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Automation and Public Policy Preferences

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Abstract

Automation and globalization triggered sizeable labor market adjustments in the US. While the backlash against globalization has been well-identified in the political economy literature, this is not the case for automation. Using a survey experiment, we study how Americans update their public policy preferences after priming them with an automation story. We show it does not increase their support for government intervention and uncover two explanatory channels behind it: fairness considerations and perceived vulnerability to automation. First, respondents do not see automation as particularly unfair to workers and think that firms are justified in automating. Second, our automation treatment increases respondents' anxiety regarding automation's impact on American jobs in general but not on their own occupations. Hence, while an automation prime increases average anxiety levels, respondents do not feel personally threatened by robots. Finally, we find that respondents are less likely to support nationalist policies once they know the cause of the shock is automation. This suggests that misperceptions about the cause of the shock have partly driven the increase in anti-trade and anti-immigration sentiment following robot adoption.

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1 Introduction

Over the last decades, automation and globalization triggered sizeable labor market adjustments in the US. Work by Autor et al. (2013) has shown that rising exposures to Chinese import competition increased unemployment, reduced wages, and lowered labor force participation[1]. Prior to that, an important literature on skill-biased technological change described the phenomenon of job polarization that started in the 1980s (Autor et al., 2003, 2006), and recent estimates show that automation accounts for 50 to 70% of the surge in wage inequality in the US between 1980 and 2016 (Acemoglu and Restrepo, 2022). Overall, import competition and automation have been identified as primary drivers behind the decline in the labor share and the parallel increase in income inequality (Abdih and Danninger, 2017; Aum and Shino, 2020; Elsby et al., 2013).

While the economic consequences of these two shocks have been similar, they have triggered different political reactions. The backlash against globalization has been well-identified in the political economy literature in the form of growing anti-trade and anti-immigrant sentiments [2]. This is not the case for automation where no consensus on its political consequences has emerged. Previous survey experiments find that automation primes generate limited push for compensation or government intervention (Di Tella and Rodrik, 2020; Gallego et al., 2021; Jeffrey, 2021; Jeffrey and Matakos, 2021; Zhang, 2019). Yet, cross-sectional survey data in Europe and a set OECD countries show that the perception of technology-related employment risks correlates with more demand for redistribution and government protection (Busemeyer et al., 2022; Thewissen and Rueda, 2019). Finally, others highlight that automation increases support for right-wing populist parties as well as limits on immigration and trade (Anelli et al., 2021; Frey et al., 2018; Im et al., 2019; Wu, 2021, 2022)[3].

We investigate this puzzle and provide a unifying framework on automation and public policy preferences that reconciles previous findings. We do so by running a survey experiment on a large representative sample of the US population where we prime them with a newspaper-style text on the restructuring of a company leading to substantial lay-offs. In one treatment arm, the article does not specify the cause of the lay-offs (control), in the other treatment arm, the article specifies that robots will replace workers (automation treatment). After the treatments, we measure support for various social, retaliatory, and

[1]Several papers later on confirmed those findings and provided further precisions on the causes and conditions under which trade increases inequality (Antràs et al., 2017; Burstein and Vogel, 2017; Costinot and Rodríguez-Clare, 2014; Ebenstein et al., 2015)

[2]See for example Autor et al. (2020), Colantone and Stanig (2018), Colantone et al. (2019), and Dorn et al. (2020)

[3]We note that Anelli et al. (2021) also observe that automation exposure increases support for the radical left, but the effect is significantly lower.

nationalist policies as well as views on who should be responsible for helping negatively affected workers. We find an average null effect of the automation treatment: respondents do not update their policy preferences once they know that automation caused job displacement. We uncover two mechanisms behind this result. First, automation is not seen as particularly unfair, and respondents are more likely to think that firms are justified in automating in the automation treatment arm. Second, while respondents become more worried about automation in general, they do not believe that their own occupation is more likely to be automated. This indicates that, on average, they do not feel personally threatened when thinking about automation and, as a result, do not update their policy preferences.

We also test whether the previous experience of unemployment, trust in government, and views on government effectiveness play a mitigating or aggravating role in the demand for government intervention. We find it is not the case for the former two and that favorable views of government effectiveness lower the support for government intervention. Finally, we zoom in on respondents that declare to have been displaced by robots or foreign competition before. We show that they are more likely to support nationalist policies in the control group, but the effect disappears once they know the cause of the shock. This suggests that misperceptions regarding the cause of the shock partly drive the increase in anti-trade and anti-immigration sentiments that follows an automation shock.

Contribution to the literature. This paper adds to a small but growing literature that uses survey experiments to study automation and public policy preferences in the US[4]. Zhang (2019) shows that informing respondents about their chances of losing their jobs to automation corrects their views on the threat that automation poses to American jobs. Nevertheless, it does not lead to a change in their preferences on redistribution, immigration and trade policies. Di Tella and Rodrik (2020) prime respondents with different types of labour market shocks and find that trade shocks trigger high demand for protectionism while automation ones have relatively small effects on the demand for transfers and protectionism. Using similar treatments, Wu (2022) obtains an average null impact of an automation prime on support for trade restriction and immigration, with heterogeneous effects along partisan lines. She also finds it increases the demand to restrict companies' use of new technology. Finally, Jeffrey and Matakos (2021) show that knowing about the risk automation poses to inequality has little effect on preferences for redistribution. Nevertheless, their informational treatment appears to change views on redistribution among those that recently experienced a negative labour market shock.

We contribute to the literature in several ways. First, we use a large representative

[4]Surveys have also been run in the UK and Spain which also show a subdued demand for compensation following an automation prime (see for example Gallego et al. (2021) and Jeffrey (2021)).

sample of the US population to study the question of attitudes towards automation. With a sample size close to 3000, we can detect an effect size of 0.13 of standard deviation, as specified in the pre-analysis plan.[5]. Our sample is also representative of the US population in terms of gender, age, race, income, education, and region of residence. This enables us to confirm previous null effect findings of smaller sample sizes or non-representative samples. To our knowledge no other survey experiment of this type uses a representative sample. Jeffrey and Matakos (2021) are the only ones to attempt to do so using post-stratification weights.

Second, we focus on the mechanisms and test for four channels that could explain the lack of backlash against automation: fairness considerations, perceived vulnerability to automation, views on government effectiveness, and trust in government. We measure a range of pre- and post-treatment beliefs to test for heterogeneous effects and belief updating. We also run heterogeneity analysis by demographic characteristics. Our aim is to examine whether competing mechanisms are at play.

Third, we benchmark our results against the baseline level of support for government intervention following a labor market shock of unknown cause. Studies so far look at differences between an automation treatment and either a placebo or a control group with no job losses. For instance, Di Tella and Rodrik (2020) and Wu (2022) also prime participants to think about different labor market shocks with newspaper style treatments that narrate job losses in a manufacturing company. Yet, their control group is not exposed to factory closure or lay-offs. We aim here to isolate the reaction to the cause of the furlough and estimate the reaction to automation net of the effect of job loss itself.

Four, we measure support for a range of public policies and in particular try to see if the lack of demand for social policies is compensated by demand for more regulation or taxes on firms, or nationalist policies. We also test whether respondents believe the responsibility to help affected workers is not the government's but another entity's. This enables us to see whether the limited support for government intervention hides discontentment towards firms.

The paper is structured as follows: section 2 details the experimental design and sample recruitment, section 3 presents the results, and section 4 concludes.

2 Experimental Design and Sample

Our experiment has three treatment arms: one control and two treatments. We describe the sample and structure of the experiment below.

[5]With a power of 0.8 and a 0.05 significance level.

2.1 Sample

We recruited respondents using Dynata, previously Research Now, an online research market company widely used in the literature (Haaland et al., Forthcoming; Stantcheva, 2022). We conducted the survey in August and September 2022[6]. A pre-analysis plan was submitted to the AEA RCT Registry prior to data collection[7], which specified the sample size, hypotheses, and empirical setting.

We applied quota samples to obtain a representative sample of the US population in terms of gender, age, race, income, education, and region. We dropped participants who did not pass our attention check, whose answers to our open-ended questions were non-sensical, flagged by Qualtrics as potential bots or duplicates, and whose completion time is below 3 minutes or above 60 minutes. In total, we end up with 2977 responses with a median completion time of 7.1 minutes. Our sample matches the distributions of the US population (table A1).

2.2 Experiment

We start the survey by asking respondents to complete a demographic questionnaire. We also ask if they have ever been unemployed before, and elicit pre-treatment beliefs on trust in government, government efficiency, and fairness. After eliciting these prior beliefs, we ask them about their political affiliation. Respondents are then randomly assigned to one of three treatment arms: a control, an automation treatment, and an automation treatment preceded by an anchoring of government effectiveness views. Table A2 shows that our control and two treatment groups are balanced in terms of observable and reject an F-test of joint-significance.

2.3 Treatments

2.3.1 Treatment 1: Automation shock

Treatment 1 assigns respondents a short newspaper-style article to read. The article describes a food manufacturer that is restructuring and decided to lay off 20% of its labor force. The article specifies that the company will "automate part of its production with machines" and that "many employees [...] will likely become unemployed or have to take lower-paid jobs". Hence, the article clearly links robot adoption and job displacement.

[6] We ran the survey in a post-pandemic era, which could influence perceptions of the labor market and the government. It should not be an issue to the extent that our treatment and control groups all suffer from the same bias. It could be an issue for the external validity of our results, although our average results are in line with previous findings.

[7] https://www.socialscienceregistry.org/trials/9836

2.3.2 Treatment 2: Government effectiveness + Automation shock

Treatment 2 begins by anchoring the level of government effectiveness in the US. Respondents read a short text about a government effectiveness ranking conducted by the World Bank every year [8]. The text describes the different items taken into account to build the ranking. Respondents then estimate how well the US ranked compared to the rest of the world in 2020, the last year of data available. They choose among four options: among the best, better than most, worse than most, and among the worst. After answering, the correct answer is shown to them, which is that the US ranked as one of the most effective governments in the world in 2020. We use a design similar to Kuziemko et al. (2015) where we ask respondents to give an estimate first and then give them the correct answer. This makes our treatment more salient.

After this "government effectiveness treatment", Respondents are shown the same automation newspaper-style article as in Treatment 1.

2.3.3 Control

The control group is what Haaland et al. (Forthcoming) describe as an active control group. Respondents are shown a newspaper article similar to treatment 1's, except it does not specify the cause of the lay-off. Hence, respondents are treated with a negative labor market shock but do not know the reason for it.

2.4 Outcomes

2.4.1 Self-Reported Policy Preferences

We measure people's preferences on a five-point Likert scale[9] for six policies:

1. Providing re-training programs
2. Providing financial assistance to workers who lose their jobs
3. Increasing taxes for firms
4. Regulating the ways in which firms operate
5. Raising tariffs on foreign goods
6. Restricting immigration to the US

[8]Data available at `http://info.worldbank.org/governance/wgi/`. See Kaufmann et al. (2010) for more details

[9]Strongly oppose, Somewhat oppose, Neither oppose nor support, Somewhat support, Strongly support

The policies are shown in random order to respondents. To limit the issue of multiple hypothesis testing, we create indices following Anderson (2008). We group policies 1 and 2 as social policies, 3 and 4 as retaliatory ones[10], and 5 and 6 as nationalist ones. In particular, we interpret an increase in support for policies 3 and 4 as ways to punish firms

We also measure people's views on who should be responsible for helping displaced workers. We follow the OECD's Risk that Matters survey (2021) and measure it on a four-point Likert scale[11] for the following entities:

1. Firms, businesses, and employers
2. Civil society groups, such as professional associations, non-profit organizations, and charitable organizations
3. The national government
4. Individual workers themselves

These entities are also displayed in random order to each survey participant.

2.4.2 Mechanisms

We try to uncover some mechanisms behind our policy preference outcomes and do so by two means. First, we conduct a heterogeneity analysis according to some pre-treatment variables and check whether respondents who view inequality as an issue, have been employed before, trust the government, and have positive views on government efficiency react differently to the treatments. Second, we investigate whether the treatments affect participants' perceptions of fairness, vulnerability to automation and globalization, views of government efficiency, and trust in government. To minimize the risk that respondents realize we are trying to measure whether they update these beliefs, we word the questions differently than the pre-treatment ones (see questions in sub-sections A11 and A12 in section B).

2.4.3 Definition of outcome variables

We consider all the self-reported measures on a Likert scale as continuous and standardize them. In particular, we subtract the control group mean and divide it by the control group standard deviation for each observation. As specified earlier, we also create indices of the

[10]We depart slightly from the pre-analysis plan, which interpreted policies 3 and 4 as regulatory. In line with Di Tella et al. (2016), we interpret an increase in support for policies 3 and 4 as ways to punish firms. In particular, we see an increase in support for taxing firms as a retaliatory measure rather than an increase in support for redistribution

[11]Definitely should not be responsible, Probably should not be responsible, Probably should be responsible, Definitely should be responsible

support for different types of public policies. Finally, we code dichotomous variables as dummies.

Details on the treatment and the survey questions are available in Appendix B and a summary chart in Figure A1.

3 Results

3.1 Determinants of support for intervention following a negative labor market shock

We first look at the baseline support for each type of public policy following a negative labor market shock of unspecified cause. Figure 1 shows that all policies have more supporters than opponents. Retraining programs and financial assistance to displaced workers are the most popular policies, with close to 75% of our sample strongly supporting or somewhat supporting these two policies. The other four policies - regulations, taxes, restrictions on immigration, and tariffs - while not as popular, still exhibit a larger share of respondents that support rather than oppose. They also have a significant percentage of respondents that neither oppose nor support the policy (between 25 and 35%).

