A Appendix

A.1 Robustness checks

Table 5: Attitudes toward globalization (entire labor force), with weights

	Reduce Immigration		Oppose Trade		Discourage Outsourcing	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk of computerization	0.49***	0.38*	0.67***	0.31*	0.05	0.28
	(0.13)	(0.15)	(0.12)	(0.14)	(0.14)	(0.19)
Past level of automation	0.58	0.22	−1.18*	−0.91	0.32	−0.15
	(0.39)	(0.48)	(0.47)	(0.54)	(0.51)	(0.55)
Offshorability		−0.00		0.05		0.02
		(0.04)		(0.05)		(0.06)
Import penetration		−0.11		−0.50**		−0.03
		(0.11)		(0.16)		(0.22)
Foreign born		−1.55**		−1.08*		−1.32*
		(0.49)		(0.46)		(0.64)
Gender (Male)		−0.16		−0.15		−0.01
		(0.11)		(0.10)		(0.13)
Party ID (GOP)		0.29***		0.11***		0.08*
		(0.03)		(0.03)		(0.03)
Age		0.02***		−0.01*		0.02***
		(0.00)		(0.00)		(0.00)
Education		−0.07**		−0.13***		0.01
		(0.03)		(0.03)		(0.03)
Nationalism		0.21***		0.06		−0.09
		(0.05)		(0.05)		(0.06)
Ethnocentrism		2.28***		0.43		−0.20
		(0.36)		(0.31)		(0.34)
Family Income		0.01		0.00		0.02*
		(0.01)		(0.01)		(0.01)
Observations	2511	2232	2498	2222	2515	2235

Note: Results from ordered logistic regressions, with sample weights specified according to DeBell (2010). Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Attitudes toward tech spending (entire labor force), with weights

	Decrease government STEM spending		
	(7)	(8)	(9)
Risk of computerization	0.28	−0.07	−0.06
	(0.16)	(0.18)	(0.18)
Past level of automation	−0.79	−0.42	−0.36
	(0.48)	(0.51)	(0.53)
Gender (Male)		-0.37^{**}	-0.35^{**}
		(0.12)	(0.12)
Party ID (GOP)		0.14^{***}	0.11^{***}
		(0.03)	(0.03)
Age		−0.01	−0.01
		(0.00)	(0.00)
Education		-0.12^{***}	-0.08^{*}
		(0.03)	(0.03)
Family Income		−0.01	−0.00
		(0.01)	(0.01)
Offshorability			−0.05
			(0.05)
Import penetration			−0.21
			(0.21)
Foreign born			-1.42^{*}
			(0.62)
Nationalism			0.02
			(0.05)
Ethnocentrism			0.87^{**}
			(0.32)
Observations	2517	2417	2235

Note: Results from ordered logistic regressions, with sample weights specified according to DeBell (2010). Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Attitudes toward globalization and technology (potentially displaced individuals, excluding retirees)

	Oppose Trade	Reduce Immigration	Discourage Outsourcing	Cut STEM funding
Past level of automation	1.08^{*}	1.39^{**}	-0.15	-0.36
	(0.50)	(0.52)	(0.59)	(0.56)
Foreign born	-3.03^{***}	-2.38^{***}	-0.90	-1.98^{**}
	(0.64)	(0.66)	(0.74)	(0.75)
Gender (Male)	-0.20	-0.11	-0.23	-0.51^{***}
	(0.12)	(0.12)	(0.14)	(0.13)
Party ID (GOP)	0.10^{***}	0.32^{***}	0.01	0.11^{***}
	(0.03)	(0.03)	(0.03)	(0.03)
Age	-0.01^{*}	0.01^{*}	0.01	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)
Education	-0.12^{***}	-0.09^{***}	-0.02	-0.09^{**}
	(0.03)	(0.03)	(0.03)	(0.03)
Nationalism	0.08	0.20^{***}	0.03	0.07
	(0.05)	(0.06)	(0.06)	(0.06)
Ethnocentrism	-0.05	2.82^{***}	-0.33	0.11
	(0.35)	(0.38)	(0.40)	(0.39)
Observations	987	995	993	998

Note: Results from ordered logistic regressions. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.2 Survey questions

These questions, drawn from the ANES, are used in the analyses:

1. Trade: "Do you favor, oppose, or neither favor nor oppose the U.S. making free trade agreements with other countries?"

