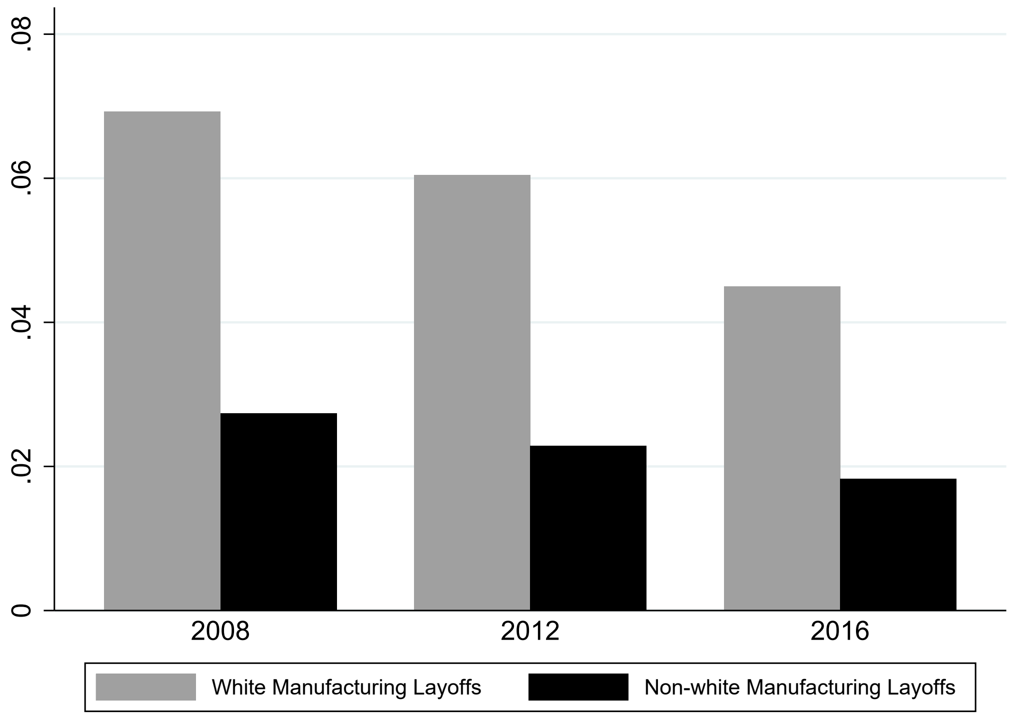
Appendix A

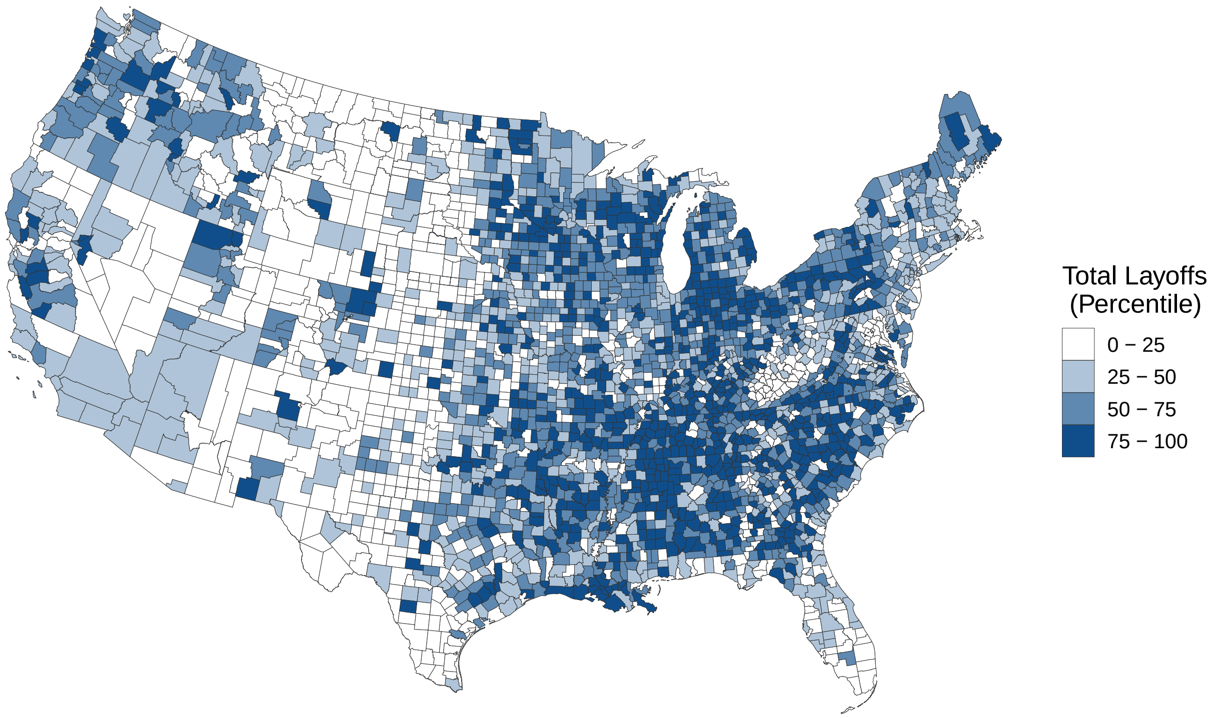
Descriptive Statistics

Figure A1: White Manufacturing Layoffs and Non-white Manufacturing Layoffs