We also find that participants' support for different types of public policies varies significantly with their background characteristics (Table 1). Republicans and Democrats exhibit pronounced differences, and so do Republicans and Independents, but to a lower extent. Other significant characteristics include gender, age, whether one is born in the US, whether one is divorced or single, the number of children, and living in a Southern State. The ethnic background does not correlate with the support for some policies, but Hispanic respondents are less likely to favor immigration restrictions. Employment status does not display any strong pattern. We only note that part-time employees and the unemployed are less likely to support tariffs than full-time employees. While currently unemployed respondents do not exhibit a different level of policy support compared to full-time employees, respondents that have been unemployed before are more likely to support financial assistance for displaced workers and more taxes on firms.

Pre-treatment beliefs are strong predictors of supporting specific policies. Trust in government increases support for more regulation and taxes on firms, while people who view the government as efficient are more likely to support all types of policies. Believing that inequality is unfair also correlates with more support for all policies but restrictions on immigration.

We then look at who respondents believe should be responsible for helping workers affected by the adverse labor market shock (Figure 2). On average, most respondents

Figure 1: Support for public policies following a negative labor market shock

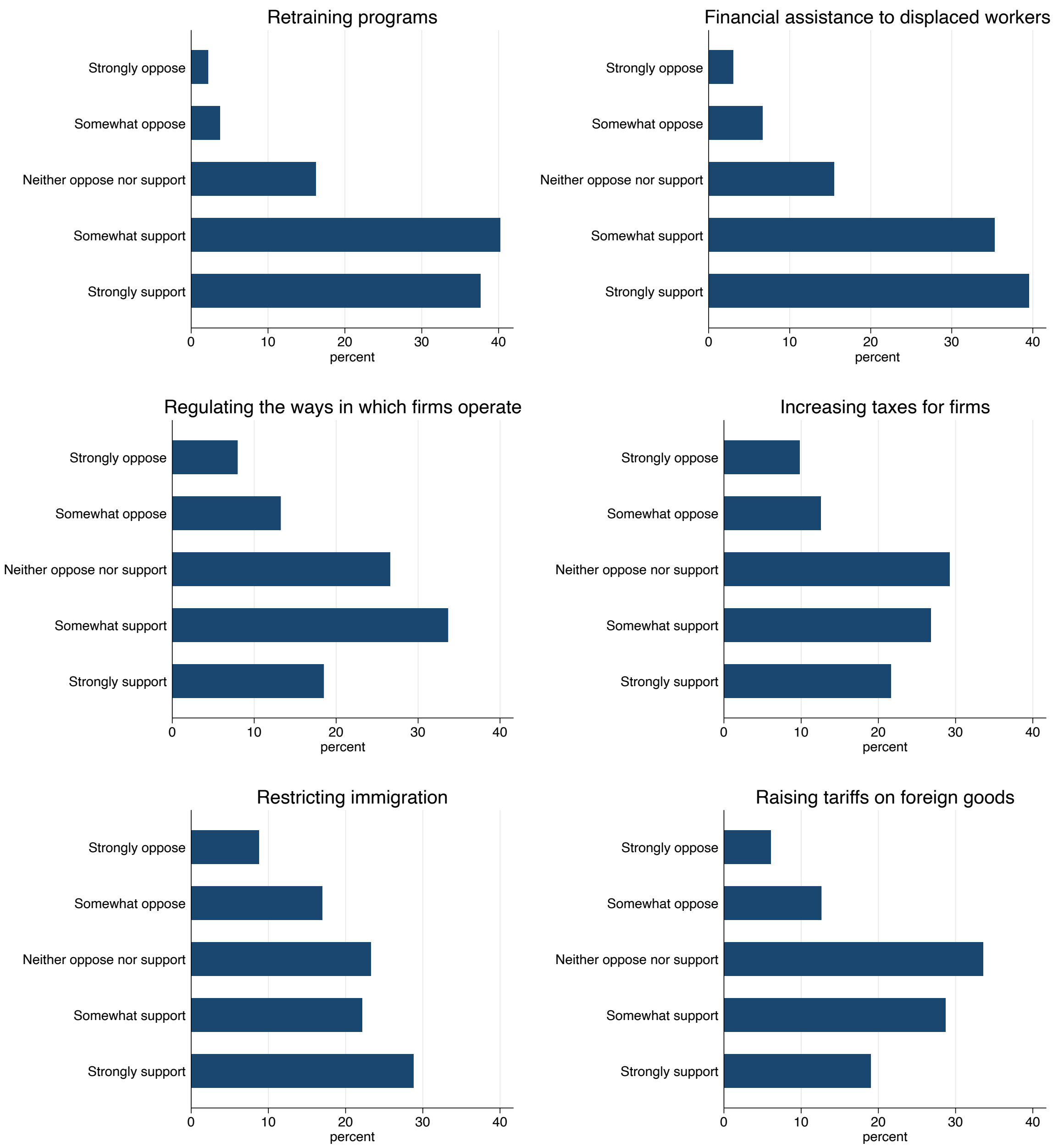


Table 1: Covariates of support for public policies following a negative labor market shock

	(1) Retraining	(2) Financial Assistance	(3) Regulate	(4) Tax Firms	(5) Restrict Immigration	(6) Tariffs
Female	0.11*	0.20***	0.11	0.17**	-0.02	0.03
	(1.73)	(3.05)	(1.47)	(2.23)	(-0.26)	(0.34)
Age Category	0.09***	0.03	-0.01	0.05*	0.11***	0.08**
	(3.48)	(1.07)	(-0.43)	(1.72)	(3.02)	(2.53)
Household Income	0.09**	0.03	0.01	0.09*	0.03	0.04
	(2.20)	(0.65)	(0.21)	(1.86)	(0.57)	(0.87)
Highest education level	0.00	-0.04	-0.02	0.05*	-0.03	-0.00
	(0.10)	(-1.57)	(-0.76)	(1.73)	(-0.85)	(-0.16)
Born in the US	-0.27**	-0.20	-0.15	0.04	0.19	0.14
	(-2.04)	(-1.27)	(-0.90)	(0.22)	(1.06)	(0.79)
Ethinicity/Race (ref: White Only)						
Black Only	0.03	0.14	0.02	0.04	-0.02	-0.06
	(0.27)	(1.30)	(0.15)	(0.34)	(-0.16)	(-0.46)
Asian Only	-0.01	-0.02	0.10	-0.06	-0.31	-0.08
	(-0.10)	(-0.10)	(0.50)	(-0.27)	(-1.54)	(-0.47)
Mixed	-0.06	-0.05	0.19	0.22	0.04	0.12
	(-0.54)	(-0.37)	(1.39)	(1.49)	(0.23)	(0.71)
Hispanic	0.09	0.01	-0.02	-0.07	-0.56***	-0.24
	(0.77)	(0.10)	(-0.15)	(-0.45)	(-3.21)	(-1.43)
Marital Status (ref: Married)						
Single	0.16**	0.16*	0.20**	0.12	-0.02	-0.04
	(2.12)	(1.93)	(2.04)	(1.23)	(-0.18)	(-0.45)
Divorced	0.17*	0.18*	0.14	0.22*	-0.05	0.28**
	(1.83)	(1.86)	(1.29)	(1.81)	(-0.45)	(2.47)
Widowed	-0.06	-0.10	0.05	0.19	0.14	0.13
	(-0.35)	(-0.51)	(0.29)	(1.12)	(0.71)	(0.80)
Nb of children	0.06**	0.10***	0.16***	0.02	0.06	-0.01
	(2.05)	(2.78)	(4.34)	(0.56)	(1.24)	(-0.28)
Employment Status (ref: Full-time employee)						
Part-time employee	0.14	-0.04	-0.02	-0.17	-0.17	-0.25*
	(1.41)	(-0.34)	(-0.14)	(-1.29)	(-1.22)	(-1.93)
Self-empl. w dependent workers	0.09	0.06	0.05	-0.01	0.13	-0.14
	(0.58)	(0.32)	(0.27)	(-0.04)	(0.58)	(-0.69)
Self-empl. w/o dependent workers	0.00	-0.00	0.03	-0.10	0.13	-0.14
	(0.02)	(-0.01)	(0.11)	(-0.39)	(0.45)	(-0.43)
Unemployed	0.13	0.14	0.21	-0.14	-0.26	-0.26*
	(0.95)	(0.97)	(1.36)	(-0.91)	(-1.57)	(-1.69)
Student	0.27*	0.12	-0.10	-0.09	-0.19	-0.17
	(1.89)	(0.66)	(-0.40)	(-0.39)	(-0.69)	(-0.72)
Not in the labor force	0.09	0.07	0.08	0.05	-0.08	-0.10
	(1.02)	(0.75)	(0.77)	(0.48)	(-0.70)	(-0.99)
Political Afficliation (ref: Republican)						
Democrat	0.21***	0.33***	0.40***	0.60***	-1.00***	-0.21***
	(3.27)	(4.61)	(5.20)	(7.33)	(-11.39)	(-2.64)
Independent	0.27***	0.27**	0.11	0.15	-0.81***	-0.39***
	(2.78)	(2.38)	(0.89)	(1.16)	(-5.45)	(-3.16)
Other	-0.15	0.04	-0.17	-0.13	-0.76***	-0.67***
	(-0.76)	(0.20)	(-0.86)	(-0.56)	(-3.83)	(-3.51)
Region (ref: MidWest)						
NorthEast	-0.09	-0.01	-0.03	-0.08	0.03	-0.10
	(-1.07)	(-0.06)	(-0.25)	(-0.72)	(0.29)	(-0.88)
West	-0.15	0.01	-0.10	-0.10	-0.05	-0.20*
	(-1.60)	(0.08)	(-0.95)	(-0.85)	(-0.43)	(-1.89)
South	-0.15**	-0.08	-0.16*	-0.15	-0.07	-0.12
	(-2.08)	(-1.01)	(-1.78)	(-1.62)	(-0.80)	(-1.43)
Pre-Treatment Beliefs & Work Experience						
Trusts the govt	0.09	0.09	0.24***	0.17**	0.05	0.01
	(1.37)	(1.20)	(3.18)	(2.06)	(0.56)	(0.10)
Govt is efficient	0.36***	0.42***	0.58***	0.28*	0.57***	0.57***
	(3.32)	(3.41)	(4.58)	(1.91)	(3.29)	(3.72)
Inequality is unfair	0.51***	0.56***	0.60***	0.69***	-0.09	0.15**
	(8.08)	(7.95)	(8.24)	(9.03)	(-1.07)	(2.03)
Unemployed before	0.04	0.15*	0.05	0.22***	0.02	0.05
	(0.53)	(1.85)	(0.58)	(2.66)	(0.20)	(0.66)
Constant	2.30***	2.93***	2.61***	0.88	3.33***	2.71***
	(4.56)	(5.15)	(4.53)	(1.43)	(4.94)	(4.48)
Observations	988	989	989	989	989	989

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

believe that the government, civil society, individuals, and firms have a responsibility. Nevertheless, the share of respondents that think firms should be held responsible is significant, with 84% of the sample that answered that firms should probably or definitely be responsible. The government is also seen as responsible by more than 70% of respondents, while the share decreases to 64% for individuals and 56% for civil society.

Fewer background characteristics significantly correlate with views on who should be responsible for helping displaced workers (Table 2). Those variables are also more staggered over categories. It is worth noting that those born in the US are less likely to think the government and civil society should be responsible, Blacks and Asians are more likely to declare individuals should be held responsible, and Democrats are more likely to say the government, civil society, and firms should be responsible.

Pre-treatment beliefs have, again, important explanatory power. Trust in government decreases support for firms' responsibility, positive views on government efficiency raise support for all entities' responsibility, and seeing inequality as unfair correlates with more support for the responsibility of the government, civil societies, and firms and less support for an individual one.

