive effect on labor demand both at at the firm level and industry level.[8] Much of this literature is also indicative of distributional effects of automation, with most structural shifts in favor of high-skilled workers, workers in non-routine analytic occupations (at the expense of routine manual and/or routine cognitive occupations) and service jobs (at the expense of manufacturing jobs). Recent examples explicitly focusing on distributional effects are Acemoglu and Restrepo (2020b), Acemoglu and Restrepo (2021), and Boustan et al. (2022).[9]

This literature provides the empirical basis for our survey experiment. Our paper complements this literature by providing novel evidence on the extent and role of perceptions as well as the malleability of perceptions and concerns to information. This is important even in light of robust evidence based on observational data, because labor-

[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]Obviously, empirical studies naturally reflect past developments and the effects of latest technologies such as ChatGPT or Bard remain largely unknown as of today. Note that our survey was conducted before the emergence of these AI technologies in late 2022 and early 2023.

[9]There is also an older literature focusing on the asymmetric effects of technologies on skill groups, see e.g. Autor et al. (2003, 2006); Autor and Dorn (2013); Goos et al. (2014).

market behavior and 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 perceptions does not necessarily mitigate other dimensions thereof, and the same information may have different effects depending on prior beliefs.

Using survey data, we further relate to a small but evolving set of papers that survey distinct aspects of automation (e.g., Dekker et al., 2017; McClure, 2018; Mulas-Granados et al., 2019; Rodriguez-Bustelo et al., 2020) and the implications of automation for policy preferences (e.g., Mulas-Granados et al., 2019; Zhang, 2019; Thewissen and Rueda, 2019; Di Tella and Rodrik, 2020; Jeffrey, 2021; Gallego et al., 2022; Golin and Rauh, 2023).[10] Compared to our paper, these surveys do not consider automation perceptions along different dimensions, their respective determinants, and associations with policy attitudes and individual labor-market strategies. Yet, as we show, our multilayered approach is important: our findings suggest that different dimensions of automation perceptions show distinct patterns and that focusing on one proxy of automation concern omits relevant channels of how perceptions shape preference formation and behavior. Importantly, our paper is the first to run survey experiments to investigate whether scientific information about unemployment and distributional effects of automation affect labor-market perceptions, policy demand and personal labor-market choices.

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 reviews by Haaland et al. (2022) and Stantcheva (2022). There is generally 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 perceptions and preferences. Di Tella and Rodrik (2020) constitute a rare exception with a focus on how trade shocks affect policy demand. Our study advances the understanding of individual perceptions in the context of automation as a very important labor-market trend. Lastly, there is, of course, a long tradition in using surveys in labor economics (not automation related); recent examples include Mueller et al. (2021) and Jäger et al. (2021).

[10] Acemoglu et al. (022a) survey firms about the state of automation adoption.

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.[11] All respondents are residents of the respective country in which they were surveyed. We commissioned the commercial survey provider *YouGov* to implement the survey.[12] Participants enroll on the Yougov online panel. Yougov then invites online panelists to participate in our survey via email. Invited survey participants 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 15 minutes, on average, 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 perceived (future) labor-market implications of automation, our sample is limited to individuals aged 18-55 who are either employed or currently unemployed, but actively seeking employment. We focus on this group because it allows us to study labor market expectations among the active part of the labor force that is likely to build expectations about future labor market processes. The corresponding final sample comprises 5,147 respondents (US: 3,066 and Germany: 2,081). We 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] Our weighted survey sample is also comparable to major population statistics in both countries. Details on sample restrictions, non-response analysis, and representativeness can be found in Appendix Section A.1. Summary statistics are presented and described in Appendix Section A.2.

2.2 Structure of the Main Survey and Information Treatments

The questionnaire (see Appendix Section E) surveys standard background information (block A), perceptions of digital technologies and automation (block B), policy preferences as well as labor market and donation choices (block C) and further sensitive background

[11] The survey and any surveyed perceptions of digital technologies should thus not be affected by the most recent debate about the role of AI that was triggered by the release of Chat GPT in fall 2022.

[12] 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/`.

[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).

information (block D). The sequence of the survey blocks is important as block B includes a randomized survey experiment which may affect subsequent responses. In the following, we summarize the sequence of the survey and it's main contents.[14]

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).

Block B: Perceptions about Automation (incl. randomized interventions). Block B begins with an opening text for all survey participants which defines the topic of this survey block and our concept of "digital technologies":

"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 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 a randomized sub-sample of respondents with further information. We consider prior attitudes to be a potential source of heterogeneity how people respond to the subsequent information treatments as the same information might be processed differently depending on such prior beliefs.

B.2 – Information Treatments. In a next step, the survey includes a randomized information experiment. In particular, we have four randomized groups in a between-subjects design; see Table 1 for an overview of the four groups and their corresponding sample size by country. We subsequently describe the four groups:

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

[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`.

are exposed to one of two information treatments (denoted by subscripts 1 and 2, respectively) that aim at distinct aspects of digital technologies, see section 2.3 for a detailed discussion of these treatments:

Information I_1 - "no net employment losses". Respondents in treatment group $\mathbf{ABCD_1}$ receive information I_1 that *"the use of the latest digital technologies does not necessarily lead to a decline in employment, because it can improve the competitiveness of the firm [...] which in turn increases employment"*. We then provide supportive evidence from a recent study by Graetz and Michaels (2018) who show that *"the number of hours worked has remained the same despite an increasing use of digital technologies"*. To underline its credibility, the treatment information include the exact bibliographic reference of Graetz and Michaels (2018). A screenshot of the treatment (including its exact wording) is displayed in Figure 1.

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, namely "*the occasionally expressed concern [...] 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*". It subsequently summarizes supportive evidence for this statement from Graetz and Michaels (2018) that *"more qualified workers have displaced less qualified workers"*. We deliberately do not include information on zero net employment effects from automation (as in information treatment I_1) since I_2 is supposed to aim at distributional perceptions, albeit I_2 may theoretically affect other aspects of automation perceptions. We discuss this possibility of cross-learning with the related results in Section 4.3. Again, we provide the exact bibliographic reference of Graetz and Michaels (2018). A screenshot of the treatment (including its exact wording) is displayed in Figure 2.

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 section 2.3 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 3.2).

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).

B.3 – Perception Measures. We then survey perceptions regarding the impact of automation with respect to three main dimensions (see Section 3.1 for a conceptual framework). 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 overall desirability 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 (see section 3.2).

Block C: Policy Demand, Labor Market and Donation Decision. Question block C first surveys respondents' **policy demand**. For this, the survey contains 15 questions that 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 A.3 for details). In order to reduce the amount of information, we select the survey questions belonging to each respective policy type and calculate a standardized total z-score.[15] We compared this approach to running a factor analysis instead and find very similar results, see Appendix A.3 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 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

[15]This is calculated by dividing the composite z-score by its standard deviation as the mean value of the total z-score equals zero. For a similar procedure see e.g. Kling et al. (2007) and Alesina et al. (2022).

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.

To address concerns that the responses in conventional survey questions are different from actual decisions, question block C also includes an **actual donation decision** (see Appendix Figure E.5 for a screenshot). Respondents were informed that upon survey completion, they automatically enter 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 donation decision thus 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 allows us to study what type of solidarity respondents consider most suitable to address the implications of digital technologies for the labor market. For this, the choice in both countries 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.[16] In the subsequent analysis, we will investigate to what extent people donate any prize money of the lottery, the share of the prize money they donate and the related structure of the respective beneficiaries. Appendix Section A.3 gives an overview and summary statistics of all block C questions used in the subsequent analysis.

Block D: Workplace Characteristics, Household Income and Survey Quality. This block includes workplace-related characteristics that could have introduced a priming if already surveyed in block A. This includes 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. In addition, we 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.

For the median respondent, the survey took 18.9 minutes to complete. In order to not apply any arbitrary sample restrictions based on survey duration, we always use the

[16] 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/`).

full sample, but find almost identical results when excluding respondents with survey durations below the 1st or above the 99th percentile.[17]

2.3 Discussion of Randomized Treatments

Motivation for Treatment Choice. The two treatments are chosen to provide respondents with two insights from empirical research, namely that (1) *"the use of the latest digital technologies does not necessarily lead to a decline in employment"* (treatment 1) and that (2) "*the occasionally expressed concern [...] 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*" (treatment 2).

The statements in both treatments inform respondents about possible implications of automation that go beyond the labor-replacing narrative. They are supported by contemporary academic literature at the time of the survey. In particular, our statement in treatment 1 aligns with the majority of studies finding no negative net employment effects (see the review in the Introduction). Although there are a few studies that indicate negative employment effects, the statement of labor-creating effects potentially compensating labor-saving effects from digital technologies appears justified by the overall tenor of the literature, as summarized also in the review by Aghion et al. (2022). Similarly, the distributional statement in treatment 2 reflects an extensive strand of the literature, as reviewed in the Introduction, suggestsing heterogeneous effects for different skill and worker groups, see e.g. Acemoglu and Restrepo (2021) for a recent example. Still, since there also exists some contrasting evidence and empirical studies considering future periods and other technologies (such as latest AI technologies) might reach other conclusions, we deliberately chose not to give the impression that the two treatment messages reflect some universal truth. We hence phrase both treatments very cautiously by using formulations such as "not necessarily" and "occasionally expressed concern".

Since the objective of our survey experiment is to study if automation perceptions are responsive to scientifically grounded information, each treatment is backed-up by empirical evidence from Graetz and Michaels (2018). We chose this study for a number of reasons. First, it offers credible causal identification (using an instrumental variable strategy) and went through rigorous peer review at a prestigious academic journal. It 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. In addition, important studies for the US and Germany, such as Acemoglu and Restrepo (2020a) and Dauth et al. (2021), had not been published at

[17] 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.

the time of the survey (i.e., had not yet gone through full peer review), and they do not provide comparable cross-country results for the two countries. Second, using Graetz and Michaels (2018) allows us to provide supportive evidence for both treatment information as it includes both net employment effects and distributional consequences estimated within the same unified empirical approach. In particular, the paper finds that robots do not significantly decrease overall employment, but they decrease the employment share of low-skilled workers.[18] 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. Third, the chosen scientific evidence should be credible, non-deceptive and not represent an outlier in the literature in order to meet our objective to study if automation perceptions are responsive to scientifically grounded information. Graetz and Michaels (2018) clearly meets these requirements as it is in line with much of the existing literature as discussed above. The existence of studies reaching different conclusions does not harm our objective of providing scientific evidence that supports our treatment messages. Finally, we are not concerned with the fact that Graetz and Michaels (2018) examine effects of robot adoption rather than covering digitalization technologies more generally, because we leverage the empirical evidence only as an example that supports the statements of the treatments. Moreover, there simply was no published study available at the time of the survey with a broader focus on digitalization that had a similar cross-country perspective and unified approach for both of our treatments. Hence, if at all, the limited scope of not covering all digital technologies in the example study could weaken our treatment information.

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 this assumption, Appendix Table C.1 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 rejects any significant explanatory power of the model. The number of significant point estimates 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.

Hence, comparing the information-treatment groups, $ABCD_1$ and $ABCD_2$, to the control group, $ABCD_0$, should identify the effects of the information treatment if aspects of priming and salience do not play any decisive role. This is likely to be the case because all three groups face the same order of survey questions ($ABCD$) and are thus similarly exposed to the topic, e.g. by the introduction of the topic. Moreover, the results

[18] Boustan et al. (2022) find similar employment and distributional results for the adoption of CNC technology in the US.

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 D). This supports the idea that the control group and the information-treatment groups are indeed only different with respect to the information level.

Yet, we can only expect our treatment to have an effect if treatment-group respondents paid attention to the information treatments and found them relevant and reliable. In that respect, it seems reassuring that about 90% of all treatment-group respondents assessed the treatment information at the end of the survey (block D) and that a large majority considers the treatment information to be trustworthy (87%) and helpful (82%). In fact, this latter finding already hints at the fact that the treatments contained new information for the majority of respondents that they had not been exposed to before.

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]

A general concern with surveys is that self-reported survey replies are not accurate and do not align with actual behavior and revealed preferences. However, as also noted and summarized by Dechezlepretre et al. (2022), there is growing evidence that survey responses are correlated with actual behavior (e.g., Dohmen et al., 2011; Hainmueller et al., 2015; Funk, 2016; Fehr et al., 2020; Dechezlepretre et al., 2022; Tannenbaum et al., 2022).

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., 2018b; Haaland and Roth, 2021; and Haaland and Roth, 2020). 2,225 participants (∼75%) completed the short

[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.

follow-up-questionnaire. A non-response analysis, depicted in Appendix Table C.2, suggests that there is no systematic evidence for selective attrition.[20] The follow-up survey is available in Appendix Section F.

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. 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 consider 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

This section starts with a brief conceptual framework to provide guidance on the perception dimensions that we consider in our survey. We then discuss related perceptions in both the US and Germany, before analyzing their anatomy and correlates. At this stage, we do not yet leverage the experimental setting (which we leave to Section 4). The analysis is largely descriptive and does not make any claims of causality, albeit multivariate regressions in this section condition on a rich set of covariates. For a similar procedure, see the recent papers of Stantcheva (2021) and Dechezlepretre et al. (2022). Among others, understanding systematic patterns and correlations in automation perceptions also helps to form expectations about the effects of the information treatments in Section 4 and guide their interpretation.

3.1 Conceptual Framework of Automation Perceptions

The impact of digital technologies is often discussed for a specific skill type, job or task, but is also often part of a broader narrative that highlights the impact on society and the workforce as a whole. Perceptions and concerns relating to digital technologies are thus multilayered and have different dimensions and aspects to it. For this reason, it is our objective to capture different dimensions of perception for a comprehensive concept of

[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.

digitization.[21] In particular, we surveyed perceptions and subjective concerns[22] related to three dimensions:

I **General implications** of digital technologies and automation for the aggregate labor-market situation, the overall economy and society as a whole.

II **Individual implications** of digital technologies and automation for a respondent's own situation.

III **Distributional implications** of digital technologies and automation (e.g., effects on different skill groups).

Dimension I captures general perceptions and concerns about the aggregate level of 'available' work or levels of employment in the economy. Implicitly, this dimension surveys the overall perceived sensitivity/elasticity of human-labor substitution with respect to automation processes. Concerns in this dimension likely reflect a one-sided public debate about automation risks. We conjecture that these 'abstract' concerns 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 job characteristics and their specific workplace tasks. **Dimension II** captures the subjective concerns that workers have about their own individual labor market prospects (e.g., the perceived likelihood of losing one's own job). Compared to the more general and aggregate concerns in Dimension I, these concerns are more likely determined by individual job 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 perceptions and concerns related to the inequality impact of automation and digital technologies. This dimension is likely to be shaped by economic beliefs about automation effects 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. An overview of perception questions (which are labeled P_1 to P_{12}) belonging to each of the three

[21] See section 2.2 for its definition. Despite this broad concept, we sometimes use *automation* as an umbrella term for the recent general digitalization trends in the labor market as discussed in footnote 4.