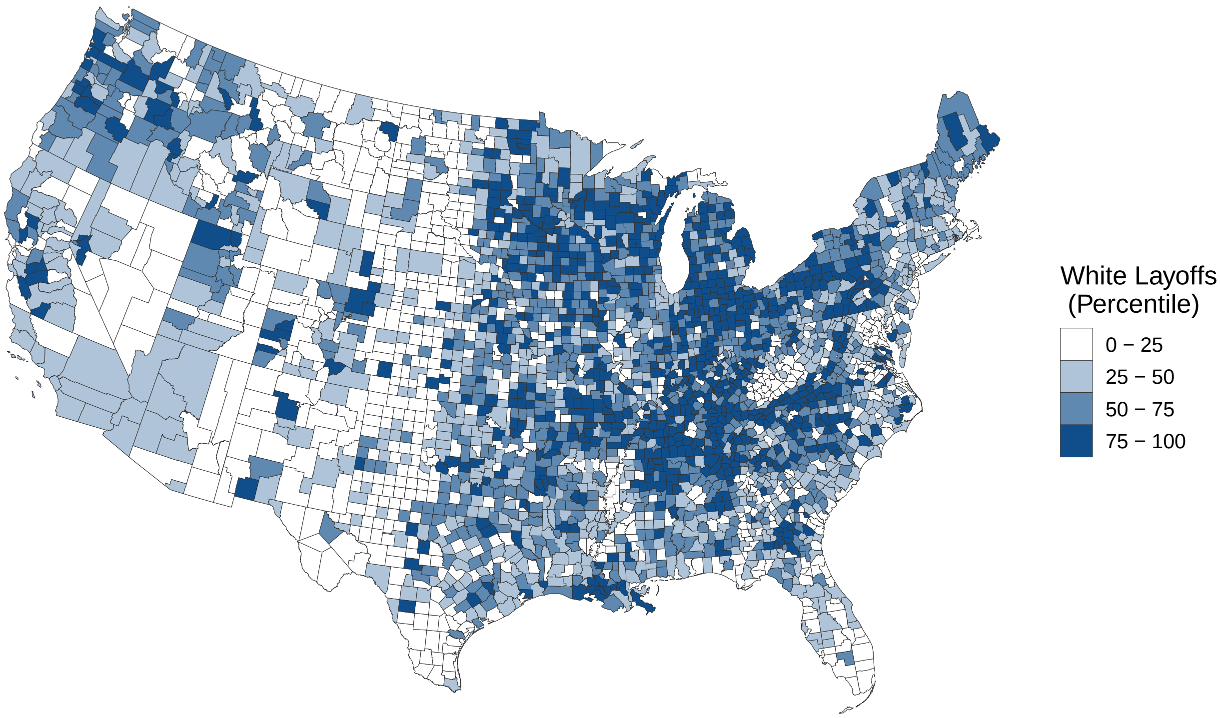
Note: *White Manufacturing Layoffs* and *Non-white Manufacturing Layoffs* are the mean of manufacturing layoffs per worker broken down by race. Source: QWI (2018).