Figure 2: Responsibility to help displaced workers following a negative labor market shock

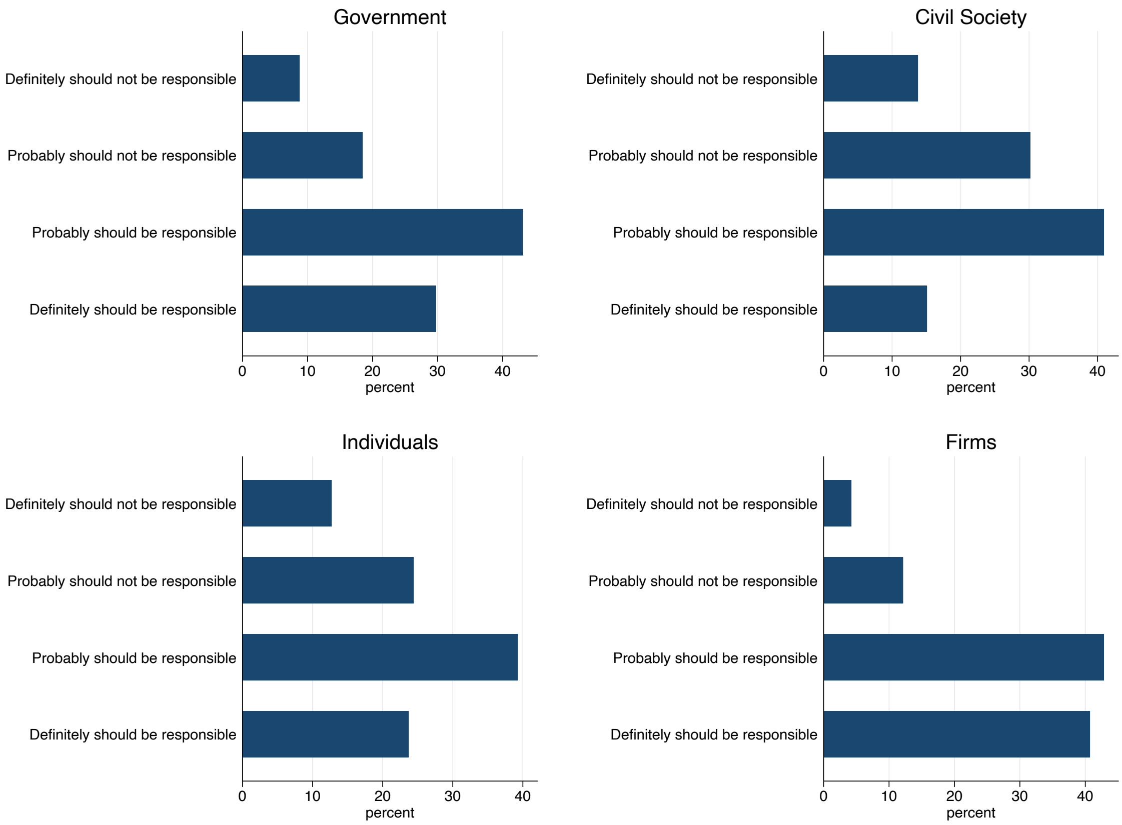


Table 2: Covariates of institutional responsibility to help displaced workers following a negative labor market shock

	(1) Government	(2) Civil Society	(3) Individuals	(4) Firms
Female	0.00	0.05	-0.16**	0.04
	(0.07)	(0.81)	(-2.48)	(0.78)
Age Category	-0.04	-0.03	-0.01	0.03
	(-1.50)	(-1.16)	(-0.37)	(1.27)
Household Income	0.03	-0.02	0.07*	0.04
	(0.69)	(-0.59)	(1.70)	(1.23)
Highest education level	-0.01	0.02	0.02	0.02
	(-0.37)	(0.94)	(0.84)	(0.93)
Born in the US	-0.34***	-0.27*	0.08	-0.07
	(-2.61)	(-1.90)	(0.51)	(-0.56)
Ethinicity/Race (ref: White Only)				
Black Only	0.12	-0.07	0.17*	-0.11
	(1.46)	(-0.73)	(1.73)	(-1.34)
Asian Only	-0.20	-0.09	0.28*	0.01
	(-1.22)	(-0.55)	(1.66)	(0.09)
Mixed	0.04	0.04	-0.16	-0.09
	(0.29)	(0.29)	(-1.13)	(-0.82)
Hispanic	-0.02	-0.06	0.05	0.10
	(-0.17)	(-0.51)	(0.35)	(0.95)
Marital Status (ref: Married)				
Single	0.15**	-0.18**	-0.20**	-0.01
	(2.01)	(-2.28)	(-2.35)	(-0.14)
Divorced	0.15*	-0.08	-0.11	-0.01
	(1.65)	(-0.81)	(-1.02)	(-0.17)
Widowed	-0.21	-0.05	0.06	-0.11
	(-1.23)	(-0.33)	(0.31)	(-0.88)
Nb of children	0.10***	-0.01	-0.06*	-0.00
	(3.38)	(-0.42)	(-1.81)	(-0.13)
Employment Status (ref: Full-time employee)				
Part-time employee	-0.03	-0.12	-0.17	-0.03
	(-0.35)	(-1.21)	(-1.47)	(-0.30)
Self-empl. w dependent workers	-0.14	-0.08	-0.17	-0.34**
	(-0.78)	(-0.56)	(-0.87)	(-2.16)
Self-empl. w/o dependent workers	0.03	0.06	-0.01	-0.02
	(0.21)	(0.28)	(-0.02)	(-0.10)
Unemployed	0.27**	-0.16	-0.29**	-0.01
	(2.35)	(-1.26)	(-2.20)	(-0.07)
Student	0.05	0.08	0.05	0.15
	(0.30)	(0.53)	(0.33)	(1.00)
Not in the labor force	0.05	-0.16*	-0.09	0.01
	(0.60)	(-1.85)	(-0.95)	(0.18)
Political Afficliation (ref: Republican)				
Democrat	0.18***	0.18***	0.06	0.23***
	(2.77)	(2.76)	(0.84)	(4.14)
Independent	0.09	0.07	0.03	0.14
	(0.84)	(0.67)	(0.28)	(1.50)
Other	0.05	-0.38**	-0.01	-0.37*
	(0.23)	(-2.07)	(-0.03)	(-1.90)
Region (ref: MidWest)				
NorthEast	-0.07	-0.14	-0.07	-0.06
	(-0.87)	(-1.62)	(-0.68)	(-0.81)
West	-0.07	-0.10	-0.03	0.01
	(-0.78)	(-1.14)	(-0.32)	(0.11)
South	-0.06	-0.11	0.01	-0.04
	(-0.86)	(-1.54)	(0.07)	(-0.54)
Pre-Treatment Beliefs & Work Experience				
Trusts the govt	0.07	0.10	-0.03	-0.12*
	(1.03)	(1.63)	(-0.36)	(-1.92)
Govt is efficient	0.37***	0.58***	0.39***	0.21**
	(3.79)	(5.57)	(3.24)	(2.43)
Inequality is unfair	0.46***	0.18***	-0.16**	0.39***
	(7.43)	(2.93)	(-2.36)	(6.94)
Unemployed before	-0.01	-0.02	0.08	0.03
	(-0.09)	(-0.24)	(1.10)	(0.60)
Constant	2.58***	3.08***	2.11***	2.28***
	(5.62)	(6.41)	(4.14)	(5.56)
Observations	986	987	987	987

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

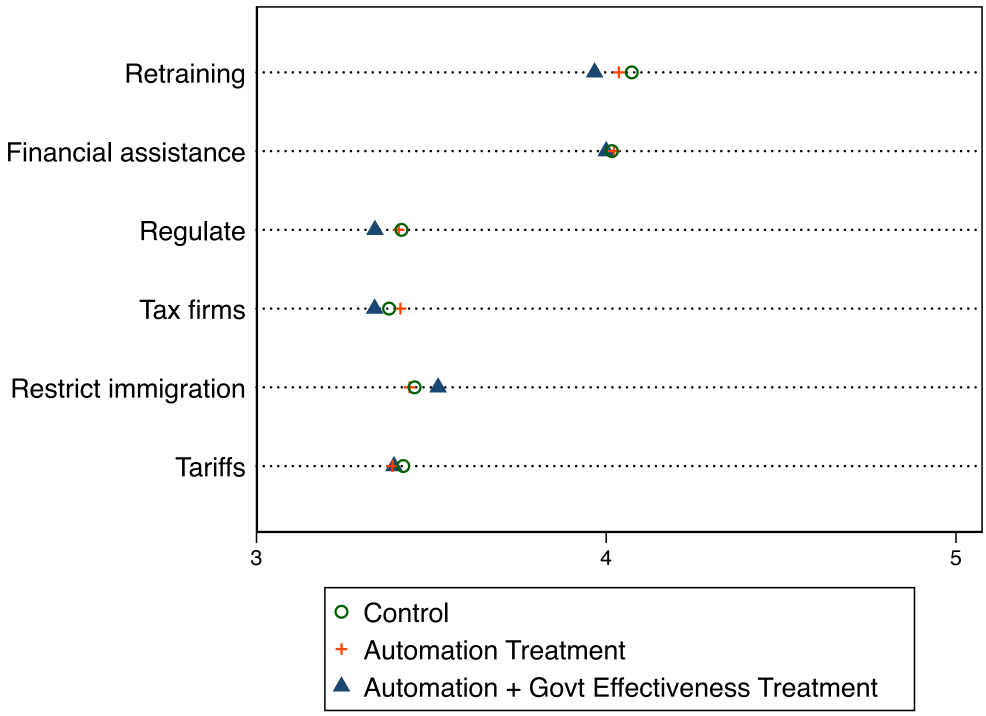
Overall, these results show that pre-treatment beliefs are essential in explaining support for the types of public and who implements them. In the rest of the analysis, and as specified in the pre-analysis plan, we control for all the background characteristics and pre-treatment beliefs presented here.

3.2 Do participants respond differently to an automation shock?

We investigate whether respondents update their public policy preferences and views on who should be responsible for helping displaced workers when we specify that automation is the cause of the shock.

Figures 3 and 4 plot the average level of support for each policy and each entity for the control and each treatment. They show minimal differences in means according to the treatment group, suggesting that knowing automation is the cause of the shock has no effect.

Figure 3: Average support for public policies by treatment group

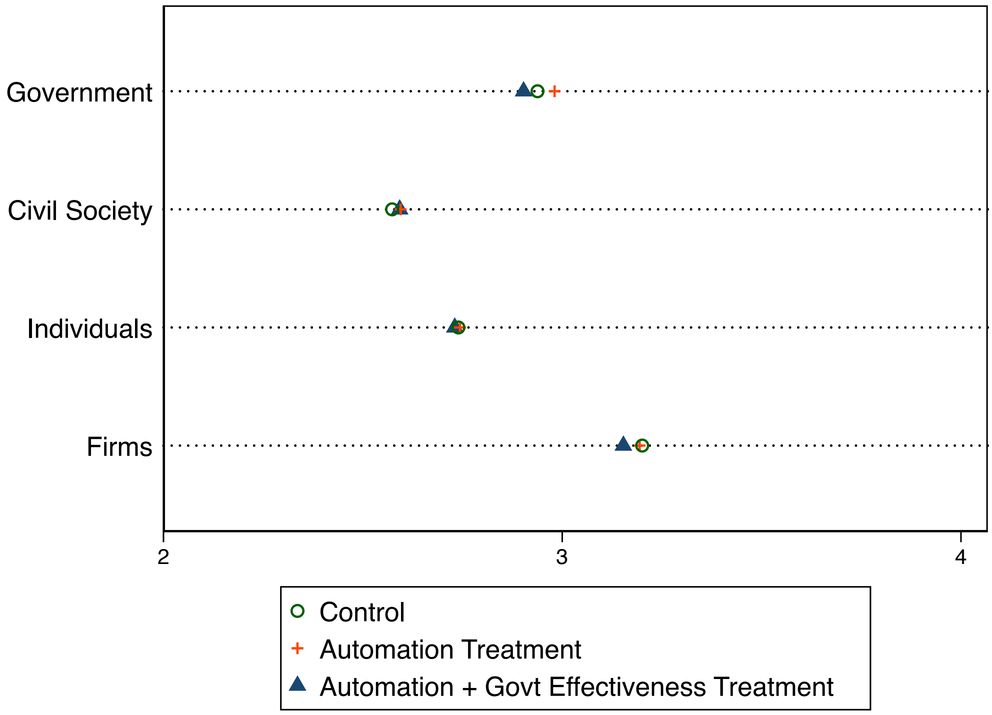


As specified in the pre-analysis plan, we then estimate the following equation:

$$y_i = \alpha_0 + \alpha_1 T1_i + \alpha_2 T2_i + \boldsymbol{A^T X_i} + \epsilon_i \tag{1}$$

where

Figure 4: Average support for entities' responsibility by treatment group



- y_i is the outcome of interest
- $T1_i$ is an indicator for whether respondent i received treatment 1, i.e. only the automation treatment
- $T2_i$ is an indicator for whether respondent i received treatment 2, i.e. the government effectiveness + automation treatment
- $\boldsymbol{X_i}$ is a vector of pre-specified controls (as described in Section 3.1) [12]
- $\epsilon_{j,i}$ is an individual-specific error term. We use robust standard errors for all specifications.

We first focus on the effect of treatment one only, i.e., the automation treatment.

Table 3 displays results for the post-treatment support for public policies and Table 4 for the views on who should be responsible [13].

We see no significant increase in support for social, retaliatory, or nationalist policies due to the automation treatment. The automation treatment slightly increases the share

[12] We also report the results without controls in the appendix.

[13] A breakdown of the impact for each policy is available in Table A3. As specified in our pre-analysis plan, we also run the regressions without controls, and the results remain unchanged (see Tables A4, A5, and A6)

of people that believe the government should be responsible for helping displaced workers by 0.07 of a standard deviation. Nevertheless, the result is only significant at the 10% level. There is no discernible effect on other entities.

Overall, these results confirm the average null effect of an automation prime on public policy preferences (Jeffrey, 2021; Jeffrey and Matakos, 2021; Wu, 2022; Zhang, 2019). Respondents do not favor any particular type of public policy once knowing that robots displace workers and are marginally more likely to see the government as responsible for helping affected workers. Interestingly, the treatment does not affect views on firms' responsibility. Some ceiling effects could be at play as more than 80% of the control sample already sees firms as having a responsibility to help in the case of a labor market shock of unspecified causes.

We investigate potential reasons for this lack of reaction in the next section.

Table 3: Effect of the automation treatment on public policy preferences

	(1) Social Policies Index	(2) Retaliatory Policies Index	(3) Nationalist Policies Index
Automation Treatment	0.0016	0.032	-0.034
	(0.04)	(0.83)	(-0.82)
Controls	Yes	Yes	Yes
Observations	2976	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect of the automation treatment on views on who should be responsible to help affected workers

	(1) Government	(2) Civil Society	(3) Individuals	(4) Firms
Automation Treatment	0.071*	0.039	0.0073	0.0028
	(1.77)	(0.94)	(0.17)	(0.07)
Controls	Yes	Yes	Yes	Yes
Observations	2970	2973	2973	2972

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.3 Explanatory mechanisms: fairness considerations and perceived vulnerability to automation

We identify two main explanatory mechanisms behind the absence of "automation backlash": fairness consideration and perceived vulnerability to automation.

