Gone For Good: Deindustrialization, White Voter Backlash, and U.S. Presidential Voting *

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Abstract

Globalization and automation contributed to US deindustrialization and the loss of millions of manufacturing jobs. Do these manufacturing layoffs affect voting in US presidential elections? We consider how deindustrialization may represent a unique social status threat, which leads to increases in anti-incumbent voting among whites. We use a shift-share instrumental variables strategy to estimate the causal effect of manufacturing layoffs on US presidential elections, 2008–2016, with county- and individual-level voting data. At the county level, voters penalize incumbents more for white worker layoffs than for non-white layoffs. At the individual level, white voters are more likely than non-whites to vote against incumbents where manufacturing layoffs are high. Exploring possible mechanisms, we find that white voters are more likely to associate manufacturing job losses with broader American decline. US deindustrialization appears to be central to the white voter backlash that culminated in the election of Donald Trump.

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1 Introduction

In *Janesville: An American Story*, Amy Goldstein describes how the closure of a century-old General Motors (GM) plant reverberated throughout the community of Janesville, Wisconsin (Goldstein, 2017). A casualty of US deindustrialization, the plant's shuttering brought economic turmoil to the affected workers and their families: good jobs, with high wages and generous pensions, disappeared; in many cases, multi-generational employment ties to GM were severed. But the closure also profoundly shaped the broader community. Nearby firms within the GM production network shed workers or moved elsewhere, tax revenues and social services declined, and the community's identity as a thriving industrial hub eroded. Janesville is not unique: more than 8 million manufacturing jobs have been lost in the US over the past 30 years.

We investigate how deindustrialization has shaped US presidential politics by examining the relationship between manufacturing job losses and voting in the three most recent US presidential elections (2008–2016). We develop theoretical expectations about the possible electoral effects of localized manufacturing job losses by drawing on recent studies that have found that economic hardship harms incumbents (Margalit, 2011; Jensen, Quinn, and Weymouth, 2017; Rickard, 2018), increases polarization (Autor, Dorn, Hanson et al., 2016), and contributes to support for nationalist parties (Colantone and Stanig, 2017). Our approach departs from this literature by also considering how group-based identities influence politics (Tajfel, 1974; Shayo, 2009; Mutz, 2018; Jardina, 2019; Mansfield and Mutz, 2009, 2013; Gaikwad, 2018). We incorporate insights from research on identity politics and voting that emphasizes how Donald Trump and other outsider candidates and parties challenge incumbents by focusing on threats to the status of historically dominant groups, namely whites (Sides, Tesler, and Vavreck, 2018; Mutz, 2018; Inglehart and Norris, 2017; Jardina, 2019). We propose that deindustrialization represents one such status threat, which allows us to develop theoretical expectations about how US manufacturing job losses may make some white voters more likely than non-whites to express their grievances by voting against incumbents.

The empirical analysis examines how the electoral effects of manufacturing layoffs[1] may differ depending on the race of displaced workers and voters. We rely on novel county-level manufacturing layoffs data, broken down by race, which we link to county- and individual-level voting

[1]We use "layoffs" as a synonym for "job losses" throughout.

data. Our panel dataset allows us to derive difference-in-differences (DID) estimates of: 1) the county-level electoral effects of layoffs broken down by race and 2) the differential effects of layoffs on white and non-white voters. Since layoffs are not randomly assigned, we develop an instrumental variables strategy using shift-share methodology (Bartik, 1991) derived from national layoff shocks, weighted by initial county-level employment. To our knowledge, our paper is the first to estimate the causal effect of manufacturing layoffs on voting – and how this effect may vary by worker and voter demographics.

Our results are threefold. First, studying county-level voting results across three US presidential elections, we find that voters penalize incumbent parties more for white worker layoffs than for non-white layoffs. The results are robust to potentially confounding explanations, including the shock of Chinese imports (Autor, Dorn, and Hanson, 2013) and the racial makeup of manufacturing communities (Freund and Sidhu, 2017; Noland, 2019).

Second, examining individual vote choice data from the YouGov Cooperative Congressional Election Study (CCES), we find that layoffs are associated with anti-incumbent voting by white voters, but not by non-whites. The estimated white voter effect is strongest in the 2016 election. To understand the political significance of the results for the 2016 presidential election, we conduct a simple counterfactual simulation for closely contested states. Our counterfactual analysis suggests that Hillary Clinton would have won Michigan, Wisconsin, and Pennsylvania – and therefore the presidency – if, *ceteris paribus*, manufacturing layoffs had been 20–40% lower during the period of analysis.

Third, we explore potential mechanisms driving white voters' anti-incumbent response to manufacturing layoffs using survey data from the American National Election Studies (ANES). Consistent with prior studies on the status threats that globalization poses to the identities of white Americans (Jardina, 2019; Mutz, 2018), we find that whites in areas with more manufacturing layoffs are more likely than non-whites to report that: 1) the US is on the *wrong* track and 2) the US position in the world has grown *weaker*. That is, white voters appear to be more likely to associate deindustrialization with American decline. This is not to say that non-whites are sheltered from the deleterious economic effects of deindustrialization; indeed, there is evidence that blacks in particular have suffered even more from lost manufacturing jobs than have whites (Gould, 2018). Rather, it is consistent with the view that different groups of voters respond to similar forms of economic hardship in different ways (Green and McElwee, 2019).

Our paper informs debates about recent populist and anti-incumbent voting in developed democracies, including the election of Donald Trump as US president. These debates largely center on the extent to which localized economic hardship, as opposed to cultural identities, explain the rising tide of right-wing nationalism and populism. According to some economic explanations, globalization has decimated former manufacturing hubs, which has triggered a voter backlash in the US and Europe (Ballard-Rosa, Jensen, and Scheve, 2018; Ballard-Rosa, Malik, Rickard et al., 2017; Colantone and Stanig, 2017, 2018; Rickard, 2018). While this research focuses almost exclusively on the role of international trade – particularly Chinese imports – other factors such as automation have also contributed to the decline in manufacturing employment. Our paper provides a comprehensive account by examining the overall effects of manufacturing job losses – caused by import competition, offshoring, and automation – on elections; it also contributes to the literature examining white identity politics (Sides, Tesler, and Vavreck, 2018; Mutz, 2018; Jardina, 2019). To our knowledge, our paper is the first to examine the electoral effects of the status threat posed by deindustrialization. Like Ballard-Rosa, Jensen, and Scheve (2018), our results suggest that economic hardship threatens the identity of some white voters, which in turn affects voting behavior.

In sum, our main contribution is to provide the first direct study of the electoral effects of deindustrialization – the most profound structural change to the US economy over the past 50 years. As an early industrializing nation, the US enjoyed an exorbitant advantage in manufacturing for over a century. But in recent decades, globalization and technology have decimated the industrial jobs upon which individuals and communities identified, and upon which they relied for high wages and secure pensions. Our study indicates that white voters are more likely to vote against incumbents, particularly Democratic Party candidates, in areas that have experienced more manufacturing job losses. Our findings are consistent with the view that white Americans appear particularly aggrieved by economic hardship (Hochschild, 2018). US deindustrialization, and its associated deterioration in employment, wages, and communities, appears to be central to the recent white voter backlash that culminated in the election of Donald Trump.

2 Deindustrialization, White Identity, and Voting

In this section we develop theoretical expectations about the ways in which manufacturing layoffs may influence elections – focusing first on possible economic voting channels, and then on group identity channels.

2.1 Localized Manufacturing Layoffs and Economic Voting

Manufacturing layoffs could influence elections through the economic hardship they cause laid-off workers and their communities. Perhaps the most direct channel involves lost wages in areas experiencing these layoffs. One driving factor is that manufacturing wage premiums are high: workers in the manufacturing sector earn higher wages than those in the services sector with the same level of education (Krueger and Summers, 1988; Ebenstein, Harrison, McMillan et al., 2014).[2] As plants shut down and manufacturing jobs disappear, workers who lose jobs in manufacturing tend to earn less after they are laid off. Therefore, workers who are displaced from manufacturing tend to suffer greater relative economic harm compared to those laid off from the service sector.[3]

In a deindustrializing economy, plant closures often precipitate manufacturing layoffs. When a factory closes, the negative economic effects often extend to nearby businesses, including suppliers and/or downstream firms (Acemoglu, Autor, Dorn et al., 2016). The loss of one factory often leads to lost jobs and wages for other businesses in the supply chain. These negative spillovers may decrease the local demand for retail, dining, and other local services, which can trigger a widespread regional economic downturn.

The economic effects of manufacturing job losses have been shown to contribute to the social decline of local communities. Plant closures, layoffs, and reduced earnings weaken local demand, which causes a host of detrimental knock-on economic and social effects. These include a deterioration in public goods provision (Feler and Senses, 2017), which may produce a strong

[2]Jensen, Quinn, and Weymouth (2017) estimate an average wage premium of $9,136 among manufacturing workers in industries in which fewer than 20% of employees had college degrees (compared to services industries with similar employee educational levels).

[3]Using individual-level data, Autor, Dorn, Hanson et al. (2014) document a substantial decline in earnings for workers in manufacturing industries exposed to a surge in imported goods from China.

political backlash (Lizzeri and Persico, 2001; Besley and Coate, 2003; Magaloni, 2006; Lake and Baum, 2001); increases in local crime rates (Che, Xu, and Zhang, 2018); spikes in mortality rates (Sullivan and Von Wachter, 2009); and higher rates of opioid addiction and overdose (Pierce and Schott, 2016). To the extent that individuals' views of the economy are based on the conditions of their own communities (Ansolabehere, Meredith, and Snowberg, 2014), news of local plant closures and layoffs is likely to negatively affect perceptions of the health of the local economy even for residents who have not personally been laid off.

Political challengers can exploit the economic and social decline in former manufacturing hubs to motivate voters to punish incumbents for the poor economic conditions (Key, 1966; Fiorina, 1978; Fair, 1978; Kramer, 1971; Hibbs, 2006; Lewis-Beck, 1986; Brender and Drazen, 2008; Lewis-Beck and Stegmaier, 2007). Indeed, the economic voting literature finds that voters engage in retrospective economic voting (Alvarez and Nagler, 1995, 1998; Kinder and Kiewiet, 1981; Kiewiet, 1983; Kramer, 1983; Lewis-Beck, 1988), which suggests that they will punish incumbents for past manufacturing layoffs.

Despite the straightforward logic of these claims, individuals in areas most affected by manufacturing job losses may not necessarily turn against incumbents. The majority of the literature on economic voting shows that national-level conditions, rather than local or personal economic experiences, are most salient to voters (Jardina, 2019). Therefore local job losses may not affect how people vote. Interest in the effects of local economic shocks such as unemployment (Healy and Lenz, 2017) or trade exposure (Margalit, 2011; Jensen, Quinn, and Weymouth, 2017) on voting is relatively recent, and there remains considerable skepticism over whether localized economic hardship has a discernible impact on voting (Hall, Yoder, and Karandikar, 2017; Margalit, 2019).[4]

Different types of voters may respond to economic shocks in different ways, complicating the identification of average effects. For instance, layoffs of lower-skilled workers may be particularly harmful to incumbents since these workers have fewer alternative sources of employment; higher-skilled worker layoffs may be less damaging to incumbents since these workers are more easily

[4] Hall, Yoder, and Karandikar (2017) find that US counties that suffered larger increases in home foreclosures during the Great Recession did not punish or reward members of the incumbent president's party more than less affected counties.

re-employed. The political effects of layoffs may also depend on other, noneconomic factors such as race and group-based social identity, which we discuss in the next section.

2.2 Localized Manufacturing Layoffs and White Identity Politics

Social identity encompasses an individual's association with certain social groups, and the value significance they place on being a part of a particular group (Tajfel, 1974). An individual's social identity can shape her stances on issues and political candidates. An axiom of social identity approaches is that society consists of various groups with differing levels of power and status relative to one another (Tajfel, Turner, Austin et al., 1979). Relevant divisions include race and ethnicity, class, gender, and religion. While voters may consider the interests of others, they tend to care most about the wellbeing of those with whom they most closely identify, and tend to take political positions that are consistent with their group's interests (Shayo, 2009).

According to many contemporary accounts, social identity divisions along racial and ethnic lines explain the outcome of recent elections in the US and beyond. In particular, the perceived grievances and status concerns of white voters lie at the heart of recent backlashes against incumbents and mainstream candidates. Accounts of white voter support for Trump in the 2016 election emphasize how he cultivated and manipulated perceived threats to whites' dominant group status (Jardina, 2019; Mutz, 2018; Sides, Tesler, and Vavreck, 2018). Moreover, it has been shown that Trump used more populist and nationalist rhetoric when campaigning in regions suffering from more manufacturing job losses (Gennaro, Lecce, and Morelli, 2019).