Figure A2: Manufacturing Layoffs by US County



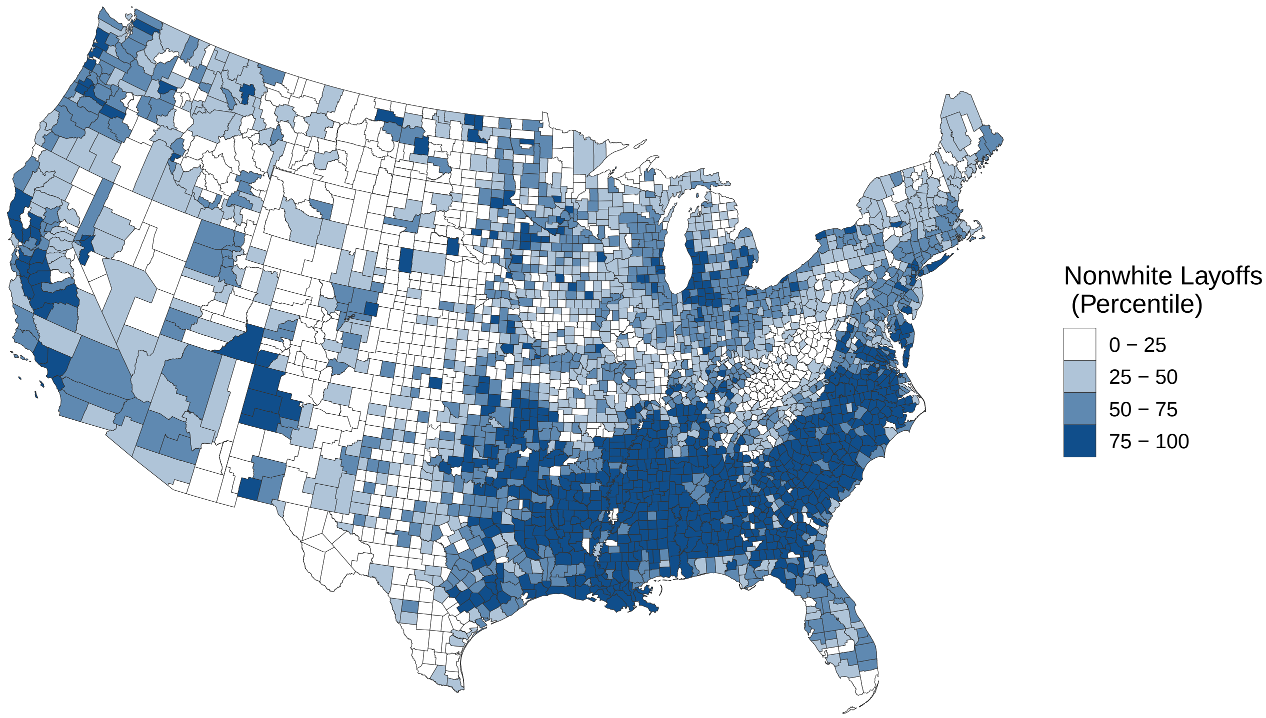
Note: Manufacturing Layoffs is the mean of manufacturing layoffs per worker from 2004 through 2016. Source: Quarterly Workforce Indicators.

Figure A3: White Manufacturing Worker Layoffs by US County



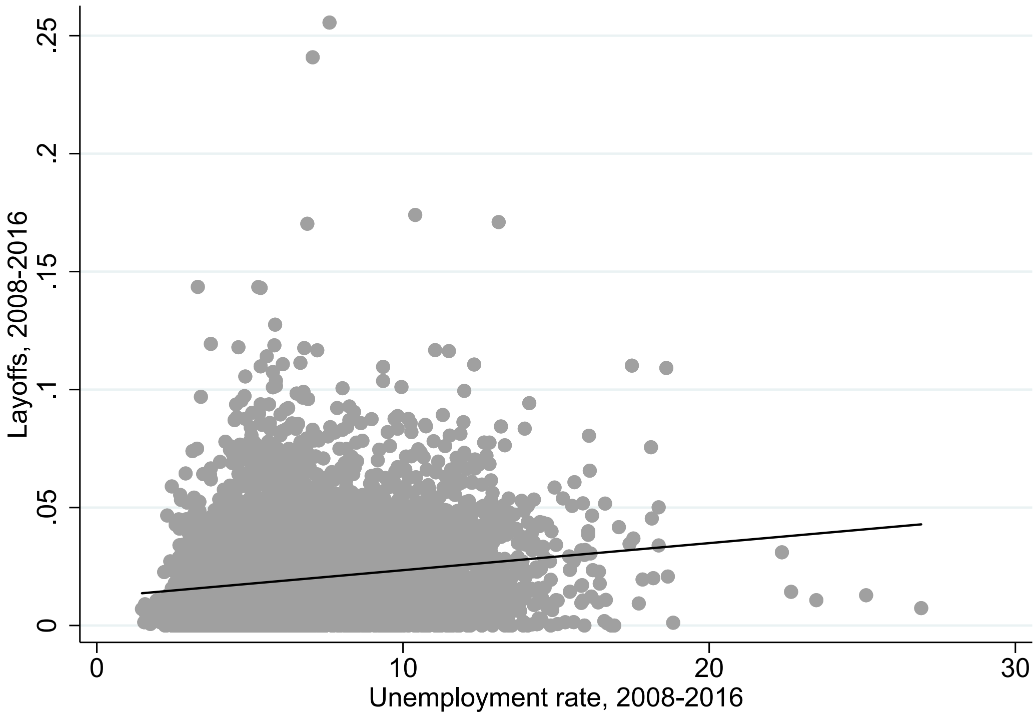
Note: White Manufacturing Layoffs is the mean white manufacturing layoffs per worker from 2004 through 2016. Source: Quarterly Workforce Indicators.