3.3.1 Fairness considerations

We test whether fairness considerations play a role by (i) looking at heterogeneous effects by pre-treatment views on fairness and (ii) measuring fairness considerations after the treatment.

We measure pre-treatment views on fairness by asking respondents how much they agree with the statement, "In the United States, the economic differences between the rich and the poor are unfair". We take this question from Almås et al. (2021)'s survey questionnaire, which was implemented in collaboration with Gallup. Almås et al. (2021)'s paper measures to which extent global inequality differences relate to fairness views of people in each country. We code it as one if the respondent answers "Strongly agree" or "Agree" and zero otherwise. We use this variable as a proxy measure of fairness views in the US.

Tables 5 and 6 show that those who see inequality as unfair do not respond differently to the automation treatment[14]. We note that while the interaction of pre-treatment fairness views and the automation treatment for civil society is not significant in Table 6, it causes the main coefficient to become positive and significant. In other words, respondents who do not see the gap between the rich and poor as unfair are more likely to think civil society should be responsible for helping affected workers in the case of an automation shock. The coefficient is only significant at the 10% level but highlights that these respondents tend to place responsibility on non-governmental organizations rather than the government or firms. Interestingly, civil society is the only variable affected. In particular, respondents who believe inequality is unfair do not view the government and firms as more responsible.

These results suggest that pre-treatment views on fairness do not interact with the automation treatment in any meaningful way. Viewing inequality as unfair does not induce any significant differential reaction to the automation shock.

Table 5: Heterogeneous effects by fairness views - Support for policies

	(1) Social Policies Index	(2) Retaliatory Policies Index	(3) Nationalist Policies Index
Automation Treatment	0.021	0.088	0.021
	(0.29)	(1.35)	(0.33)
Automation Treatment × Inequality is unfair=1	-0.031	-0.090	-0.087
	(-0.36)	(-1.12)	(-1.05)
Controls	Yes	Yes	Yes
Observations	2976	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[14]Results by type of public policy are displayed in Table A7.

Table 6: Heterogeneous effects by fairness views - Responsibility to help affected workers

	(1) Government	(2) Civil Society	(3) Individuals	(4) Firms
Automation Treatment	0.093	0.12*	0.030	0.045
	(1.30)	(1.71)	(0.42)	(0.75)
Automation Treatment × Inequality is unfair=1	-0.034	-0.13	-0.037	-0.068
	(-0.40)	(-1.45)	(-0.41)	(-0.93)
Controls	Yes	Yes	Yes	
Observations	2970	2973	2973	2972

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We then test whether fairness considerations are affected by our treatment. After measuring participants' policy preferences, we measure whether they view the automation shock as more unfair compared to other shocks. We do this with two questions. First, we ask participants to tell us to what extent they think it is unfair for those workers to lose their jobs. Participants answer on a five-point Likert scale from completely unfair to completely fair. We adapt this question from a survey question in Hvidberg et al. (2020) 's paper on social positions and fairness views on inequality[15]. Second, we ask participants to choose between two statements: that firms are justified in replacing humans with robots if they can receive better work at a lower cost, or that there should be limits on how many jobs businesses can replace with robots[16]. This question is extracted from Pew's 2017 survey on automation.

Table 7 shows that respondents do not see automation as being more unfair than a labor market shock of unknown cause: column 1 displays no effect of the automation treatment on fairness views. In addition, column 2 provides evidence that respondents believe that firms are justified in automating. The automation treatment increases the probability that a respondent declares that firms are justified in automation by 4.2 percentage points. This compares to a 35.7% share of respondents that choose this statement in the control group. Hence it consists of an 11.8% rise compared to the control group, a non-trivial increase.

Overall, these findings indicate that the respondents do not view automation as particularly unfair and are more likely to see just cause for the displacement of workers by robots after the automation treatment. Hence, fairness considerations are one explanatory channel behind the lack of reaction to our automation treatment.

[15]In particular, we adapt it from the question: *On a scale from 1 to 7 where 1 is "Completely fair", 4 is "Neither fair nor unfair" and 7 is "Completely unfair", indicate to what extent you think that it is fair or unfair that there are differences in income among people born the same year as you WITHIN the following groups that you are yourself a part of ?*

[16]See appendix B for details on the questions.

Table 7: Effects on post-treatment fairness views

	(1) Unfair to lose job	(2) Firms are justified in automating
Automation Treatment	-0.0014	0.042**
	(-0.03)	(2.06)
Controls	Yes	Yes
Observations	2971	2965

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.3.2 Perceived vulnerability to automation

We then focus on the role of automation anxiety and whether it plays a mediating role in supporting intervention following an automation shock.

We first try to see whether there are heterogeneous effects according to one's previous experience of economic hardship. Jeffrey and Matakos (2021) find that those displaced or temporarily suspended from work during the COVID-19 pandemic are more likely to react to a treatment highlighting automation's inequality implications. Therefore, prior to the treatment, we ask respondents whether they have ever been unemployed before. We create a dummy equal to one if the person has been unemployed before and interact it with the automation treatment.

Table 8 shows that individuals who have been unemployed before are less likely to support retaliatory policies as a result of the automation treatment. The opposite is true for individuals who have never been unemployed before, as adding the interaction term renders the main coefficient positive. Preferences for social and nationalist policies remain unaffected. We observe no heterogenous effect regarding who should be responsible for helping affected workers (Table 9).

A look at the breakdown by types of public policies (Table A8) shows that the item "Increasing taxes on firms" drives this result. Individuals who have never been unemployed increase their support for the taxation of firms, while others do not (as reflected by the sum of 0.14 - 0.15). Hence, individuals that have never been unemployed seem to retaliate against firms in the form of an increase in support for corporate taxation[17]. Two interpretations are possible regarding the absence of reaction among individuals that have been unemployed before. They do not increase their demand for taxes (i) because they are more fearful of the potential negative consequences of an increase in taxation on their employment prospects or (ii) because they are already supportive of an increase in taxation regardless of the source of the shock. Table 1 provides evidence in favor of the latter, as individuals that have been unemployed are more likely to support increasing

[17]The interpretation of a rise in support for taxation as a retaliatory act is further supported by the lack of heterogeneous effect on the responsibility of firms to take care of displaced workers.

taxes on firms in the control group.

This result contrasts with Jeffrey and Matakos (2021)'s, who find that respondents affected by the COVID-19 crisis were more likely to support redistributive policies after their treatment. We first note that our results compare how people react to different shocks, one of unknown causes vs. one due to automation. Jeffrey and Matakos (2021) use a placebo control that does not mention any economic shock. Hence, they partly pick up an effect that is a reaction to the negative economic shock rather than automation being the driver. We show in Figure 1 that the support for social policies is already high in the control group and that having experienced economic hardship increases the support for financial assistance to workers (Table 1). Second, Jeffrey and Matakos (2021) leverage on a recent shock. Their survey takes place during the COVID pandemic and asks participants whether they have been laid off or temporarily suspended due to the COVID crisis. Our measure of economic vulnerability is much looser as we include respondents that have been unemployed at any point in their lives. Hence, the distress unemployment can cause is probably less vivid in respondents' minds.

On average, our heterogeneous analysis according to the previous experience of unemployment suggests it does not lead to more support for intervention in the case of automation.

Table 8: Heterogeneous effects by previous unemployment experience - Support for policies

	(1) Social Policies Index	(2) Retaliatory Policies Index	(3) Nationalist Policies Index
Automation Treatment	0.054	0.14**	0.042
	(0.73)	(1.97)	(0.56)
Automation Treatment × Unemployed before=1	-0.078	-0.15*	-0.11
	(-0.88)	(-1.86)	(-1.25)
Controls	Yes	Yes	Yes
Observations	2976	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Heterogeneous effects by previous unemployment experience - Responsibility to help affected workers

	(1) Government	(2) Civil Society	(3) Individuals	(4) Firms
Automation Treatment	0.053	-0.0074	0.0026	0.11
	(0.73)	(-0.10)	(0.03)	(1.42)
Automation Treatment × Unemployed before=1	0.027	0.0100	0.055	-0.15
	(0.31)	(0.11)	(0.61)	(-1.59)
Controls	Yes	Yes	Yes	Yes
Observations	2970	2972	2973	2973

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We then check whether our treatments increase participants' perceived vulnerability to an automation shock. In particular, we ask them to estimate the impact of new technologies on (i) them and their own job or career and (ii) American workers in general. Participants answer on a five-point Likert scale from very negative (=1) to very positive (=5).

Table 10 shows that, following the automation treatment, respondents are more likely to declare that technology negatively impacted American jobs but not their own job or career. Hence, while participants are more anxious following the treatment, they appear to view their own occupation as insulated from an automation shock. It echoes Smith and Anderson (2017) and Zhang (2019) who find that while Americans are worried about automation "in general", they feel relatively optimistic when it comes to their own occupation. Hence, as participants do not feel personally affected, they are less likely to have strong policy demands regarding automation.

Previous literature highlights that Americans appear to misattribute their blame of automation to immigrants and globalization (Wu, 2021; Zhang, 2019). This would be one interpretation as to why robot displacement increases support for radical right parties (Anelli et al., 2021; Frey et al., 2018). Our results so far do not point to an increase in demand for nationalist policies as a result of automation. Nevertheless, we also ask participants to evaluate how much globalization impacted their job and American jobs in general. We find that priming respondents about automation does not increase one's perceived vulnerability to import competition (see columns 3 and 4 in Table 10). Hence, any increase in anti-globalization sentiment following automation would likely be driven by a misidentification of the cause of the shock.

Finally, we check whether our automation treatment affects one's perception of previous job displacement. We aim to see whether our automation treatment can bias one's perception of "reality" and make participants more likely to think they have been previously affected by automation or globalization. In particular, we ask participants if they have previously lost their jobs to a robot or a foreign worker. We detect no effect, in line with previous results (Table 11).

Table 10: Effects on post-treatment views on own job and American jobs' vulnerability to automation and globalization

Impact of ...	(1) ...technology on own job	(2) ...technology on American jobs	(3) ...globalization on own job	(4) ...globalization on American job
Automation Treatment	-0.031	-0.083**	-0.040	-0.033
	(-0.78)	(-2.04)	(-0.98)	(-0.82)
Controls	Yes	Yes	Yes	Yes
Observations	2945	2945	2931	2939

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Effects on post-treatment declaration of job displacement by robots or foreign workers

	(1) Displaced by robot	(2) Displaced by foreign worker
Automation Treatment	-0.0082	0.012
	(-0.18)	(0.27)
Controls	Yes	Yes
Observations	2818	2814

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We identify two main mechanisms behind the average null effect of our automation treatment: fairness considerations and perceived vulnerability to automation. Participants do not perceive automation as unfair and find that firms are legitimate in replacing workers with robots. In addition, we find that while respondents update their average level of anxiety with regard to automation and its impact on American jobs, they are not more likely to feel personally threatened by robots. There might be a connection between the two mechanisms we identify. In particular, participants' fairness consideration might be more influenced by egotropic concerns rather than sociotropic ones.

3.4 Do views on government effectiveness and trust in government play a role?

We zoom in on the impact of government effectiveness and trust in government as additional mechanisms. Previous literature highlights that government efficacy plays a mediating role in the demand for government intervention (Alesina et al., 2018; Algan et al., 2011; Kuziemko et al., 2015; Yamamura, 2014).

We test this assumption and look at the potential impact of (i) views on government effectiveness and (ii) trust in government. We see the former as measuring views on the quality and competence of the government, while the latter measures confidence and lack of (corruption) suspicion. We give details below on how we measure both variables but note that the correlation between views on government effectiveness and trust in government is 0.43. Hence, both variables capture different dimensions of government efficacy.

Our focus on government effectiveness tests whether people dismiss government intervention because they see it as inefficient and incompetent or, on the contrary, whether firm beliefs in State efficiency trigger limited additional for public provision when a crisis occurs. Previous literature has already examined the link between public trust and the demand for public action (Kuziemko et al., 2015; Yamamura, 2014). In particular, Kuziemko et al. (2015) provide causal evidence that distrust in government inhibits support for government intervention even when concerns for inequality are high. Consistent with these findings, Table 1 shows that trust in government correlates with more support for regulation and taxation on firms.

Table 1 also indicates that views on government efficiency are essential determinants of support for public policies. As most research so far has focused on the role of trust in government in demand for redistribution, we emphasize government effectiveness and use a third treatment arm to study its impact.

3.4.1 Government effectiveness

In a third treatment arm, we first anchor respondents' views of government effectiveness at a high level and then provide them with the same automation treatment as in section 3.2. The second rows of Tables 12 and 13 display the result of the "automation + government effectiveness treatment"[18].

Table 12: Effect of the automation treatment on public policy preferences

	(1) Social Policies Index	(2) Retaliatory Policies Index	(3) Nationalist Policies Index
Automation Treatment	0.0016 (0.04)	0.032 (0.83)	-0.034 (-0.82)
Automation + Govt Effectiveness Treatment	-0.045 (-1.09)	-0.020 (-0.53)	-0.00031 (-0.01)
Controls	Yes	Yes	Yes
Observations	2976	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[18]Breakdown by type of public policy is available in Table A3

Table 13: Effect of the automation treatment on views on who should be responsible to help affected workers

	(1) Government	(2) Civil Society	(3) Individuals	(4) Firms
Automation Treatment	0.071*	0.039	0.0073	0.0028
	(1.77)	(0.94)	(0.17)	(0.07)
Automation + Govt Effectiveness Treatment	-0.016	0.032	-0.0035	-0.039
	(-0.38)	(0.75)	(-0.08)	(-0.92)
Controls	Yes	Yes	Yes	Yes
Observations	2970	2973	2973	2972

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Adding our government effectiveness treatment does not lead to any significant effect in support of public policies. Nevertheless, the sign flips on the social and retaliatory policies indices and becomes closer to zero for the nationalist policies index. This is indicative evidence that increasing government effectiveness reduces the demand for government intervention. In fact, a look at the breakdown of the effect by type of public policy shows that respondents are significantly less likely to support retraining programs[19]. In addition, anchoring views of government effectiveness at a high level cancels the positive effect of our automation treatment on the government's responsibility. These results highlight a potential mitigating role of government effectiveness in response to automation. We explore this channel further by looking at heterogeneous effects according to pre-treatment views on government efficiency and post-treatment updating of these views.