2. Immigration: "Do you think the number of immigrants from foreign countries who are permitted to come to the United States to live should be [increased a lot, increased a little, left the same as it is now, decreased a little, or decreased a lot]?"

3. Offshoring: "Recently, some big American companies have been hiring workers in foreign countries to replace workers in the U.S. Do you think the federal government should discourage companies from doing this, encourage companies to do this, or stay out of this matter?"

Other variables used in the Appendix:

1. Job insecurity: "How worried are you about losing your job in the near future?"

2. Federal spending cuts on science and technology: "Should federal spending on science and technology be increased, decreased, or kept about the same?"

A.3 Coding ANES data

Both measures of automation used in the analyses are estimated at the occupation level according to the Standard Occupational Classification (SOC) as defined by the U.S. Bureau of Labor Statistics. Frey and Osborne (2017) estimated the risk of automation of 702 occupations. Missing occupations mostly consist of "all other" titles. A relatively small number of individuals belong to this residual category. These 702 occupational categories collectively capture about 97% of total US employment. The measure of past levels of automation from the Department of Labor asks a representative sample of job incumbents or occupation experts the extent of automation of their jobs for each SOC code. Traditional measurements of occupation in surveys, including that in the ANES (e.g. "Top Executives," "Computer Occupations"), are too coarse for the analysis.

To obtain a more nuanced classification of respondents' occupations, I leveraged their responses to an open-ended question about their jobs: "What is your main occupation? (What kind of work do you do? What are your most important activities or duties?)" For the web version of the ANES, if the response to this item is fewer than 15 characters, individuals are prompted to "please write a little more about what you do in your job." I also coded individuals' previous occupations ("What kind of work did you do on your last regular job?") to account for those who were potentially displaced by technology for additional analysis (main text, Table 5).

In most cases, assigning individuals a SOC code was a straightforward task. I used the 2010 SOC Definitions database search function on the Bureau of Labor Statistics website to locate the corresponding SOC code. It searches detailed task descriptions for closest job matches. Unfortunately, the searchable database with detailed descriptions of occupations has since then become defunct following an update of the SOC in 2018, but the 2010 SOC Definitions can be found at www.bls.gov/soc/soc_2010_definitions.pdf. For example, the job/task description of "Maids and Housekeeping Cleaners" (37-2012) is "Perform any combination of light cleaning duties to maintain private households or commercial establishments, such as hotels and hospitals, in a clean and orderly manner. Duties may include making beds, replenishing linens, cleaning rooms and halls, and vacuuming. Illustrative examples: Chambermaid, House Cleaner, Housekeeping Staff". I manually checked for congruence between job titles and descriptions across respondents' answers and the BLS site. In slightly more ambiguous cases, I consulted responses to an additional question, "What kind of business or industry is that", to get additional information about the job (e.g. to differentiate if a respondent belongs to the "Maids and Housekeeping Cleaners" (37-2012) or "Janitors and Cleaners" (37-2011) category).

Despite these procedures, some respondents' occupations did not fall neatly under one category. One common example was "teachers." The BLS separates "teachers" into many groups, including "Teachers, Elementary School, Except Special Education" (25-2021), "Middle School Teachers, Except Special and Career/Technical Education" (25-2022), and more. In this and other similar cases, I assigned the individual more than one SOC code and took the average of their associated automation risks. According to the Bureau of Labor Statistics, about 5 percent of Americans held more than one job at a time. These individuals were likewise also assigned more than one SOC code.