Figure A4: Non-White Manufacturing Worker Layoffs by US County



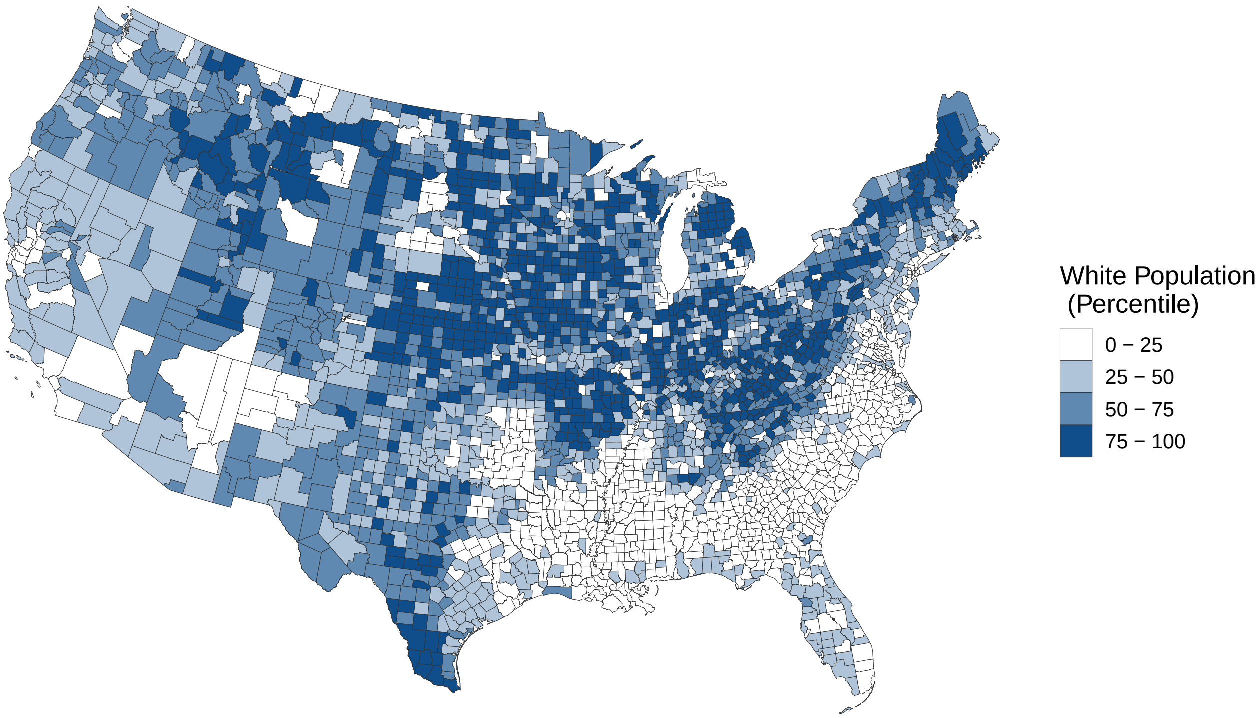
Note: Non-white Manufacturing Layoffs is the mean of non-white manufacturing layoffs per worker from 2004 through 2016. Source: Quarterly Workforce Indicators.

Figure A5: Manufacturing Layoffs and Unemployment



Note: Manufacturing Layoffs is the mean of manufacturing layoffs per worker from 2004 through 2016. Unemployment is the average unemployment rate from 2004 through 2016. Source: QWI (2018) and LAUS (2018).

Figure A6: White Population Shares



Note: White Population Share is the mean of white share of the total population in each county from 2004 through 2016. Source: US Census Bureau.

Table A1: Correlations between Bartik Instrument and Potential Confounders

	Unemployment	Share of College Educated	Share of Male	White Population Share	Service Layoffs
Bartik Instrument	0.1	-0.23	-0.1	0.02	-0.32

Note: Bartik instrument refers to the Bartik instrument for *Manufacturingl Layoffs* as for equation 2. Sources: QWI (2018) and LAUS (2018).

Table A2: Share of respondents by race and ethnicity in the CCES survey

	2016	2008-16
Race/Ethnicity	Share	
White	71.65%	74.77%
Black	12.27%	10.98%
Hispanic or Latino	8.11%	7.49%
Asian	3.53%	2.34%
Native American	0.81%	0.82%
Middle Eastern	0.21%	0.15%
Mixed	2.25%	1.96%
Other	1.18%	1.51%

Sources: CCES (2018).

Appendix B

County-level evidence

Table B1 shows the results of the reduced-form models.