Trump also exploited the perceived decline in American economic power in the context of globalization (Mutz, 2018). Trade and offshoring have increased the United States' economic dependence on other countries. US offshoring has accelerated the economic rise of labor-abundant countries such as China – and the corresponding decline in US manufacturing employment (Autor, Dorn, and Hanson, 2013).[5] To the extent that voters' attitudes toward economic globalization are shaped more by ingroup versus outgroup identities than by globalization's purely distributional economic consequences (Mansfield and Mutz, 2009, 2013; Mutz and Kim, 2017; Jardina, 2019;

[5] Voters who have been more exposed to the negative effects of trade competition are more likely to vote against incumbents (Margalit, 2011; Jensen, Quinn, and Weymouth, 2017) and to support more extreme candidates (Autor, Dorn, Hanson et al., 2016; Colantone and Stanig, 2018).

Ballard-Rosa, Jensen, and Scheve, 2018), Trump and other nationalists may gain an edge over more traditional candidates by linking trade-induced job losses to outgroups.

A plausible application of identity frameworks to the politics of deindustrialization is that localized manufacturing layoffs may activate the social identity concerns of some white voters. For some, the shuttering of manufacturing plants and the ensuing layoffs embody the country's declining standing as a global economic force. Moreover, the localized social and economic effects of plant closures and layoffs outlined above could negatively affect perceptions of dominant group standing. To the extent that manufacturing jobs are perceived as historically important sources of employment and economic security for whites (Guisinger, 2017), layoffs, stagnant incomes, and localized social decay may contribute to a sense of declining social status among some white voters. For white Americans who view the economic standing of the US as synonymous with their own (Jardina, 2019), the decline of American industry may represent a unique status threat. Jardina (2019) finds evidence consistent with this reasoning: whites with stronger ties to their ingroup are significantly more opposed to offshoring, a key driver of manufacturing layoffs in the US.

As such, deindustrialization may contribute to anti-incumbent voting, particularly among white voters in areas with more manufacturing layoffs. Such a reaction is consistent with the recent trend toward right-wing nationalist parties in response to negative economic shocks in other advanced democracies (Colantone and Stanig, 2018; Ballard-Rosa, Malik, Rickard et al., 2017; Dehdari, 2018). Threats to the social and economic status of historically dominant groups appear to be initiating intense political reactions against incumbents and traditional parties, including support for hierarchical social and political arrangements, conformity with group norms, and increased outgroup negativity (Mutz, 2018; Schaffner, MacWilliams, and Nteta, 2018). While the backlash became particularly apparent in the US in 2016, deindustrialization and manufacturing layoffs are not new; they may have weakened incumbent party support among white voters in prior US presidential elections as well.

Together, the economic voting and social identity literatures suggest that deindustrialization could have important effects on voting in US presidential elections. While often framed as competing explanations, economic and cultural interests need not operate in isolation (Noland, 2019). The two channels may interact to influence political attitudes and voting behavior, particularly to the extent that economic downturns threaten group identities (Ballard-Rosa, Jensen, and Scheve, 2018; Mutz, 2018).

Group interests as shaped by voters' racial identities may therefore represent a particularly salient driver of political behavior in a deindustrializing economy. Economic voting frameworks indicate that localized manufacturing layoffs could weaken support for incumbents in affected communities. The social status loss associated with economic interdependence and negative employment shocks could lead some white voters to shun incumbent candidates and parties. The threats to economic and social status represented by deindustrialization may therefore lead some white voters to express their dissatisfaction by voting against the incumbent party in the areas most affected by manufacturing job losses. We devote the remainder of the paper to examining this claim.

3 Data and Empirical Strategy

3.1 Localized Manufacturing Layoffs

The national collapse in US manufacturing employment began several decades ago. In 1979, 23% of the country's workforce – nearly 20 million workers – was employed in approximately 326,000 manufacturing establishments around the country. By 2012, 8 million manufacturing jobs and 43,000 establishments had disappeared;[6] less than 10% of the workforce is currently employed in manufacturing.

There are two main explanations for US deindustrialization and manufacturing layoffs. The first is globalization: extensive tariff liberalization and reduced transportation costs over the past several decades have increased trade among countries. Firms in labor-intensive industries have sought to lower their costs by shifting production to lower-wage nations. This offshoring of production has reduced the demand for lower-skilled manufacturing workers in the US. The second force behind US manufacturing layoffs is the advance of technologies such as computer-aided design, automation, and robotics (Graetz and Michaels, 2017; Acemoglu and Restrepo, 2017;

[6] https://www.census.gov/ces/dataproducts/bds/data_estab.html

Collard-Wexler and De Loecker, 2015). Technology expands labor productivity, which means fewer workers are needed to meet consumer demand.[7]

Our data on manufacturing job losses come from the Quarterly Workforce Indicators (QWI) statistics collected and managed by the United States Census Bureau to quantify growth, decline, and change in the nation's workforce. The QWI employment data are the most comprehensive publicly available labor market microdata in the US, covering employment, job creation, and job losses. The dataset contains unique detailed worker demographics (such as sex, age, education, race and ethnicity) and firm characteristics (such geography, industry, age, and size).[8] Therefore, we are able to observe manufacturing job losses by worker age, sex, educational attainment, and race/ethnicity. This allows us to disaggregate job losses by demographic characteristics, for instance layoffs of white and non-white workers. Our sample of manufacturing layoff data begins in 2004, which is the first year for which coverage includes over 90% of US employment.[9]

Using the Census Bureau application programming interface (API),[10] we queried the QWI data to obtain yearly manufacturing job loss counts at the county level for all 50 states from 1990 to 2016.[11] This process was repeated for all major disaggregations of the QWI data – sex, age,

[7]It is extraordinarily difficult to establish which channel (globalization or technology) has had a greater effect on US manufacturing job losses. Technological adoption and import competition seldom occur in isolation (Fort, Pierce, and Schott, 2018). Many manufacturing firms adopt new technologies in order to compete with imports – that is, trade induces technology. However, advances in information and communications technology have been critical in overcoming impediments to establishing offshoring capabilities and organizing global supply chains (Baldwin, 2016). In this way, technology induces trade, and the routine jobs that tend to be offshored may also be the most likely to be automated (Ebenstein, Harrison, McMillan et al., 2014).

[8]The QWI draws on a wide variety of sources, including administrative employment records collected by the states, Social Security data, federal tax records, and other census and survey data. The appendix contains further details on these data.

[9]For additional details on the yearly coverage, see https://www2.vrdc.cornell.edu/news/data/qwi-public-use-data/

[10]Breakstone, C. (26 June 2017). Census Data API User Guide: Version 1.5. United States Census Bureau. Available from: `https://www.census.gov/data/developers/guidance/api-user-guide.html`.

[11]We restricted this query to the manufacturing industry (QWI Industry Codes 31-33) and all privately owned firms (QWI Owner Code A05).

education, and race/ethnicity.[12] To ensure that we were extracting the proper values, we compared the data drawn from the API queries to the interactive, user-friendly QWI Explorer.[13]

Our study is partly motivated by the fact that the decline of manufacturing work has affected various parts of the country in different ways. While overall US manufacturing employment has fallen sharply, the job losses are unequally distributed across the country. Figure A1 in Appendix A shows the distribution of manufacturing layoffs between 2008 and 2016 by race (i.e. white and non-white workers). The figure illustrates that the number of layoffs peaked in 2008 during the global financial crisis, and that the large majority of layoffs (about 80%) have been of white workers. Figures A2, A3, and A4 in Appendix A display the geographical distribution of manufacturing layoffs across US counties. White layoffs are mainly concentrated in the Midwest, whereas non-white layoffs are localized in the South.

3.2 County-level Models

Our analysis first examines the electoral effect of manufacturing layoffs on county-level voting in the 2008, 2012, and 2016 presidential elections.[14] Following standard practice, we compute county-level two-party vote shares of the Democratic and Republican candidates during the study period (2008-2016). We use the following baseline model to estimate the effects for the Democratic vote share:

[12] Abowd, et. al., The LEHD Infrastructure Files and the Creation of the Quarterly Workforce Indicators, 2006. Available from: `http://lehd.ces.census.gov/doc/technical_paper/tp-2006-01.pdf`.

[13] U.S. Census Bureau. (2018). Quarterly Workforce Indicators (1998–2016). Washington, DC: U.S. Census Bureau, Longitudinal-Employer Household Dynamics Program [distributor], accessed in July 2018 at `https://qwiexplorer.ces.census.gov`. The downloaded data from the API required cleaning and transformation. We then combined the data into three endpoint datasets (i.e. sex/age, sex/education, and race/ethnicity) and transformed each dataset to obtain average manufacturing job losses for each county-state-year combination. This required creating a new distinct ID based on the endpoint (i.e. for the sex/age data this resulted in a new singular sex-age ID) and reshaping the data before collapsing. Lastly, we generated a series of aggregated total variables (e.g. we calculated the total job losses for all age and sex groups by summing all job loss variables for each age group and sex group). As with the data downloading step, we compared these new variables to the QWI Explorer results and downloaded the data to ensure the correct totals were reached.

[14] We obtained the election data from Dave Leip's *Atlas of US Presidential Elections*. `https://uselectionatlas.org/BOTTOM/store_data.php`.

$$\Delta Dem\ Vote\ Share_{ct} = \alpha_0 + \beta_1 Layoffs_{c\tau} + \beta_2 Layoffs_{c\tau} \times Dem\ Inc_t + \beta_3 Unemployment_{c\tau} + \beta_4 Unemployment_{c\tau} \times Dem\ Inc_t + \beta_5 Controls_{c\tau} + \delta_c + \delta_{st} + \epsilon_{ct}, \tag{1}$$

where $\Delta Dem\ Vote\ Share_{ct}$ measures the change in the Democratic candidate's percentage of the two-party vote in county c in presidential election t compared to presidential election t–*1*. We use change rather than the *level* of the Democratic candidate's percentage, since there is a great deal of path dependence in US county-level voting behavior, i.e. the Democratic candidate's percentage in election t depends heavily on his or her percentage in election $t-1$. While not accounting for this temporal dependence would bias our results, our results are not sensitive to this modelling choice.[15]

The variable $Layoffs_{c\tau}$ measures the layoffs per worker in county c from the last presidential election to the election at time t, which we denote with τ (i.e. over the previous four years).[16] This variable is interacted with $Dem\ Inc_t$, which takes a value of one when the incumbent president was a Democrat (2012 and 2016) and zero when the incumbent was a Republican (2008). In some models, we break down layoffs by race to explore the differential effect of white vs. non-white workers' layoffs.

Since county-level trends represent a threat to identification in a DID setup, we model Democratic Party vote share rather than incumbent party vote share. That is, given the strong geographic polarization of American politics, we use a similar approach to that of Hall, Yoder, and Karandikar (2017), allowing counties to trend in terms of their partisanship, rather than their general support for the incumbent. The coefficient of interest thus corresponds to the interaction term $Layoffs_{c\tau} \times Dem\ Inc_t$, which captures the effect of manufacturing layoffs on support for the incumbent party. Since Democratic and Republican two-party vote shares are perfectly negatively correlated, as are the dummies for Democratic and Republican incumbency, our results can be

[15]For a similar approach, see Jensen, Quinn, and Weymouth (2017).

[16]This variable is built by summing the layoffs in county c during the period from the last presidential election to the election at time t and dividing this total by the number of workers in county c in the year before the last presidential election. In other words, we lagged the denominator by five years, since layoffs affect the number of workers in each county. Data of the number of workers by county come from QWI.

interpreted as a general test of support for the incumbent party. In other words, should we find that layoffs reduce the Democratic Party's vote share when the incumbent is a Democrat, an analogous interpretation would hold for a Republican incumbent, albeit with a different magnitude. Our research design also allows us to test whether unemployment caused by manufacturing layoffs is a partisan issue, as found in Wright (2012).

To distinguish manufacturing layoffs from broader employment conditions, we include additional county-level economic and demographic variables. One is the average level of unemployment in county c over the previous four years ($Unemployment_{i\tau}$) and its interaction with the dummy $Dem\ Inc_t$.[17] We note that the correlation between *Layoffs* and unemployment is quite low, $\rho = 0.2$. Figure A5 in Appendix A shows the scatterplot of unemployment and manufacturing job losses, highlighting the difference between these two variables. We also control for three potential confounders as a share of the county population: college educated, male, and foreign born.[18]

Furthermore, δ_c and δ_{st} denote county and state-election year fixed effects, respectively. County fixed effects net out time-invariant differences across counties, whereas state-election year fixed effects capture and control for any time-varying confounders at the state (and national) levels. Two additional considerations are necessary. First, since we do not use first differences of right-hand-side variables, we can still include county fixed effects. Second, the constitutive term $Dem\ Inc_t$ is omitted because its coefficient is absorbed by state-election fixed effects. The error term ϵ_{ct} accounts for all residual determinants of the outcome variable.