[22] Note that the perceptions and concerns that we consider could also be broadly interpreted as reflecting something like automation angst (which is a term popularized by The Economist, 2015, others have used 'automation fears' or 'automation anxiety' to describe the same phenomenon). We prefer to speak of 'perceptions' and 'subjective concerns' because we believe that language such as anxiety or angst may be too strong for what we elicit in the survey.

dimensions is provided in Table 2. Note that perceptions are being elicited against a different time horizon and are thus not directly comparable but should be interpreted in their own right. We did so since relevant time horizons are likely to differ across the perception dimensions. Expected aggregate and distributional implications are being elicited against a rather generic time horizon, i.e. the future per se, since people are unlikely to have a concrete understanding of when a slow process such as automation would materialize on the labor market (which is an interesting question in its own right). Expected, individual consequences, on the other hand, are queried for a period of 5 to 10 years, since the individual planning horizon is likely to be short and medium-term. Also, retirement considerations might otherwise affect related expectations of older respondents.

3.2 Automation Perceptions in the US and Germany

The following univariate descriptives are based on the sample of those respondents who were randomly assigned to the control group of our survey experiment. This ensures that the results are not driven by the informtion treatments. Subsequent regression analyses further below include all respondents, but condition on the experimental group. For the sake of brevity, the subsequent analysis focuses on one survey question of key interest for each dimension of perceptions, while we report more detailed results for all other perceptions in the Appendix. Moreover, Table 2 features summary statistics by country for all relevant perceptions. Note that higher values for all measures always denote stronger concerns or more negative perceptions.

For the **general implications** of digital technologies and automation (Dimension I), 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 3(a). We find that more than half of all respondents in both countries expect the unemployment rate to increase or even substantially increase due to automation. On average, people thus seem to have concerns about rising unemployment that are stronger than what is warranted by the empirical evidence during the time of the survey. 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.[23] This result appears consistent with observed political polarization documented in a number of recent papers (Alesina et al., 2020; Canen et al., 2021; Boxell et al., 2020; Coibion et al., 2020).

[23]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 Appendix Figure B.1).

With respect to **individual implications** (Dimension II), we focus on the perceived own risk of becoming unemployed (P_5) as this measure has also been used before in other studies on automation concerns (Morikawa, 2017; McClure, 2018; Coupe, 2019) and perceived job security (e.g. Dominitz and Manski, 1997 and Manski and Straub, 2000). Interestingly, we find quite comparable patterns between Germany and the US and differences are not significant (see also related cross-country tests in Table 2). Figure 3(b) shows that a little more than a quarter of respondents in both countries are at least somewhat concerned to become unemployed due to automation within the next five years. Note that the extent of concerns measured by individual as compared to aggregate and distributional concerns are not directly comparable as the former refers to a shorter time horizon. With a longer time horizon, individual concerns might actually be even stronger. But even for the limited five year horizon, concerns about the personal effects of automation appear quite substantial. They exceed, for instance, recent estimates of the share of workers at a high risk of being replaceable by machines (Arntz et al., 2017; Nedelkoska and Quintini, 2018; Pouliakas, 2018), despite the fact that these estimates refer to the technological frontier in 1-2 decades and correspond to an upper bound of the replacement effect. This is because they only reflect the technological potential of substitution, but do not price in any positive feedback mechanism via, for instance, rising firm productivity that may prevent actual layoffs. This suggests that people tend to overestimate the unemployment risk related to the automatability of tasks, likely because they do not take into account any positive feedback mechanisms from technology adoption. Interestingly, the share of respondents that consider 70% or more of their workplace tasks to be replaceable within the next ten years, which is the same cutoff used in the automation risk literature, is well below 10% and thus perfectly in line with the automation risk literature (see Appendix Figure B.2). Moreover, the share of respondents expecting automation-induced salary losses and who consider themselves as losers of automation is well below 20% in both countries.

Regarding the **distributional implications** of digital technologies and automation (Dimension III), we focus on the perceived impact on inequality across different skill 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.[24] Figure 3(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. Concerns for specific skill groups in the US significantly exceed related concerns in Germany though (see Appendix Figure B.3) and corresponding cross-country differences are statistically

[24]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.

significant (see Table 2). 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, distributional concerns appear to be larger in the US, especially for workers with a high-school diploma and below.

To sum up, we find strong concerns regarding the aggregate and distributional impact of automation. There is also a large share of people who are concerned about their personal job implications. Interestingly, the correlations between general perceptions and expected consequences for oneself are rather weak, see Appendix Table C.3. 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. Thus, these indicators indeed capture distinct dimensions of automation concerns.[25]

Moreover, 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 differential concerns related to aggregate outcomes of automation, individual unemployment risks are perceived to be quite similar across both countries. This indicates that the process of forming perceptions likely differs across these dimensions. This is what we turn to next.

3.3 Anatomy of Perceptions and Concerns

We now explore to what extent the three dimensions of perceptions 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 perceptions and concerns.

Empirical Approach. We estimate separate individual-level regressions for the three main indicators of interest, 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), and run simple OLS regressions of the following form based on the whole

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

sample of respondents:

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

where P_{ji} refers to perception j with $j = 1, 5, 9$ of respondent i. We use standardized (z-score) versions of the outcome variables to make the results more comparable across variables.[26] 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 perceptions; in particular, we include respondents' job and workplace characteristics (referred to as Job and Workplace$_i$) such as the share of routine and manual tasks, IT exposure at the workplace, the recent up- or deskilling of workplace-related skill requirements, and someone's current and past job status.[27] 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$_i$). If all individuals had the same information and drew the same conclusions from it, general beliefs should not have any impact on perceptions (conditional on factors determining someone's actual exposure to automation-related risks).[28] If, by contrast, perceptions relate strongly to these general beliefs, this might either indicate that such beliefs affect someone's exposure to information or the way that information is processed in the formation of perceptions. Since we use the full sample of respondents to improve statistical power in our analysis (unlike the previous Section 3.2), we further control for the respective experimental group D_i an individual has been assigned to (respective coefficients 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. Note that we find similar coefficients when excluding respondents that received an information treatment.

[26]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., $z_i = \frac{P_i - \hat{P}}{1/n \sum_{i=1}^{n} (P_i - \hat{P})^2}$), respectively.

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

[28]We did not survey a respondent's level of information. Any such assessment would be highly subjective and likely endogenous to perceptions. Such an information would thus not help to control for the actual, objective exposure to information. In fact, our experiment aims at examining the role of information when people are exposed to information in a controlled, experimental setup.

Results. Table 3 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 perception dimensions, 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 unemployment concerns 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 underlying 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.[29] 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). In the US, political beliefs 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). In line with this, we also find that political ideology and trust in government matter for individual concerns (P_5) in the US, but not in Germany.

If perceptions in the US are rooted more strongly in political beliefs, this may either give more or less scope for perception updates in the US as compared to Germany. If

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

people despite having been exposed to similar information before, have extreme views, this would speak in favor of a politically motivated resistance to such information, likely lowering the responsiveness to such information (Alesina et al., 2020). If, on the other hand, extreme views result from a combination of strong political beliefs and a previous lack of such information (be it due to a one-sided public debate or a selective information choice), being exposed to new evidence might also induce stronger shifts than in a context where political beliefs are less important.

3.4 Policy Demand, Labor Market Choices, and Donations

In a next step, we examine whether actual and stated behavior as well as the demand for policy interventions are associated with different margins of perceptions and concerns. Such correlations are the prerequisite for our information treatments (in Section 4) to affect these outcomes, albeit they are also interesting in itself. For this, we describe how the three main perception indicators are correlated with different types of policy demand, stated labor market behavior, and actual donation decisions (see Section 2.2 (block D) for details on these outcome measures).

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

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

where Y_{ji} refers to the various outcomes as described above. λ_k, with $k = 1, 2, 3$, capture the coefficients for 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). We include these perception measures simultaneously because the previous analysis suggests that they capture related, but still distinct perception dimensions of automation. 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 perceptions is most strongly related to the outcomes of interest, and the coefficients $\lambda_1, \dots \lambda_3$ will reflect the marginal impact of one dimension conditional on the respective other two perception measures. 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 3.3. We again control for the assigned experimental group D_i[30] and add a country dummy whenever we pool both countries. The results of this approach are summarized in Tables

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

4 (policy demand), 5 (labor market choices) and 6 (real donation behavior).

Results. We generally find that people in both countries, on average, demand more policy support for all types of policies (i.e., redistribution and antipoverty measures as well as active and passive labor market policies) the more they are concerned about aggregate, distributional as well as individual consequences of automation. This even holds after controlling for job and workplace characteristics that are related to actual risks of automation, the respective other dimensions as well as political and economic views.[31] 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.

By contrast, the link between the perception dimensions 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 concerns only weakly relate to 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. The latter finding on the unresponsiveness of the personal unwillingness to accept lower wages is, for instance, consistent with previous insights on downward wage rigidities (e.g. Kahneman et al., 1986). German workers are willing to switch jobs more often if they expect 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 expect rising inequality, the latter potentially reflecting some form of last-place aversion.

Finally, different margins of automation perceptions affect generosity of donation

[31]Table C.4 in Appendix C 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.

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 reduce donation generosity (Germany only). The former result speaks in favor of increased sensibility and solidarity with those who are in a disadvantaged position, as has been argued before in the donation-economics literature such as 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 and thus social cohesion.

The analysis thus reveals some interesting correlations between the perceived impact of automation and the considered outcome dimensions, suggesting that perceptions are likely to have economic consequences. However, these findings should only be considered as indicative of what to expect from the information treatments that we turn to next as they reflect correlations rather than causal effects. Still, we cautiously expect lower policy demand if the treatment information generally reduces automation concerns. For stated labor market choices as well as charitable donations, by contrast, deriving hypotheses is complicated by the fact that general, individual and distributional 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 perceptions and concerns respond to the treatment.

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 scientifically backed-up information and, in turn, affect policy demand as well as labor market choices and donations to charities (for details see Section 2.2 and 2.3). Given the findings in section 3, the updating effect of the first information treatment of a zero net employment effect (I_1) likely works against predominant existing concerns about 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. With regard to the information treatment of employment shifts from unskilled to skilled labor (I_2), the updating effect on perceptions is potentially rather 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. In fact, the general public in both countries seems to be quite aware of the skill-biased nature of recent labor market trends due to automation (see Section 3.2 for details on this). Hence, we also expect effects from this information treatment on policy demands and behavioral responses to be weak compared to the first information treatment. Finally, albeit both treatments mainly aim at different perception dimensions, there may be cross-learning if the distributional information in the second treatment also affects people's perceptions of aggregate employment trends in response to automation.

4.1 Empirical Strategy

In what follows, we focus on the causal impact of providing information on either "no net 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 2) and ii) policy demands, stated labor market choices and donations (all summarized in Appendix A.3). 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:

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

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 very 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 further estimate a series of similar regressions that allow treatment effects to vary for certain sub-groups of the population which might differ in the responsiveness to being exposed to information. In particular, we allow for country-specific treatment effects in order to examine whether the fact that perceptions concerning the impact of automation on the economy as a whole are more negative in the US (see Section 3.2) translates into a stronger or weaker responsiveness to the treatments in the US as compared to Germany.[34]

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

[33]See Appendix Table C.1 for tests of balance across treatment groups.

[34]Note that we estimate group-specific effects rather than an interaction model, because the sample

In addition, we allow treatment effects to vary with beliefs about 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*). As shown in Appendix Figure B.4, most people expect the value of human labor in the future to decline rather than to increase. We allow for a related heterogeneity because we expect people's responsiveness to the provision of scientific evidence to depend on prior beliefs about digital technologies and automation. If strong prior beliefs reflect genuine misinformation about the state of evidence regarding automation effects on the labor market, 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 move by objective information, especially because they are similarly related to political and economic views as the perception measures discussed in Section 3.3.[35] In this case, people may be less responsive to scientifically grounded information that contradicts their prior beliefs.

Finally, we also allow the ITT to differ along the skills distribution because the treatment information likely has different implications for workers with a high-school degree or less, some college or college education and beyond.[36]

Due to a large set of potential outcome variables and multiple treatments, we test the robustness of all our findings to adjusting standard errors for multiple hypothesis testing, using the Stata command *mhtreg* which is based on List et al. (2019). The corresponding adjusted standard errors, along with the conventional standard errors, are reported in Table C.6. We also present evidence on the joint irrelevance of our respective treatment conditions for all outcome measures of interest using the *RANDCMD* randomization test in Stata (Young, 2018). For the sake of brevity, we only discuss significant results of our treatment interventions which are robust to multiple-hypothesis testing in the following main text. Other insignificant or less robust results are delegated or referred to in the

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]Multivariate analyses in Appendix Table C.5 reveal that 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.

[36]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.

Appendix.

4.2 Information Treatment I_1 - no net employment losses

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 concerns related to automation. Moreover, a test of joint significance for all 12 perception outcomes is significant at the 1% significance level (see Table C.6), implying that the treatment 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 perception difference regarding rising aggregate unemployment (P_1) for someone in the US who mistrusts the government compared to someone who trusts the government (see Table 3). Interestingly, the treatment also significantly reduces concerns that skilled workers and graduates might suffer from automation (P_{11}, P_{12}; the latter is not robust to multiple-hypothesis testing), 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, perceptions about the effects of automation on aggregate employment are malleable to being exposed to scientifically grounded information about the role of automation for aggregate labor demand. However, this only seems to reduce concerns about the implications of automation for skilled workers and graduates, while perceived implications for unskilled workers remain unaffected. This apparent asymmetry may also be the reason why the treatment significantly reduces concerns only among skilled workers and graduates, but not among the unskilled (see Appendix Figure B.6).

We also find some evidence that information falls on a more fertile ground in the US than in Germany. Many of the shifts in perceptions that we discuss above are driven by US rather than German respondents (although the general patterns are visible in both countries – see Appendix Figure B.5).[37] 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. This suggests that the stronger link of perceptions to political views (see above) in the US does not reflect a general resistance to scientific evidence, but rather a lack of information either because of

[37]A test of joint significance for all 12 perception outcomes suggests significance of the sub-group analysis by country, prior beliefs as well as by skill level, see Table C.7.

a one-sided public debate or because people select one-sided information sources, possibly due to their political attitudes. Hence, there is room for perception updates when being (involuntarily) exposed to relevant and credible information.

Moreover, prior beliefs about the future role of human labor turn out to be an important source of heterogeneity in the treatment response pattern (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 treatment, again indicating a lack of such information in the public debate or a selective choice or processing of 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. These heterogeneous response patterns by prior beliefs are likely to translate into treatment heterogeneity for other outcome measures that we turn to next.