2,701 and 1,346 individuals described their present and past occupation respectively. A respondent's past occupation was treated as moot in this exercise *if* they currently hold a job — their current automation risk is associated with their present job, but not their previous job. Overall, the data set contains written responses from 3,936 individuals (present or past occupation). 3,775 and 3,532 of them could be linked to the two measures of retrospective and prospective job automation threat respectively. Those who were not coded worked in the military (with information redacted by the ANES), provided insufficient information (e.g. "confidential; no comment", "9999999999999"), or are not in fact working despite indicating that they were in an earlier question (e.g. "Retired would like to go back to school get a degree"). In addition, recall that individuals in "all other" categories also cannot be linked back to the Frey and Osborne automation estimate.[19]

Most of my analyses concerned individuals who were in the labor force at the time of the survey (those who were employed, temporarily laid off, and those unemployed but seeking work), as indicated in the main text. People not in the labor force were excluded from the main analysis because they were no longer *directly* exposed to the automation risks, but I analyzed individuals who were no longer in the labor force for additional insights (as indicated in the main text). Civilian labor force participation rate in the United States was 63 percent in 2016. If there were no missing values in the dependent variables (globalization attitudes) and other control variables, the sample size would be 2,451. Part of the missingness was due to "don't know" and "refused" responses and (a 15 percent) attrition from the post-election wave of ANES interview/questionnaire.[20][21] The consistent results from weighted analyses (using ANES-recommended procedures) in this appendix (A.1) should partially address the problem of sample attrition due to survey dropout.

The decision to manually code respondents into different occupational groups as opposed to using machine learning techniques was based on the structure of the data and the likely size of the learning set. With less than 4,000 of these written responses on past *and* present job descriptions in total, but about 700 occupational categories, coding by machine is unlikely to improve performance.

[19] Although there are nearly 100 "all other" categories, they only take up about 3 percent of US employment.

[20] The ANES consists of a pre-election and a post-election survey. Globalization questions were in the post-election survey.

[21] When the control variable that contributed most to the missingness problem (ethnocentrism) is excluded, results remain consistent.

A.4 Multicollinearity diagnostics

There are concerns about the non-independence of predictor variables in the regression models. Two commonly used diagnostic tests show that the issue of multicollinearity is unlikely to be severe.

A.4.1 Correlation matrix

This matrix of correlations show that most variables are only weakly correlated. There is no generally accepted threshold of when collinearity constitutes a significant problem, although some suggest critical values of 0.5 to 0.7 (?). None of the pairwise correlations exceeds the threshold.

Risk of computerization											
0.246	Past level of automation										
0.035	0.369	Offshorability									
0.015	0.057	0.144	Import Penetration								
-0.056	0.005	0.020	0.041	Foreign Born %							
0.020	0.006	0.047	0.101	0.026	Gender (Male)						
0.058	0.015	0.013	0.047	-0.129	0.125	Party ID (GOP)					
-0.020	0.107	0.101	0.069	-0.022	0.002	0.090	Age				
-0.379	0.029	0.091	-0.041	0.076	-0.043	-0.012	0.081	Education			
0.062	0.045	0.009	0.036	-0.074	0.091	0.238	0.151	-0.135	Nationalism		
0.093	0.035	-0.067	0.015	-0.016	-0.024	0.105	0.039	-0.163	0.202	Ethnocentrism	
-0.245	0.086	0.134	0.010	0.072	0.131	0.118	0.174	0.369	-0.022	-0.109	Family Income

A.4.2 Variance inflation factor

Below, I estimate the extent to which the variance of a regression coefficient is inflated due to multicollinearity to detect potential issues in the model. Generally speaking, variance inflation factor (VIF) values that exceed 10 indicate cause for concern. None of the VIF values in the following table exceed 2.