The model in equation 1 is a DID variant in which we compare within-county changes in incumbent and non-incumbent party vote shares over time across within-county changes in layoffs per worker. A key difference with standard DID methods is that $Layoffs_{c\tau}$ is a continuous rather than dichotomous variable, which implies that our "treated" units receive heterogeneous treatments

[17]The unemployment data come from the Local Area Unemployment Statistics (LAUS) database. The Bureau of Labor Statistics (BLS) of the US Department of Labor is responsible for the concepts, definitions, technical procedures, validation, and publication of the estimates that state workforce agencies prepare under agreement with the BLS. The concepts and definitions underlying the LAUS data come from the household-level Current Population Survey, which is used to calculate the national unemployment rate. More information is available at `https://www.bls.gov/lau/lauov.htm`.

[18]These variables are lagged and taken from the US Census and County Business Patterns.

of differing intensity. One concern with this model specification is that because layoffs do not occur randomly, there may be systematic correlation between layoffs and a county's partisan orientation.

To attempt to achieve exogenous variation in layoffs at the county level, we construct a Bartik instrument that relies on the sectoral composition of each county and industry-specific national trends in layoffs (see Bartik (1991)). Our approach assumes that each county's exposure to national trends depends on the sectoral composition of its labor force, as well as the number of manufacturing layoffs in all other counties. We use detailed administrative data on worker demographics to construct measures of predicted exposure to layoffs due to national employment shocks across different demographics (i.e. white and non-white). We use the following measure:

$$Bartik\ instrument^{j}_{c\tau} = \frac{Manufacturing\ Employment^{j}_{ct}}{Total\ Employment^{j}_{ct}} \times \frac{Layoffs^{j}_{-c\tau}}{Total\ Employment^{j}_{-ct}} \tag{2}$$

where $Bartik\ instrument^{j}_{c\tau}$ is the Bartik instrument for social group $j = \{total, white, non\text{-}white\}$ in county c over time period τ. $Manufacturing\ Employment^{j}_{ct}$ is the number of manufacturing workers from social group j in county c in time t, and $Total\ Employment_{ct}$ is total employment in county c in time t (t is the year preceding time period τ). $Layoffs^{j}_{-c\tau}$ is the number of manufacturing layoffs of social group j in the US, excluding county c over the time period τ, whereas $Total\ Employment^{j}_{-ct}$ is the number of workers from social group j in the US, excluding county c in time t (preceding time period τ). Simply put, this measure captures the number of layoffs within social group j in county c as predicted by the national shifts and sectoral composition in county c, and is unrelated to the impact of local factors.[19]

Armed with these instruments, we estimate the following first-stage model:

$$\begin{aligned} Layoffs^{j}_{c\tau} = {} & \alpha_1 + \gamma_1 Bartik\ instrument^{j}_{c\tau} + \gamma_2 Bartik\ instrument^{j}_{c\tau} \times Dem\ Inc_t \\ & + \gamma_3 Unemployment_{c\tau} + \gamma_4 Unemployment_{c\tau} \times Dem\ Inc_t \\ & + \gamma_5 Controls_{c\tau} + \delta_c + \delta_{st} + \epsilon_{c\tau} \end{aligned} \tag{3}$$

[19]We divide the national trend of manufacturing layoffs by the total number of workers rather than the number of manufacturing workers, because our framework emphasizes that manufacturing layoffs affect other business activities through supply chains and other externalities.

$$
\begin{aligned}
Layoffs^j_{i\tau} \times Dem\ Inc_t = \alpha_2 + \zeta_1 Bartik\ instrument^j_{i\tau} + \zeta_2 Bartik\ instrument^j_{i\tau} \times Dem\ Inc_t \\
+ \gamma_3 Unemployment_{c\tau} + \gamma_4 Unemployment_{c\tau} \times Dem\ Inc_t \\
+ \gamma_5 Controls_{c\tau} + \delta_c + \delta_{st} + \epsilon_{ct}.
\end{aligned} \tag{4}
$$

We plug the instrumented variables (i.e. *Layoffs* and its interaction with $Dem\ Inc_t$), the endogenous variation of which has been pruned in the first stage, into equation 1 and run the second stage with the exogenous regressor and its interaction.[20] This approach ultimately relies on an instrumented DID design that combines the pre- and post-treatment differences between the treated (high layoffs) and control (no or low layoffs) groups with the exogenous source of variation provided by the Bartik instrument since treated units are not randomly assigned.[21] More formally, we modify equation 1 and estimate the following:

$$
\begin{aligned}
\Delta Dem\ Vote\ Share_{ct} = \alpha_0 + \beta_1 \widehat{Layoffs}_{c\tau} + \beta_2 Layoffs_{c\tau} \widehat{\times D}em\ Inc_t + \beta_3 Unemployment_{c\tau} \\
+ \beta_4 Unemployment_{c\tau} \times Dem\ Inc_t + \beta_5 Controls_{c\tau} + \delta_c + \delta_{st} + \epsilon_{ct},
\end{aligned} \tag{5}
$$

The identifying variance is the initial sectoral composition of each county. In order for the Bartik instrument to allow a causal interpretation, the sectoral composition must only affect the outcome through its effect on layoffs. We therefore control for the unemployment level, which captures general economic conditions that are potentially collinear to local shocks, and for the three potential confounders described above (college educated, male, and foreign born). Furthermore, we include county and state-election year fixed effects in our baseline model.[22]

[20] When we instrument white (non-white) workers' layoffs, we use the Bartik instrument with j = *white (non-white)*.

[21] For a similar approach, see (Duflo, 2001).

[22] Table A1 in Appendix B shows that these confounders are weakly correlated with our instruments, suggesting that they are as good as random. Note that these low correlations imply that the strength of our instrument depends mostly on the national trend component of the Bartik instrument, a result in line with (Goldsmith-Pinkham, Sorkin, and Swift, 2018).

3.3 Individual-Level Models

To estimate the effect of manufacturing layoffs on individual vote choice, we link our manufacturing layoffs data to individual-level survey data from the CCES survey administered by YouGov/Polimetrix in 2008, 2012, and 2016 *after* each election. Our analysis uses the full, nationally representative, stratified sample of (up to) 63,946 respondents in (up to) 2,674 counties. This dataset identifies each respondent's county of residence, which allows us to match the survey respondents to layoffs.

We estimate the effects of layoffs on Democratic vote share at the individual level using the following baseline model:

$$\begin{aligned} Pr(Dem\ Vote_{ict} = 1) = {} & \alpha_1 + \beta_1 \mathit{Layoffs}_{c\tau} + \beta_2 White_{ic} + \beta_3 \mathit{Layoffs}_{c\tau} \times White_{ic} \\ & + \beta_4 Unemployment_{c\tau} + \beta_5 Unemployment_{c\tau} \times White_{ict} + \beta_6 X_{ic} \\ & + \beta_7 X_{ic} \times White_{ic} + \beta_8 Controls_{c\tau} + \delta_c + \delta_{st} + \epsilon_{ict}, \end{aligned} \tag{6}$$

where $Dem\ Vote_{ict}$ is a dummy variable scoring one if respondent i in county c voted for the Democratic candidate in election year t. The variable $\mathit{Layoffs}_{c\tau}$ measures the total layoffs per worker in county c from the last presidential election to the election at time t (denoted τ). This variable is interacted with $White_{ic}$, which takes a value of one if respondent i in county c is white, and zero otherwise. Moreover, we include the average level of unemployment in county c over the previous four years ($Unemployment_{ct}$) interacted with the dummy White_{ic}. We also include a number of individual-level controls in the matrix X_{ic} – age, education, gender, employment, and Senate approval – as well as their interaction with White_{ic}. In addition, we include the same county-level controls as in equation 1. ϵ_{ict} accounts for all residual determinants of the outcome variable.

As in our county-level analysis, the individual-level model includes county fixed effects (δ_c) and state-election year fixed effects (δ_{st}). However, we expand our baseline model with county-election fixed effects, which net out time-varying differences across counties. Notice that in this expanded model specification, we are unable to include δ_{st}, which is absorbed by county-election fixed effects. Furthermore, in these models, we are unable to estimate $\mathit{Layoffs}_{c\tau}$, $Unemployment_{c\tau}$, and $Controls_{c\tau}$, since they are absorbed by county-election year fixed effects. In some model specifications, we include linear county-specific trends to check the validity of the parallel-trends assumption.[23] We run OLS regressions with robust standard errors.[24]

We employ a similar identification strategy as in the county-level analysis, using our shift-share manufacturing layoffs instrument. Moreover, we include county-specific trends to better substantiate the parallel-trends assumption.

4 Results

4.1 County-Level Results

Table 1 reports the results of the county-level election models. We first report the results of the reduced-form model from equation 1 (Model 1) and then move to the two-stage least-squares model (2SLS) from equation 5 (Model 2).[25] The coefficient of the interaction between layoffs and *Dem Inc* is negative and significant across both model specifications. These findings indicate that counties hit by layoffs are less likely to vote for the Democratic Party when the president is a Democrat.

Next we investigate the effects of layoffs disaggregated by race. We include white and non-white layoff variables on the right-hand-side of the model as well as their interaction with *Dem Inc*. Models 3 (OLS) and 4 (2SLS) show that while the interaction between white layoffs and *Dem Inc* is negative and significant, the interaction between non-white layoffs and *Dem Inc* is not significant. Taken together, the results suggest that whites may respond to layoffs differently than non-whites. We will rely on the individual level analysis to further substantiate this claim.

The 2016 election stands out in our period of study in that the Republican candidate explicitly cultivated status threats related to white identity, while also promising to revive US

[23]Our results are robust to including quadratic county-specific trends (available upon request).

[24]Our results are virtually the same if we rely on logit and probit models (available upon request). We use OLS regressions in order to avoid the incidental parameter problem.

[25]The first stage of Model 2 is reported in Table A2 in Appendix B. Our instruments are always significant in the first stage ($p < 0.01$), and the F statistic is always much larger than 10. The first stage of the other models shows similar estimates (available upon request). We also note that standard diagnostic tests for 2SLS show no concern of weak identification or under-identification, i.e. both the Kleibergen-Paap rk LM statistic and the Kleibergen-Paap rk Wald statistic are significant.

manufacturing. To the extent that our analytical framework has purchase, we might expect larger anti-incumbent effects in 2016 compared to prior elections. Models 5–7 report the estimates of white and non-white layoffs by election year. The coefficient of white layoffs is negative and significant for the 2012 and 2016 elections, but positive and significant for the 2008 election. Moreover, the estimated effect is over three times larger in 2016 compared to 2012.[26]

We conduct a counterfactual exercise on the 2016 election to determine the magnitude of the effect by exploring how the composition of votes in a number of closely contested states would have differed if there had been fewer white manufacturing layoffs. The computation of the counterfactual is based on the coefficient estimate in Model 7 of Table 1, which indicates that the Democratic vote share decreases by 2 percentage points for a 1-percentage-point increase in the average number of white layoffs in a county. For each county, we compute the fraction of two-party votes that Clinton would have received if the manufacturing shock had been X% smaller as: $2 \times \textit{White layoffs}_{c,2016} \times$ X% – i.e. the point estimate of the effect of white layoffs on the vote share, the size of each county's measured white layoffs, and the scaling factor X%. We next multiply this product by the number of two-party votes in a county to calculate the number of additional votes that Clinton would have obtained in the counterfactual scenario. We then aggregate these county-level votes into state totals.

Table 2 presents the results of this counterfactual analysis. Column 1 shows the actual vote margin in favor of Clinton in the 2016 election for a set of closely contested states. The three subsequent columns show counterfactual outcomes had white layoffs been 20%, 30%, or 40% fewer. Since we find that white layoffs increased Trump's vote share, the counterfactual analyses for fewer white layoffs correspondingly increase Clinton's counterfactual vote totals. The results in Table 2 show that Clinton would have won Michigan in a counterfactual scenario with 20% fewer white

[26]We also run our main models without the demographic controls, since we are concerned about the possibility of post-treatment bias with respect to these covariates. The results, which appear in Table A3, are very similar to those reported in Table 1. Moreover, we re-run Models 2–8 in Table 1 using OLS rather than 2SLS to confirm that our reduced-form estimates align with our 2SLS estimates. Indeed, this is the case (see Table A4).