Table B1: Manufacturing Layoffs and 2016 Presidential Election, County Level

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS					
	Change of Democratic Vote Share					
Manufacturing Layoffs	-0.027**	-0.014	-0.013			
	(0.011)	(0.011)	(0.011)			
White Manufacturing Layoffs				-0.202***	-0.141***	-0.140***
				(0.019)	(0.020)	(0.020)
Non-white Manufacturing Layoffs				0.173***	0.127***	0.127***
				(0.031)	(0.028)	(0.028)
Constant	0.015	0.063***	0.065***	0.015*	0.056***	0.057***
	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Observations	3,068	3,066	3,065	3,068	3,066	3,065
R-squared	0.709	0.732	0.731	0.724	0.738	0.738
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes
White Population Share	No	Yes	Yes	No	Yes	Yes
Service Layoffs	No	No	Yes	No	No	Yes
State fixed	Yes	Yes	Yes	Yes	Yes	Yes

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

Note: OLS with robust standard errors in parentheses. The unit of observation is county. The outcome variable is the change in the Democratic candidate's vote share in county c in the 2016 presidential election. The key independent variables are manufacturing layoffs per worker broken down by race. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Table B2 shows the results of the first stage of Models 1 and 4 of Table 2.

Table B2: Manufacturing Layoffs and 2016 Presidential Election, County Level (First Stage)

	2SLS	
	Change of Democratic Vote Share	
	(1)	(2)
	Manufacturing Layoffs	*White Manufacturing Layoffs*
Bartik instrument (total)	106.62***	
	(4.61)	
Bartik instrument (white)		108.21***
		(7.07)
Observations	3,068	2,767
R-squared	0.500	0.564
Unemployment Control	Yes	Yes
Demography Controls	Yes	Yes
White Population Share	No	No
Service Layoffs	No	No
State fixed effects	Yes	Yes

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

Note: 2SLS with robust standard errors in parentheses. The unit of observation is county. The instrumented variable is manufacturing layoffs. The instrument is the Bartik instrument described in 3. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Table B3 reports the magnitude of the effects of manufacturing layoffs.

Table B3: Counterfactual Outcomes in the US and in Closely Contested States

	Predicted probability actual layoffs value ($\hat{Y}$)	Lower quartile layoffs value	Predicted probability lower quartile layoffs value ($\hat{Y}$*)	Change ($\hat{Y}$-$\hat{Y}$*)/$\hat{Y}$*	Actual vote margin for Donald Trump
National (all counties)	-0.110	0.02	-0.106	3.56%	-2.10%
Florida	-0.092	0.01	-0.084	9.49%	1.27%
Michigan	-0.150	0.05	-0.135	10.79%	0.27%
Pennsylvania	-0.176	0.04	-0.165	6.60%	1.24%
Wisconsin	-0.118	0.05	-0.101	16.34%	0.81%

Note: The computation of the counterfactual at the national level is based on the estimates from Model 5 of Table 1. The first column reports predicted probabilities. The second column reports the value of the lower quartile of *White Manufacturing Layoffs*, nationally and by state. The third column reports predicted probabilities from the counterfactual exercise, which sets *White Manufacturing Layoffs* equal to the value of the lower quartile. The fourth column shows the difference between our models and the counterfactual predictions. The last column reports the margin in favor of Trump at the national level and by state in the 2016 election.

Robustness checks. We perform several tests to corroborate the validity of our findings. We re-run our main models with three different outcome variables. First, we recalculate our main models using levels rather than *changes* in Democratic candidates' percentages. Table B4 (Models 1–2) reports the results, which are similar to those discussed above. Second, our results are similar if we use Democratic votes as a share of all votes as the operationalization of our outcome variable (Table B4, Models 3–4). Third, we examine the relationship between layoffs and turnout. One possible interpretation of our results is that manufacturing layoffs reduce the turnout of non-white voters; we find suggestive evidence that this might be the case (Table B4, Models 5–6). Note that we do not have turnout data broken down by partisanship or race.

Moreover, we include potential confounders in our main model specification to check whether our results are driven by omitted variable bias. First, we include worker layoffs, broken down by education level, age, and gender (Table B5, Models 1–2), which could be potential confounders of *White Layoffs*. All of these variables enter with statistically significant coefficients.[51]

The second additional covariate is the 'China trade shock' measure developed by Autor, Dorn, and Hanson (2013) to capture the localized effect of Chinese imports to the US (*China trade shock*).[52] Our main results hold even after including this potential confounder (see Table B5, Models 3–4).[53] In Models 5–6, we also instrument for the China trade shock using the same identification strategy as in Autor, Dorn and Hanson (2013). Our main results remain unchanged.

Third, we include district fixed effects in our models, which allow us to account for within-state heterogeneity. These estimates are very similar to the ones with state fixed effects (B6).

We also explore the effect of cumulative manufacturing layoffs on the 2016 presidential election, which confirms our main findings (Table B7).

One possible issue is that the distribution of workers in adjacent counties may influence voting. Since county boundaries may not adequately capture local economies, we also estimate models at the commuting zone (CZ) level. We estimate our main DID and 2SLS models using CZ as the unit of analysis. The results are virtually the same as those reported above (see Tables B8). If anything, the results are even stronger than the county-level findings, suggesting that any bias works against our key findings.