Effects on Further Outcomes. Despite the leftward shift in perceptions of automation induced by the treatment (see above), we do not find significant average responses for policy demands, stated labor market choices and donations, neither among US nor German respondents.[38] However, these insignificant average effects mask some heterogeneous and opposing effects along the distribution of prior beliefs (Figure 6). The respective tests of joint irrelevance across prior beliefs in Table C.7 show that the treatment has significant effects across priors for both policy demand and stated labor market choices (for the latter, only among optimists). For example, the treatment reduces policy demand 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. Albeit we can only speculate about the reasons underlying these opposing responses, one potential reason might be that there are two counteracting forces at work. On the one hand, reduced concerns should come with a lower demand for supportive policies, which is also what the estimates in section 3.4 suggest. On the other hand, if people are concerned that the implications of automation are too difficult to be addressed adequately by policy interventions, reduced concerns may give rise to an increased demand for such policies. Hence, the increased demand for supportive policies among neutral respondents could partly reflect such an encouragement effect. In addition, the differential shifts in automation perceptions along the distribution of prior beliefs in response to the treatment may

[38]See Table C.7 for tests of joint irrelevance. Detailed regression results are available upon request.

also contribute to the heterogeneous result pattern. Among neutral respondents, for instance, I_1 also (insignificantly) raises inequality concerns which may translate into higher policy demand despite the zero net employment loss information. By contrast, we find the other outcomes, i.e. stated labor market choices and donation decisions, to be largely unresponsive to the treatment information along the distribution of prior beliefs.[39]

Overall, the results for the first treatment suggest that the provision of scientifically grounded information reduces concerns related to automation, on average. Yet, this effect does not 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.

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

Perception Measures and Other Outcome Variables. Figure 4 suggests that perception shifts induced by the second treatment are mainly limited to distributional concerns about automation, which is plausible given the treatment's focus on distributional implications. The absence of any effects on aggregate-employment perceptions (which were shifted in response to the first treatment) indicates that cross-learning is not relevant and that our treatment has the desired effect of isolating distributional from aggregate automation implications.

Increased concerns about an unequal impact of automation (P_9) due to somewhat lower perceived risks for skilled workers and graduates (P_{11}, P_{12}) have fairly large coefficients going in the expected direction, but significance is not robust to multiple-hypothesis testing (with the standard error for distribution perception P_{11} being borderline significant; see Table C.6). As expected, treatment-induced shifts in the perceived risks for unskilled workers (P_9) are small and insignificant, suggesting that the already extremely pessimistic view on automation-related effects on unskilled workers (see Section 3) is in line with the treatment information. For perceptions on the general and individual implications of automation, the coefficient are mostly small and insignificant throughout. Testing for joint irrelevance of the treatment for all perception measures narrowly misses the 10% significance level. Heterogeneities by priors and skill group in Figure B.8 and B.9, respectively, are small and do not survive the corresponding tests of joint irrelevance of the treatment (Table C.7).

Given the rather limited effects on perceptions, it is not surprising that we do not

[39] 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.

find systematic effects of I_2 on policy demands, stated labor market choices or real-world donations; see Figure B.10.[40]

4.4 Follow-up Survey

As we have seen, especially information treatment 1 significantly shifted various dimensions of automation concerns. We now test the persistence of these effects by analyzing whether they 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 concerns 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 $ABCD_2$:

$$P_{kti} = \alpha + \beta_1 ABCD_{1i} + \beta_2 ABCD_{2i} + \beta_3 FU_{it} + \beta_4 ABCD_{1i} \times FU_t + \beta_5 ABCD_{2i} \times FU_t + u_{it} \tag{4}$$

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. Hence, β_3 captures any perception shifts between the main and the follow-up survey for the control group, while β_4 and β_5 capture the corresponding shifts across time for the two treatment groups.

Figure 7(a) provides corresponding results for perception measures capturing general and individual concerns. The Figure reports predicted perception levels separately for each group ($ABCD_0$, $ABCD_1$, $ABCD_2$) and "time period" (main survey, follow-up survey) – see the Notes to Figure 7 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 though, both the control group as well as the group treated with I_2 also report significantly lower

[40]The only exception is the field of policy demand where college graduates show significantly higher demands for active labor market policies and anti-poverty measures in response to the treatment (results available upon request). 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 in response to the treatment. Interestingly, no notable effects can be found for unskilled workers who are most exposed to suffering from automation according to the treatment information.

concerns in the follow-up than in the main survey, 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.

One potential explanation for this convergence in perceptions is that respondents have been exposed to some information between the main and follow-up survey that had quite similar updating effects as our treatment information I_1.Though we can of course only speculate about such confounding events, one potential candidate is 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 net employment loss"). This episode was first broadcasted[41] on March 4, 2019, which is around two weeks after the main survey and one week prior to the follow-up survey. The John Oliver Show is widely considered to have an influence on the public debate in the US, commonly referred to as the "John Oliver Effect".[42] 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.[43]

Given this evidence, we cannot derive any clear conclusion as to whether there is a persistent effect of our first treatment. On the one hand, the coincidence of having this influential show being broadcasted in between our surveys may have contaminated our control group in the follow-up, while the treatment effect would have been persistent also in absence of the show. On the other hand, though, it could as well be that any direct treatment effect of the first survey faded out, and all effects emerging in the follow-up are due to the "John Oliver" effect. The two interpretations are observationally equivalent. 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 thus no conclusive evidence for or against persistent effects of our treatment information. However, no major control group shifts between the main and the follow-up survey can be found for distributional concerns (see Figure 7(b)) and shifts in these perceptions in the main survey for both treatment groups tend to bounce

[41]The video can be seen via `https://youtu.be/_h1ooyyFkF0`.

[42]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`).

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

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 concerns that we find for our first treatment group in Figure 7(a) may in part be driven by a repeated exposure to information similar to the "zero net 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 the scope and relevance of perceptions in the context of labor-market automation. We show that people tend to have negative perceptions of labor market automation compared to the more optimistic view in the scientific literature. This is likely due to either a one-sided narrative of automation in the public debate or a selective choice of information sources based on pre-existing attitudes. The relevance of this latter explanation is supported by the finding that, especially in the US, general political preferences are strongly associated with all dimensions of automation concerns. Hence, threats of automation are likely perceived through an individual lens that is shaped by pre-existing attitudes. Our survey also indicates that automation perceptions matter: we find different dimensions of automation perceptions 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.

Can information update people's automation perceptions? Our randomized information experiments show that providing scientifically grounded information on how digital technologies and automation affect labor market outcomes mitigates related concerns. This supports the notion that automation perceptions are indeed malleable to being exposed to scientific information and that they may have been inconsistent with the majority of empirical findings in the literature before. Combined with the finding that perceptions are associated with stated behavior and policy preferences, this indicates that information can potentially affect economic outcomes. 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, 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. Hence, although exposing people to scientific information shifts average perceptions, our results also imply that different groups of people draw different and even opposing conclusions from the same information depending on their prior beliefs that are, again, rooted in political and economic views.

With the recent technological breakthrough in AI and the publication of powerful AI tools such as ChatGPT, the recurring narrative of technologies destroying jobs recently gained new momentum. Similar to the previous debate on digital technologies in the 2010s, much emphasis again is on the potentially labor-saving effects of this technology which likely fosters a pessimistic view about this technology. Our results suggest that there may be a potential for alleviating pessimistic views with the provision of scientific evidence. However, our findings also highlight the limitations of science-based information campaigns in harmonizing perceptions on issues whose perceptions are influenced by political beliefs. Our paper thus also supports the evidence from other studies that stress the role of general political beliefs as a major determinant of how information enters the formation of perceptions and opinions (Alesina et al., 2020, 2018a; Bursztyn et al., 2023).

References

Acemoglu, D., G. W. Anderson, D. N. Beede, C. Buffington, E. E. Childress, E. Dinlersoz, L. S. Foster, N. Goldschlag, J. C. Haltiwanger, Z. Kroff, P. Restrepo, and N. Zolas (2022a). Automation and the workforce: A firm-level view from the 2019 annual business survey. NBER Working Paper 30659.

Acemoglu, D., D. Autor, J. Hazell, and P. Restrepo (2022). Artificial intelligence and jobs: Evidence from online vacancies. Journal of Labor Economics 40(S1), S293–S340.

Acemoglu, D. and P. Restrepo (2019). Artificial intelligence, automation, and the future of work. In A. Agrawal, J. Gans, and A. Goldfarb (Eds.), The Economics of Artificial Intelligence: An Agenda. University of Chicago Press.

Acemoglu, D. and P. Restrepo (2020a). Robots and jobs: Evidence from US labor markets. Journal of Political Economy 128(6), 2188–2244.

Acemoglu, D. and P. Restrepo (2020b). Unpacking skill bias: Automation and new tasks. AEA Papers and Proceedings 110, 356–61.

Acemoglu, D. and P. Restrepo (2021). Tasks, automation, and the rise in us wage inequality. Technical report, National Bureau of Economic Research.

Aghion, P., C. Antonin, S. Bunel, and X. Jaravel (2020). What are the labor and product market effects of automation? New evidence from France. CEPR Discussion Paper No. 14443.

Aghion, P., C. Antonin, S. Bunel, and X. Jaravel (2022). The effects of automation on labor demand: A survey of the recent literature. CEPR Discussion Paper 16868.

Alesina, A., A. Miano, and S. Stantcheva (2020). The polarization of reality. AEA Papers and Proceedings 110, 324–28.

Alesina, A., A. Miano, and S. Stantcheva (2022, 03). Immigration and redistribution. The Review of Economic Studies.

Alesina, A., S. Stantcheva, and E. Teso (2018a). Intergenerational mobility and preferences for redistribution. American Economic Review 108(2), 521–54.

Alesina, A., S. Stantcheva, and E. Teso (2018b). Intergenerational mobility and support for redistribution. American Economic Review 108(2), 521 – 554.

Alliance for American Manufacturing (2019). John Oliver's segment on jobs and automation doesn't quite get it right. Alliance for American Manufacturing article, as of march 7, 2019, online at https://www.americanmanufacturing.org/blog/john-olivers-segment-on-jobs-and-automation-doesnt-quite-get-it-right/.

Anelli, M., I. Colantone, and P. Stanig (2021). Individual vulnerability to industrial robot adoption increases support for the radical right. Proceedings of the National Academy of Sciences 118(47).

Anton, J.-I., D. Klenert, E. Fernández-Macías, M. C. Urzì Brancati, and G. Alaveras (2022). The labour market impact of robotisation in europe. European Journal of Industrial Relations 28(3), 317–339.

Arntz, M., T. Gregory, and U. Zierahn (2017). Revisiting the risk of automation. Economics Letters 159, 157–160.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. The Journal of Economic Perspectives 29(3), 3–30.

Autor, D. H. and D. Dorn (2013). The growth of low-skill service jobs and the polarization of the US labor market. American Economic Review 103(5), 1553–97.

Autor, D. H., L. F. Katz, and M. S. Kearney (2006). The polarization of the us labor market. American economic review 96(2), 189–194.

Autor, D. H., F. Levy, and R. J. Murnane (2003). The skill content of recent technological change: An empirical exploration. The Quarterly journal of economics 118(4), 1279–1333.

Bachman, R., M. Gonschor, P. Lewandowski, and K. MadoÅ„ (2022, January). The Impact of Robots on Labour Market Transitions in Europe. IBS Working Papers 01/2022, Instytut Badan Strukturalnych.

BBC (2015). Intelligent machines: The jobs robots will steal first. BBC article, online at https://www.bbc.com/news/technology-33327659.

BBC (2019). Robots' to replace up to 20 million factory jobs' by 2030. British Broadcasting Corporation (BBC) article, online at https://www.bbc.com/news/business-48760799.

Bessen, J. E., M. Goos, A. Salomons, and W. Van den Berge (2019). Automatic reaction-what happens to workers at firms that automate? Boston Univ. School of Law, Law and Economics Research Paper No. 19-2.

Boustan, L. P., J. Choi, and D. Clingingsmith (2022). Automation after the assembly line: Computerized machine tools, employment and productivity in the United States. NBER Working Paper No. 30400.

Boxell, L., M. Gentzkow, and J. M. Shapiro (2020). Cross-country trends in affective polarization. The Review of Economics and Statistics, 1–60.

Bursztyn, L., G. Egorov, I. Haaland, A. Rao, and C. Roth (2023). Justifying dissent. The Quarterly Journal of Economics 138(3), 1403–1451.

Canen, N. J., C. Kendall, and F. Trebbi (2021). Political parties as drivers of us polarization: 1927-2018. NBER Working Paper No. 28296.

Capital (2023). Ki könnte 300 millionen jobs vernichten: Diese berufe gefährdet chatgpt. Capital article, online at https://www.capital.de/wirtschaft-politik/chatgpt--kuenstliche-intelligenz-gefaehrdet-millionen-jobs-33374508.html.

Caprettini, B. and H.-J. Voth (2020). Rage against the machines: Labor-saving technology and unrest in England, 1830-32. American Economic Review: Insights 2(3), 305–20.

Caselli, M., A. Fracasso, and S. Traverso (2021). Globalization, robotization, and electoral outcomes: Evidence from spatial regressions for Italy. Journal of Regional Science 61(1), 86–111.

CNBC (2017). McKinsey: One-third of US workers could be jobless by 2030 due to automation. CNBC article, online at https://www.cnbc.com/2017/11/29/one-third-of-us-workers-could-be-jobless-by-2030-due-to-automation.html.

CNN (2023). 300 million jobs could be affected by latest wave of ai, says goldman sachs. CNN article, online at https://edition.cnn.com/2023/03/29/tech/chatgpt-ai-automation-jobs-impact-intl-hnk/index.html.

Coibion, O., Y. Gorodnichenko, and M. Weber (2020). Political polarization and expected economic outcomes. NBER Working Paper No. 28044.

Coppock, A. (2016). The persistence of survey experimental treatment effects. Unpublished Manuscript.

Coupe, T. (2019). Automation, job characteristics and job insecurity. International Journal of Manpower 40(7), 1288–1304.

Daniele, G., A. F. Martinangeli, F. Passarelli, W. Sas, and L. Windsteiger (2020a). Fear and loathing in times of distress–causal impact of social and economic insecurity on anti-immigration sentiment. Max Planck Institute for Tax Law and Public Finance Working Paper No. 17.

Daniele, G., A. F. Martinangeli, F. Passarelli, W. Sas, and L. Windsteiger (2020b). Wind of change? Experimental survey evidence on the COVID-19 shock and socio-political attitudes in Europe. Max Planck Institute for Tax Law and Public Finance Working Paper No. 10.

Dauth, W., S. Findeisen, J. Suedekum, and N. Woessner (2021). The adjustment of labor markets to robots. Journal of the European Economic Association 19(6), 3104–3153.

de Quidt, J., J. Haushofer, and C. Roth (2018). Measuring and bounding experimenter demand. American Economic Review 108(11).

Dechezlepretre, A., A. Fabre, T. Kruse, B. Planterose, A. S. Chico, and S. Stantcheva (2022). Fighting climate change: International attitudes toward climate policies. NBER Working Paper 30265.

Dekker, F., A. Salomons, and J. v. d. Waal (2017). Fear of robots at work: The role of economic self-interest. Socio-Economic Review 15(3), 539–562.

Di Tella, R. and D. Rodrik (2020). Labour market shocks and the demand for trade protection: Evidence from online surveys. The Economic Journal 130(628), 1008–1030.

Die Zeit (2016). Die Massenarbeitslosigkeit kommt zurück. ZEIT Online (ZEIT) article, online at `https://www.zeit.de/karriere/beruf/2016-01/zukunft-arbeit-arbeitsmarkt/komplettansicht`.

Dixon, J., B. Hong, and L. Wu (2021). The robot revolution: Managerial and employment consequences for firms. Management Science 67(9), 5586–5605.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. G. Wagner (2011). Individual Risk Attitudes: Measurement, Determinants, and Behavioral Consequences. Journal of the European Economic Association 9(3), 522–550.