Table 1: Layoffs and Presidential Elections, County Level, 2008–2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	2SLS	OLS	2SLS	2SLS	2SLS	2SLS
	Change of Democratic Vote Share						
	Full Sample				2008	2012	2016
Layoffs total	0.089	0.597**					
	(0.046)	(0.147)					
Layoffs total*Dem incumbent	-0.178**	-0.230**					
	(0.047)	(0.079)					
White layoffs			0.168*	0.924**	0.323**	-0.590**	-2.003**
			(0.066)	(0.192)	(0.110)	(0.066)	(0.122)
Non-white layoffs			-0.116	-0.680**	-0.202	1.678**	1.967**
			(0.100)	(0.187)	(0.103)	(0.163)	(0.400)
White layoffs*Dem incumbent			-0.295**	-0.320**			
			(0.068)	(0.112)			
Non-white layoffs*Dem incumbent			0.155	0.217			
			(0.099)	(0.135)			
Constant	-0.025*				-0.107**	0.008	0.047**
	(0.012)				(0.026)	(0.017)	(0.011)
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	No	No	No
State-Election FE	Yes	Yes	Yes	Yes	No	No	No
Underidentification test		152.64**		189.40**	421.40**	524.78**	382.10**
Weak identification test		81.57**		71.94**	519.21**	912.25**	562.12**
Observations	9,160	9,132	9,132	8,108	2,701	2,763	2,767
R-squared	0.792	0.009	0.030	0.007	0.170	0.234	0.498
Number of counties	3,086	3,058	3,058	2,755	2,701	2,763	2,767

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

Note: OLS and 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is county-election. The outcome variable is the change in the Democratic candidate's two-party vote share in county c in the presidential election t. The key independent variables are layoffs per worker with a dummy scoring one if the US president is a Democrat. Sources: QWI (2018), Dave Leip's Atlas of U.S. Presidential Elections (2018), LAUS (2018).

layoffs, and would have won Wisconsin with 30% fewer white layoffs, and Pennsylvania with 40% fewer white layoffs. These results would have flipped the 2016 election in Clinton's favor.[27]

Table 2: Counterfactual Outcomes in Closely Contested States

		White Layoffs		
State	Actual Outcome	20% Smaller	30% Smaller	40% Smaller
Arizona	-91234	-84633	-81332	-78032
Florida	-112911	-94178	-84811	-75444
Michigan	-10704	**13596**	**25746**	**37895**
Minnesota	**44593**	**59666**	**67203**	**74739**
New Hampshire	**2736**	**5332**	**6631**	**7929**
North Carolina	-173315	-157025	-148880	-140736
Pennsylvania	-44292	-16621	-2786	**11049**
Wisconsin	-22748	-5788	**2692**	**11172**
Electoral Votes Trump	306	290	280	260
Electoral Votes Clinton	232	248	258	278

Note: The computation of the counterfactual is based on the estimate that a 1-percentage-point increase in per worker layoffs reduces the Democratic share of the two-party vote by 2 percentage points (see Model 8 in Table 1). The actual outcome in column 2 reports the margin in favor of the Democratic Party in each state. Positive values indicate that the Democratic Party won the state in 2016. The reported values in columns 3–5 are estimated margins in favor of the Democratic Party in the counterfactual scenario of fewer layoffs.

We perform a number of additional tests, whose details are discussed in the Appendix B. Here we summarize the main findings. First, we run our models with different outcomes. In particular, we show that (a) our results are similar if we use *levels* rather than *changes* in Democratic candidates' percentages (Table A5), (b) layoffs do not affect turnout (Table A6, Model 1), and (c) our findings are the same if use overall Democratic vote shares (rather than two-party) in the operationalization of our outcome variable (Table A6, Model 2). Moreover, we show that our results hold if we include potential confounders, i.e. *White population share*, localized Chinese import surges *China Shock* (Autor, Dorn, and Hanson, 2013), and layoffs broken down

[27]The magnitude of our effect is larger than the magnitude of the effect estimated using the surge of imports from China (`https://www.washingtonpost.com/news/wonk/wp/2016/12/01/how-china-may-have-cost-clinton-the-election/?utm_term=.8be54095313f`).

by level of education, age, and gender (Table A7).[28] Importantly, in Model 8 of Table A7 we use the instruments as in Autor, Dorn, and Hanson (2013) to test the Sargan's J statistic for over-identification. The test is not significant, which implies no concerns of over-identification.

Furthermore, we explore heterogeneous treatment effects across swing states and non-swing states (Table A8); estimates for swing states are particularly large in line with the counterfactual exercise reported in Table 2. Moreover, we show that our results hold if we use commuting zone (CZ), rather than county, as the unit of analysis to avoid the potential "checkerboard problem" (Busch and Reinhardt, 2000) (Table A9). Finally, our results are robust to the inclusion of CZ and district trends, which corroborate the validity of the parallel trend assumption (Table A10).

4.2 Individual-level Results

So far, we have shown that manufacturing job losses in general, and white worker layoffs in particular, significantly decrease incumbent party vote shares. In this section, we further explore the impact of layoffs on the 2008–2016 presidential elections using individual-level data, which allow us to overcome some of the shortcomings of the previous analysis in three ways. First and most importantly, we are able to identify the race of the respondents, i.e. white or non-white. This allows us to examine the possibility that manufacturing layoffs lead to more anti-incumbent voting by white voters in particular. Second, we can control for a set of potentially confounding individual-level characteristics. Third, since we have a much larger number of observations, we can include county-specific linear trends, which allow us to validate the parallel-trends assumption at a more disaggregated level.

Our main results are reported in Table 3. We begin by running our baseline model in line with the previous analysis at the county level. Model 1 shows that the coefficient of the interaction between layoffs and *White* is negative and significant. This finding implies that whites are less likely to vote for Democratic candidates in counties that have experienced a large number of manufacturing layoffs, which is in line with the county-level analysis. Note that the coefficient corresponding to *Layoffs* is not significant, which indicates that layoffs do not affect the voting behavior of non-whites. We then modify the baseline model to include county-specific trends,

[28] Figure A6 in Appendix A shows the geographical distribution of this variable across US counties.

which do not affect our results (Model 2); this mitigates concerns about possible violations of the parallel-trends assumption.

In Models 3 and 4 we estimate the 2SLS regression without and with county-specific trends.[29] The coefficient of the interaction between layoffs and white respondents remains negative and significant. We note that the estimated interaction coefficient in the 2SLS regression is almost twice as large as the coefficient in reduced form. Model 5 includes county-election year fixed effects as well as trends. Although this is a very conservative test since the model absorbs all county-level variation, our main results hold. Thus, time-varying unobservables at the county level do not drive our results.[30]

Models 6–8 show the results of the 2SLS regressions by election. The coefficient of the interaction between *Layoffs* and *White* is negative in each election, but it is only significant in 2012 and 2016, which is in line with the analysis at the county level. Also similar to the county-level analysis, the coefficient of the interaction term is the largest in 2016: it is 90% larger in 2016 than it is in 2012. This appears consistent with the view that Trump successfully cultivated white voter status anxieties in deindustrializing counties. We will further probe this mechanism in the next section.[31]

We report the full results of additional robustness tests in Appendix C and briefly discuss the main findings here. In particular, the interaction between *White* and *Layoffs* is not significant when turnout is the outcome (Table A15). Moreover, our results are unchanged when we include *White population share* and *China shock* (Table A16). Furthermore, our results hold for both swing and non-swing states, with a larger effect in swing states compared to non-swing states (Table A17). Finally, our results are similar if we use layoffs per worker in CZs, in which there is a significant larger number of respondents compared to counties. In these models, we include CZ fixed effects and we cluster standard errors at the level of CZ (Table A18).

[29]The first stage of Model 3 is reported in Table A11 in Appendix C. The first stages of the other models show similar estimates (available upon request). Standard diagnostic tests show no concerns of under-identification or weak identification.

[30]The results are similar if we rely on an OLS regression (see Table A13 in Appendix C).

[31]We re-estimate our main models without the individual-level controls; the main results are unchanged (Table A14).

Table 3: Layoffs and the 2008–2016 Presidential Elections, Individual Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	Pr(Vote for the Democratic Candidate=1)							
	Full Sample					2008	2012	2016
White	0.15**	0.15**	0.16**	0.16**	0.15**	-0.01	0.08**	0.19***
	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)	(0.050)	(0.035)	(0.030)
Layoffs	0.47	-0.78	2.91**	-0.64		1.25	-0.22	0.35
	(0.460)	(0.683)	(0.851)	(2.887)		(0.881)	(0.654)	(0.791)
White*Layoffs	-1.00**	-1.20**	-1.82**	-2.00**	-1.80**	-1.76	-1.70**	-3.18***
	(0.339)	(0.351)	(0.426)	(0.439)	(0.449)	(0.914)	(0.680)	(0.830)
Constant						0.45**	0.70**	0.14**
						(0.132)	(0.103)	(0.044)
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	No	No	No	No
State-Election FE	Yes	Yes	Yes	Yes	No	No	No	No
County-Election FE	No	No	No	No	Yes	No	No	No
Trends	No	Yes	No	Yes	No	No	No	No
Underidentification test			304**	6855**	944**	681**	2211**	3753**
Weak identification test			214**	3464**	205**	1046**	4273**	3653**
Observations	147,264	147,254	147,264	147,254	146,217	30,980	52,480	63,966
R-squared	0.168	0.182	0.167	0.182	0.188	0.072	0.157	0.144

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

Note: OLS and 2SLS regressions with robust standard errors clustered by county in parentheses. Unit of observation is individual-county-election. The outcome variable is a dummy scored one if the respondent voted for the Democratic candidate in the 2008–2016 presidential elections. The key independent variable is layoffs per worker in interaction with a dummy that takes a value of one if the respondent is white. Sources: QWI (2018), CCES (2018), LAUS (2018).

4.3 Exploring the Possible Mechanisms

So far, we have shown that whites' voting response to manufacturing layoffs differs from that of non-whites. In this section, we explore possible mechanisms driving this result. Combining economic hardship and social identity theoretical frameworks suggests that some whites may be more likely to perceive a decline in US status if they reside in counties that have been hit harder by deindustrialization.

We use ANES data to test this mechanism. We focus on two questions, both of which were administered prior to the election, designed to capture the possible theoretical mechanism: 1) Is the country on the "right track"?[32] and 2) Has the US position in the world gotten stronger?[33] We rely on two waves of the survey conducted in 2012 and 2016, the two election years in our sample in which we find white voters responding electorally to layoffs. The respondents are geo-located at the congressional district level, so for congressional districts with more than one county, we use the average value of county-level layoffs, weighted by county population in 2000. We use the same model specification as in equation 6 with different individual-level controls. Following Jardina (2019), these include dummies for: Democrat, gender, unemployed, college degree, and trade union membership, as well as an ordinal variable capturing the respondent's ideology.

The results of the 2SLS regressions are reported in Table 4 (Models 1 and 2).[34] The coefficient of the interaction between *White* and *Layoffs* is negative and significant. This implies that white respondents in counties hit by layoffs are more likely than non-white respondents to believe the country is on the wrong track and that the US position in the world has become weaker. These findings resonate with Mutz (2018) and Jardina (2019) and indicate that economic

[32]The exact wording is: "Do you feel things in this country are generally going in the right direction, or do you feel things have pretty seriously gotten off on the wrong track?" We create a dummy equal to 1 if the respondent indicates "right track".

[33]The exact wording is: "Turning to some other types of issues facing the country. During the past year, would you say that the United States' position in the world has grown weaker, stayed about the same, or has it grown stronger? We create a variable equal to -1 if the respondent indicates "weaker", zero for "stayed about the same", and 1 for "stronger".

[34]The first stage of Model 1 is reported in Table A12 in Appendix C. The first stages of the other models show similar estimates (available upon request). Diagnostic tests show no concerns about weak or under-identification.

Table 4: Layoffs and Individual Attitudes, 2012–2016

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS					
	US on the Right Track	US Position in the World	Status of the US Economy	Personal Financial Situation	Offshoring	Immigration
White	-0.01	-0.12*	0.04	0.05	0.01	0.13
	(0.038)	(0.054)	(0.034)	(0.036)	(0.044)	(0.088)
Layoffs	2.70	-3.27	-3.33	12.52	7.79	5.08
	(6.518)	(9.325)	(7.684)	(7.065)	(7.287)	(16.390)
White*Layoffs	-8.16**	-7.38*	1.12	1.30	3.54	3.77
	(2.225)	(3.454)	(2.122)	(2.261)	(2.642)	(5.448)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Election FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls FE	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification test	47.30**	46.54**	46.54**	46.54**	46.54**	45.62**
Weak identification test	89.25**	90.19**	90.15**	90.15**	90.15**	87.36**
Observations	5,753	5,796	5,819	5,819	5,819	5,495
R-squared	0.213	0.201	0.142	0.088	0.019	0.100

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

Note: 2SLS regressions with robust standard errors clustered by district in parentheses. The unit of observation is individual-district-election. The outcome variables capture (1) attitude toward the general situation of the country, (2) attitude toward the US position in the world, (3) attitude toward the status of the economy, (4) attitude toward respondent's economic situation, (5) attitude toward offshoring, and (6) attitude toward immigration. The key independent variable is layoffs per worker interacted with a dummy scoring one if the respondent is white. Sources: QWI (2018), ANES (2018), LAUS (2018).

and cultural factors interact to affect voting behavior. Whites are more likely to associate local manufacturing layoffs with American decline.

Models 3 and 4 of Table 4 report the results of other ANES questions designed to assess economic perceptions. Specifically, we include respondents' perceptions of the status of the US economy (Model 3) and the strength of respondents' personal financial situation in previous years (Model 4). We find no relationship between layoffs and these alternative economic outcomes.