Before the treatment, we ask respondents to rate the government's efficiency in terms of public services and policy implementation. Respondents choose between not efficient at all, somewhat efficient, or very efficient[20]. We create a dummy variable equal to one if they answer very efficient and look at heterogeneous effects by pre-treatment views on government effectiveness.

Table 14 shows that reactions to the automation shock exhibit clear heterogeneous effects according to government efficiency views. People that view the government as efficient are less likely to support social, retaliatory, and nationalist policies following the automation treatment. The main coefficient becomes positive in the case of retaliatory policies, indicating that people who do not view the government as efficient are more likely to ask for retaliatory policies. A breakdown of the results by type of public policy (Table 16) shows this result is mainly driven by more support for taxing firms rather than regulation. Table 16 also indicates a negative interaction effect between automation and

[19]It is puzzling that this policy is the only one significantly affected, and we have no clear interpretation of it. One explanation could be that the level of support for retraining is particularly high in the control and would have more room for a negative revision.

[20]We take this question from Robinson et al. (1999)

government efficiency in the case of tariffs, but not immigration. In other words, people that view the government as efficient are less likely to support the implementation of tariffs following an automation shock. In contrast, their immigration policy views are not differentially affected.

These heterogeneous effects lose significance once we add the government effectiveness treatment, as the gap in pre-treatment views on government efficiency narrows.

Table 14: Heterogeneous effects by views on government effectiveness - Support for policies

	(1) Social Policies Index	(2) Retaliatory Policies Index	(3) Nationalist Policies Index
Automation Treatment	0.041	0.070*	-0.0033
	(0.97)	(1.74)	(-0.08)
Automation Treatment × Govt is efficient=1	-0.42***	-0.41***	-0.33*
	(-2.63)	(-2.89)	(-1.83)
Automation + Govt Effectiveness Treatment	-0.020	-0.0061	0.016
	(-0.47)	(-0.15)	(0.38)
Automation + Govt Effectiveness Treatment × Govt is efficient=1	-0.25*	-0.15	-0.16
	(-1.70)	(-1.11)	(-1.02)
Controls	Yes	Yes	Yes
Observations	2976	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Heterogeneous effects by views on government effectiveness - Responsibility to help affected workers

	(1) Government	(2) Civil Society	(3) Individuals	(4) Firms
Automation Treatment	0.083*	0.051	0.0099	0.0067
	(1.96)	(1.17)	(0.21)	(0.15)
Automation Treatment × Govt is efficient=1	-0.12	-0.13	-0.025	-0.043
	(-0.83)	(-0.83)	(-0.16)	(-0.28)
Automation + Govt Effectiveness Treatment	0.0016	0.048	0.0060	-0.041
	(0.04)	(1.09)	(0.13)	(-0.89)
Automation + Govt Effectiveness Treatment × Govt is efficient=1	-0.18	-0.17	-0.097	0.012
	(-1.29)	(-1.14)	(-0.68)	(0.09)
Controls	Yes	Yes	Yes	Yes
Observations	2970	2973	2973	2972

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Breakdown of government efficiency heterogeneous effects by type of public policy

	(1) Retraining	(2) Financial Assistance	(3) Regulate	(4) Tax Firms	(5) Restrict Immigration	(6) Tariffs
Automation Treatment	0.0082	0.060	0.048	0.076*	-0.011	0.0048
	(0.19)	(1.40)	(1.14)	(1.80)	(-0.27)	(0.11)
Automation Treatment × Govt is efficient=1	-0.37**	-0.37**	-0.36***	-0.36**	-0.14	-0.40**
	(-2.35)	(-2.33)	(-2.63)	(-2.30)	(-0.84)	(-2.29)
Automation + Govt Effectiveness Treatment	-0.069	0.027	-0.017	0.0063	0.031	-0.0033
	(-1.51)	(0.62)	(-0.40)	(0.15)	(0.76)	(-0.07)
Automation + Govt Effectiveness Treatment × Govt is efficient=1	-0.25	-0.21	-0.20	-0.062	-0.12	-0.16
	(-1.58)	(-1.42)	(-1.55)	(-0.42)	(-0.75)	(-0.99)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2976	2977	2977	2977	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We also test whether the treatments affect views on government effectiveness and, for comparison purposes, public trust. To limit experimenter demand, we use a different question from our pre-treatment one and place it toward the end of the survey. Following Pew's American Trends Panel 2019, we ask respondents to choose between two statements: "*Government is almost always wasteful and inefficient*" and "*Government often does a better job than people give it credit for.*" We create a dummy equal to one if respondents choose the latter. Our measure of trust in government is very similar to the World Value Survey's and asks respondents how much confidence they have in the federal government on a four-point Likert scale. To reduce experiment demand, we also include other organizations in the list, making it less obvious we focus on trust in government [21].

Table 17 provides suggestive evidence that the automation shock lowers views on government effectiveness, although the coefficient fails to be significant at the 10% level. Interestingly, trust in the government remains unaffected by our automation treatment. Unsurprisingly, our government effectiveness treatment leads to an apparent increase in post-treatment government effectiveness. It also seems to increase trust in the government marginally, but the result is not significant.

[21] See appendix B for the exact wording

Table 17: Effects on post-treatment views on government effectiveness and public trust

	(1) Post-treatment govt effectiveness	(2) Post-treatment trust in govt
Automation Treatment	-0.029	-0.015
	(-1.54)	(-0.43)
Automation + Govt Effectiveness Treatment	0.050**	0.043
	(2.53)	(1.21)
Controls	Yes	Yes
Observations	2955	2955

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These results show that views on government effectiveness play a significant role in the demand for government intervention. In particular, individuals that view the government as efficient are less likely to see a need for government intervention in the face of automation. This mechanism is an unlikely explanation for the low backlash against automation in the US, as less than 10% see the government as "very efficient" in our sample. Nevertheless, this channel could be important in explaining different reactions across countries.

3.4.2 Trust in government

As shown in Table 17, individuals do not significantly update their level of public trust following the treatments. We also test for heterogeneous effects according to pre-treatment levels of confidence in the government. We use a different question than in Table 17 and ask respondents "How much of the time do you think you can trust the federal government in Washington to do what is right?"[22]. We code it as a dummy equal to one if the respondent answers "Most of the time" or "Just about always" and interact it with our treatment variable. We find no heterogeneous effects in Table 19 and the first part of Table 18. The automation + government effectiveness case results are interesting: the interaction of trust in government with the treatment leads to a negative coefficient. Table 20 indicates that views on immigration policies drive this result. In particular, individuals with low trust in government subject to the favorable government effectiveness treatment first and then the automation prime increase their support for restricting immigration by 0.09 of a standard deviation. On the contrary, the average effect for individuals with high trust in government is negative (0.092-0.27). Hence, the interaction of government effectiveness and trust appears to play a part in the increase in anti-immigration sentiment following robot displacement.

[22]This question is a classic measure of trust in government used in the General Social Survey, Pew's survey on public trust in government, or the Michigan Public Policy Survey.

Table 18: Heterogeneous effects trust in government - Support for policies

	(1) Social Policies Index	(2) Retaliatory Policies Index	(3) Nationalist Policies Index
Automation Treatment	0.029	0.059	-0.031
	(0.60)	(1.30)	(-0.66)
Automation Treatment × Trusts the govt=1	-0.10	-0.099	0.0019
	(-1.13)	(-1.17)	(0.02)
Automation + Govt Effectiveness Treatment	-0.029	0.0073	0.057
	(-0.60)	(0.16)	(1.24)
Automation + Govt Effectiveness Treatment × Trusts the govt=1	-0.054	-0.098	-0.21**
	(-0.58)	(-1.16)	(-2.26)
Controls	Yes	Yes	Yes
Observations	2976	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Heterogeneous effects trust in government - Responsibility to help affected workers

	(1) Government	(2) Civil Society	(3) Individuals	(4) Firms
Automation Treatment	0.066	0.044	-0.013	-0.034
	(1.35)	(0.89)	(-0.26)	(-0.67)
Automation Treatment × Trusts the govt=1	0.021	-0.016	0.076	0.14
	(0.25)	(-0.17)	(0.79)	(1.46)
Automation + Govt Effectiveness Treatment	-0.010	0.048	-0.018	-0.064
	(-0.21)	(0.95)	(-0.34)	(-1.24)
Automation + Govt Effectiveness Treatment × Trusts the govt=1	-0.021	-0.060	0.049	0.084
	(-0.23)	(-0.65)	(0.53)	(0.91)
Controls	Yes	Yes	Yes	Yes
Observations	2970	2973	2973	2972

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Breakdown of trust heterogeneous effects by type of public policy

	(1) Retraining	(2) Financial Assistance	(3) Regulate	(4) Tax Firms	(5) Restrict Immigration	(6) Tariffs
Automation Treatment	-0.0016	0.049	0.050	0.055	-0.0079	-0.042
	(-0.03)	(1.00)	(1.04)	(1.15)	(-0.17)	(-0.84)
Automation Treatment × Trusts the govt=1	-0.093	-0.088	-0.13	-0.043	-0.046	0.045
	(-1.00)	(-0.96)	(-1.48)	(-0.48)	(-0.48)	(0.46)
Automation + Govt Effectiveness Treatment	-0.078	0.019	-0.0075	0.021	0.092**	0.0082
	(-1.50)	(0.39)	(-0.16)	(0.44)	(2.02)	(0.17)
Automation + Govt Effectiveness Treatment × Trusts the govt=1	-0.052	-0.043	-0.099	-0.074	-0.27***	-0.10
	(-0.53)	(-0.46)	(-1.16)	(-0.83)	(-2.85)	(-1.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2976	2977	2977	2977	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Overall, we find that public trust plays little role in explaining participants' reaction to automation, while positive views on government efficiency reduce the demand for public policies. The latter suggests that institutional settings matter when citizens formulate their response to an automation shock.

3.5 The case of nationalist policies

Our results show that automation does not affect the demand for government intervention, and, in particular, we find no increase in support for nationalist policies. This contrasts with Anelli et al. (2021), Frey et al. (2018), Gingrich (2019), and Im et al. (2019) who identify a relation between automation and support for extreme right-wing candidates at the macro level. Our result on the interactive effect of government effectiveness with trust in government provides a first element of response, yet it is unlikely to be the main explanation. Instead, we focus on the misattribution hypothesis highlighted by Zhang (2019) and Wu (2021). Indeed, the gap between the average null effect we obtain and observational studies could be due to respondents misidentifying the source of their displacement. In other words, respondents displaced by robots might mistakenly think that immigration or globalization is the cause of their job loss. Such a hypothesis appears likely as automation is not as easily identifiable as an import competition shock and as there is a strong interdependence between globalization and technological advancement (Wang, 2021).

We use our questions on post-treatment declaration of job displacement to try to answer this question. In particular, we restrict our survey to the control group and regress the dummy variables for individuals that declare to have been displaced by robots or by foreign workers on our nationalist policies, along with our usual set of controls[23]. Table 21 shows a clear positive relation between robot displacement and anti-immigration and anti-trade sentiments in our control group. The effect is sizeable. Individuals that declare to have been displaced by robots are 0.42 of a standard deviation ($p<0.01$) more likely to support restrictions on immigration and 0.27 of a standard deviation more likely to support tariffs ($p<0.1$). A correlation is also visible for those declaring foreign workers have displaced them, and the coefficients are respectively 0.25 of standard deviation ($p<0.01$) and 0.28 of standard deviation ($p<0.01$).

The significant correlation disappears once we specify that the source of the shock is automation. Tables 22 and 23 present our results for the automation and the automation + government effectiveness treatment group. Figures 5 and 6 show the average support

[23] We note that post-treatment declaration of job displacement by robots or foreign workers are "bad controls" as they might have been affected by the treatment. Yet we are not worried about that for two reasons. First, we capture an effect in the control group, not the treated groups. Second, Table 11 shows that our treatments do not affect these declarations.

for nationalist policies for displaced respondents and non-displaced participants by treatment group. The figures show how the gap between displaced and non-displaced workers closes once we provide them with the information that automation caused the lay-offs. This is evidence that part of the effect captured in macro-level observational studies is probably driven by misperceptions about the cause of the shock among those displaced by globalization or automation.