Dominitz, J. and C. F. Manski (1997). Perceptions of economic insecurity: Evidence from the survey of economic expectations. Public Opinion Quarterly 61(2), 261–287.

Druckman, J. N. and K. R. Nelson (2003). Framing and deliberation: How citizens' conversations limit elite influence. American Journal of Political Science 47(4), 729–745.

Eißer, J., M. Torrini, and S. Böhm (2020). Automation anxiety as a barrier to workplace automation: An empirical analysis of the example of recruiting chatbots in Germany. In Proceedings of the 2020 on Computers and People Research Conference, pp. 47–51.

Entertainment Weekly (2019). John Oliver questions kids about their robot-filled future. Entertainment Weekly article, as of March 4, 2019, online at `https://ew.com/tv/2019/03/04/john-oliver-automation/`.

FAZ (2018). Digitalisierung zerstört 3,4 Millionen Stellen. Frankfurter Allgemeine Zeitung (FAZ) article, online at `https://www.faz.net/aktuell/wirtschaft/digitec/digitalisierung-wird-jeden-zehnten-die-arbeit-kosten-15428341.html`.

Fehr, E., T. Epper, and J. Senn (2020). Other-regarding preferences and redistributive politics. University of zurich, department of economics, working paper no. 339.

Felten, E. W., M. Raj, and R. Seamans (2019). The occupational impact of artificial intelligence: Labor, skills, and polarization. NYU Stern School of Business.

Frey, C. B. and M. A. Osborne (2017). The future of employment: How susceptible are jobs to computerisation? Technological forecasting and social change 114, 254–280.

Funk, P. (2016). How Accurate Are Surveyed Preferences for Public Policies? Evidence from a Unique Institutional Setup. The Review of Economics and Statistics 98(3), 442–454.

Gallego, A., A. Kuo, D. Manzano, and J. Fernández-Albertos (2022). Technological risk and policy preferences. Comparative Political Studies 55(1), 60–92.

Genz, S., T. Gregory, M. Janser, F. Lehmer, and B. Matthes (2021). How do workers adjust when firms adopt new technologies? ZEW-Centre for European Economic Research Discussion Paper No. 73.

Georgieff, A. and R. Hyee (2021). Artificial intelligence and employment: New cross-country evidence.

Golin, M. and C. Rauh (2023). The impact of fear of automation. *mimeo*, available on authors' websites.

Goos, M., A. Manning, and A. Salomons (2014). Explaining job polarization: Routine-biased technological change and offshoring. American economic review 104(8), 2509–2526.

Graetz, G. and G. Michaels (2018). Robots at work. Review of Economics and Statistics 100(5), 753–768.

Gregory, T., A. Salomons, and U. Zierahn (2022). Racing with or against the machine? Evidence on the role of trade in Europe. Journal of the European Economic Association 20(2), 869–906.

Guardian (2023). Ai will take some jobs, but mass unemployment isn't inevitable. Guardian article, online at https://www.theguardian.com/commentisfree/2023/may/22/ai-jobs-policies.

Haaland, I. and C. Roth (2020). Labor market concerns and support for immigration. Journal of Public Economics 191, 104256.

Haaland, I. and C. Roth (2021). Beliefs about racial discrimination and support for pro-black policies. The Review of Economics and Statistics, 1–38.

Haaland, I., C. Roth, and J. Wohlfart (2022). Designing information provision experiments. Journal of Economic Literature.

Hainmueller, J., D. Hangartner, and T. Yamamoto (2015). Validating vignette and conjoint survey experiments against real-world behavior. Proceedings of the National Academy of Sciences 112(8), 2395–2400.

Hirvonen, J., A. Stenhammar, and J. Tuhkuri (2022). New evidence on the effect of technology on employment and skill demand. Available at SSRN 4081625.

Im, Z. J., N. Mayer, B. Palier, and J. Rovny (2019). The "losers of automation": A reservoir of votes for the radical right? Research & Politics 6(1), 2053168018822395.

Inverse (2019). John Oliver gives kids a tough lesson on A.I. and robot job losses. Inverse article, as of march 4, 2019, online at https://www.inverse.com/article/53769-john-oliver-gives-kids-a-tough-lesson-on-a-i-and-robot-job-losses.

Jäger, S., C. Roth, N. Roussille, and B. Schoefer (2021). Worker beliefs about rents and outside options. Working Paper.

Jeffrey, K. (2021). Automation and the future of work: How rhetoric shapes the response in policy preferences. Journal of Economic Behavior & Organization 192, 417–433.

Kahneman, D., J. L. Knetsch, and R. Thaler (1986). Fairness as a constraint on profit seeking: Entitlements in the market. The American economic review, 728–741.

Kerschbamer, R. and D. Mueller (2020). Social preferences and political attitudes: An online experiment on a large heterogeneous sample. Journal of Public Economics 182, 104076.

Kling, J. R., J. B. Liebman, and L. F. Katz (2007). Experimental analysis of neighborhood effects. Econometrica 75(1), 83–119.

Koch, M., I. Manuylov, and M. Smolka (2021). Robots and firms. The Economic Journal 131(638), 2553–2584.

Kregel, I., J. Koch, and R. Plattfaut (2021). Beyond the hype: Robotic process automation's public perception over time. Journal of Organizational Computing and Electronic Commerce 31(2), 130–150.

Lange, A., J. Schmitz, and C. Schwirplies (2022). Inequality, role reversal and cooperation in multiple group membership settings. Experimental economics 25, 68–110.

List, J. A., A. M. Shaikh, and Y. Xu (2019). Multiple hypothesis testing in experimental economics. Experimental Economics 22(4), 773–793.

Mann, K. and L. Püttmann (2018). Benign effects of automation: New evidence from patent texts. Available at SSRN 2959584.

Manski, C. F. and J. D. Straub (2000). Worker perceptions of job insecurity in the mid-1990s. Journal of Human Resources 35(3), 447–79.

McClure, P. K. (2018). "You're fired," says the robot: The rise of automation in the workplace, technophobes, and fears of unemployment. Social Science Computer Review 36(2), 139–156.

Mokyr, J., C. Vickers, and N. L. Ziebarth (2015). The history of technological anxiety and the future of economic growth: Is this time different? Journal of Economic Perspectives 29(3), 31–50.

Morikawa, M. (2017). Who are afraid of losing their jobs to artificial intelligence and robots? Evidence from a survey. Technical report, RIETI Discussion Paper Series 17-E-069.

Mueller, A. I., J. Spinnewijn, and G. Topa (2021). Job seekers' perceptions and employment prospects: Heterogeneity, duration dependence, and bias. American Economic Review 111(1), 324–63.

Mulas-Granados, C., R. Varghese, J. Wallenstein, V. Boranova, and A. deChalendar (2019). Automation, skills and the future of work: What do workers think? Available at SSRN 3524309.

Mummolo, J. and E. Peterson (2019). Demand effects in survey experiments: An empirical assessment. American Political Science Review 113(2), 517–529.

Nedelkoska, L. and G. Quintini (2018). Automation, skills use and training. OECD Social, Employment and Migration Working Papers, No. 202, OECD Publishing, Paris.

Neue Zürcher Zeitung (2023). Die ki kommt: Treibt uns chat-gpt in die arbeitslosigkeit? NZZ article, online at `https://www.nzz.ch/wissenschaft/wird-die-ki-unsere-jobs-killen-ld.1740404?reduced=true`.

New York Post (2023). Chatgpt could make these jobs obsolete: 'the wolf is at the door'. New York Post article, online at https://nypost.com/2023/01/25/chat-gpt-could-make-these-jobs-obsolete/.

New York Times (2016). The long-term jobs killer is not China. it's automation. New York Times article, online at https://www.nytimes.com/2016/12/21/upshot/the-long-term-jobs-killer-is-not-china-its-automation.html.

New York Times (2020). The robots are coming. Prepare for trouble. New York Times article, online at https://www.nytimes.com/2020/01/30/business/artificial-intelligence-robots-retail.html.

Pouliakas, K. (2018). Determinants of automation risk in the EU labour market: A skills-needs approach. IZA Discussion Paper No. 11829.

Precht, R. D. (2018). *Jäger, Hirten, Kritiker: Eine Utopie für die digitale Gesellschaft*. Goldmann Verlag.

Rodriguez-Bustelo, C., J. M. Batista-Foguet, and R. Serlavós (2020). Debating the future of work: The perception and reaction of the Spanish workforce to digitization and automation technologies. *Frontiers in Psychology* *11*, 1965.

Shiller, R. J. (2019). Narratives about technology-induced job degradations then and now. NBER Working Paper No. 25536.

Shiller, R. J. (2020). *Narrative economics*. Princeton University Press.

Socialeurope (2018). The world(s) of work in transition: Managing the "megatrends" impacting labour markets and society. Socialeurope.eu article, online at https://socialeurope.eu/the-worlds-of-work-in-transition-managing-the-megatrends-impacting-labour-markets-a

Spiegel (2018). Facebook ist gefährlicher als Trump. philosoph precht im interview. SPIEGEL article, online at https://www.spiegel.de/spiegel/richard-david-precht-die-digitalisierung-bedroht-alles-was-ist-a-1204080.html.

Stantcheva, S. (2021). Understanding tax policy: How do people reason? *The Quarterly Journal of Economics* *136*(4), 2309–2369.

Stantcheva, S. (2022). How to run surveys: A guide to creating your identifying variation and revealing the invisible. *Annual Review of Economics*.

Tannenbaum, D., A. Cohn, C. L. Zuend, and M. A. Marechal (2022). What Do Cross-Country Surveys Tell Us about Social Capital? The Review of Economics and Statistics, 1–30.

The Economist (2015). Automation angst – three new papers examine fears that machines will put humans out of work. The Economist article, online at https://www.economist.com/finance-and-economics/2015/08/13/automation-angst.

The Economist (2018). A study finds nearly half of jobs are vulnerable to automation. The Economist article, online at https://www.economist.com/graphic-detail/2018/04/24/a-study-finds-nearly-half-of-jobs-are-vulnerable-to-automation.

The Guardian (2017). What jobs will still be around in 20 years? Read this to prepare your future. The Guardian article, online at https://www.theguardian.com/us-news/2017/jun/26/jobs-future-automation-robots-skills-creative-health.

Thewissen, S. and D. Rueda (2019). Automation and the welfare state: Technological change as a determinant of redistribution preferences. Comparative Political Studies 52(2), 171–208.

TIME (2015). How the 'John Oliver effect' is having a real-life impact. TIME article, online at https://time.com/3674807/john-oliver-net-neutrality-civil-forfeiture-miss-america/.

TIME (2019). John Oliver tries to prepare kids for the coming automation of the job market. TIME article, as of March 8, 2019, online at https://time.com/5538622/john-oliver-last-week-tonight-jobs-automation/.

Walsh, T. (2018). Expert and non-expert opinion about technological unemployment. International Journal of Automation and Computing 15, 637 – 642.

Young, A. (2018, 11). Channeling Fisher: Randomization tests and the statistical insignificance of seemingly significant experimental results. The Quarterly Journal of Economics 134(2), 557–598.

Zhang, B. (2019). No rage against the machines: Threat of automation does not change policy preferences. MIT Political Science Department Research Paper No. 2019-25.

Figures and Tables (in order of appearance in main body of paper)

Table 1: Experimental Groups and Sample Size by Country

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

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

Figure 1: 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 2: 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).

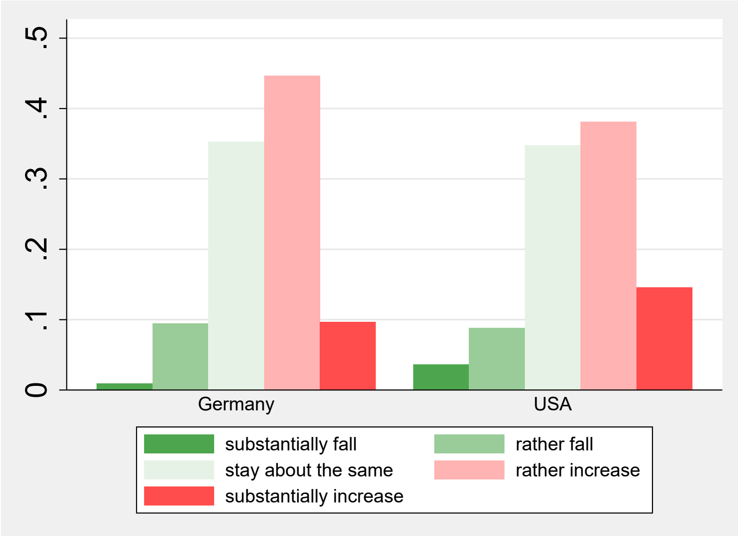
Table 2: Descriptive Statistics of Perception Measures related to Automation in Germany and the US

	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	Ger	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	Ger	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	Ger	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	Ger	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	Ger	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	$0-10 \ldots 91-100$	Ger	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	Ger	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	Ger	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	Ger	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	Ger	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	Ger	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	Ger	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	

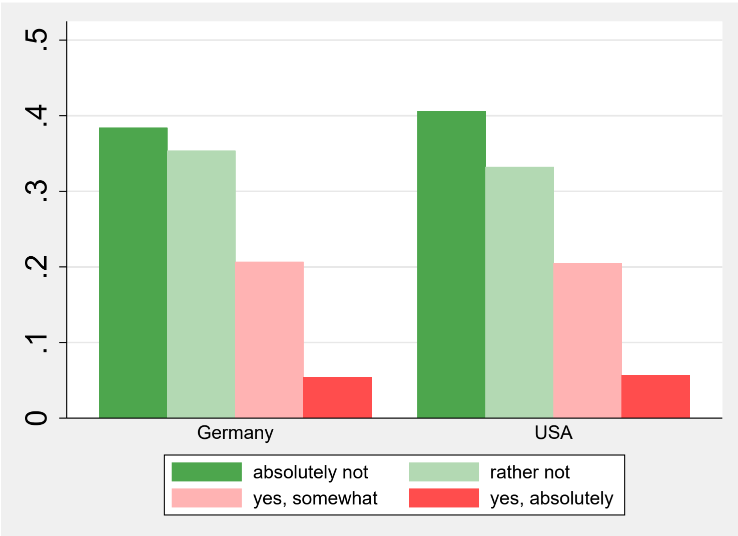
Notes: Sample only contains respondents assigned to the control group $ABCD_0$, Ger refers to Germany, US to United States. *pval* denotes the pvalue for a Pearson-Chi^2 test of cross-country differences.