Finally, we examine whether white respondents in counties hit by manufacturing layoffs are more likely to oppose offshoring (Model 5) and immigration (Model 6). Here too we find no statistically significant relationships. In short, there is no evidence that voters in communities that have been more significantly affected by deindustrialization demand protectionist and anti-immigration policies, regardless of race.[35]

5 Conclusion

The decline of US manufacturing jobs has profoundly altered the country's economic and social landscape. Our study examines how manufacturing layoffs have affected recent US presidential elections. Our findings indicate that localized manufacturing job losses have eroded white voters' support of incumbents. Layoffs are associated with anxieties over American economic standing among whites, which is consistent with findings from recent studies that economic shocks are a source of white voter status anxieties (Mutz, 2018; Jardina, 2019).

The surprising election of Donald Trump initiated a body of research examining its fundamental causes. Two main explanations have emerged. The first emphasizes localized economic hardship, mainly associated with a rise in imports from China, and the ways in which the candidate's protectionist message resonated with those left behind by globalization. The second explanation highlights white voter grievances associated with a decline in majority group status. Our paper demonstrates that these two determinants are not mutually exclusive. Deindustrialization

[35]The results are similar if we rely on logistic and OLS regressions (Table A19 in Appendix C). Moreover, Table A20 in Appendix C reports similar models using ANES data from 2008, when the Republicans were the incumbent party. We do not find that white respondents in counties hit by layoffs were more likely to believe that the US was on the wrong track or that the US position in the world had weakened. Indeed, for all other outcomes the interaction term is not significant.

appears to represent a unique status threat. The decline of manufacturing has fomented white voter anxieties and set the stage for a nationalist political movement grounded in racial appeals and protectionism. Due to globalization and automation, most lost US manufacturing jobs may be gone for good. But the impact of deindustrialization on US politics will likely resonate for years to come.

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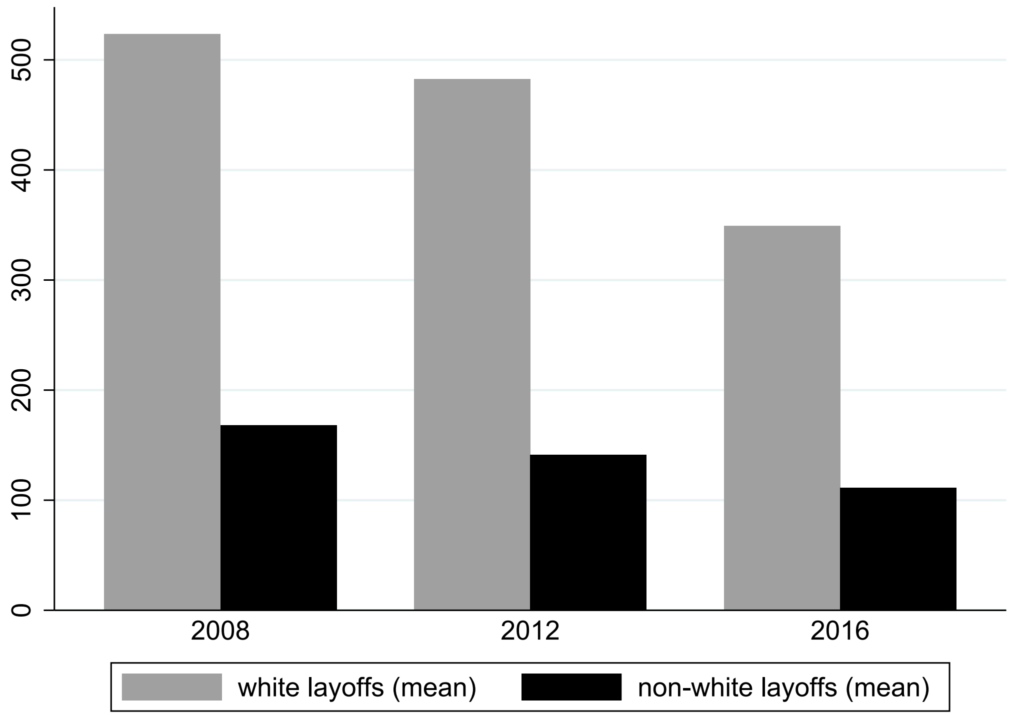
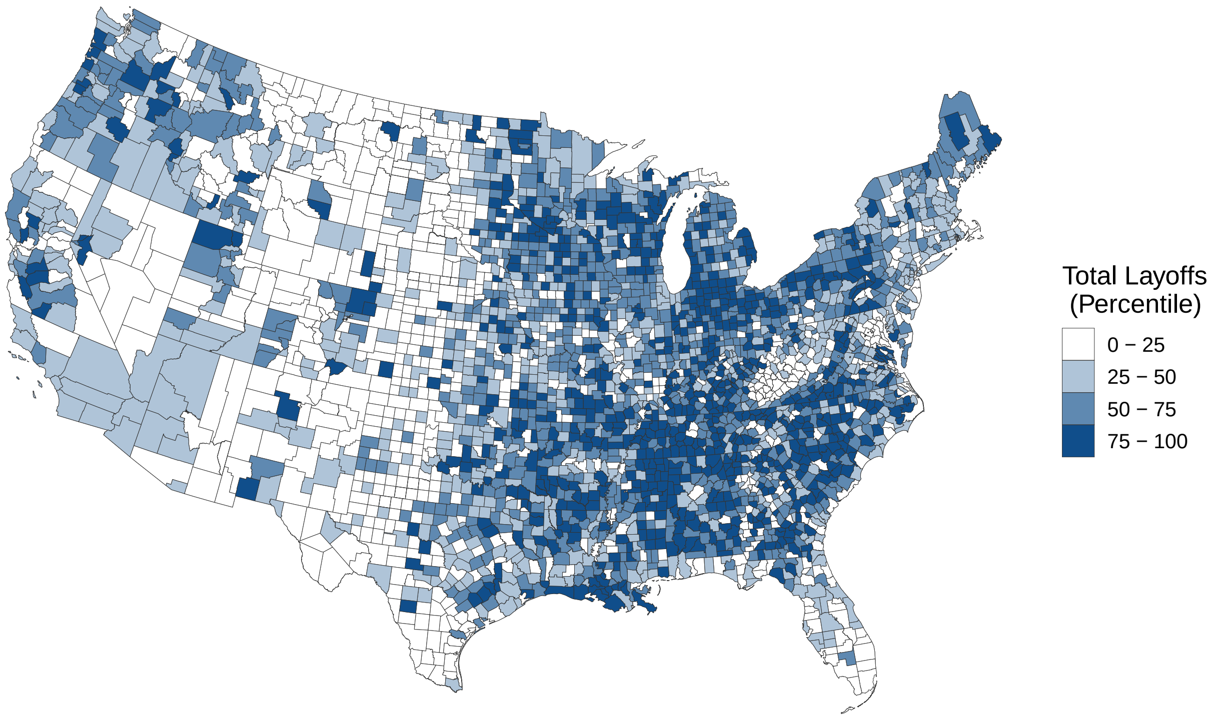
Appendix A

Figure A1: Layoffs of White and Non-white Workers, 1990–2016



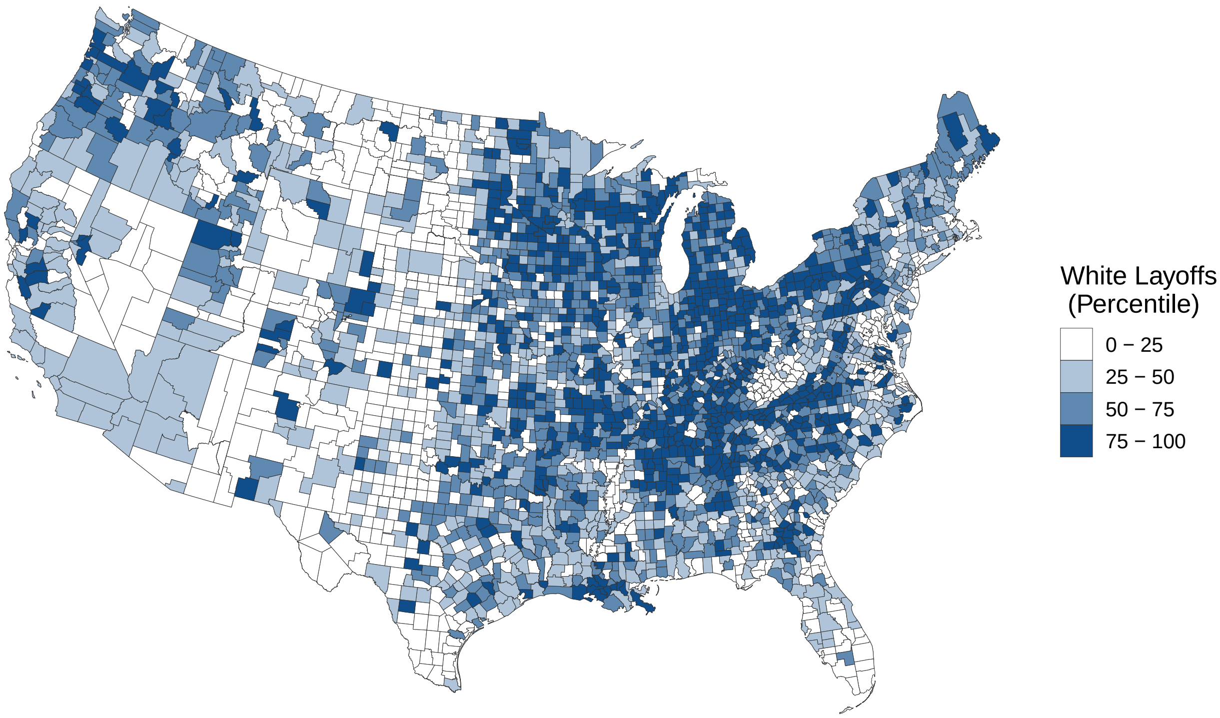
Note: Source: QWI (2018).

Figure A2: Total Per Worker Layoffs by US County, 2008–2016



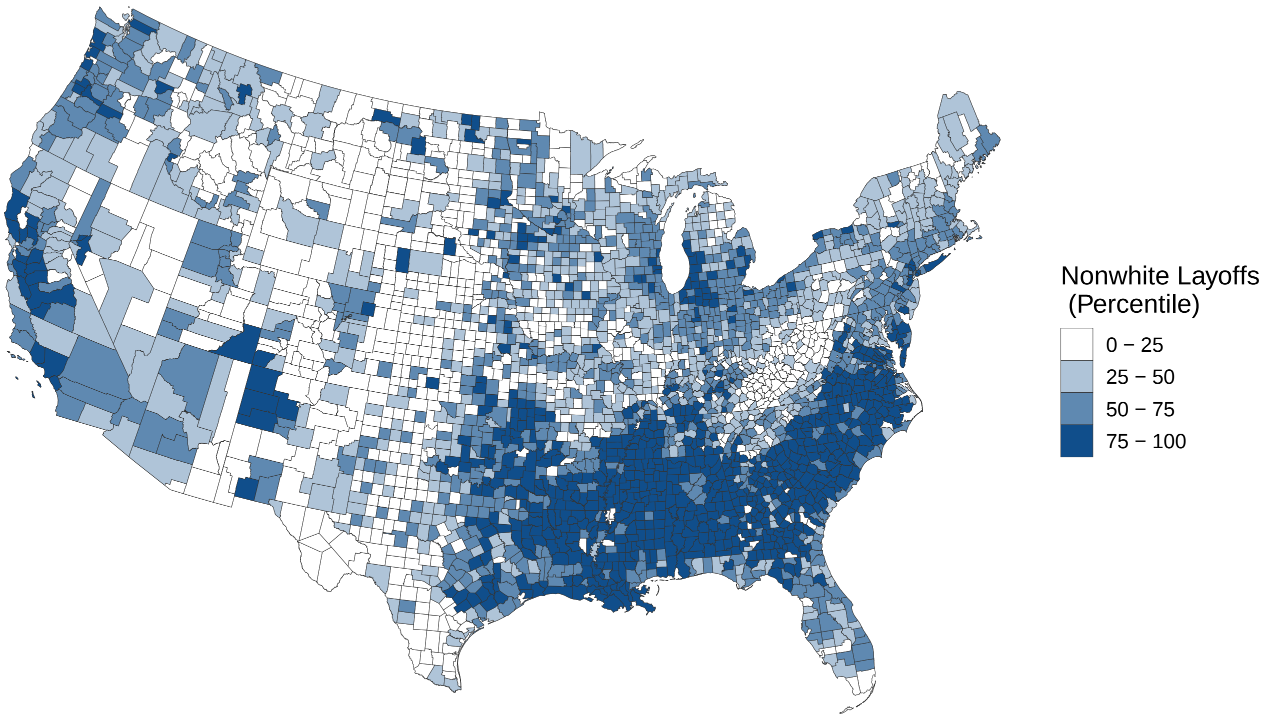
Source: Quarterly Workforce Indicators.