[51] We include the share of these variables rather than their level, since the correlation among layoffs of different categories of workers is quite high, i.e. ρ is 0.8.

[52] In contrast to their original variable, our measure of the China trade shock varies across counties. We thank Andrea Cerrato, Federico Maria Ferrara, and Francesco Ruggieri for sharing their data with us.

[53] When we include the *China trade shock* variable, we are *de facto* controlling for job losses caused by trade liberalization. Thus, *Layoffs* captures plant closures mainly caused by automation in these estimates.

Table B4: Manufacturing Layoffs and 2016 Presidential Election, County Level (Other Outcomes)

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS					
	Change of Democratic Vote Share		Change of Democratic Vote Share (third party)		Change of Turnout	
Manufacturing Layoffs	-0.171**		-0.070***		0.025**	
	(0.070)		(0.018)		(0.011)	
White Manufacturing Layoffs		-0.911***		-0.221***		0.105***
		(0.126)		(0.033)		(0.017)
Non-white Manufacturing Layoffs		0.753***		0.169***		-0.090***
		(0.142)		(0.032)		(0.016)
Observations	3,068	2,767	3,068	2,767	3,067	2,766
R-squared	0.296	0.369	0.419	0.483	0.008	0.058
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes
White Counties	No	No	No	No	No	No
Service Layoffs	No	No	No	No	No	No
State FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Note: 2SLS with robust standard errors in parentheses. The unit of observation is county. The outcome variables are (1) the Democratic candidate's vote share (Models 1–2), (2) the change in the Democratic candidate's vote share including third parties (Models 3–4); (3) the change in turnout (Models 5–6). The key independent variable is manufacturing layoffs per worker broken down by race. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Table B5: Manufacturing Layoffs and 2016 Presidential Election, County Level (Including Confounders)

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS					
	Change of Democratic Vote Share					
Manufacturing Layoffs	-0.046**		-0.021		-0.022	
	(0.019)		(0.018)		(0.018)	
White Manufacturing Layoffs		-0.147***		-0.115***		-0.115***
		(0.035)		(0.036)		(0.036)
Non-white Manufacturing Layoffs		0.129***		0.130***		0.130***
		(0.032)		(0.034)		(0.034)
China Trade Shock			-0.356***	-0.266***	-0.343***	-0.270***
			(0.052)	(0.051)	(0.056)	(0.055)
Observations	3,066	2,766	2,863	2,617	2,863	2,617
R-squared	0.540	0.590	0.562	0.604	0.562	0.604
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes
White Counties	Yes	Yes	Yes	Yes	Yes	Yes
Service Layoffs	No	No	No	No	No	No
Other Layoffs	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Note: 2SLS with robust standard errors in parentheses. The unit of observation is the county. The outcome variable is the change in the Democratic candidate's two-party vote share in county c in presidential election t. The key independent variable is manufacturing layoffs per worker broken down by race. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Table B6: Manufacturing Layoffs and 2016 Presidential Election, County Level (with District Fixed Effects)

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS					
	Change of Democratic Vote Share					
Manufacturing Layoffs	-0.056***	-0.039**	-0.036**			
	(0.018)	(0.017)	(0.018)			
White Manufacturing Layoffs				-0.205***	-0.141***	-0.150***
				(0.034)	(0.035)	(0.036)
Non-white Manufacturing Layoffs				0.152***	0.114***	0.116***
				(0.030)	(0.029)	(0.029)
Observations	3,067	3,065	3,065	2,766	2,765	2,765
R-squared	0.474	0.512	0.513	0.534	0.559	0.558
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes
White Population Share	No	Yes	Yes	No	Yes	Yes
Service Layoffs	No	No	Yes	No	No	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Note: 2SLS with robust standard errors in parentheses. The unit of observation is the county. The outcome variable is the change in the Democratic candidate's vote share in county c in presidential election t. The key independent variable is manufacturing layoffs per worker broken down by race. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Table B7: Manufacturing Layoffs and 2016 Presidential Election, County Level (Cumulative Manufacturing Layoffs, 2004-2015)

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS					
	Change of Democratic Vote Share					
Manufacturing Layoffs (cumulative)	-0.017***	-0.011***	-0.011***			
	(0.004)	(0.004)	(0.004)			
White Manufacturing Layoffs (cumulative)				-0.052***	-0.034***	-0.034***
				(0.006)	(0.006)	(0.006)
Non-white Manufacturing Layoffs (cumulative)				0.064***	0.043***	0.043***
				(0.006)	(0.006)	(0.006)
Observations	2,928	2,926	2,925	2,653	2,652	2,652
R-squared	0.500	0.542	0.542	0.581	0.598	0.598
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes
White Population Share	No	Yes	Yes	No	Yes	Yes
Service Layoffs	No	No	Yes	No	No	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Note: 2SLS with robust standard errors in parentheses. The unit of observation is the county. The outcome variable is the change in the Democratic candidate's vote share in county c in presidential election t. The key independent variable is cumulative manufacturing layoffs per worker broken down by race. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Table B8: Manufacturing Layoffs and 2016 Presidential Election, County Level (CZ as the Unit of Analysis)