Figure 3: Main indicators for general concerns (a), individual concerns (b), and distributional concerns (c) in the US and Germany

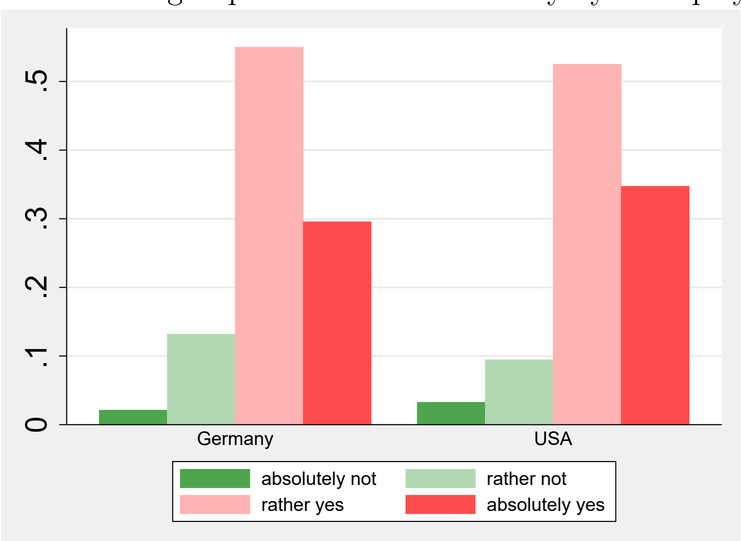
(a) P_1: Unemployment in the future will ...



(b) P_5: I am concerned that I will become unemployed within 5 yrs.



(c) P_9: Will social groups be affected differently by unemployment?



Notes: Sample only consists of respondents assigned to the control group $ABCD_0$. For detailed statistics see Table 2.

Table 3: 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 2.

Table 4: OLS regressions of Policy Preferences on Main Perception Indicators by Country

	(1) redistr	(2) antipov	(3) plmp	(4) almp
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
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

*** 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 A.3 for details. Perception measures P_1, P_5, and P_9 as defined in Table 2.

Table 5: OLS Regressions of Stated Labor Market Outcomes on Main Perception Measures by Country

	(1) all	(2) training	(3) lowsal	(4) occswitch
Estimates related to concerns regarding ...				
Germany				
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
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

*** 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 A.3 for details. Perception measures P_1, P_5, and P_9 as defined in Table 2.

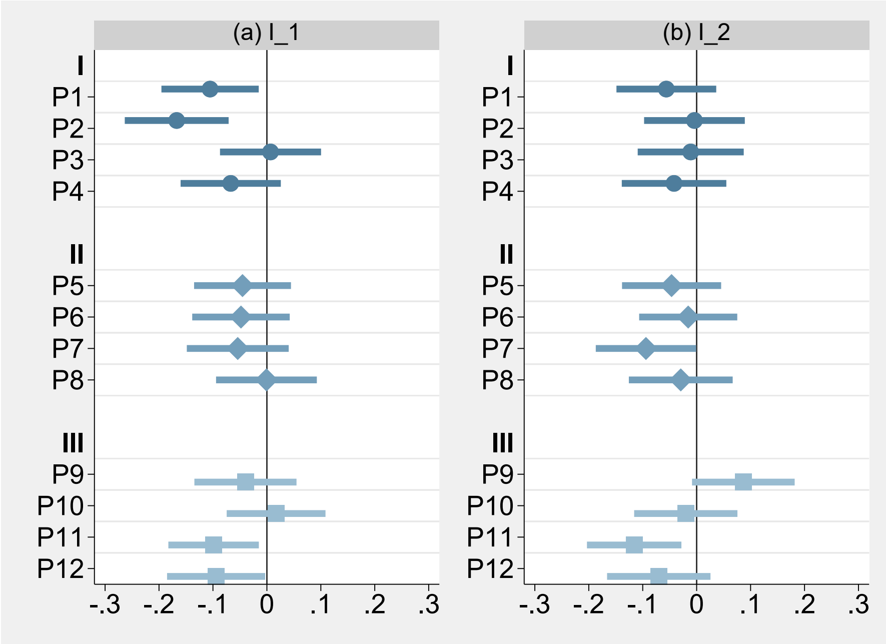
Table 6: OLS regressions of Donation Outcomes on Main Perception Measures by Country

	(1) donator	(2) share don.	(3) digital	(4) food bank	(5) equal opp.
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
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

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

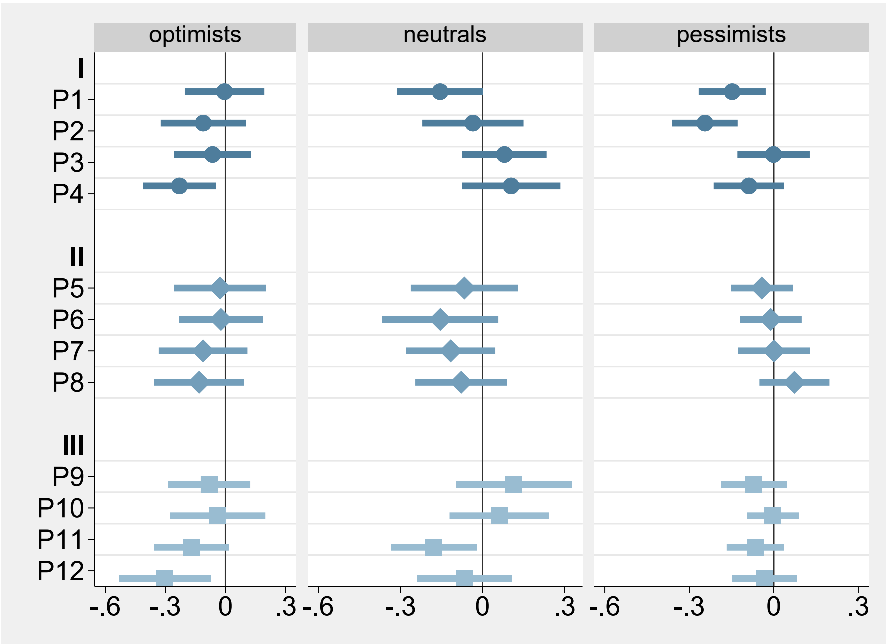
Notes: Regressions based on equation (2), including controls for demographics, job and workplace characteristics, political and economic beliefs, dummies for the experimental group, and dummies for missing categories. Outcomes refer to whether someone donates at all (donator), the share donated (share)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

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 net 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 2 for details. For p-values that are robust to multiple hypothesis testing as well as a test of joint significance, see Table C.6.

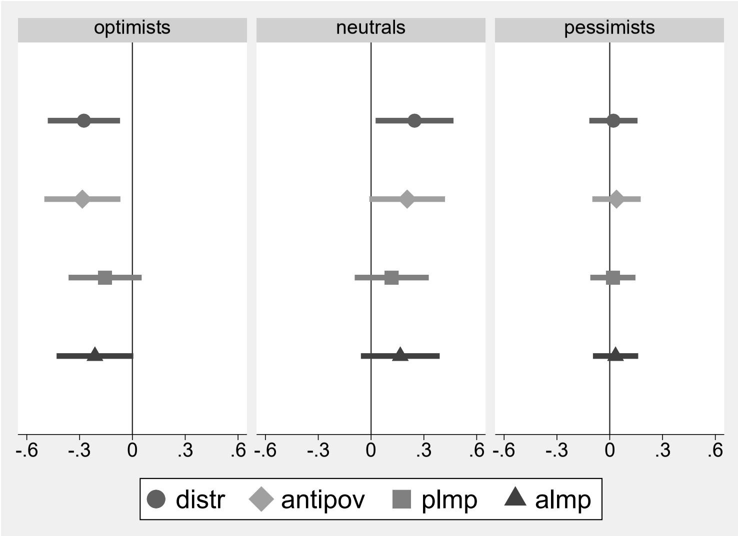
Figure 5: ITT Effect of "No net employment losses"-Information (I_1) on Perceptions of Automation by Prior Belief ($\alpha = 0.05$)



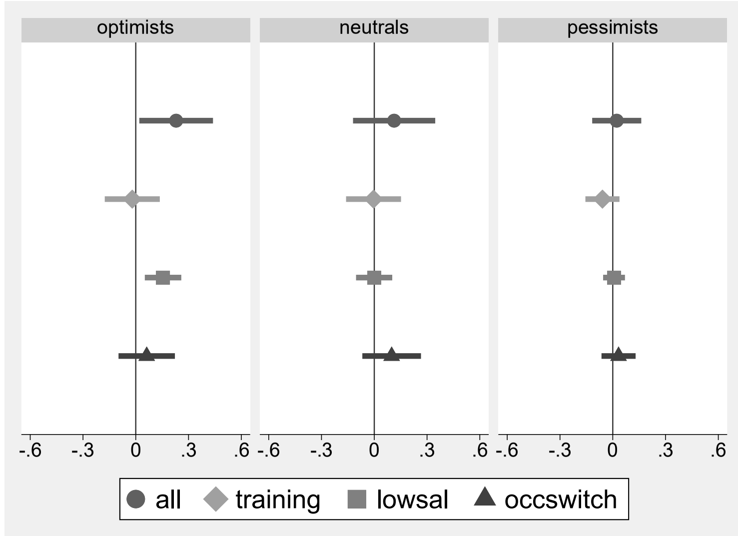
Notes: Pooled estimations for US and Germany showing ITT for "optimists" (β_3), "neutrals" (β_4) and "pessimists" (β_5) regarding the future value of human work, see equation (**??**). Perception measures (estimated separately) refer to (I) General concerns: unemployment rate (P_1), human substitutability (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 2 for details. For a multiple hypothesis test of the joint significance of the treatment for all perceptions, see Table C.7.

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

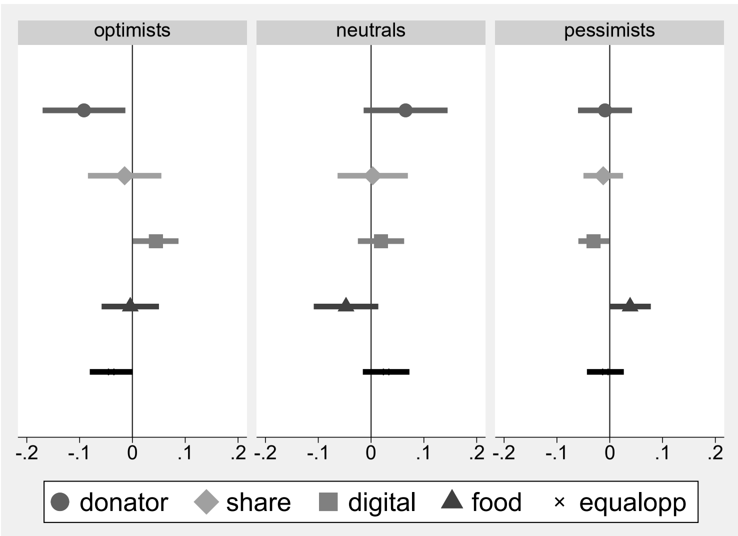
(a) Policy Demands



(b) Stated Labor Market Choices



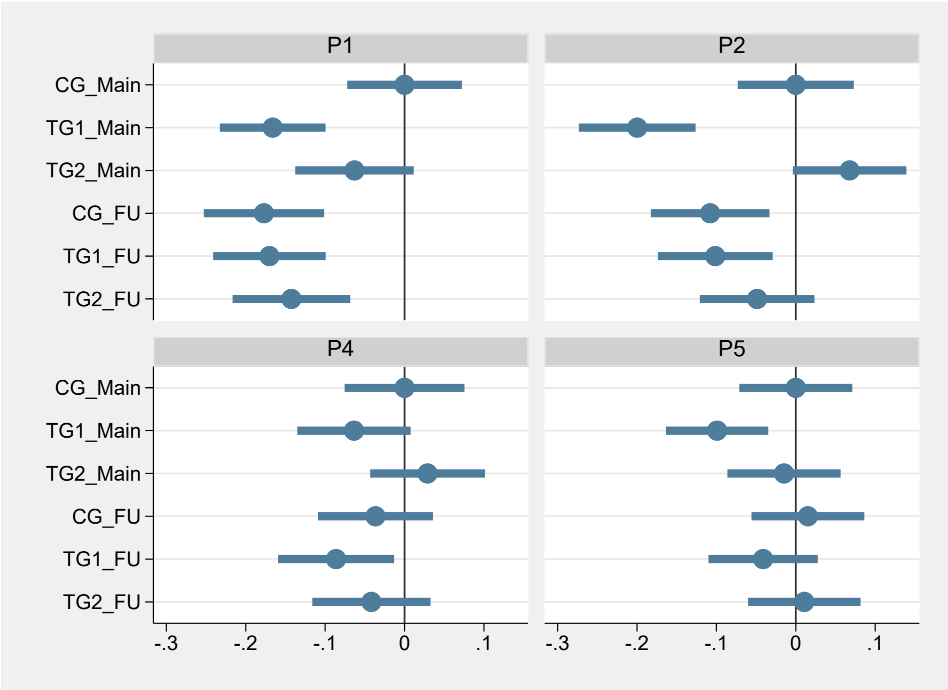
(c) Donations to Charities



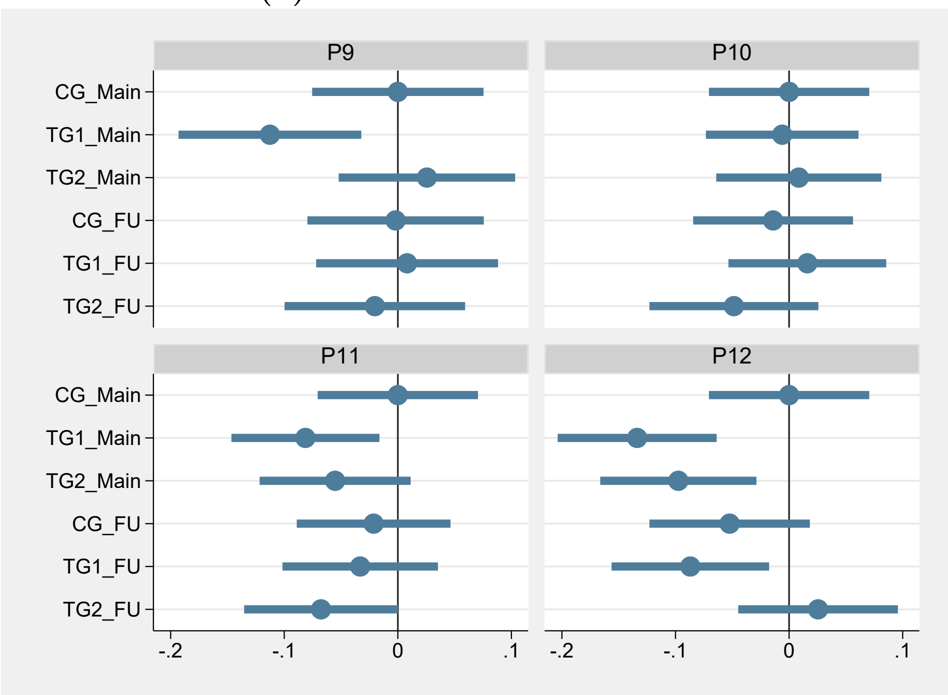
Notes: ITT by prior belief, i.e. for “optimists” (β_3), “neutrals” (β_4) and “pessimists” (β_5) regarding the future value of human work, see equation (**??**). Separate estimations for each outcome. Policy Demand captures redistributive policies (*distr*), anti-poverty measures (*antipov*), passive 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 A.3 for details. For a multiple hypothesis test that tests the joint significance of the treatment for the three outcome groups, see Table C.7.

Figure 7: 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 4 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 2 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= $\alpha+\beta2+\beta3+\beta5$).