Figure A3: Total Per Worker White Worker Layoffs by US County, 2008–2016



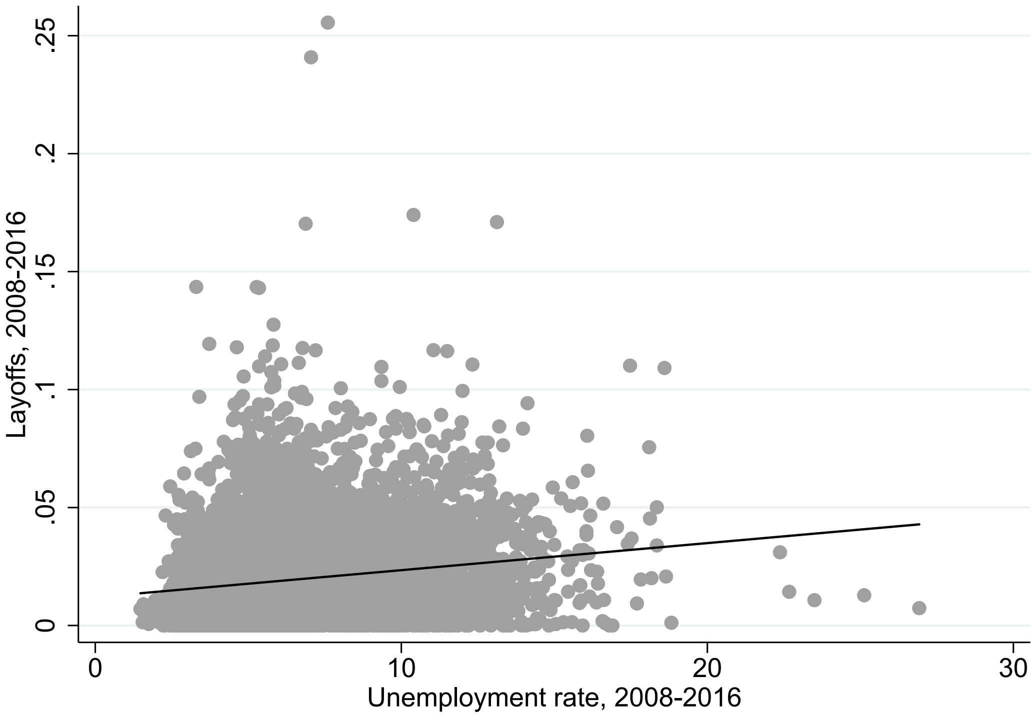
Source: Quarterly Workforce Indicators.

Figure A4: Total Per Worker Non-white Worker Layoffs by US County, 2008–2016



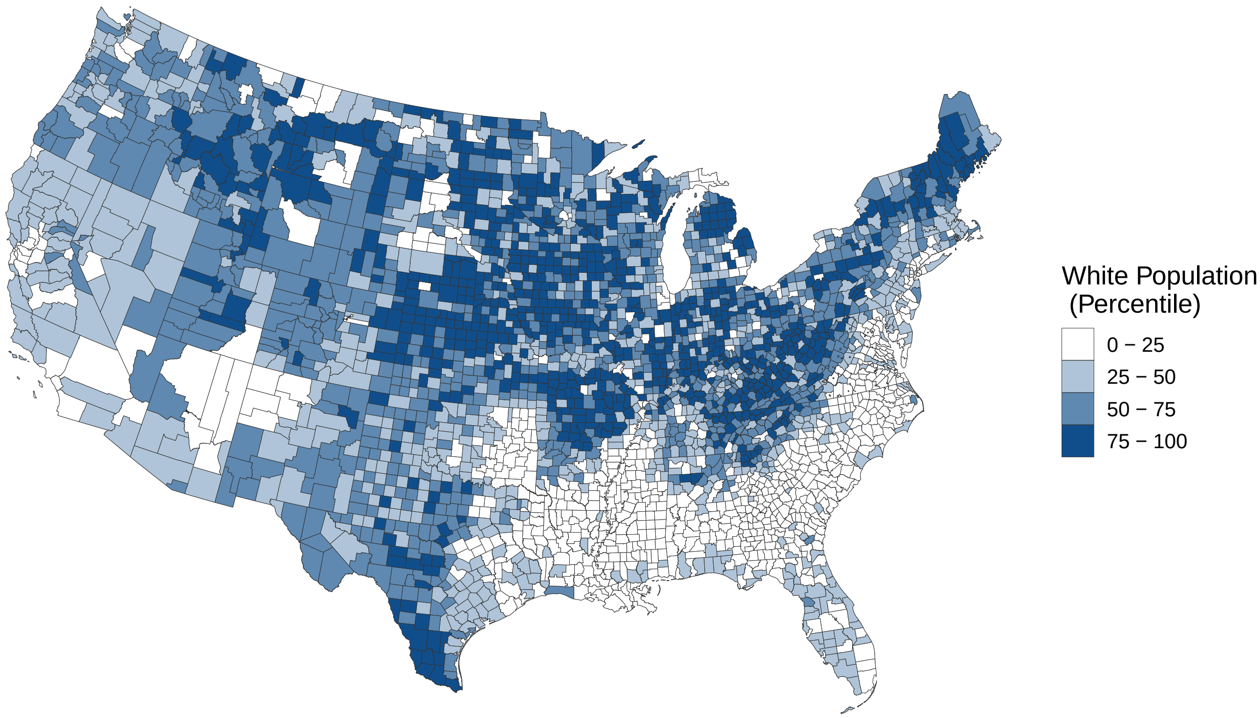
Source: Quarterly Workforce Indicators.

Figure A5: Layoffs and Unemployment, 2008–2016



Source: QWI (2018) and LAUS (2018).

Figure A6: White Population Shares, 2008–2016



Source: US Census Bureau.

Appendix B: County-level Evidence

Instrumental variables: diagnostics

Table A1: Correlations between Bartik Instrument and Potential Confounders

	Unemployment	Income	Share of Foreign Born	Share of College Educated	Share of Male	Population
Bartik Instrument	**-0.14**	**0.09**	**0.02**	**0.01**	**0.03**	**0.09**
	Manufacturing		Service		Natural Resources	
	# Establishment	Employment	# Establishment	Employment	# Establishment	Employment
Bartik Instrument	**0.03**	**0.09**	**-0.01**	**-0.002**	**-0.03**	**-0.03**

Note: Bartik instrument refers to the Bartik instrument for total layoffs.

Table A2: Layoffs and Presidential Elections, County Level, 2008–2016 (first stage)

	2SLS
	Change of Democratic Vote Share
	(1)
	First stage (Layoffs)
Bartik instrument	76.402***
	(5.378)
Bartik instrument*Dem Inc	2.275
	(3.447)
	*First stage (Layoffs*Dem Inc)*
Bartik instrument	-12.301***
	(4.090)
Bartik instrument*Dem Inc	100.056***
	(2.921)
Unemployment Control	Yes
Demography Controls	Yes
County FE	Yes
State-Year FE	Yes

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

Note: 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is county-election. 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 the interaction between layoffs per worker and a dummy scoring one if the US president is a Democrat. The first stage is related to Model 2 in Table 1. Sources: QWI (2018), Dave Leip's *Atlas of U.S. Presidential Elections (2018)*, LAUS (2018).

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, our main models with levels rather than *changes* in Democratic candidates' percentages. Table A5 reports the results, which are similar to those discussed above. Second, we examine the relationship between layoffs and turnout. One possible interpretation of our results is that manufacturing layoffs reduce turnout. Yet we find that layoffs have no effect on turnout in elections in which the incumbent president is a Democrat (Table A6, Model 1). However, we do not have turnout data broken down by partisanship or by race. Third, our results are similar if we use Democratic votes as a share of all votes as the operationalization of our outcome variable (Table A6, Model 2).

Moreover, we include potential confounders in our main model specification to check whether our results are driven by omitted variable bias. In particular, we include two additional covariates in our main model. The first is the share of whites in each county (*White population share*).The second additional covariate is the 'China shock' measure developed by Autor, Dorn, and H Hanson (2013) to capture the localized effect of Chinese imports to the US (*China shock*). We interact both of these additional control variables with *Dem Inc*.[36] Since white workers constitute the majority of manufacturing layoffs, and since layoffs may increase the probability of relocating to other counties, the share of the county population that is white may be subject to reverse causality, making it a poor control variable. This is why we do not include this variable in the baseline model. Even when we include these potential confounders, our main results hold (see Table A7).[37]

In Model 8 we also instrument for the China shock using the same identification strategy as in Autor, Dorn and Hanson (2013). Our main results remain unchanged. In Model 8 we drop the interaction between the China shock and *Dem Inc*, but we keep both the China shock instrument and its interaction with *Dem Inc*. This approach gives us more exogenous regressors than endogenous variables, which allows us to test the Sargan's J statistic for over-identification. The test indicates no concerns about over-identification, which corroborates the validity of our instruments.

Furthermore, we include worker layoffs, broken down by level of education, age, and gender (Table A7, Model 9), which could be potential confounders of *White Layoffs*. All these variables enter with statistically significant coefficients.[38] We also explore effect heterogeneity. In particular,

[36] In contrast to the original variable built by Autor, Dorn, and H Hanson (2013), our measure of China shock varies across counties. We thank Andrea Cerrato, Federico Maria Ferrara, and Francesco Ruggieri for sharing their data with us.

[37] When we include the *China shock* variable and its interaction, we are *de facto* controlling for job losses caused by trade liberalization. Thus, *Layoffs* and its interaction captures plant closures mainly caused by automation.

[38] 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

we show that our estimates are particularly large in swing states (Table A8), which is in line with the counterfactual exercise reported in Table 2.[39]

One potential concern is that the spatial distribution of workers in adjacent counties may influence how each county's residents vote. Our measures of county-level worker layoffs do not account for neighborhood effects in spatial agglomerations that cross county borders (Chase 2015). This could lead to a "checkerboard problem" (Busch and Reinhardt 2000, 708) whereby workers with similar economic interests who are in close geographic proximity – even if spread across adjoining counties – exhibit political behavior that is different from that of workers who are more geographically dispersed (Busch and Reinhardt 2000, 2005). As Chase (2015) notes, the consideration of space raises complicated methodological obstacles: county boundaries may not capture the spatial dependence of local economies since counties often reflect political boundaries rather than an area's local economy. This is potentially problematic for our 2SLS analysis, since commuters who work in a different county from the one in which they live represent a threat to the exclusion restriction. To address this issue, we re-run our main DID and 2SLS models using commuting zone (CZ) as the unit of analysis. The results are virtually the same as those reported above (see Tables A9). If anything, the results are even stronger than the county-level findings, suggesting that any bias works against our key findings.

Finally, we show that our results hold if we include CZ and state linear-specific trends to validate the parallel-trends assumption (see Table A10). Note that we are unable to include county linear-specific trends, since we would end up with more than 3,000 covariates. Since we have only 9,000 observations, our models never converge and there are concerns about degrees of freedom.

[39] The ten swing states are Colorado, Florida, Iowa, Nevada, New Hampshire, North Carolina, Ohio, Pennsylvania, Virginia and Wisconsin.

Table A3: Layoffs and Presidential Elections, County Level, 2008–2016 (with no controls)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	Change of Democratic Vote Share							
	All Sample		Non-White Counties	White Counties	All Sample	2008	2012	2016
Layoffs total	0.100**	0.581***	0.571***	0.543				
	(0.045)	(0.146)	(0.167)	(0.355)				
Layoffs total*Dem incumbent	-0.183***	-0.226***	0.071	-0.908***				
	(0.047)	(0.078)	(0.087)	(0.189)				
White layoffs					0.969***	-0.258**	-0.716***	-3.184***
					(0.194)	(0.110)	(0.061)	(0.155)
Non-white layoffs					-0.688***	-0.325***	1.706***	2.567***
					(0.186)	(0.114)	(0.157)	(0.457)
White layoffs*Dem incumbent					-0.327***			
					(0.114)			
Non-white layoffs*Dem incumbe					0.197			
					(0.126)			
Constant	-0.081***					0.056***	-0.035***	-0.010**
	(0.004)					(0.004)	(0.002)	(0.005)
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	No	No	No	No	No	No	No	No
County FE	Yes	Yes	Yes	Yes	Yes	No	No	No
State-Year FE	Yes	Yes	Yes	Yes	Yes	No	No	No
Underidentification test		151.95***	110.75***	38.65***	188.99***	432.92***	543.30***	389.58***
Weak identification test		81.00***	63.58***	14.61***	71.21***	573.80***	965.53***	630.62***
Observations	9,161	9,133	6,906	1,900	8,109	2,702	2,763	2,767
R-squared	0.789	-0.004	-0.014	0.028	-0.017	0.028	0.186	0.121
Number of counties	3,086	3,058	2,352	694	2,755	2,702	2,763	2,767

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

Note: OLS and 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is county-election. 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 layoffs per worker with a dummy scoring one if the US president is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of U.S. Presidential Elections (2018)*, LAUS (2018).