Table 21: Covariates of support for nationalist policies in the control group

	(1) Nationalist Policies Index	(2) Nationalist Policies Index	(3) Restrict Immigration	(4) Restrict Immigration	(5) Tariffs	(6) Tariffs
Displaced by robot	0.41***		0.42***		0.27*	
	(2.97)		(3.42)		(1.89)	
Displaced by foreign worker		0.32***		0.25***		0.28***
		(3.20)		(2.59)		(2.63)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	906	869	906	869	906	869

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Covariates of support for nationalist policies in the automation group

	(1) Nationalist Policies Index	(2) Nationalist Policies Index	(3) Restrict Immigration	(4) Restrict Immigration	(5) Tariffs	(6) Tariffs
Displaced by robot	0.20		0.16		0.17	
	(1.37)		(1.24)		(1.20)	
Displaced by foreign worker		0.17		0.26**		0.044
		(1.55)		(2.41)		(0.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	904	874	904	874	904	874

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Covariates of support for nationalist policies in the automation + government effectiveness group

	(1) Nationalist Policies Index	(2) Nationalist Policies Index	(3) Restrict Immigration	(4) Restrict Immigration	(5) Tariffs	(6) Tariffs
Displaced by robot	0.053		0.12		-0.024	
	(0.39)		(1.00)		(-0.16)	
Displaced by foreign worker		0.030		0.075		-0.021
		(0.29)		(0.73)		(-0.18)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	902	882	902	882	902	882

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 5: **Average support for nationalist policies for respondents displaced by robots and non-displaced participants by treatment group**

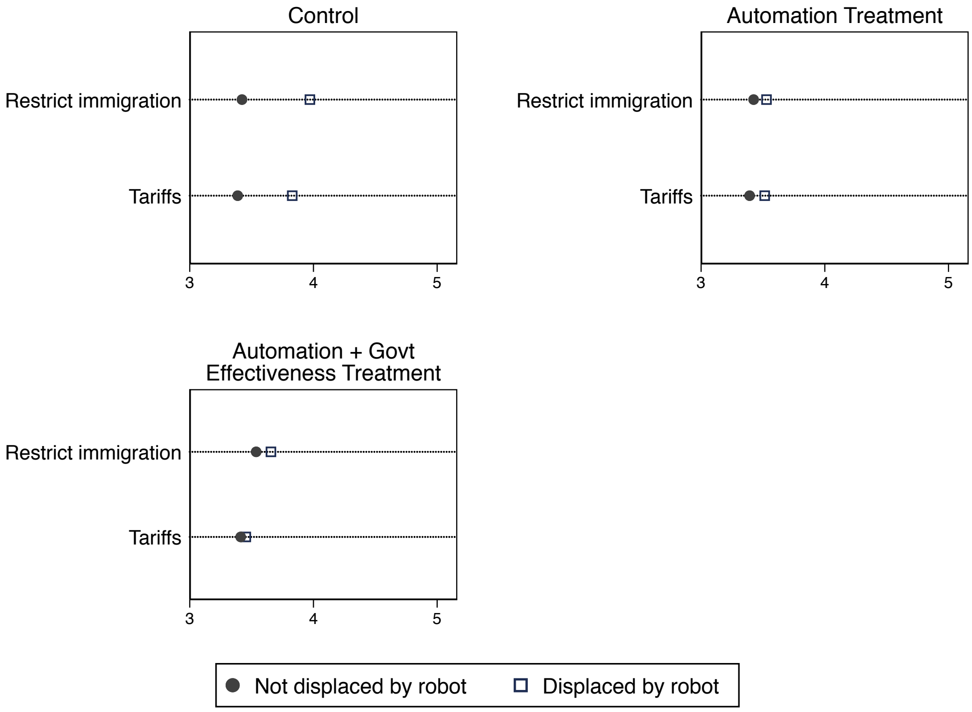
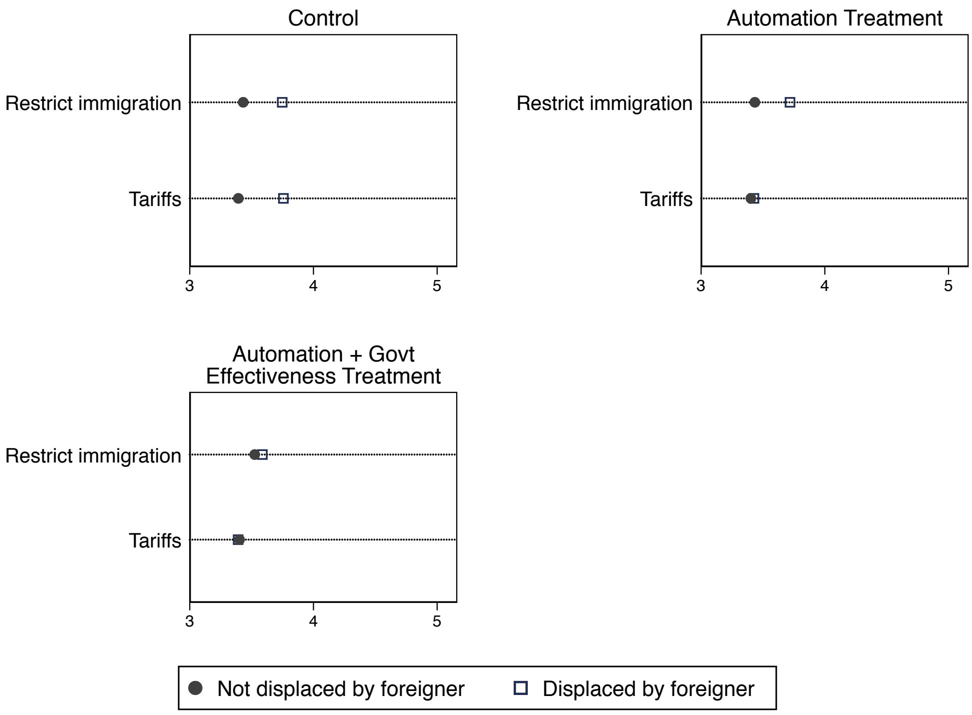


Figure 6: **Average support for nationalist policies for respondents displaced by foreigner workers and non-displaced participants by treatment group**



3.6 Additional heterogeneous effects

As specified in the pre-analysis plan, we also investigate whether survey participants respond differently to the treatments according to political affiliation and education level.

As visible in Table 24, Democrats and Independents are less likely to support social policies in the case of the automation + government effectiveness treatment but not the automation one[24]. This can seem counter-intuitive as they are more likely to support social policies to address labor shocks in general (Table 1). One interpretation could be that they are more receptive to the government effectiveness treatment and therefore are less likely to see a need to demand social policies when the government is effective. Unsurprisingly, Democrats are less likely than Republicans to think the responsibility to help affected workers falls on the individual following the automation treatment (Table 25). The effect disappears once the government effectiveness treatment is added.

We find no evidence of heterogeneous effects by education level in Tables 26 and 27. A look at the breakdown by type of public policies shows striking heterogeneous reactions regarding taxes (Table A10). Respondents with no college degree are more likely to support taxes on firms after the automation treatment, while those with a college degree or a postgraduate degree are less likely. The government effectiveness treatment reduces the effect.

Table 24: Heterogeneous effects by political affiliation - Support for policies

	(1) Social Policies Index	(2) Retaliatory Policies Index	(3) Nationalist Policies Index
Automation Treatment	0.083	0.029	0.011
	(1.20)	(0.44)	(0.17)
Automation Treatment × Democrat	-0.14	-0.039	-0.069
	(-1.60)	(-0.46)	(-0.78)
Automation Treatment × Independent	-0.13	0.15	-0.17
	(-0.85)	(1.10)	(-1.16)
Automation + Govt Effectiveness Treatment	0.098	0.0085	0.021
	(1.42)	(0.13)	(0.33)
Automation + Govt Effectiveness Treatment × Democrat	-0.21**	-0.086	-0.082
	(-2.33)	(-1.02)	(-0.93)
Automation + Govt Effectiveness Treatment × Independent	-0.38***	0.14	0.097
	(-2.83)	(1.02)	(0.71)
Controls	Yes	Yes	Yes
Observations	2976	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[24]The breakdown by type of public policy is included in Table A9

Table 25: Heterogeneous effects by political affiliation - Responsibility to help affected workers

	(1) Government	(2) Civil Society	(3) Individuals	(4) Firms
Automation Treatment	0.097	0.041	0.11*	0.090
	(1.52)	(0.70)	(1.82)	(1.33)
Automation Treatment × Democrat	-0.059	-0.086	-0.16**	-0.12
	(-0.73)	(-1.14)	(-1.98)	(-1.37)
Automation Treatment × Independent	-0.047	-0.11	-0.029	-0.15
	(-0.35)	(-0.88)	(-0.21)	(-1.04)
Automation + Govt Effectiveness Treatment	-0.021	0.040	0.063	0.043
	(-0.32)	(0.66)	(1.00)	(0.63)
Automation + Govt Effectiveness Treatment × Democrat	-0.011	-0.13*	-0.093	-0.070
	(-0.14)	(-1.75)	(-1.11)	(-0.78)
Automation + Govt Effectiveness Treatment × Independent	0.098	-0.14	0.076	-0.12
	(0.77)	(-1.19)	(0.56)	(-0.86)
Controls	Yes	Yes	Yes	Yes
Observations	2970	2972	2973	2973

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26: Heterogeneous effects by education - Support for policies

	(1) Social Policies Index	(2) Retaliatory Policies Index	(3) Nationalist Policies Index
Automation Treatment	-0.00094	0.067	-0.045
	(-0.02)	(1.38)	(-0.87)
Automation Treatment × College degree	-0.025	-0.069	0.060
	(-0.27)	(-0.81)	(0.65)
Automation Treatment × Postgraduate degree	0.090	-0.13	-0.056
	(0.66)	(-0.94)	(-0.37)
Automation + Govt Effectiveness Treatment	-0.037	0.022	0.019
	(-0.71)	(0.46)	(0.37)
Automation + Govt Effectiveness Treatment × College degree	-0.032	-0.13	-0.036
	(-0.34)	(-1.52)	(-0.39)
Automation + Govt Effectiveness Treatment × Postgraduate degree	0.015	-0.050	-0.081
	(0.11)	(-0.37)	(-0.58)
Controls	Yes	Yes	Yes
Observations	2976	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 27: Heterogeneous effects by education - Responsibility to help affected workers

	(1) Government	(2) Civil Society	(3) Individuals	(4) Firms
Automation Treatment	0.041	-0.0085	0.021	-0.017
	(0.85)	(-0.19)	(0.43)	(-0.31)
Automation Treatment × College degree	0.061	0.056	0.012	0.068
	(0.74)	(0.71)	(0.14)	(0.72)
Automation Treatment × Postgraduate degree	0.037	-0.046	0.091	0.060
	(0.32)	(-0.44)	(0.76)	(0.46)
Automation + Govt Effectiveness Treatment	0.0077	-0.0099	0.027	-0.023
	(0.16)	(-0.22)	(0.53)	(-0.42)
Automation + Govt Effectiveness Treatment × College degree	-0.044	-0.056	-0.035	0.077
	(-0.51)	(-0.68)	(-0.40)	(0.82)
Automation + Govt Effectiveness Treatment × Postgraduate degree	-0.096	-0.071	0.099	-0.028
	(-0.80)	(-0.70)	(0.82)	(-0.23)
Controls	Yes	Yes	Yes	Yes
Observations	2970	2972	2973	2973

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.7 Threats to validity and robustness checks

3.7.1 Experimenter demand

Issues regarding experimenter demand effects (EDE) in survey settings have gained increasing attention over recent years (De Quidt et al., 2018; Mummolo and Peterson, 2019). It seems unlikely that our survey experiment suffers from EDE for two reasons. The first is that our average main result is a null effect. Had our survey experiment triggered EDE, we should have seen some positive coefficients in section 3.1. Second, we use an active control group in which participants are treated with a negative labor market shock. This reduces the probability of EDE in our setting as highlighted by Haaland et al. (Forthcoming).

3.7.2 Within-survey attrition

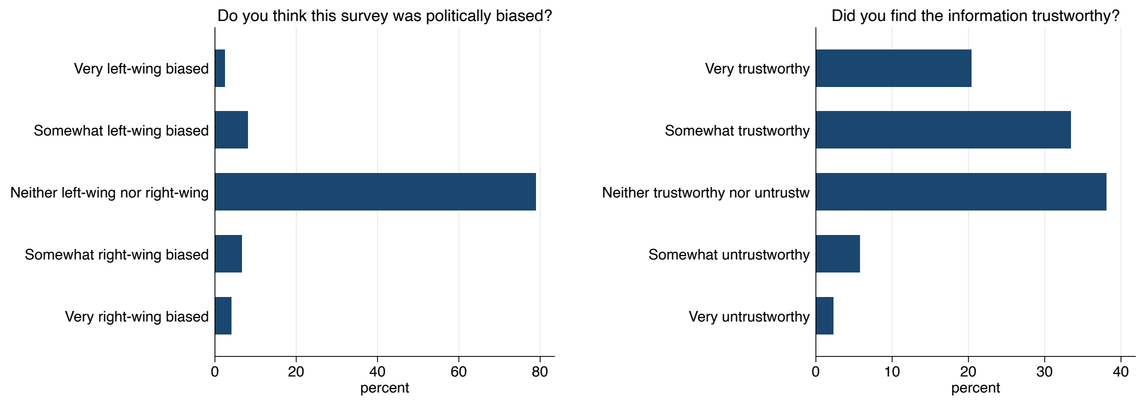
There is attrition as participants progress toward the end of the survey. The attrition rate remains very low: 23 participants fail to answer all questions after the treatment. This corresponds to a 0.77% attrition rate. Attrition does not correlate with the assignment to a specific treatment group, and our results are robust to restricting our sample only to those that answered all questions.

3.7.3 Perception of the research setting

At the end of the survey, we measure participants' perceptions of the treatment and survey questions.

The vast majority of respondents do not think that the survey was politically biased as close to 80% of respondents answer that the survey was "neither left-wing nor right-wing" (see left panel of figure 7). In addition, more than 90% of participants found the information provided in the survey "Very trustworthy", "Somewhat trustworthy", or "Neither trustworthy nor untrustworthy" (figure 7, right panel).