Appendix

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A Data

A.1 Sample and Variable Definitions

The sample is drawn from the Yougov online panel. For the analysis, we impose a number of sample restrictions. In particular, we exclude subjects close to retirement since they may not form any future labor market expectations for themselves anymore and might generally care less about future labor market processes. To meet this sample objective, the survey provider only invited residents in the US and Germany between 18 and 55 years old to participate in the survey. 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 no resident of the US and Germany, respectively. This screens out 1.2% of the gross sample. We further exclude those who we do not consider to be part of the active labor force with at least some previous work experience. We consider this an important prerequisite for forming expectations about labor market trends and for being able to refer to a previous workplace when answering the questions. In particular, we screen out those who are currently in education such as vocational training, general or tertiary education (-3.0%), pensioners or retirees (-1.8%), consider themselves incapable of working due to health issues or disabilities (-5.3%) or due to care work or voluntary work (-3.0%), never worked before (-5.6%) or are not in work and not looking for a job for some unspecified reason (-5.6%). In total this screens out 25.7% of the gross sample. While the exclusion of these groups directly serves the purpose of studying survey responses of relevant labor market participants, we might run the risk of loosing information about potential losers of automation (i.e., those who are unemployed and have given up on job search). However, this group is likely to be limited as such discouraged individuals are likely to fall mainly in the unspecified category which encompasses 5.6% only.

Since another 4.1% of the gross sample does not participate in the survey –either due to the fact that they did not want to participate ultimately or stopped to continue with the survey– despite fulfilling all necessary criteria, we finally end up with a net sample of 5,147 observations consisting of respondents who are either currently employed or currently unemployed, but seeking employment. Since we do not have data on all panelists of the survey provider and, therefore, of all those who would have fulfilled the participation requirements, we cannot conduct a typical non-response analysis. i.e. compare those that participated with the representative sample of those invited and eligible to participate. To still get some insights, we regress participation in the survey among those of the gross sample who could have participated due to fulfilling all participation criteria. In particular, we regress participation on dummies of region and country of residence, education level, employment status, gender and age dummies. The results (available upon request) show that most characteristics are insignificant, but that low-skilled and those on temporary leave are slightly less likely to participate in the survey. However, when comparing summary statistics for key demographics in our weighted survey sample and compares these to population statistics (separately by country), see Table A.1, our sample proves fairly comparable to the overall US and German population along these dimensions, respectively. While most characteristics are matched well between our samples and the respective populations, some discrepancies do occur, for example with respect to the share of foreign born subjects in both countries. However, this could be due to the fact that we screen out individuals who are non-resident in Germany or the US, respectively, while such individuals may partly be covered by the data used for comparison.

Table A.2 provides an overview of categorical control variables used in the analysis, including reference categories and number of missing observations.

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.

A.2 Summary Statistics

Table A.3 below contains summary statistics of the main survey variables from question blocks A and D[44] for the US and German sample. While most demographic characteristics are quite comparable across 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.

[44] 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).

Table A.3: 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.

A.3 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 A.4: Policy Measures by Type of Policy

	q	f	N
Redistributive Policies (*redistr*)			
Support for gov. measures to reduce income differences	Cq43	0.71	4,955
Support for higher inc. taxes for high-inc. people	Cq44	0.74	4,988
Preferred top personal income tax rate	Cq45	0.48	3,998
Policies preventing poverty (*antipov*)			
Support for EITC (US)	Cq52	0.59	2,147
Support for food stamps (US)	Cq51	0.71	
Support for unemp. assistance ALG II (Germany)	Cq51	0.59	4,829
Support for unconditional basic income in US/Germany	Cq55	0.15/0.49	4,528
Support for higher minimum wage in US/Germany	Cq53	0.72/0.47	4,963
Passive labor market policies (*plmp*)			
Support for higher unemployment benefits	Cq49	0.79	4,788
Support for longer unemployment benefit duration	Cq50	0.79	4,719
Support for solidary basic income	Cq56	0.28	4,516
Active labor Market Policies (*almp*)			
Support for job creation schemes	Cq54_a	0.57	4,420
Support for voc. training and qualification	Cq54_b	0.57	4,733
Support for improved job search assistance	Cq54_c	0.65	4,523
Support for income subsidies for reintegration	Cq54_d	0.63	4,481
Support for measures to increase job mobility	Cq54_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). Passive labor market policies also include a solidarity basic income for German respondents which is a policy that replaces social welfare transfers with benefits for being employed in a permanent non-market job provided by the government. 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.

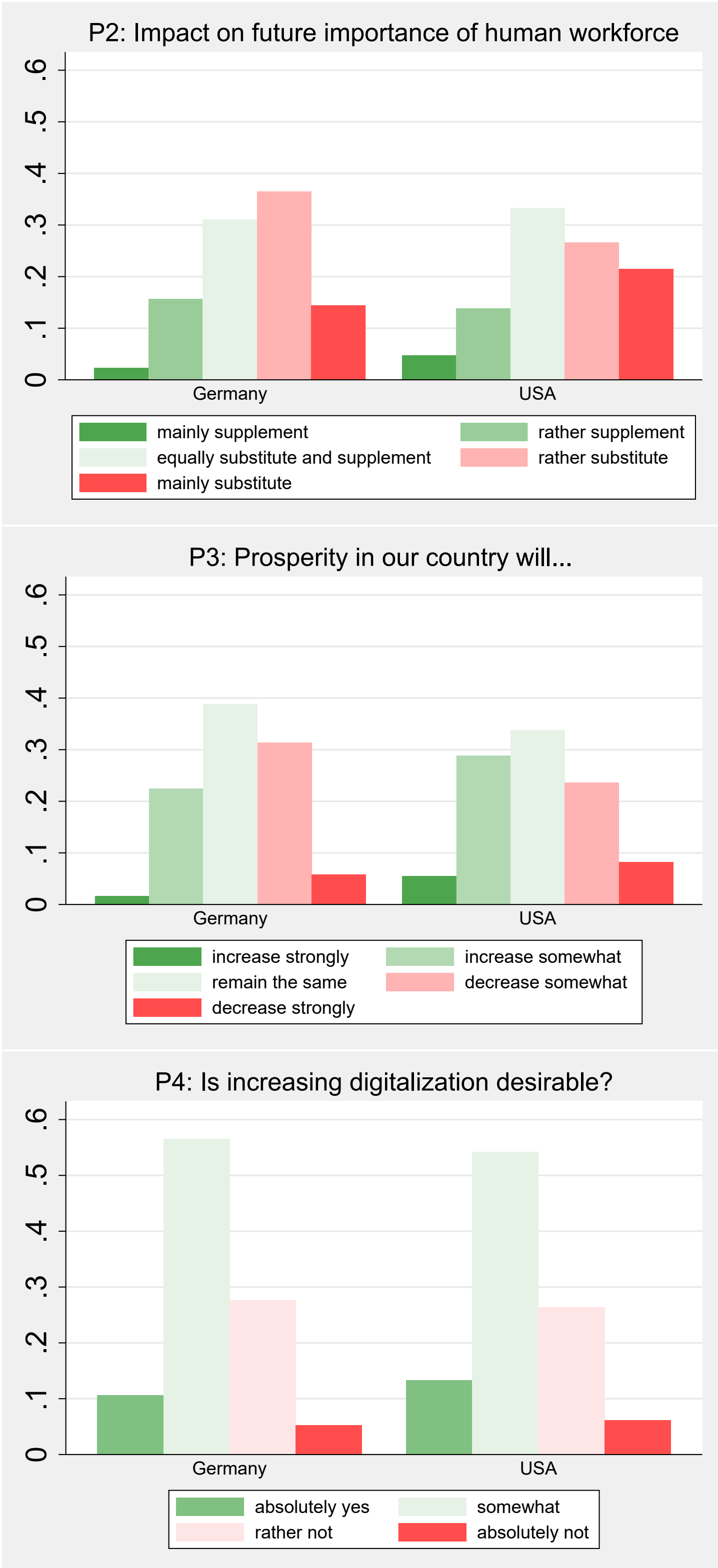
Table A.5: Summary Statistics of Outcome Variables by Country

	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

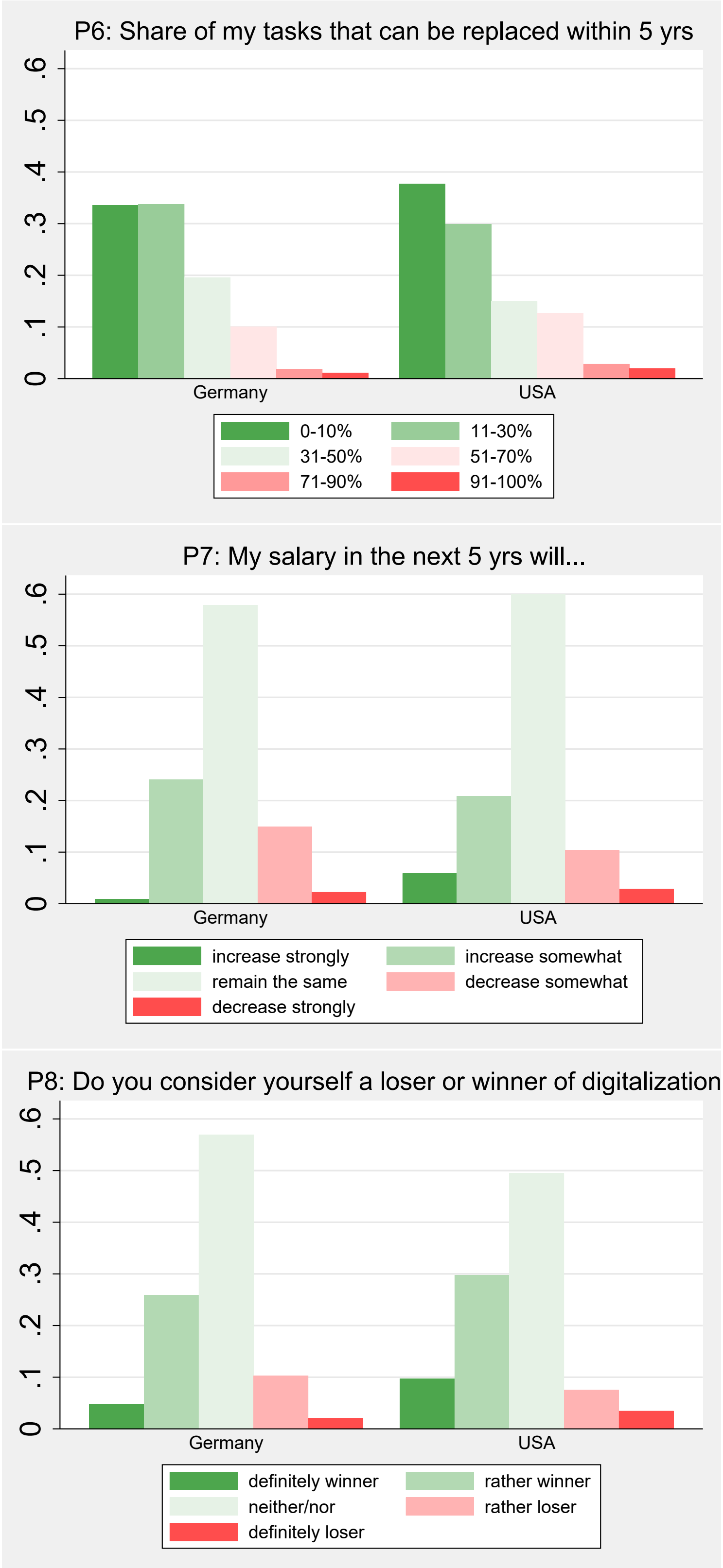
B Further Figures

Figure B.1: Perceptions of General Implications by Country



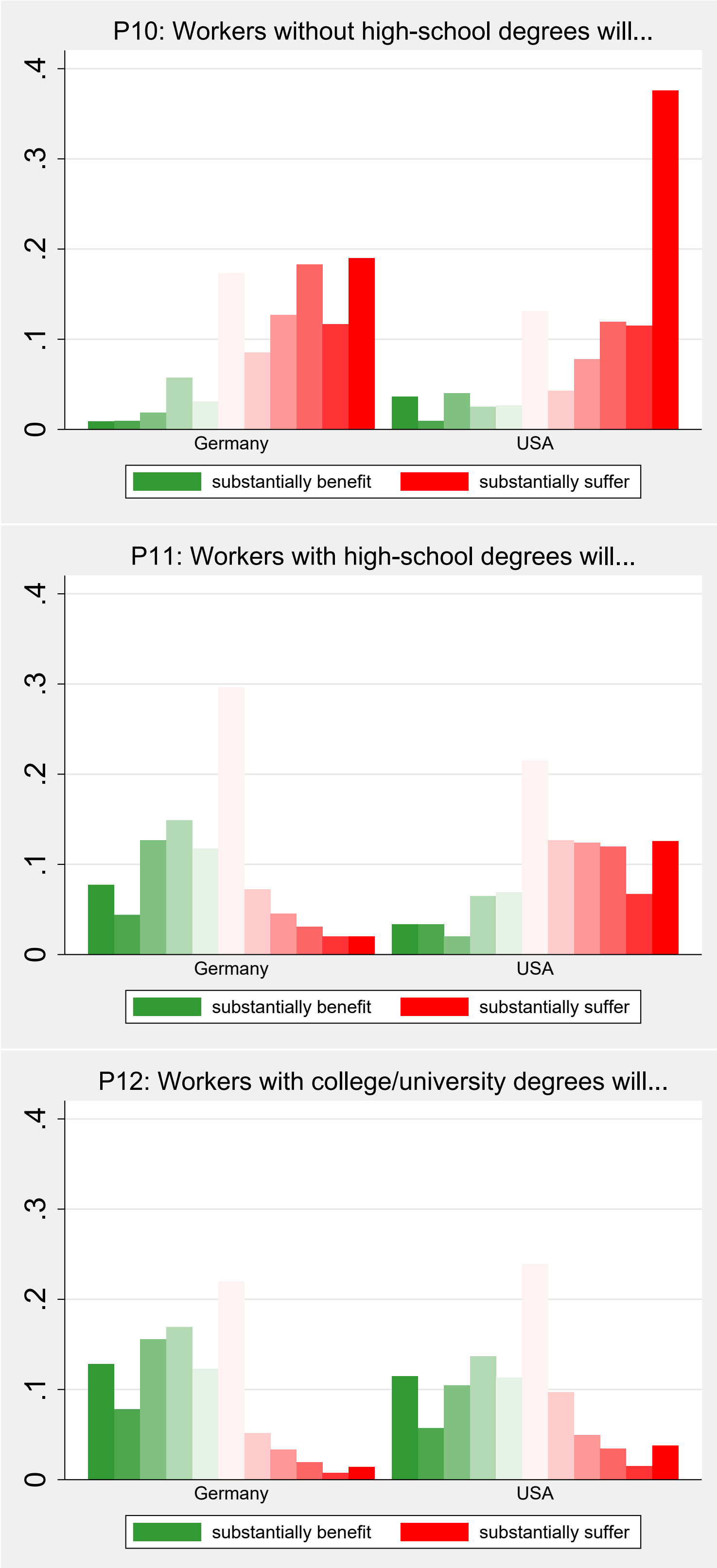
Notes: Sample only consists of respondents assigned to the control group $ABCD_0$. Detailed statistics of perception measures in Table 2.