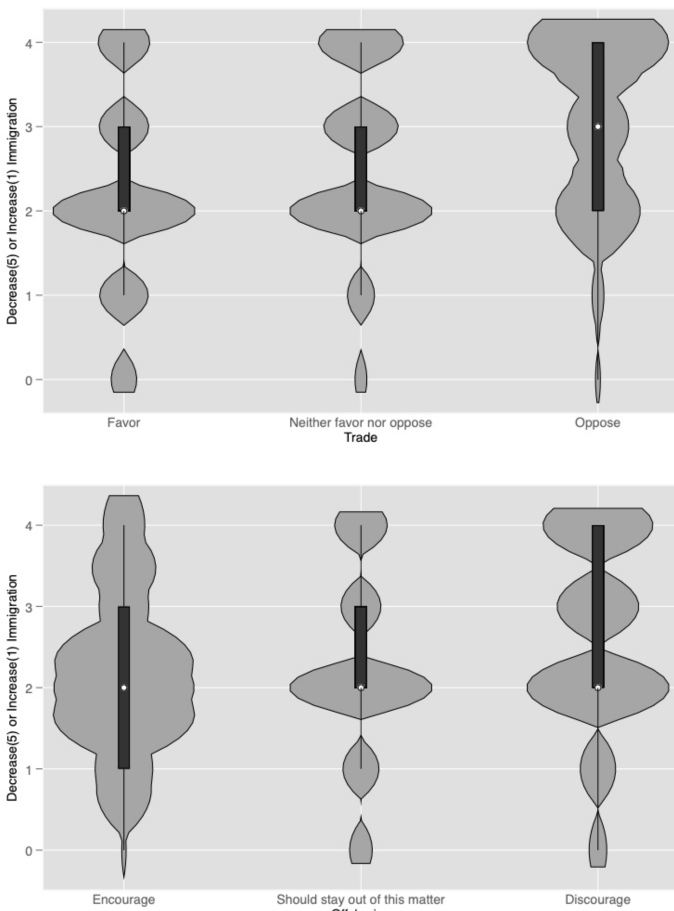
Table 8: Collinearity Diagnostics

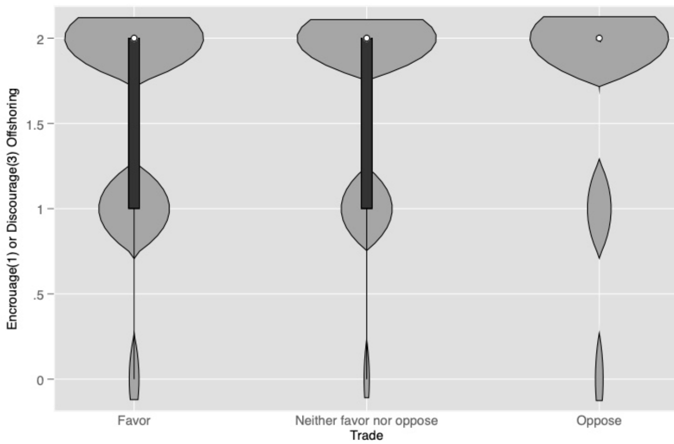
Variable	VIF	SQRT VIF	Tolerance	R-squared
Risk of automation	1.31	1.14	0.77	0.23
Past level of automation	1.27	1.13	0.79	0.21
Offshorability	1.21	1.10	0.83	0.17
Import penetration	1.04	1.02	0.96	0.04
Foreign born %	1.03	1.02	0.97	0.03
Gender (male)	1.06	1.03	0.94	0.06
Party ID (GOP)	1.12	1.06	0.89	0.11
Age	1.08	1.04	0.92	0.07
Education	1.35	1.16	0.74	0.26
Nationalism	1.14	1.07	0.88	0.12
Ethnocentrism	1.08	1.04	0.92	0.08
Family income	1.28	1.13	0.78	0.22
Mean VIF	1.16			

A.5 Preferences for immigration, trade, and offshoring

Even though immigration, trade, and offshoring are all facets of globalization, individuals' preferences for related policies are weakly correlated as shown in the correlation matrix and violin plots below. It is thus appropriate to examine how automation anxiety affects these attitudes separately.