Table A4: Layoffs and Presidential Elections, County Level, 2008–2016 (OLS models)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS						
	Change of Democratic Vote Share						
	All Sample	Non-White Counties	White Counties	All Sample	2008	2012	2016
Layoffs total	0.086*	0.147					
	(0.046)	(0.131)					
Layoffs total*Dem incumbent	-0.030	-0.573***					
	(0.049)	(0.128)					
White layoffs			0.182***	0.182***	-0.205***	-0.562***	-1.848***
			(0.067)	(0.067)	(0.076)	(0.044)	(0.122)
Non-white layoffs			-0.114	-0.114	-0.294***	1.742***	2.086***
			(0.098)	(0.098)	(0.105)	(0.162)	(0.433)
White layoffs*Dem incumbent			-0.305***	-0.305***			
			(0.068)	(0.068)			
Non-white layoffs*Dem incumbe			0.165*	0.165*			
			(0.096)	(0.096)			
Constant	-0.066***	-0.132***	-0.081***	-0.081***	0.054***	-0.040***	-0.033***
	(0.005)	(0.012)	(0.004)	(0.004)	(0.003)	(0.002)	(0.004)
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	No	No	No
State-Year FE	Yes	Yes	Yes	Yes	No	No	No
Observations	7,103	2,033	9,161	9,161	3,041	3,052	3,068
R-squared	0.747	0.874	0.789	0.789	0.026	0.168	0.131
Number of counties	2,549	827	3,086	3,086	3,041	3,052	3,068

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

Note: OLS with robust standard errors clustered by county in parentheses. The unit of observation is county-election. 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 layoffs per worker with a dummy scoring one if the US president is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of U.S. Presidential Elections (2018)*, LAUS (2018).

Table A5: Layoffs and Presidential Elections, County Level, 2008–2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	2SLS	OLS	2SLS	2SLS	2SLS	2SLS
	Democratic Vote Share						
	Full Sample				2008	2012	2016
Layoffs total	0.198***	0.838***					
	(0.042)	(0.139)					
Layoffs total*Dem incumbent	-0.202***	-0.162***					
	(0.039)	(0.062)					
White layoffs			0.593***	1.677***	-0.016	-1.269***	-1.512***
			(0.063)	(0.193)	(0.223)	(0.261)	(0.357)
Non-white layoffs			-0.850***	-1.590***	1.137***	3.126***	4.090***
			(0.120)	(0.221)	(0.279)	(0.456)	(1.184)
White layoffs*Dem incumbent			-0.581***	-0.635***			
			(0.055)	(0.094)			
Non-white layoffs*Dem incumbent			0.883***	0.871***			
			(0.121)	(0.124)			
Constant	0.492***				0.279***	0.252***	0.137***
	(0.013)				(0.065)	(0.070)	(0.032)
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	No	No	No
State-Election FE	Yes	Yes	Yes	Yes	No	No	No
Underidentification test		152.64**		189.40**	421.40**	524.78**	382.10**
Weak identification test		81.57**		71.94**	519.21**	912.25**	562.12**
Observations	9,160	9,132	9,132	8,108	2,701	2,763	2,767
R-squared	0.818	0.093	0.160	0.131	0.317	0.302	0.507
Number of counties	3,086	3,058	3,058	2,755	2,701	2,763	2,767

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

Note: OLS and 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is county-election. The outcome variable is the Democratic candidate's two-party vote share (0–100) in county c in presidential election t. The key independent variable is layoffs per worker with a dummy scoring one if the US president is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of U.S. Presidential Elections (2018)*, LAUS (2018).

Table A6: Layoffs and Presidential Elections, County Level, 2008–2016 (Turnout and Democratic vote share)

	(1)	(2)
	2SLS	
	Change of Turnout	Democratic Candidate's Share of all Votes Cast
	Full Sample	Full Sample
Layoffs total	-0.039	0.597***
	(0.098)	(0.147)
Layoffs total*Dem incumbent	0.086*	-0.230***
	(0.052)	(0.079)
Unemployment Control	Yes	Yes
Demography Controls	Yes	Yes
County FE	Yes	Yes
State-Year FE	Yes	Yes
Other Layoffs	No	No
Underidentification test	152.66***	152.64***
Weak identification test	81.57***	81.57***
Observations	9,129	9,132
R-squared	0.003	0.009
Number of counties	3,057	3,058

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

Note: 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is county-election. The outcome variables are the change in turnout and the change in the Democratic candidate's share of all votes cast (Model 2). The key independent variable is layoffs per worker with a dummy scoring one if the US president is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of U.S. Presidential Elections (2018)*, LAUS (2018).

Table A7: Layoffs and Presidential Elections, County Level, 2008–2016 (with confounders)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	2SLS	OLS	2SLS	OLS	2SLS	2SLS	2SLS	2SLS
	Change of Democratic Vote Share								
Layoffs total	0.093**	0.609***	0.072	0.542***	0.074*	0.548***	0.563***	0.546***	0.586***
	(0.046)	(0.147)	(0.045)	(0.148)	(0.045)	(0.148)	(0.149)	(0.147)	(0.147)
Layoffs total*Dem incumbent	-0.184***	-0.235***	-0.157***	-0.229***	-0.159***	-0.229***	-0.239***	-0.225***	-0.223***
	(0.047)	(0.080)	(0.047)	(0.080)	(0.047)	(0.081)	(0.081)	(0.079)	(0.079)
White population share	0.117	0.136*			0.094	0.114			
	(0.072)	(0.073)			(0.074)	(0.076)			
White population share*Dem incumbent	-0.000	0.001			-0.003	-0.001			
	(0.007)	(0.007)			(0.007)	(0.007)			
China shock			0.039	-0.018	0.041	-0.012	0.165	0.248***	
			(0.121)	(0.124)	(0.122)	(0.124)	(0.144)	(0.091)	
China shock*Dem incumbent			-0.042	0.038	-0.042	0.034	0.078		
			(0.092)	(0.096)	(0.094)	(0.097)	(0.112)		
Constant	-0.124**		-0.018		-0.096				
	(0.062)		(0.013)		(0.064)				
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Layoffs	No	No	No	No	No	No	No	No	Yes
Underidentification test		152.87***		143.20***		143.33***	143.64***	389.58***	153.62***
Weak identification test		81.96***		78.06***		78.23***	38.90***	630.62***	81.93***
Hansen J statistic								0.49	
Observations	9,152	9,125	8,859	8,827	8,851	8,820	8,827	8,827	9,132
R-squared	0.792	0.008	0.791	0.012	0.791	0.013	0.010	0.011	0.012
Number of counties	3,083	3,057	3,085	3,053	3,082	3,052	3,053	3,053	3,058

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

Note: OLS and 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is county-election. 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 layoffs per worker with a dummy scoring one if the US president is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of U.S. Presidential Elections (2018)*, LAUS (2018).

Table A8: Layoffs and Presidential Elections, County Level, 2008–2016 (heterogeneous effects)

	(1)	(2)
	2SLS	2SLS
	Change of Democratic Vote Share	
	Swing States	Non-swing States
Layoffs total	1.124***	0.464***
	(0.302)	(0.180)
Layoffs total*Dem incumbent	-0.836***	-0.221**
	(0.165)	(0.091)
Unemployment Control	Yes	Yes
Demography Controls	Yes	Yes
County FE	Yes	Yes
State-Year FE	No	Yes
Other Layoffs	No	No
Underidentification test	43.78***	131.51***
Weak identification test	34.88***	61.29***
Observations	2,144	6,988
R-squared	0.683	0.014
Number of counties	716	2,342

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

Note: 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is county-election. 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 layoffs per worker with a dummy scoring one if the US president is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of U.S. Presidential Elections (2018)*, LAUS (2018).

Table A9: Layoffs and Presidential Elections, County Level, 2008–2016 (CZ as the unit of analysis)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	Change of Democratic Vote Share							
	All Sample		Non-White Counties	White Counties	All Sample	2008	2012	2016
Layoffs total	-0.101	-0.067	0.286	-0.919				
	(0.152)	(0.347)	(0.324)	(0.867)				
Layoffs total*Dem incumbent	-0.355**	-0.461**	0.134	-1.447***				
	(0.142)	(0.189)	(0.214)	(0.369)				
White layoffs					-0.144	0.375	-0.413***	-2.843***
					(0.573)	(0.234)	(0.159)	(0.261)
Non-white layoffs					-0.071	-0.328	3.005***	3.185***
					(0.528)	(0.250)	(0.217)	(0.509)
White layoffs*Dem incumbent					-0.717***			
					(0.264)			
Non-white layoffs*Dem incumbe					0.440			
					(0.443)			
Constant	-0.083***					-0.211***	-0.072**	0.021
	(0.029)					(0.062)	(0.032)	(0.025)
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	No	No	No
State-Year FE	Yes	Yes	Yes	Yes	Yes	No	No	No
Underidentification test		86.18***	56.30***	22.09***	51.77***	119.10***	138.19***	119.10***
Weak identification test		60.89***	36.55***	19.35***	6.17*	361.19***	186.25***	361.19***
Observations	2,148	2,144	1,520	530	2,036	675	688	688
R-squared	0.865	0.028	0.010	0.038	0.032	0.219	0.334	0.485
Number of CZs	720	716	523	193	686	675	688	688

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

Note: OLS and 2SLS with robust standard errors clustered by CZ in parentheses. The unit of observation is CZ-election. The outcome variable is the change in the Democratic candidate's two-party vote share in CZ c in presidential election t. The key independent variable is layoffs per worker (average values by CZ) in interaction with a dummy scoring one if the US president is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of U.S. Presidential Elections (2018)*; LAUS (2018).

Table A10: Layoffs and Presidential Elections, County Level, 2008–2016 (with trends)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	2SLS	2SLS	OLS	2SLS	2SLS
	Change of Democratic Vote Share					
Layoffs total	0.089*	0.597***		0.079*	0.742***	
	(0.046)	(0.147)		(0.044)	(0.146)	
Layoffs total*Dem incumbent	-0.178***	-0.230***		-0.140***	-0.203***	
	(0.047)	(0.079)		(0.044)	(0.078)	
White layoffs			0.924***			1.084***
			(0.192)			(0.198)
Non-white layoffs			-0.680***			-0.837***
			(0.187)			(0.206)
White layoffs*Dem incumbent			-0.320***			-0.290**
			(0.112)			(0.116)
Non-white layoffs*Dem incumbe			0.217			0.187
			(0.135)			(0.155)
Constant	30.386***			29.881***		
	(2.688)			(2.566)		
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State trends	Yes	Yes	Yes	No	No	No
CZ trends	No	No	No	Yes	Yes	Yes
Underidentification test		152.65***	189.40***		146.94***	175.55***
Weak identification test		81.57***	71.94***		75.98***	64.37***
Observations	9,160	9,132	8,108	9,158	9,130	8,106
R-squared	0.792	0.009	0.007	0.824	-0.012	-0.010
Number of counties	3,086	3,058	2,755	3,085	3,057	2,754

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

Note: OLS and 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is county-election. 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 layoffs per worker with a dummy scoring one if the US president is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of U.S. Presidential Elections (2018)*, LAUS (2018).

Appendix C: Individual-level Evidence

Instrumental variables: diagnostics

Table A11: Layoffs and Presidential Elections, Individual Level, 2008–2016 (first stage)

	2SLS
	Change of Democratic Vote Share
	(1)
	First stage (Layoffs)
Bartik instrument	94.526***
	(5.347)
Bartik instrument*Dem Inc	-0.341
	(0.889)
	*First stage (Layoffs*White)*
Bartik instrument	-12.184***
	(4.457)
Bartik instrument*Dem Inc	107.389***
	(2.155)
Unemployment Control	Yes
Demography Controls	Yes
Individual Controls	Yes
County FE	Yes
State-Election FE	Yes

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

Note: 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is individual-county-election. The outcome variable is a dummy scoring one if the respondent voted for the Democratic candidate in the 2008–2016 presidential elections. The key independent variable is layoffs per worker in interaction with a dummy scoring one if the respondent is white. The first stage is related to Model 3 in Table 3. Sources: QWI (2018), CCES (2018), LAUS (2018).

Table A12: Layoffs and Individual Attitudes, 2012–2016 (first stage)

	2SLS
	Change of Democratic Vote Share
	(1)
	First stage (Layoffs)
Bartik instrument	109.562***
	(8.074)
Bartik instrument*Dem Inc	-0.310
	(0.527)
	*First stage (Layoffs*White)*
Bartik instrument	-4.098
	(7.303)
Bartik instrument*Dem Inc	112.082***
	(3.216)
Individual Controls	Yes
District FE	Yes
State-Election FE	Yes

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

Note: 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is individual-district-election. The outcome is a variable capturing the attitude toward the general situation of the country. The key independent variable is the interaction between layoffs per worker and a dummy scoring one if the respondent is white. The first stage is related to Model 1 in Table 3. Sources: QWI (2018), ANES (2018), LAUS (2018).