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS					
	Change of Democratic Vote Share					
Manufacturing Layoffs	-0.143***	-0.118***	-0.098**			
	(0.043)	(0.043)	(0.045)			
White Manufacturing Layoffs				-0.381***	-0.332***	-0.308***
				(0.071)	(0.078)	(0.080)
Non-white Manufacturing Layoffs				0.245***	0.207***	0.210***
				(0.053)	(0.054)	(0.054)
Observations	721	721	720	688	688	687
R-squared	0.360	0.384	0.383	0.415	0.421	0.420
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes
White Population Share	No	Yes	Yes	No	Yes	Yes
Service Layoffs	No	No	Yes	No	No	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Note: 2SLS with robust standard in parentheses. The unit of observation is CZ. The outcome variable is the change in the Democratic candidate's vote share in county c in presidential election t. The key independent variable is manufacturing layoffs per worker broken down by race. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Individual-Level Evidence

Table B9 shows the results of the first stage of Model 1 of Table 3.

Table B9: Manufacturing Layoffs and 2016 Presidential Election, Individual Level (First Stage)

	2SLS
	Pr(Voting for Clinton = 1)
	(1)
	*Manufacturing Layoffs*White*
Bartik instrument (total)*White	451.420***
	(13.00)
Observations	63,964
Number of district	2,592
R-squared	0.109
Unemployment Control	Yes
Individual Controls	Yes
Demography Controls	No
White Population Share	No
Service Layoffs	No
County fixed effects	Yes

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

Note: 2SLS regressions with robust standard errors clustered by county in parentheses. Unit of observation is individual-county. The instrumented variable is manufacturing layoffs interacted with a dummy scoring one if the respondent is White. The instrument is the Bartik instrument described in 3. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Table B10: Manufacturing Layoffs and the 2016 Presidential Election, Individual Level (by gender)

	(1)	(2)
	OLS	
	Pr(Voting for Clinton = 1)	
	Female	Male
White	-0.16***	-0.07
	(0.045)	(0.048)
White*Manufacturing Layoffs	-0.82**	-2.03***
	(0.385)	(0.392)
Observations	28,789	34,370
R-squared	0.002	0.002
Unemployment Control	No	No
Individual Controls	No	No
Demography Controls	No	No
White Population Share	Yes	Yes
Service Layoffs	No	No
County fixed effects	Yes	Yes

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

Note: 2SLS regressions with robust standard errors clustered by county in parentheses. The unit of observation is individual-county. The outcome variables are a dummy scored one if the respondent voted for the Democratic candidate in the 2016 election. The key independent variables are manufacturing layoffs per worker interacted with a dummy that takes a value of one if the respondent is White. Sources: QWI (2018), CCES (2018), LAUS (2018).

Robustness checks. We perform several robustness checks in line with the county-level analysis. First, we replace *Manufacturing Layoffs* with *White Manufacturing Layoffs* and its interaction with *White* (Table B11) and the results are similar to those reported in 3.

Second, we include in our models *China trade shock*, along with its interaction with *White*. Table B12 shows that our results hold even when we include this potential confounder.[54]

Third, we explore the effect of cumulative manufacturing layoffs on the 2016 presidential election at the individual level. Even in this case, the estimates confirm our main findings (Table B13).

Finally, our results are similar if we use layoffs per worker in CZs rather than counties (Table B14). The concern is that there is a relatively low number of respondents in each county. On the contrary, there are many respondents in each CZ, since the number of counties is more than three times the number of CZs. In these models, we use CZ fixed effects and cluster standard errors at the level of CZ.

[54]In our 2SLS regressions, we always instrument the *China trade shock* using Autor et al.'s (2013) approach.

Table B11: Manufacturing Layoffs and the 2016 Presidential Election, Individual Level

	(1)	(2)
	2SLS	
	Pr(Voting for Clinton = 1)	Pr(Voting = 1)
White	-0.01	0.07
	(0.041)	(0.043)
White*White Manufacturing Layoffs	-1.13***	0.91***
	(0.331)	(0.349)
White*Non-white Manufacturing Layoffs	-0.33	0.19
	(0.268)	(0.283)
Observations	63,315	63,315
R-squared	0.165	0.150
Unemployment Control	Yes	Yes
Individual Controls	Yes	Yes
Demography Controls	No	No
White Counties	Yes	Yes
Service Layoffs	No	No
County fixed effects	Yes	Yes

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: 2SLS regressions with robust standard errors clustered by county in parentheses. The unit of observation is individual-county. The outcome variables are a dummy scored one if the respondent voted for the Democratic candidate in the 2016 presidential election (Model 1) and a dummy scored one if the respondent voted in the 2016 presidential election (Model 2). The key independent variable is manufacturing layoffs per worker broken down by race interacted with a dummy that takes a value of one if the respondent is white. Sources: QWI (2018), CCES (2018), LAUS (2018).