Reduce Immigration		
0.260	Oppose Trade	
0.161	0.135	Discourage Outsource



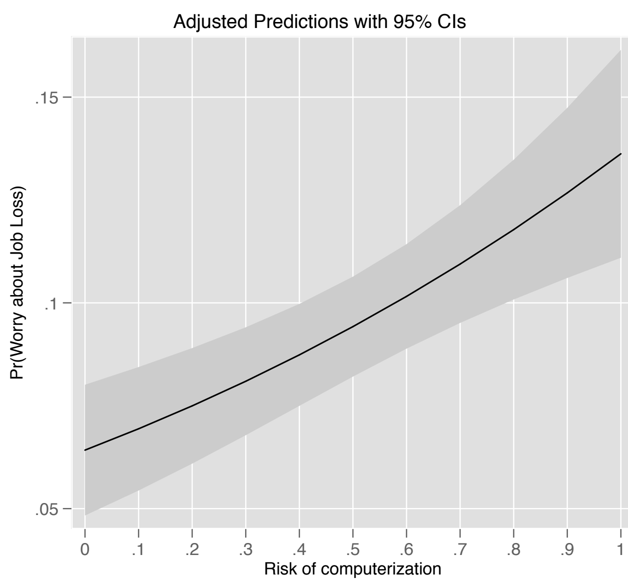


Encrouage(1) or Discourage(3) Offshoring
2
1.5
1
.5
0
Favor
Neither favor nor oppose
Oppose
Trade

A.6 Automation and job insecurity

Individuals who are more exposed to the threat of automation are more worried about losing their jobs in the near future. Subjective assessments of job security do not require a high level of sophistication or deep economic knowledge (**?**). The figure below shows the predicted probabilities for expressing concerns over job loss at different levels of prospective automation risk. This finding echoes results from a recent study by **?** that there is a positive, statistically significant impact of automation risk on job insecurity at the county level.

Figure 6: Predicted probabilities at different levels of automation risk



A.7 Exploratory analysis: automation risk and technology attitudes

While automation threat is linked to anti-trade and anti-immigration sentiments, it does not appear to predict attitudes toward technology (Table 9). Although firms, rather than the government, invest directly on automation, respondents' views on federal spending on science and engineering should give us a window to understand their general attitudes toward technology.

Without adding any control variables, future risk of automation is associated with preference for federal STEM spending cuts, whereas higher past levels of automation are linked to support for higher STEM spending. However, the effects disappear once we take into account individuals' characteristics and their surrounding environments. In models 8 and 9, there are no statistically significant relationships between the dependent and independent variables. In other words, individuals who face higher risk of computerization are no more likely to oppose government spending on science and engineering, fields where the very technology that displaces workers are developed.

The lack of correlation between automation threat and preferences for federal spending on technology suggests that individuals are either tolerant of the adverse labor effects of technological change (in contrast to globalization) or they fail to make the connection that government programs (such as, the American Artificial Intelligence Initiative) may hurt some workers. As this analysis is exploratory (with an admittedly crude measure of technology attitudes), future research would do well to consider the relationship between automation risk and attitudes toward workplace technology.

Table 9: **Attitudes toward technology spending (workers in labor force)**

	Decrease government STEM spending		
Risk of computerization	0.25*	−0.10	−0.07
	(0.12)	(0.14)	(0.17)
Past level of automation	−0.80*	−0.63	−0.39
	(0.37)	(0.42)	(0.53)
Gender (Male)		−0.46***	−0.45***
		(0.11)	(0.13)
Party ID (GOP)		0.15***	0.13***
		(0.04)	(0.04)
Age		−0.00	−0.01
		(0.00)	(0.00)
Education		−0.11***	−0.08*
		(0.03)	(0.03)
Family Income		−0.01	−0.00
		(0.01)	(0.01)
Offshorability			−0.05
			(0.05)
Import penetration			−0.34
			(0.30)
Foreign born			−1.55*
			(0.65)
Nationalism			0.06
			(0.05)
Ethnocentrism			0.82*
			(0.34)
Var(Intercept[occ])	0.00	0.00	0.02
	(0.00)	(0.00)	(0.06)
Var(Intercept[occ>ind])	0.06	0.00	0.00
	(0.06)	(0.00)	(0.00)
Var(Intercept[occ>ind>cd]	0.00	0.36	0.77
	(0.00)	(0.92)	(1.21)
Observations	2421	2296	1814

Note: Results from multilevel ordered logistic regressions of attitudes toward technology spending on hypothesized determinants. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Workers in the labor force includes those who are employed as well as those who are unemployed but seeking jobs.