Robustness checks

We perform several robustness checks in line with the county-level analysis. First, we re-run our models using turnout as the outcome. This outcome scores one if the respondent reported voting in the most recent presidential election. The coefficient of the interaction between *Layoffs* and *White* is not significant (Table A15).

Second, we include in our models *White population share* and *China shock*, along with their respective interaction with *White*. Note that county-election year fixed effects would not account for these potential confounders if race moderated their effects. Models 1–6 in Table A16 show that our results hold even when we include these variables individually and together.[40] In fact, the coefficient of the interaction between *Layoffs* and *White* is much larger when we include *White population share*, and the coefficient of *White* becomes negative.

Third, our results hold for both swing and non-swing states (Table A17). In line with the county-level analysis, the coefficient of the interaction between *Layoffs* and *White* is larger for swing states than for non-swing states, which confirms that layoffs were a key factor in President Trump's victory in 2016.

Finally, our results are similar if we use layoffs per worker in CZs rather than in counties (Table A18). The concern is that there is a relatively low number of respondents in each county. On the contrary, there are many repondents 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 we cluster the standard errors at the level of CZ.

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

Table A13: Layoffs and Presidential Elections, Individual Level, 2008–2016 (OLS and county-election fixed effects)

	(1)
	OLS
	Pr(Vote for the Democratic Candidate=1
White	0.15***
	(0.020)
White*Layoffs	-1.03***
	(0.359)
Observations	146,217
R-squared	0.188
Unemployment Control	Yes
Demography Controls	Yes
Individual Controls	Yes
County-Year FE	Yes
Observations	146,217
R-squared	0.188

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

Note: OLS with robust standard errors clustered by county in parentheses. The unit of observation is individual-county-election. The outcome variable is a dummy scoring one if the respondent voted for the Democratic candidate in the 2008–2016 presidential elections. The key independent variable is layoffs per worker in interaction with a dummy scoring one if the respondent is white. Sources: QWI (2018), CCES (2018), LAUS (2018).

Table A14: Layoffs and Presidential Elections, Individual Level, 2008–2016 (no controls)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	2SLS	OLS		2SLS		
	Pr(Vote for the Democratic Candidate=1)						
White	-0.04***	-0.04***	-0.04***	-0.04***	-0.09***	-0.18***	-0.12***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.016)	(0.010)	(0.010)
Layoffs	-0.29	0.84			-1.07	-2.30***	-2.90***
	(0.707)	(2.936)			(0.816)	(0.620)	(0.781)
White*Layoffs	-1.41***	-2.09***	-1.24***	-1.92***	-1.58*	-1.63**	-4.41***
	(0.362)	(0.451)	(0.371)	(0.462)	(0.851)	(0.662)	(0.836)
Constant					0.35***	0.59***	0.56***
					(0.026)	(0.020)	(0.019)
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	No	No	No	No	No	No	No
Individual Controls	No	No	No	No	No	No	No
County FE	Yes	Yes	No	No	No	No	No
State-Election FE	Yes	Yes	No	No	Yes	Yes	Yes
County-Election FE	No	No	Yes	Yes	No	No	No
Trends	Yes	Yes	Yes	Yes	No	No	No
Underidentification test		954***		7169***	444***	1416***	1868***
Weak identification test		265***		3631***	812***	434***	294***
Observations	148,182	148,182	147,141	147,141	31,111	53,055	64,189
R-squared	0.108	0.108	0.114	0.114	0.029	0.052	0.041

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

Note: OLS and 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is individual-county-election. The outcome variable is a dummy scoring one if the respondent voted for the Democratic candidate in the 2008–2016 presidential elections. The key independent variable is layoffs per worker in interaction with a dummy scoring one if the respondent is white. Sources: QWI (2018), CCES (2018), LAUS (2018).

Table A15: Layoffs and Presidential Elections, Individual Level, 2008–2016 (turnout)

	(1)
	2SLS
	Pr(Voting=1)
	Full Sample
White	0.15***
	(0.019)
Layoffs	1.17
	(2.833)
White*Layoffs	0.58
	(0.423)
Unemployment Control	Yes
Demography Controls	Yes
Individual Controls	Yes
China shock	No
County FE	Yes
State-Year FE	Yes
County-Year FE	No
Underidentification test	6856***
Weak identification test	3464***
Observations	147,254
R-squared	0.168

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

Note: 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is individual-county-election. The outcome variable is a dummy scoring one if the respondent voted in the 2008–2016 presidential elections. The key independent variable is layoffs per worker in interaction with a dummy scoring one if the respondent is white. Sources: QWI (2018), CCES (2018), LAUS (2018).

Table A16: Layoffs and Presidential Elections, Individual Level, 2008–2016 (with confounders)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	2SLS	OLS	2SLS	OLS	2SLS	2SLS
	Change of Democratic Vote Share						
White	-0.18***	-0.19***	0.17***	0.19***	-0.16***	-0.15***	0.18***
	(0.026)	(0.027)	(0.020)	(0.020)	(0.027)	(0.027)	(0.020)
Layoffs	0.60	0.34	-1.12	-2.81	0.25	-1.14	-0.84
	(0.686)	(2.976)	(0.693)	(2.982)	(0.696)	(2.983)	(2.977)
White*Layoffs	-2.91***	-3.74***	-0.74**	-0.85*	-2.44***	-2.79***	-1.15**
	(0.362)	(0.461)	(0.358)	(0.452)	(0.369)	(0.472)	(0.451)
White population share	-2.48*	-2.51*			-2.42*	-2.32*	
	(1.311)	(1.339)			(1.331)	(1.339)	
White*White population share	0.43***	0.44***			0.43***	0.43***	
	(0.023)	(0.023)			(0.023)	(0.023)	
China shock			1.72***	2.42***	1.66***	2.21***	1.69***
			(0.373)	(0.394)	(0.372)	(0.394)	(0.373)
White*China shock			-1.73***	-2.78***	-1.70***	-2.52***	-1.68***
			(0.248)	(0.269)	(0.248)	(0.269)	(0.250)
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
China shock	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	No	No	No	No	No	No
State-Year FE	No	No	No	No	No	No	No
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification test		6537***		6535***		6522***	6554***
Weak identification test		1648***		1648***		1644***	2204***
Observations	147,221	145,659	145,692	145,692	145,659	145,659	145,692
R-squared	0.184	0.184	0.182	0.182	0.184	0.184	0.182

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

Note: OLS and 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is individual-county-election. The outcome variable is a dummy scoring one if the respondent voted for the Democratic candidate in the 2008–2016 presidential elections. The key independent variable is layoffs per worker in interaction with a dummy scoring one if the respondent is white. Sources: QWI (2018), CCES (2018), LAUS (2018).

Table A17: Layoffs and Presidential Elections, Individual Level, 2008–2016 (heterogeneous effects)

	(1)	(2)
	2SLS	2SLS
	Pr(Vote for the Democratic Candidate=1)	
	Swing States	Non-swing States
White	0.12***	0.16***
	(0.038)	(0.023)
Layoffs	0.34	-1.10
	(6.126)	(3.269)
White*Layoffs	-2.58***	-1.72***
	(0.755)	(0.543)
Unemployment Control	Yes	Yes
Demography Controls	Yes	Yes
Individual Controls	Yes	Yes
China shock	No	No
County FE	Yes	Yes
State-Year FE	Yes	Yes
County-Year FE	No	No
Underidentification test	1636***	5186***
Weak identification test	823***	2624***
Observations	43,693	103,561
R-squared	0.189	0.182

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

Note: 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is individual-county-election. The outcome variable is a dummy scoring one if the respondent voted for the Democratic candidate in the 2008–2016 presidential elections. The key independent variable is layoffs per worker in interaction with a dummy scoring one if the respondent is white. Sources: QWI (2018), CCES (2018), LAUS (2018).

Table A18: Layoffs and the 2008–2016 Presidential Elections, Individual Level (layoffs in CZ)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS
	Pr(Vote for the Democratic Candidate=1)						
	Full Sample				2008	2012	2016
White	0.16***	0.16***	0.17***	0.17***	-0.02	0.11***	0.22***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.050)	(0.036)	(0.031)
Layoffs	1.34**	0.21	5.20***	3.03	2.97***	2.09***	5.40***
	(0.643)	(0.951)	(0.981)	(2.179)	(1.047)	(0.790)	(0.934)
White*Layoffs	-1.66***	-2.06***	-2.63***	-2.99***	-2.39**	-1.70**	-5.28***
	(0.422)	(0.437)	(0.499)	(0.516)	(1.099)	(0.837)	(1.018)
Constant	0.30***	-38.67*			0.53***	0.85***	0.10***
	(0.047)	(23.021)			(0.117)	(0.089)	(0.037)
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
China shock	No	No	No	No	No	No	No
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trends	No	Yes	No	Yes	Yes	No	No
Underidentification test			564**	254**	1445**	2177**	2456**
Weak identification test			454**	154**	4871**	124**	7206**
Observations	147,770	147,770	147,770	147,770	31,199	52,626	63,980
R-squared	0.147	0.172	0.147	0.172	0.058	0.147	0.138

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

Note: OLS and 2SLS regressions with robust standard errors clustered by CZ in parentheses. Unit of observation is individual-county-election. The outcome variable is a dummy scored one if the respondent voted for the Democratic candidate in the 2008–2016 presidential elections. The key independent variable is layoffs per worker in CZ in interaction with a dummy that takes a value of one if the respondent is white. Sources: QWI (2018), CCES (2018), LAUS (2018).

Table A19: Layoffs and Individual Attitudes, 2012–2016

	(1)	(2)	(3)	(4)	(5)	(6)
	Logit	OLS		Logit		OLS
	US on the Right Track	US Position in the World	Status of the US Economy	Personal Financial Situation	Offshoring	Immigration
White	-0.39*	-0.14***	0.30	0.32	0.22	0.13*
	(0.225)	(0.048)	(0.200)	(0.202)	(0.211)	(0.077)
Layoffs	9.31	-0.40	-36.85	28.83	-8.13	9.35
	(29.184)	(6.616)	(28.048)	(32.338)	(29.584)	(10.902)
White*Layoffs	-28.93**	-6.27**	0.55	2.47	6.46	3.96
	(13.731)	(2.918)	(11.643)	(11.608)	(12.803)	(4.692)
Constant	1.47**	0.30**	-1.50***	-2.63***	1.11**	2.21***
	(0.572)	(0.126)	(0.559)	(0.613)	(0.555)	(0.208)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Election FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls FE	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification test	5,619	5,796	5,711	5,768	5,802	5,495
Weak identification test		0.282				0.189
Observations	5,753	5,796	5,819	5,819	5,819	5,495
R-squared	0.213	0.201	0.142	0.088	0.019	0.100

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

Note: logit and OLS regressions with robust standard errors clustered by district in parentheses. The unit of observation is individual-district-election. The outcome variables capture (1) attitude toward the general situation of the country, (2) attitude toward the US position in the world, (3) attitude toward the status of the economy, (4) attitude toward respondent's economic situation, (5) attitude toward offshoring, and (6) attitude toward immigration. The key independent variable is layoffs per worker in interaction with a dummy scoring one if the respondent is white. Sources: QWI (2018), ANES (2018), LAUS (2018).

Table A20: Layoffs and Individual Attitudes, 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS					
	US on the Right Track	US Position in the World	Status of the US Economy	Personal Financial Situation	Offshoring	Immigration
White	-0.13**	-0.07	-0.01	0.02	0.21**	0.28
	(0.051)	(0.118)	(0.051)	(0.094)	(0.090)	(0.176)
Layoffs	-3.58	-2.58	-2.69	0.67	5.93	17.92**
	(2.488)	(5.882)	(2.718)	(4.753)	(4.481)	(9.025)
White*Layoffs	7.39***	4.18	2.82	-0.46	-3.96	-13.22
	(2.549)	(6.123)	(2.697)	(4.932)	(4.566)	(9.131)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Election FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls FE	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification test	199***	197***	204***	204***	204***	175***
Weak identification test	588***	580***	611***	611***	611***	597***
Observations	1,241	1,254	1,264	1,264	1,264	1,144
R-squared	0.031	0.045	0.038	0.024	0.030	0.032

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

Note: 2SLS regressions with robust standard errors clustered by district in parentheses. The unit of observation is individual-district-election. The outcome variables capture (1) attitude toward the general situation of the country, (2) attitude toward the US position in the world, (3) attitude toward the status of the economy, (4) attitude toward respondent's economic situation, (5) attitude toward offshoring, and (6) attitude toward immigration. The key independent variable is layoffs per worker in interaction with a dummy scoring one if the respondent is white. Sources: QWI (2018), ANES (2018), LAUS (2018).

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