Figure B.2: Perceptions of Individual Implications by Country



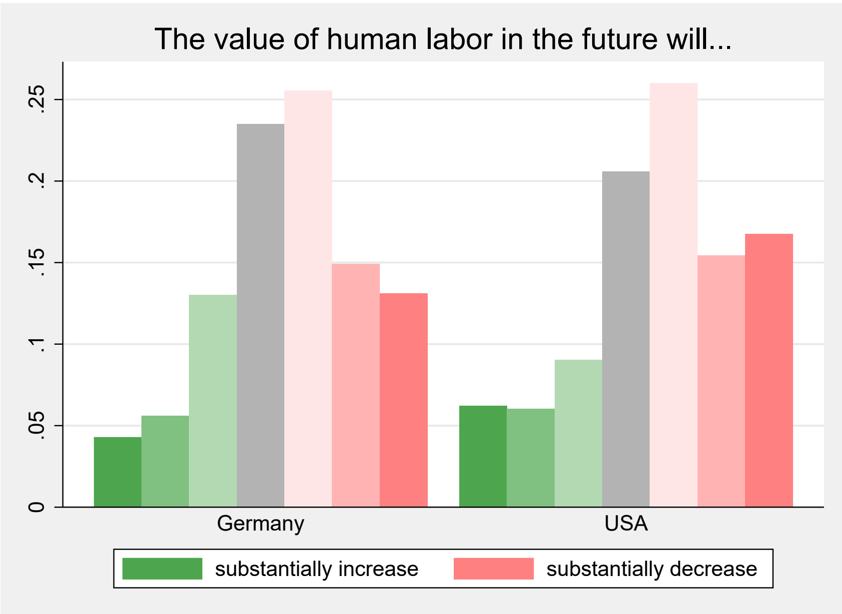
Notes: Sample only consists of respondents assigned to the control group $ABCD_0$. Detailed statistics of perception measures in Table 2.

Figure B.3: Perceptions of Distributional Implications by Country



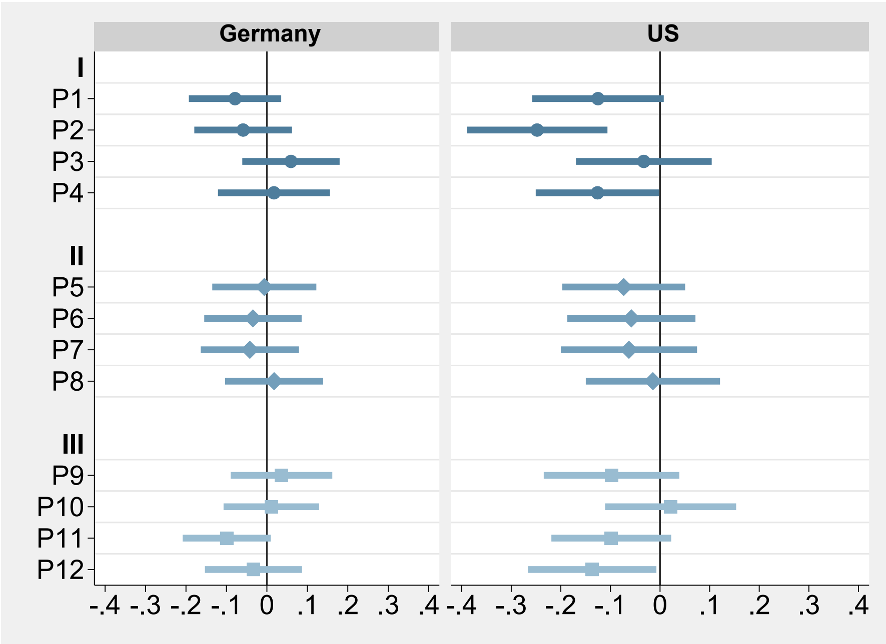
Notes: Sample only consists of respondents assigned to the control group $ABCD_0$. Detailed statistics of perception measures in Table 2.

Figure B.4: Distribution of Prior Beliefs by Country



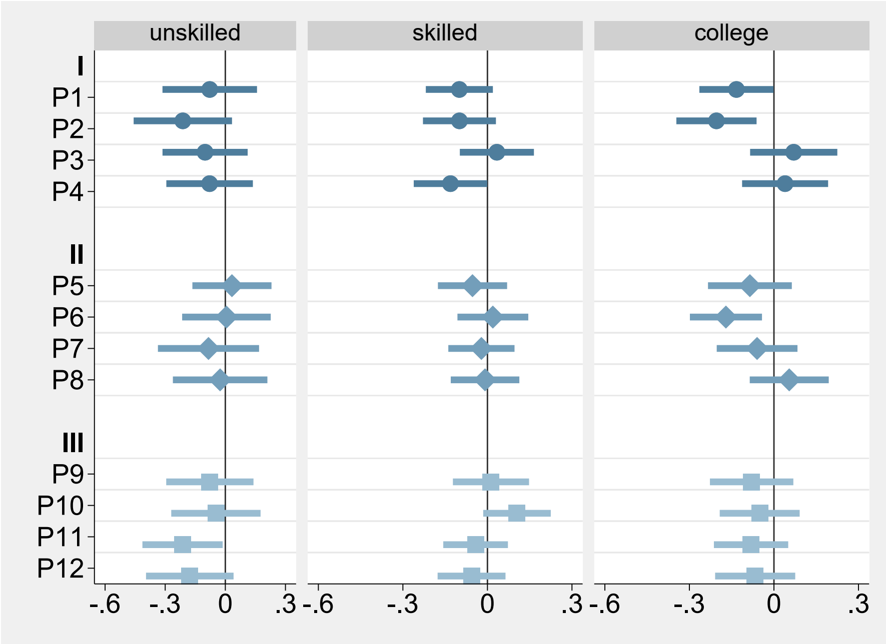
Notes: Prior beliefs were surveyed prior to the information treatments at the beginning of survey block B (see Section 2). For the analysis, we use respondents' answer to the question "What do you think about the future of work given the increasing use of digital technologies?", to define three distinct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

Figure B.5: ITT effect of "No net employment losses"-information (I_1) on perceptions of automation by country ($\alpha = 0.05$)



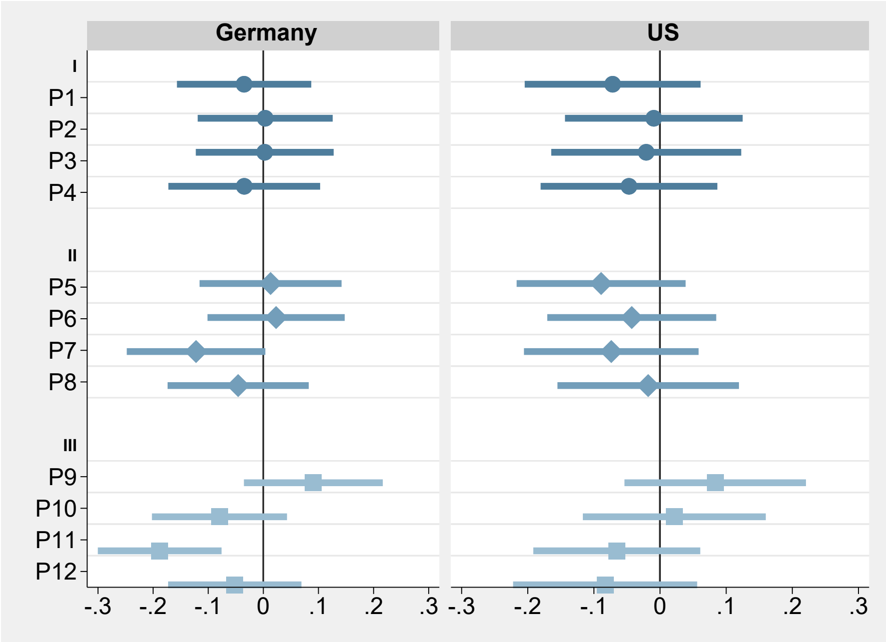
Notes: Pooled estimations for US and Germany showing ITT for Germany (β_1) and the US (β_2), see equation (**??**). Perception measures (estimated separately) refer to (I) General concerns: unemployment rate (P_1), human substitutability (P_2), overall prosperity (P_3), desirability of digitalization (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 2 for details. For a multiple hypothesis test of the joint significance of the treatment for all perceptions, see Table C.7.

Figure B.6: ITT of "No net employment losses"-Information I_1 on Perceptions of Automation by Skill Group ($\alpha = 0.05$)



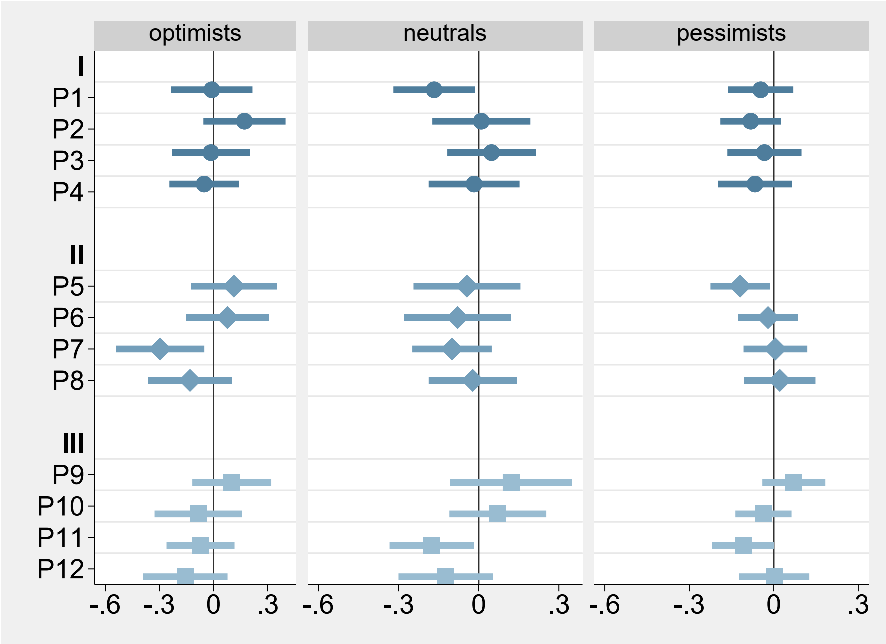
Notes: ITT by skill group, i.e. for "unskilled" (high-school or below), "skilled" (up to 2-yr college) and "college" (more than 2-yr college), see section 4.1. Perception measures refer to (I) General concerns: unemployment rate (P_1), human substitutability (P_2), overall prosperity (P_3), desirability 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 2 for details.

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



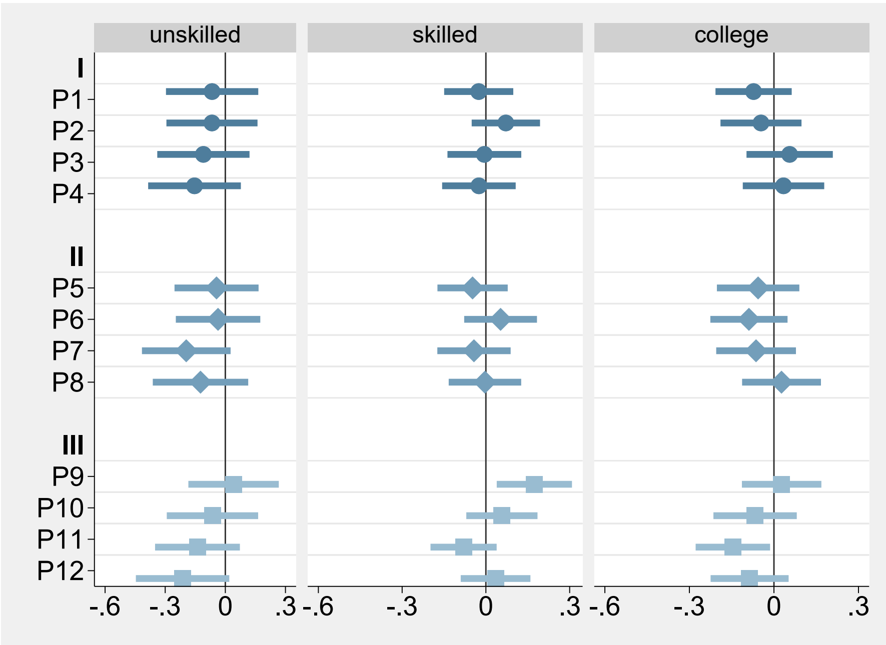
Notes: Pooled estimations for US and Germany showing ITT for Germany (β_1) and the US (β_2), see equation (**??**). Perception measures (estimated separately) refer to (I) General concerns: unemployment rate (P_1), human substitutability (P_2), overall prosperity (P_3), desirability of digitalization (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 2 for details. For a multiple hypothesis test of the joint significance of the treatment for all perceptions, see Table C.7.

Figure B.8: ITT effect of "Employment shifts from unskilled to skilled workers"-Information (I_2) on Perceptions of Automation by Prior Belief ($\alpha = 0.05$)



Notes: Pooled estimations for US and Germany showing 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 (**??**). 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 2 for details. For a multiple hypothesis test of the joint significance of the treatment for all perceptions, see Table C.7.

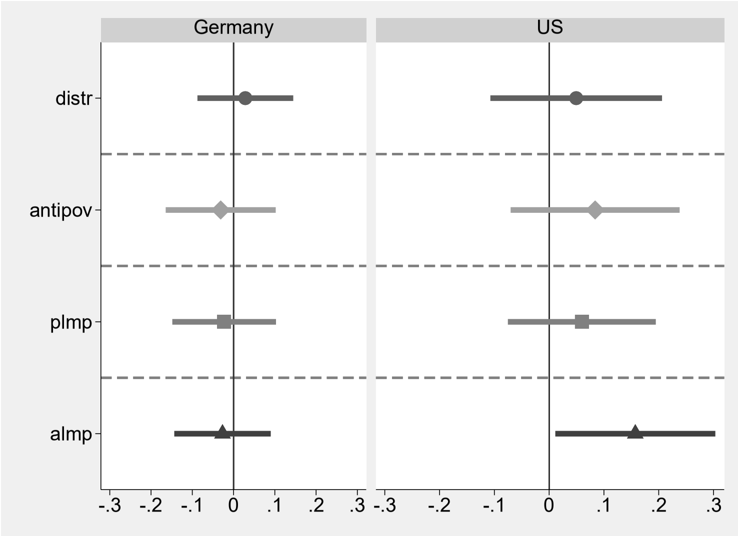
Figure B.9: ITT of "Employment Shifts from Unskilled to Skilled Labor"-Information I_2 on Perceptions of Automation by Skill Group ($\alpha = 0.05$)



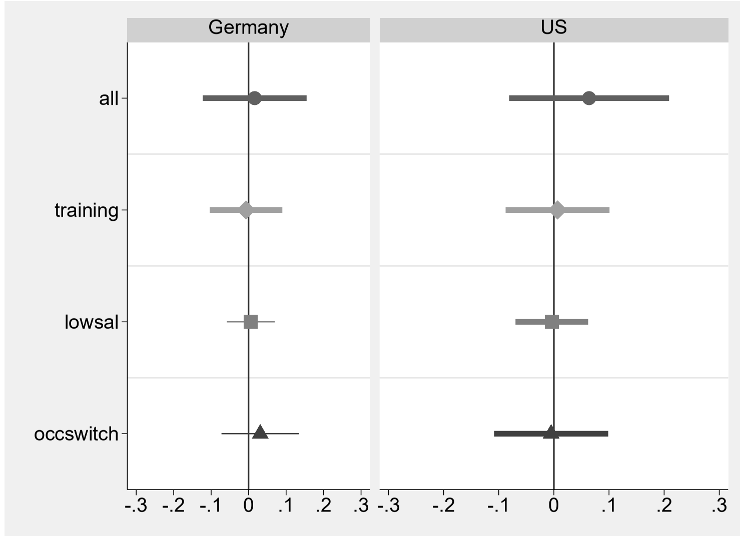
Notes: ITT by skill group, i.e. for "unskilled" (high-school or below), "skilled" (up to 2-yr college) and "college" (more than 2-yr college), see section 4.1. Perception measures refer to (I) General concerns: unemployment rate (P_1), human substitutability (P_2), overall prosperity (P_3), desirability 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 2 for details.