Figure 7: Perception of the survey



We also test whether respondents' views differ by treatment group and do not find evidence of it (Table 28).

Table 28: Perception of the survey by treatment group

	(1) Survey Political Bias	(2) Survey Trustworthiness
Automation Treatment	-0.03	0.05
	(-1.15)	(1.29)
Automation + Govt Effectiveness Treatment	-0.01	0.05
	(-0.52)	(1.29)
Controls	Yes	Yes
Observations	2954	2954

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.7.4 Multiple hypothesis testing

In our pre-analysis plan, we highlighted the risk of multiple hypothesis testing as we looked at our treatments' effect on six types of public policies and four entities that could be held responsible. We intended to address this issue by creating indices a la Anderson (2008) and controlling for the false discovery rate.

On average, we do not obtain any significant effect in our baseline specification, which enables us to discard the issue of multiple hypothesis testing.

4 Conclusion

Using a large representative sample of the US population, our results confirm an average null effect of an automation prime on public policy preferences. We test for different mechanisms and identify fairness considerations and perceived vulnerability to automation as explanatory channels.

We show that respondents do not see automation as particularly unfair to workers and think that firms are justified in automating. In addition, our automation treatment increases respondents' anxiety regarding automation's impact on American jobs in general but not on their own occupations. Hence, while an automation prime increases average anxiety levels, respondents do not feel personally threatened by robots.

Finally, we look at the case of nationalist policies and find that respondents are less likely to support nationalist policies once they know the cause of the shock is automation. This suggests that misperceptions about the cause of the shock have partly driven the increase in anti-trade and anti-immigration sentiment following automation.

Overall, this study bridges a gap in the literature by identifying explanatory channels behind the limited demand for more redistribution and increased support for nationalist policies in the face of automation.

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A Additional Tables

Table A1: Socio-demographic characteristics of the sample compared to the American Community Survey

Demographic Characteristics	Own Survey	ACS 5-Year Estimates (2020)
Female	50.3%	50.8%
18-25 y.o.	9%	12%
25-34 y.o.	17.5%	18%
35-44 y.o.	18%	16.3%
45-54 y.o.	19%	16.4%
55-64 y.o.	17.5%	16.6%
$\geq$65 y.o.	18.7%	20.7%
White	76.8%	75.1%
Black	12.7%	14.2%
Asian	5%	6.8%
Other	7.2%	9.6%
Less than HS or HS only	35.6%	38%
Some college, no degree	24.9%	21%
Associate or college degree	28.1%	28%
Graduate or professional degree	11.41%	12.7%
$0 to $14,999	11.5%	9.9%
$15,000 to $34,999	19.3%	17.1%
$35,000 to $49,999	12.5%	12%
$50,000 to $74,999	18.3%	17.2%
$75,000 to $99,999	12.7%	12.8%
$100,000 to $149,999	14.5%	15.6%
$150,000 or more	10.2%	15.4%
North East	15.7%	13.6%
Mid West	23.5%	28.1%
West	17.8%	15.8%
South	43.5%	42.3%

Table A2: Balance across the treatment and control groups

Variable	(1) Control N	(1) Control Mean	(2) Treatment 1 N	(2) Treatment 1 Mean	(3) Treatment 2 N	(3) Treatment 2 Mean	T-test P-value (1)-(2)	T-test P-value (1)-(3)	T-test P-value (2)-(3)
Female	989	0.485	996	0.508	992	0.510	0.312	0.271	0.927
Age	989	47.220	996	47.984	992	47.395	0.283	0.805	0.406
Household Income	989	73393	996	72275	992	71164	0.659	0.372	0.657
No college	989	0.607	996	0.591	992	0.610	0.487	0.884	0.400
College degree	989	0.288	996	0.296	992	0.268	0.695	0.320	0.165
Postgraduate degree	989	0.105	996	0.112	992	0.122	0.602	0.238	0.509
Born in the US	989	0.945	996	0.949	992	0.945	0.736	0.934	0.674
Caucasian/White	989	0.772	996	0.747	992	0.784	0.184	0.528	0.050
Black/African American	989	0.133	996	0.134	992	0.112	0.997	0.143	0.142
Asian/Asian American	989	0.042	996	0.056	992	0.049	0.157	0.462	0.496
Hispanic	989	0.091	996	0.083	992	0.081	0.545	0.411	0.827
Married	989	0.518	996	0.527	992	0.512	0.675	0.803	0.503
Single	989	0.325	996	0.303	992	0.330	0.305	0.810	0.205
Divorced	989	0.116	996	0.131	992	0.114	0.335	0.869	0.258
Widowed	989	0.041	996	0.039	992	0.044	0.795	0.750	0.563
Nb of children	989	0.645	996	0.605	992	0.585	0.371	0.172	0.639
Full-time employee	989	0.405	996	0.398	992	0.390	0.721	0.486	0.733
Part-time employee	989	0.104	996	0.098	992	0.092	0.671	0.353	0.613
Self-empl. w dependent workers	989	0.033	996	0.034	992	0.046	0.924	0.139	0.165
Self-empl. w/o dependent workers	989	0.018	996	0.021	992	0.024	0.644	0.355	0.641
Unemployed	989	0.077	996	0.077	992	0.091	0.969	0.265	0.281
Student	989	0.024	996	0.026	992	0.028	0.794	0.582	0.771
Not in the labor force	989	0.338	996	0.345	992	0.329	0.719	0.668	0.430
Republican	989	0.376	996	0.387	992	0.399	0.633	0.293	0.564
Democrat	989	0.503	996	0.487	992	0.442	0.488	0.007	0.042
Independent	989	0.091	996	0.101	992	0.130	0.432	0.006	0.046
Mid West	989	0.226	996	0.232	992	0.235	0.773	0.658	0.876
North East	989	0.174	996	0.146	992	0.155	0.085	0.263	0.547
West	989	0.179	996	0.176	992	0.173	0.849	0.745	0.892
South	989	0.421	996	0.447	992	0.436	0.240	0.476	0.644
Trusts the govt	989	0.295	996	0.244	992	0.258	0.010	0.064	0.469
Govt is efficient	989	0.096	996	0.089	992	0.099	0.607	0.838	0.472
Inequality is unfair	989	0.632	996	0.624	992	0.619	0.731	0.550	0.799
Unemployed before	989	0.697	996	0.648	992	0.661	0.020	0.092	0.521
F-test of joint significance (p-value)							0.484	0.203	0.793

Figure A1: Summary of the survey flow

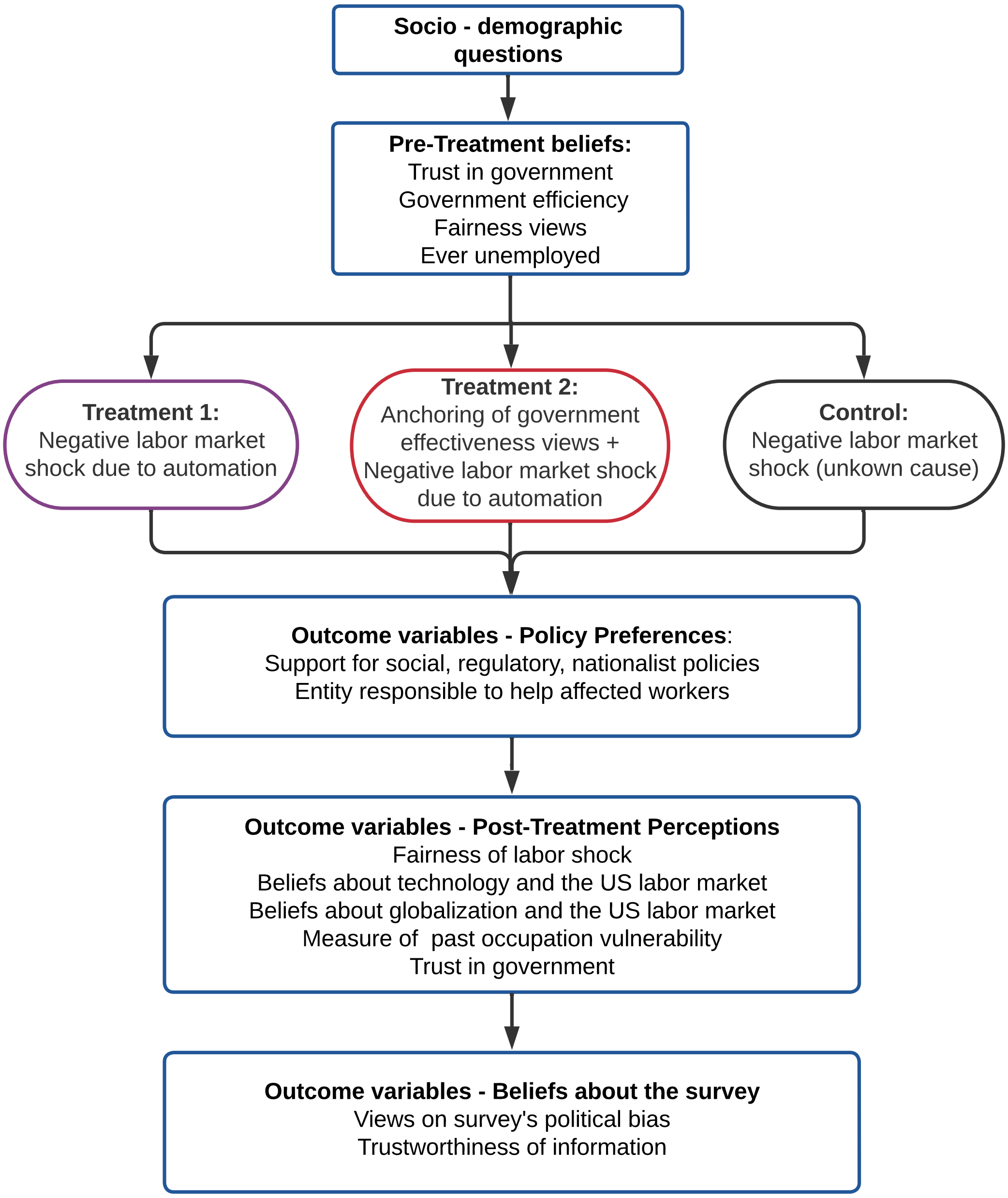

Table A3: Breakdown by type of public policy

	(1) Retraining	(2) Financial Assistance	(3) Regulate	(4) Tax Firms	(5) Restrict Immigration	(6) Tariffs
Automation Treatment	-0.027	0.026	0.015	0.043	-0.024	-0.032
	(-0.64)	(0.62)	(0.36)	(1.05)	(-0.60)	(-0.74)
Automation + Govt Effectiveness Treatment	-0.093**	0.0066	-0.036	0.00040	0.020	-0.019
	(-2.12)	(0.16)	(-0.90)	(0.01)	(0.49)	(-0.43)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2976	2977	2977	2977	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Effect of the automation treatment on public policy preferences-No controls

	(1) Social Policies Index	(2) Retaliatory Policies Index	(3) Nationalist Policies Index
Automation Treatment	-0.017	0.011	-0.024
	(-0.38)	(0.25)	(-0.53)
Automation + Govt Effectiveness Treatment	-0.068	-0.056	0.015
	(-1.54)	(-1.28)	(0.33)
Controls	No	No	No
Observations	2976	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Breakdown by type of public policy - No controls

	(1) Retraining	(2) Financial Assistance	(3) Regulate	(4) Tax Firms	(5) Restrict Immigration	(6) Tariffs
Automation Treatment	-0.039	0.0057	-0.0068	0.026	-0.011	-0.028
	(-0.88)	(0.13)	(-0.15)	(0.59)	(-0.24)	(-0.63)
Automation + Govt Effectiveness Treatment	-0.11**	-0.015	-0.065	-0.034	0.052	-0.024
	(-2.44)	(-0.35)	(-1.48)	(-0.76)	(1.15)	(-0.54)
Controls	No	No	No	No	No	No
Observations	2976	2977	2977	2977	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Responsibility to help displaced workers - No controls

	(1) Government	(2) Civil Society	(3) Individuals	(4) Firms
Automation Treatment	0.047	0.024	0.0043	-0.0079
	(1.08)	(0.54)	(0.10)	(-0.18)
Automation + Govt Effectiveness Treatment	-0.038	0.021	-0.0094	-0.058
	(-0.86)	(0.47)	(-0.21)	(-1.30)
Controls	No	No	No	No
Observations	2970	2973	2973	2972

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Breakdown of fairness heterogeneous effects by type of public policy

	(1) Retraining	(2) Financial Assistance	(3) Regulate	(4) Tax Firms	(5) Restrict Immigration	(6) Tariffs
Automation Treatment	0.022	0.016	0.057	0.10	0.025	0.011
	(0.29)	(0.22)	(0.84)	(1.50)	(0.41)	(0.16)
Automation Treatment × Inequality is unfair=1	-0.077	0.015	-0.067	-0.092	-0.078	-0.069
	(-0.85)	(0.17)	(-0.80)	(-1.10)	(-0.97)	(-0.78)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2976	2977	2977	2977	2977	2977

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: Breakdown of economic hardship heterogeneous effects by type of public policy

	(1) Retraining	(2) Financial Assistance	(3) Regulate	(4) Tax Firms	(5) Restrict Immigration	(6) Tariffs
Automation Treatment	-0.027	0.11	0.088	0.16**	0.054	0.018
	(-0.35)	(1.53)	(1.22)	(2.14)	(0.76)	(0.23)
Automation Treatment × Unemployed before=1	-0.00032	-0.13	-0.11	-0.17*	-0.12	-0.074
	(-0.00)	(-1.46)	(-1.26)	(-1.90)	(-1.36)	(-0.78)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2976	2977	2977	2977	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Breakdown of political heterogeneous effects by type of public policy