Table B12: Manufacturing Layoffs and the 2016 Presidential Election, Individual Level (Including *China Trade Shock)*

	(1)	(2)
	2SLS	
	Pr(Voting for Clinton = 1)	
White	-0.04	-0.03
	(0.057)	(0.056)
White*Manufacturing Layoffs	-0.56**	-0.48*
	(0.278)	(0.281)
White*China Trade Shock	-0.99*	-1.28**
	(0.524)	(0.540)
Observations	62,642	62,642
R-squared	0.111	0.111
Unemployment Control	Yes	Yes
Individual Controls	Yes	Yes
Demography Controls	No	No
White Counties	Yes	Yes
Service Layoffs	Yes	Yes
County fixed effects	Yes	Yes

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

Note: 2SLS regressions with robust standard errors clustered by county in parentheses. The unit of observation is individual-county. The outcome variable is a dummy scored one if the respondent voted for the Democratic candidate in the 2016 presidential election. The key independent variable is manufacturing layoffs per worker interacted with a dummy that takes a value of one if the respondent is white. Sources: QWI (2018), CCES (2018), LAUS (2018).

Table B13: Manufacturing Layoffs and the 2016 Presidential Election, Individual Level (Cumulative Manufacturing Layoffs, 2004-2015)

	(1)	(2)	(3)	(4)
	2SLS			
	Pr(Voting for Clinton = 1)			Pr(Voting=1)
White	0.24***	-0.27***	-0.28***	0.19***
	(0.038)	(0.093)	(0.091)	(0.043)
White*Manufacturing Layoffs (cumulative)	-0.15***	-0.16***	-0.14***	0.12**
	(0.044)	(0.049)	(0.050)	(0.054)
Observations	58,060	58,046	58,037	58,046
R-squared	0.166	0.167	0.168	0.153
Unemployment Control	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Demography Controls	No	Yes	Yes	No
White Population Share	No	Yes	Yes	No
Service Layoffs	No	No	Yes	No
County fixed effects	Yes	Yes	Yes	Yes

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

Note: 2SLS regressions with robust standard errors clustered by county in parentheses. The unit of observation is individual-county. The outcome variables are a dummy scored one if the respondent voted for the Democratic candidate in the 2016 election (Models 1–3) and a dummy scored one if the respondent voted in the 2016 election. The key independent variable is cumulative manufacturing layoffs per worker interacted with a dummy that takes a value of one if the respondent is white. Sources: QWI (2018), CCES (2018), LAUS (2018).

Table B14: Manufacturing Layoffs and the 2016 Presidential Election, Individual Level (Commuting Zone)

	(1)	(2)	(3)	(4)
	2SLS			
	Pr(Voting for Clinton = 1)			Pr(Voting=1)
White	0.18***	-0.77***	-0.76***	0.20***
	(0.051)	(0.125)	(0.123)	(0.044)
White*Manufacturing Layoffs	-0.87***	-0.77**	-0.81**	0.60
	(0.331)	(0.331)	(0.371)	(0.453)
Observations	63,925	63,925	63,925	63,925
R-squared	0.137	0.140	0.140	0.123
Unemployment Control	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Demography Controls	No	Yes	Yes	No
White Population Share	No	Yes	Yes	No
Service Layoffs	No	No	Yes	No
CZ fixed effects	Yes	Yes	Yes	Yes

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

Note: 2SLS regressions with robust standard errors clustered by CZ in parentheses. The unit of observation is individual-CZ. The outcome variables are a dummy scored one if the respondent voted for the Democratic candidate in the 2016 election (Models 1–3) and a dummy scored one if the respondent voted in the 2016 election. The key independent variable is manufacturing layoffs per worker (built using CZs) interacted with a dummy that takes a value of one if the respondent is white. Unemployment, demography variables, and White Population Share built using CZs as unit of analysis. Sources: QWI (2018), CCES (2018), LAUS (2018).

Table B15 shows the results of the first stage of Model 1 of Table 5.

Table B15: Manufacturing Layoffs and Individual Attitudes in the 2016 Presidential Election (First Stage)

	2SLS
	Change of Democratic Vote Share
	(1)
	*Manufacturing Layoffs*White*
Bartik instrument (total)*White	493.80***
	(29.67)
Observations	1,686
R-squared	0.119
Individual Controls	Yes
District fixed effects	Yes

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

Note: 2SLS regressions with robust standard in parentheses. Unit of observation is individual-county. The instrumented variable is manufacturing layoffs interacted with a dummy scoring one if the president is a Democrat. The instrument is the Bartik instrument described in 3. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).