Figure B.10: ITT of "Employment Shifts from Unskilled to Skilled Labor"-Information I_2 on Further Outcomes by Country ($\alpha = 0.05$)

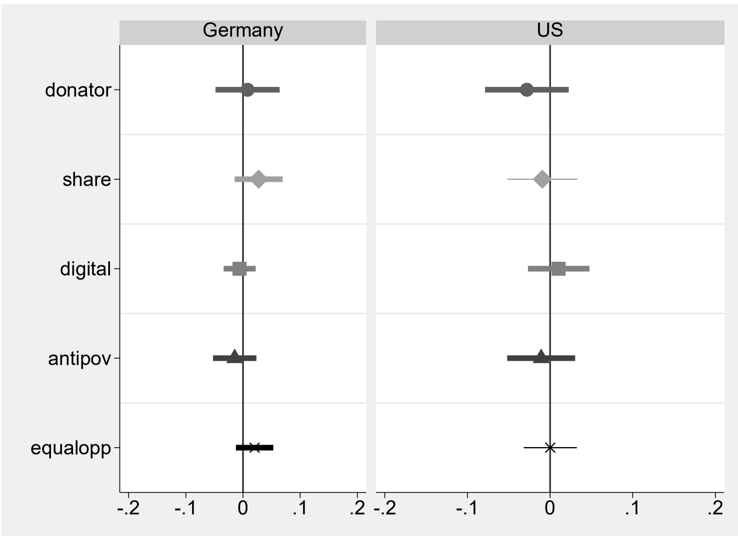
(a) Policy Demands



(b) Stated Labor Market Choices



(c) Donations to Charities



Notes: ITT for Germany (β_1) and the US (β_2), see equation (**??**). 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 A.3 for details.

C Further Tables

Table C.1: 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 C.2: 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

Table C.3: Correlation Matrix between Perception Measures (see Table 2 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 2.

Table C.4: 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 A.3), dummies for the experimental group assignment, and missing categories. Perception measures P_1, P_5, and P_9 as defined in Table 2.

Table C.5: LPM for Prior Perceptions regarding Future Value of Human work by Country

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

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

Notes: Regressions use z-scores of prior beliefs regarding the future value of human work as shown in Figure B.4 as dependent variable. Regressions are similar to equation (1), but only include covariates that have been surveyed in block A prior to the information treatment. Separate regressions for Germany and the US.

Table C.6: Multiple Hypothesis Testing for Treatment Effects in Figure 4 (p-values)

	Info treatment I_1 "no agg. emp. loss"		**Info treatment I_2 "emp. shifts"**	
	unadjusted p-value	adjusted p-value	unadjusted p-value	adjusted p-value
P_1 - unemployment rate	0.001	0.001	0.195	0.823
P_2 - relevance of human work	0.001	0.001	0.82	0.972
P_3 - overall prosperity	0.889	0.99	0.698	0.974
P_4 - desirability of digitalization	0.154	0.704	0.247	0.837
P_5 - own unemployment risk	0.226	0.63	0.539	0.991
P_6 - automatable job tasks	0.161	0.668	0.691	0.989
P_7 - own salary change	0.162	0.612	0.128	0.703
P_8 - being loser or winner	0.853	0.996	0.876	0.876
P_9 - inequality across workers	0.146	0.723	0.245	0.873
P_{10} - risks for workers w/o high-school	0.967	0.967	0.682	0.995
P_{11} - risks for workers w high-school	0.011	0.094	0.012	0.12
P_{12} - risks for college graduates	0.182	0.605	0.084	0.587
Joint test		0.009		0.118

Notes: Bootstrap-based unadjusted and adjusted p-values for Figure 4. Adjusted p-values are corrected for multiple hypothesis testing using the Stata command *mhtreg* that is based on List et al. (2019). Joint test provides p-value for testing null hypothesis of irrelevance of treatment for all perception measures jointly using Westfall-Young multiple hypothesis testing based on Stata command *randcmd*, see Young (2018) for details.

Table C.7: P-values for Westfall-Young Multiple Hypothesis Test for Joint Significance of Treatment for Different Groups of Outcomes and Sub-Groups of the Respondents

	Ger	US	optimists	neutrals	pessimists	unskilled	skilled	high-skilled
Information Treatment I_1 – "no agg. emp. loss"								
Perceptions	0.494	0.012	0.050	0.461	0.461	0.313	0.286	0.020
	(Fig. B.5)			(Fig. 5)			(Fig. B.6)	
Policy Demand	0.989	0.985	0.038	0.098	0.098	0.920	0.363	0.703
Stated Labor Market Choices	0.422	0.424	0.010	0.585	0.585	0.083	0.099	0.913
Donation Choices	0.608	0.658	0.108	0.406	0.406	0.142	0.846	0.421
	(available upon request)			(Fig. 6)			(available upon request)	
Information Treatment I_2 – "emp. shifts"								
Perceptions	0.011	0.862	0.170	0.299	0.299	0.604	0.115	0.304
	(Fig. B.7)			(Fig. B.8)			(Fig. B.9)	
Policy Demand	0.977	0.083	0.782	0.424	0.424	0.717	0.936	0.024
Stated Labor Market Choices	0.911	0.795	0.292	0.326	0.326	0.756	0.473	0.916
Donation Choices	0.030	0.690	0.296	0.104	0.104	0.473	0.542	0.097
	(Fig. B.10)			(available upon request)			(available upon request)	

Notes: P-values for the null hypothesis of joint irrelevance of treatment for outcomes in each outcome category: perceptions (12 outcomes), policy demand (4 outcomes), stated labor market choices (4 outcomes), donations to charities (5 outcomes), see A.3 for details. Test performed with Stata command randcmd, see Young (2018) for details. Tests conducted separately for sub-groups by country (US and Germany), prior beliefs (optimists, neutrals, pessimists) and skill levels (unskilled, skilled, hiigh-skilled). Hyperlinks refer to Figures providing the respective treatment effects.

D Priming Treatment

In addition to the two information treatments whose results we present and discuss in the main body of the paper, we also consider the effect of priming, i.e. of changing the order of the question blocks. While the standard order of survey questions 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

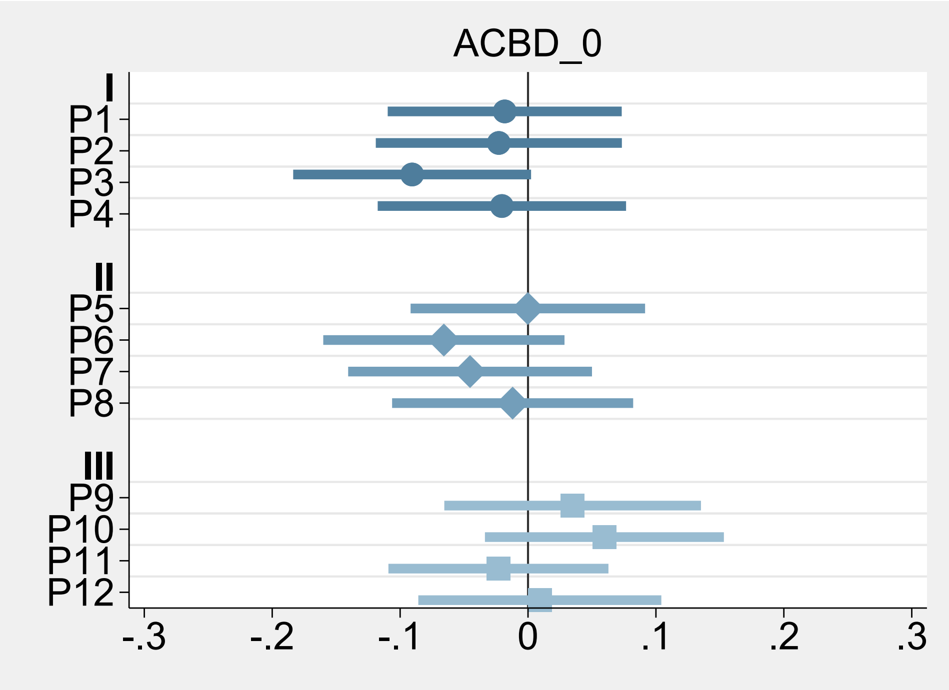
$$Y_i = \alpha + \beta ACBD_{0i} + u_i \tag{5}$$

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.[45]

As we do not find any notable cross-country differences, Figure D.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 D.2 (a) and (c). As regards stated labor market choices, see Figure D.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.

[45] 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.

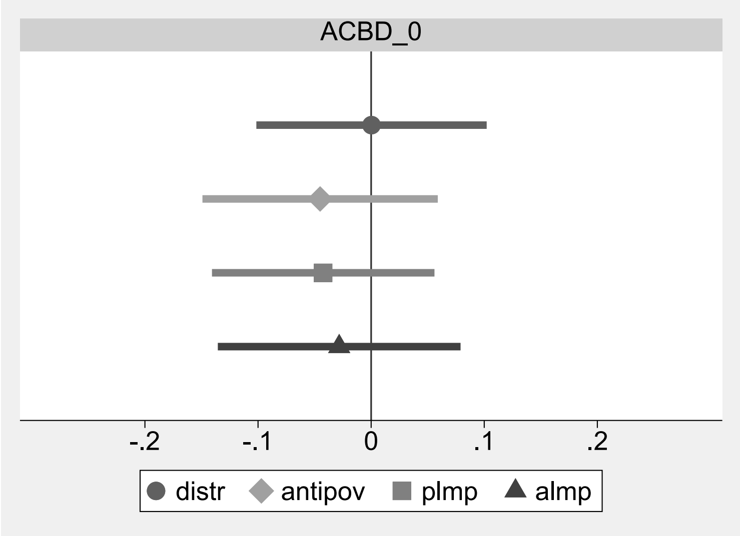
Figure D.1: Treatment Effect of Receiving Block C Prior to Automation Block B ($ACBD_0$) on Perceptions of Automation ($\alpha = 0.05$)



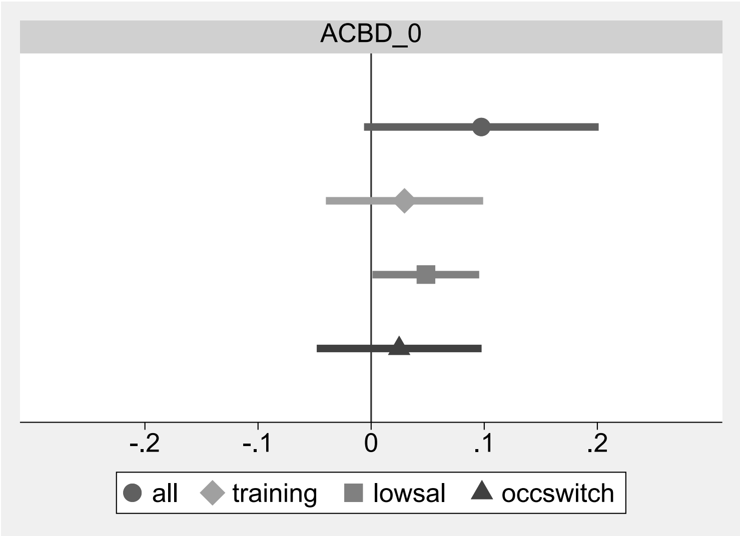
Notes: Separate regressions for all perception measures based on equation (5). Perception measures I refer to general concerns regarding unemployment rate (P_1), substitutability of human workforce (P_2), overall prosperity (P_3), and desirability of digitalization (P_4)). Perception measures II refer 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 2 for details.

Figure D.2: Treatment Effect of Receiving Block C Prior to Automation Block B ($ACBD_0$) on Various Outcomes

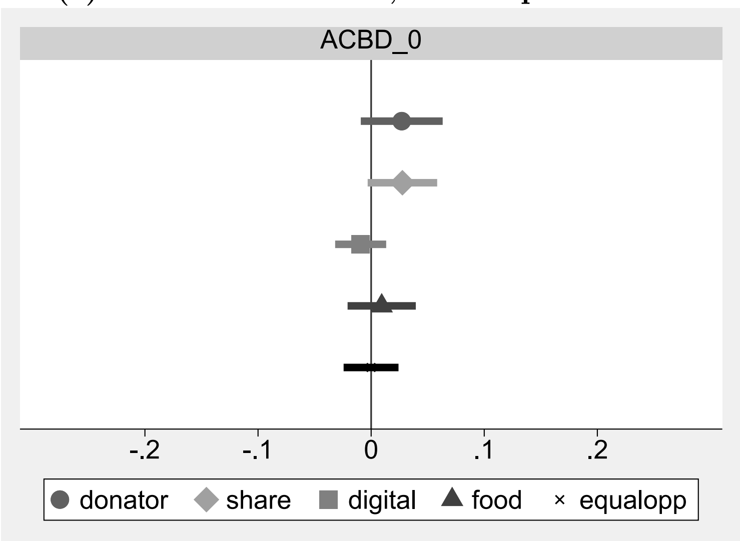
(a) Policy Preferences, MHT‡ p-val: 0.84



(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 A.3. ‡P-values refer to Westfall-Young multiple hypothesis test of all outcome equations jointly for each set of outcomes.

E 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 E.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 do not 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.*

29. 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*

30. 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*

31. 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*

32. 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 E.2) or Information Treatment 2 (see Figure E.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.

33. 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*

34. 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*

35. 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*

36. 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*

37. 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.

38. 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*

39. 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*

40. 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*

41. 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*

42. 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.

43. 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*

44. 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*

45. 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*

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

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

48. 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*

49. 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*

50. 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*

51. 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*

52. 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*

53. 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*

54. 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*

55. 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*

56. 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.

57. 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*

58. 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*

59. 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*

60. 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

61. Typical Working Day (order of items randomized): See Figure E.6

62. 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*

63. 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*

64. 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*

65. 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.

66. 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*

67. 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*

68. 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 E.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 E.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 E.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 E.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 E.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 E.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

F Questionnaire of Follow-Up Survey

The follow-up can also be accessed online via the following weblink:
`https://isurvey-us.yougov.com/refer/vYXvbxtmPhQg93`.

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 <u>without high school degree</u>

   (b) Workers <u>with high school degree</u>

   (c) Workers <u>with completed college/university education</u>

   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!