	(1) Retraining	(2) Financial Assistance	(3) Regulate	(4) Tax Firms	(5) Restrict Immigration	(6) Tariffs
Automation Treatment	0.054 (0.75)	0.089 (1.23)	-0.0031 (-0.04)	0.056 (0.81)	0.024 (0.40)	-0.0038 (-0.05)
Automation Treatment × Democrat	-0.13 (-1.40)	-0.12 (-1.33)	0.012 (0.14)	-0.082 (-0.93)	-0.070 (-0.82)	-0.047 (-0.50)
Automation Treatment × Independent	-0.16 (-1.04)	-0.064 (-0.43)	0.086 (0.58)	0.19 (1.28)	-0.14 (-0.95)	-0.14 (-0.97)
Automation + Govt Effectiveness Treatment	0.038 (0.53)	0.13* (1.80)	-0.023 (-0.35)	0.039 (0.59)	0.045 (0.73)	-0.0067 (-0.10)
Automation + Govt Effectiveness Treatment × Democrat	-0.17* (-1.74)	-0.20** (-2.20)	-0.047 (-0.54)	-0.11 (-1.22)	-0.076 (-0.88)	-0.063 (-0.67)
Automation + Govt Effectiveness Treatment × Independent	-0.47*** (-3.26)	-0.22 (-1.59)	0.077 (0.55)	0.17 (1.20)	0.090 (0.64)	0.075 (0.54)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2976	2977	2977	2977	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Breakdown of education heterogeneous effects by type of public policy

	(1) Retraining	(2) Financial Assistance	(3) Regulate	(4) Tax Firms	(5) Restrict Immigration	(6) Tariffs
Automation Treatment	-0.029 (-0.56)	0.026 (0.46)	-0.011 (-0.18)	0.16*** (2.59)	-0.053 (-0.78)	-0.040 (-0.66)
Automation Treatment × College degree	-0.012 (-0.13)	-0.031 (-0.31)	0.088 (0.83)	-0.25** (-2.28)	0.074 (0.64)	0.049 (0.45)
Automation Treatment × Postgraduate degree	0.065 (0.50)	0.095 (0.66)	0.021 (0.13)	-0.32* (-1.70)	-0.0027 (-0.01)	-0.098 (-0.57)
Automation + Govt Effectiveness Treatment	-0.074 (-1.40)	0.0075 (0.14)	-0.040 (-0.67)	0.093 (1.46)	0.061 (0.94)	-0.015 (-0.24)
Automation + Govt Effectiveness Treatment × College degree	-0.030 (-0.33)	-0.025 (-0.26)	-0.024 (-0.23)	-0.27** (-2.45)	-0.088 (-0.75)	0.0047 (0.04)
Automation + Govt Effectiveness Treatment × Postgraduate degree	-0.030 (-0.22)	0.058 (0.40)	0.025 (0.16)	-0.14 (-0.81)	-0.11 (-0.59)	-0.062 (-0.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2976	2977	2977	2977	2977	2977

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Survey Experiment Questions

B.1 Default demographic questions

- What is your gender?

  - Male
  - Female
  - Non-binary / third gender
  - Prefer not to say

- How old are you?
  - 18 to 24
  - 25 to 34
  - 35 to 44
  - 45 to 54
  - 55 to 64
  - above 64

- How would you describe your ethnicity/race? Please check all that apply.
  - White
  - African American/Black
  - Hispanic/Latino
  - Asian/Asian American
  - Other (please specify)

- In which state do you currently reside? [DROPDOWN LIST]

- Were you born in the United States?
  - Yes
  - No

- Please indicate your marital status
  - Married
  - Single
  - Divorced
  - Widowed

- How many children (aged 18 y.o. or younger) live with you in your household?

  - None
  - 1
  - 2
  - 3
  - 4
  - 5 or more

B.2 Education and Occupation questions

- What is the highest level of school you have completed or the highest degree you have received?
  - Less than high school
  - High school graduate (high school diploma or equivalent including GED)
  - Some college but no degree
  - Associate degree in college (2-year)
  - Bachelor's degree in college (4-year)
  - Master's degree
  - Doctoral degree
  - Professional degree (JD, MD, MBA)
- Have you ever been unemployed in the past?
  - Yes
  - No
- Which statement best describes your current employment status?
  - Full-time employee
  - Part-time employee
  - Self-employed or small business owner with dependent workers
  - Self-employed or small business owner without dependent workers
  - Unemployed and looking for work
  - Student
  - Not in labor force (for example: retired, full-time parent, or disabled)

- Which of the following best describes your employer? If you hold more than one job describe the one at which you worked the most hours last week. If you're unemployed describe your most recent employment.
  - Private sector: For-profit company or organization
  - Private sector: Non-profit organization (including tax-exempt and charitable organizations)
  - Local government (for example: city or county school district)
  - State government
  - Active duty US Armed Forces or Commissioned Corps
  - Federal government
- Which of the following industries most closely matches the one in which you are employed, or were employed most recently?
  - Agriculture, forestry, fishing, or hunting
  - Mining, quarrying, or oil and gas extraction
  - Construction
  - Manufacturing
  - Wholesale trade
  - Retail trade
  - Transportation or warehousing
  - Utilities
  - Information
  - Finance or insurance
  - Real estate or rental and leasing
  - Professional, scientific or technical services
  - Management of companies or enterprises
  - Admin, support, waste management or remediation services
  - Educational services
  - Health care or social assistance
  - Arts, entertainment or recreation
  - Accommodation or food services

  - Other services (except public administration)
  - Public Administration
  - Other (please specify)

- What is your main occupation? (For example: 4th grade teacher, entry-level plumber etc.) If unemployed, enter the main occupation you had most recently? [OPEN TEXT BOX]

- What was your household income before taxes in 2020?
  - Less than $10,000
  - $10,000 to $14,999
  - $15,000 to $24,999
  - $25,000 to $34,999
  - $35,000 to $49,999
  - $50,000 to $74,999
  - $75,000 to $99,999
  - $100,000 to $149,999
  - $150,000 to $199,999
  - $200,000 or more
  - Prefer not to say

B.3 Pre-treatment: Political and social attitudes

- How much of the time do you think you can trust the federal government in Washington to do what is right?
  - Never
  - Only some of the time
  - Most of the time
  - Just about always

- Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?
  - Need to be very careful
  - Most people can be trusted

- Thinking about the quality of public services and policy implementation in the U.S., how efficient do you think the government is?
  - Not efficient at all
  - Somewhat efficient
  - Very efficient
- How much do you agree with the following statement: "In the United States, the economic differences between the rich and the poor are unfair."
  - Strongly disagree
  - Disagree
  - Neither disagree nor agree
  - Agree
  - Strongly agree
- In politics today do you consider yourself a Republican, a Democrat, or an Independent?
  - Republican
  - Democrat
  - Independent
  - Other
- As of today, do you lean more to the Democratic Party or the Republican Party?
  - Republican Party
  - Democratic Party
  - Don't Know

B.4 Control

Now we'd like you to take the time to read this short article.

National food manufacturer to cut down 20% of its job force

HCYH food manufacturer, which employs more than 100,000 workers in the U.S., is facing changes this year. The company announced it would make adjustments to keep its plants competitive and lay off 20% of its workforce.

Contacted by email, a company spokesperson specified: "These adjustments are a further step towards restructuring the company", but did not give further details.

We spoke with an employee from one affected plant. Having worked there for fifteen years, the employee asked to stay anonymous and complained that the company did not communicate these changes adequately to the workers. Many employees from HCYH will likely become unemployed or have to take lower-paid jobs.

B.5 Treatment Automation

Now we'd like you to take the time to read this short article.

National food manufacturer to cut down 20% of its job force HCYH food manufacturer, which employs more than 100,000 workers in the U.S., is facing changes this year. The company announced it would make adjustments to keep its plants competitive and lay off 20% of its workforce.

Contacted by email, a company spokesperson specified: "These adjustments are a further step towards restructuring the company. New technologies enable us to produce more efficiently. As a result, we decided to automate part of our production with machines."

We spoke with an employee from one affected plant. Having worked there for fifteen years, the employee asked to stay anonymous and complained that the company did not communicate these changes adequately to the workers. Many employees from HCYH will likely become unemployed or have to take lower-paid jobs.

B.6 Treatment Government effectiveness + Automation

Each year the World Bank, an international organization based in the United States, ranks countries according to their level of government effectiveness.

The ranking takes into account: - the quality of public services, - the quality of the civil service and the degree of its independence from political pressures, - the quality of policy formulation and implementation, and - the credibility of the government's commitment to such policies. Now, think about government effectiveness in the United States and how it compares to other countries in the world.

- According to you, how well did the United States rank in terms of government effectiveness in 2020 compared to the rest of the world?
  - Among the best: The U.S. has one of the most effective governments.
  - Better than most: The U.S. has a government that is more effective than most other countries.

  - Worse than most: The U.S. has a government that is less effective than most other countries.
  - Among the worst: The U.S. has one of the least effective governments.

- You answered: [ANSWER FROM RESPONDENT]

  The correct answer is:

  In 2020, the United States ranked among the top countries in the world in terms of government effectiveness.

Now we'd like you to take the time to read this short article.

National food manufacturer to cut down 20% of its job force HCYH food manufacturer, which employs more than 100,000 workers in the U.S., is facing changes this year. The company announced it would make adjustments to keep its plants competitive and lay off 20% of its workforce.

Contacted by email, a company spokesperson specified: "These adjustments are a further step towards restructuring the company. New technologies enable us to produce more efficiently. As a result, we decided to automate part of our production with machines."

We spoke with an employee from one affected plant. Having worked there for fifteen years, the employee asked to stay anonymous and complained that the company did not communicate these changes adequately to the workers. Many employees from HCYH will likely become unemployed or have to take lower-paid jobs.

B.7 Attention Check

- This is a simple color test to check your attention, when asked for your favorite color you must enter the word "puce" in the text box below. What is your favorite color? [OPEN TEXT BOX]

B.8 Post treatment: Policy Views

We'd like to know what you think the response of the government should be, if any.

- Would you support or oppose the government implementing the following policies? [Strongly oppose, Somewhat oppose, Neither oppose nor support, Somewhat support, Strongly support]

  - Providing re-training programs
  - Providing financial assistance to workers who lose their jobs

  - Increasing taxes for firms
  - Restricting immigration to the US
  - Raising tariffs on foreign goods
  - Regulating the ways in which firms operate

- More generally, to what extent do you think each of the following should or should not be responsible for dealing with the potential negative effects workers face? [Definitely should not be responsible, Probably should not be responsible, Probably should be responsible, Definitely should be responsible]
  - The national government
  - Firms, businesses, and employers
  - Civil society groups, such as professional associations, non-profit organizations, and charitable organizations
  - Individual workers themselves

- To what extent do you think that it is fair or unfair for these workers to lose their jobs?
  - Completely unfair
  - Somewhat unfair
  - Neither unfair nor fair
  - Somewhat fair
  - Completely fair

- Which of the following statements best describes how you feel, even if neither is exactly right?
  - If businesses can receive better work at lower cost by replacing humans with robots and computers, they are justified in doing so
  - There should be limits on how many jobs businesses can replace with robots and computers, even if they can do those jobs better and more cheaply than humans can

B.9 Post Treatment: Beliefs about technology and the US labor market

The following questions are about your labor market experiences.

- Thinking about new technologies, what kind of impact have they had on... [Very negative, Mostly negative, Neither negative, nor positive, Mostly positive, Very positive]
  - You and your job or career
  - American workers in general

B.10 Post Treatment: Beliefs about globalization and the US labor market

- Thinking about globalization, what kind of impact has it had on... [Very negative, Mostly negative, Neither negative, nor positive, Mostly positive, Very positive]
  - You and your job or career
  - American workers in general

B.11 Post Treatment: Measure of occupation vulnerability

- Have you yourself ever lost a job because your employer replaced your position with a machine, robot or computer program?
  - Yes
  - No
  - I'm not sure
  - Not applicable
- What was your occupation then? [OPEN TEXT BOX]
- Have you yourself ever lost a job because your employer replaced your position with a cheaper worker in another country?
  - Yes
  - No
  - I'm not sure
  - Not applicable
- What was your occupation then? [OPEN TEXT BOX]

B.12 Post Treatment: Beliefs about institutions

Now we'd like to get your views about different organizations/institutions.

- Here is a pair of statements that will help us understand how you feel about the government. Please choose the statement that comes closer to your own views – even if neither is exactly right.
  - Government is almost always wasteful and inefficient
  - Government often does a better job than people give it credit for
- We are going to list six organizations/groups. For each one, could you tell us how much confidence you have in them: [None at all, Not very much confidence, Some confidence, A great deal of confidence]
  - Your neighbors
  - Lawyers
  - Major companies
  - The press
  - The federal government
  - The local government

B.13 Post Treatment: Beliefs about the survey

Finally, we'd like to have your opinion about this survey.

- Do you think this survey was politically biased?
  - Very left-wing biased
  - Somewhat left-wing biased
  - Neither left-wing nor right-wing biased
  - Somewhat right-wing biased
  - Very right-wing biased
- Did you find the information we provided you with trustworthy or untrustworthy?
  - Very untrustworthy
  - Somewhat untrustworthy
  - Neither trustworthy nor untrustworthy
  - Somewhat trustworthy
  - Very trustworthy

B.14 End Survey

- You've reached the end of this survey. We thank you for your time. Please enter any comment you might have about the survey in the box below. [OPEN TEXT BOX]