Gone For Good: Deindustrialization, White Voter Backlash, and US Presidential Voting

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July 9, 2020

David A. Lake Award for Best Paper (IPES 2018)

Abstract

Globalization and automation have contributed to deindustrialization and the loss of millions of manufacturing jobs, yielding important electoral implications across advanced democracies. Coupling insights from economic voting and social identity theory, we consider how different groups in society may construe manufacturing job losses in contrasting ways. We argue that deindustrialization threatens dominant group status, leading white voters in affected localities to favor candidates they believe will address economic distress and defend racial hierarchy. Examining three recent US presidential elections, we find: (1) white worker layoffs weaken support for Democratic incumbent candidates and (2) white voters are more likely to vote for Republican challengers where manufacturing layoffs are high, especially in 2016. In survey data, white respondents associate local manufacturing job losses with obstacles to individual upward mobility, and with broader American economic decline. Deindustrialization appears 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. The closure profoundly altered the fortunes of 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, geographically dispersed across the US, have been lost 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 three US presidential elections (2008–2016). We develop theoretical expectations about the possible electoral effects of localized manufacturing job losses. Our paper extends the economic voting literature by considering how group-based social identities influence politics (Cramer, 2016; Gaikwad, 2018; Jardina, 2019; Mutz, 2018; Mansfield and Mutz, 2009, 2013; Shayo, 2009; Tajfel, 1974). Building on recent research that tracks white voters' changing political preferences and behavior in response to anxieties about their perceived status as the dominant economic and social group (Cramer, 2016; Hochschild, 2018; Inglehart and Norris, 2017; Jardina, 2019; Mutz, 2018; Sides, Tesler, and Vavreck, 2018), we contend that deindustrialization represents a politically salient status threat for some whites. Unlike prior studies, we emphasize the *localized* nature of the perceived threat, which reflects the geographic variation in manufacturing decline around the country. We argue that local manufacturing job losses make white voters more likely than non-whites to vote for candidates they believe will address economic distress and defend racial hierarchy.

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

[1] We use "layoffs" and "job losses" interchangeably throughout.

voting data to examine: (1) the localized electoral effects of layoffs 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 the best of our knowledge, our paper is the first to estimate the causal effect of manufacturing job losses on voting—and how this effect may vary according to worker and voter demographics.

Our analysis yields three main results. First, studying county-level voting across three US presidential elections, we find that voters penalize Democratic incumbents more for white worker layoffs than for non-white layoffs. This result is 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, we examine individual vote choice data from the YouGov Cooperative Congressional Election Study (CCES) and find that layoffs are associated with greater support for Republican challengers among whites relative to non-whites. The estimated effect is strongest in the 2016 election. Third, we explore potential mechanisms driving white voters' political reactions to deindustrialization using data from the American National Election Studies (ANES) surveys. We find that in areas with more manufacturing layoffs, whites are more likely than non-whites to report that: (1) the US economy is *weak*, (2) the US is on the *wrong* track, and (3) individual upward mobility has *diminished*. That is, white voters are more likely to associate deindustrialization with a threat to national economic strength and individual status.

The electoral response to deindustrialization is unique to white voters. This is not to say that non-whites are sheltered from the harmful economic effects of deindustrialization. Indeed, there is evidence that blacks in particular have suffered more than whites from lost manufacturing jobs (Gould, 2018). Yet these losses do not produce similar voting patterns. Like Green and McElwee (2019), we find that distinct groups of voters respond to similar forms of economic hardship in different ways. The patterns of voting that we document suggest that white Americans experience deindustrialization as a status threat.

Our paper informs debates about the recent rise in populist and nationalist voting in developed democracies, including the election of Donald Trump. These discussions largely center on the extent to which localized economic hardship, as opposed to group-based social identities, explain the recent rise of reactionary politics. Some analysts assert that globalization 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; Mansfield, Mutz, and Brackbill, 2019; Rickard, 2018).[2] This research focuses almost exclusively on the domestic economic impact of international trade, particularly Chinese import competition. Yet other factors such as automation have also contributed to deindustrialization. We take a comprehensive approach by examining the electoral effects of manufacturing job losses, regardless of their cause.

While scholars and pundits often frame economic and cultural interests as competing explanations, we contend that they are closely related. Economics and culture jointly influence political attitudes and voting behavior, particularly when economic downturns threaten group identities (Ballard-Rosa, Jensen, and Scheve, 2018; Mutz, 2018; Noland, 2019). Our paper demonstrates that deindustrialization affects elections because some white voters believe it threatens their identity and status, which motivates them to vote for candidates who defend racial hierarchy. US deindustrialization, and the associated localized deterioration in employment, wages, and communities, appears central to the 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. We first argue that deindustrialization causes economic and social challenges in former manufacturing hubs, which lead to voter dissatisfaction with the status quo. Our argument addresses the ways in which different groups may construe manufacturing job losses in contrasting ways. Due to their privileged position as the historically dominant group in America's racial hierarchy, whites may interpret localized economic distress as a threat to their status. As a result, we expect a particularly reactionary political response in favor of candidates and policies that offer backward-looking solutions to the concerns of affected communities.

[2] Carnes and Lupu (2020) find no evidence of outsized support for Trump in the 2016 election among self-described white working-class voters, but their paper does not examine the potentially moderating force of localized economic distress due to manufacturing layoffs.

2.1 Localized Manufacturing Layoffs and Economic Voting

Deindustrialization contributes to declining economic conditions in ways that may influence voting. A large literature on 'economic voting' argues that voters assess incumbent candidates based in part on the health of the economy, punishing them following periods of slower growth and higher unemployment levels (Brender and Drazen, 2008; Fair, 1978; Healy, Persson, and Snowberg, 2017; Lewis-Beck, 1986; Lewis-Beck and Stegmaier, 2000).[3] Voters' assessments can be retrospective (Alvarez and Nagler, 1998; Norpoth, 2001): incumbent candidates are judged for the economic performance during the term of their party's president. Some voters also make *prospective* judgments about presidential candidates' likely future economic performance (Erikson, MacKuen, and Stimson, 2000; Nadeau and Lewis-Beck, 2001; Michelitch, Morales, Owen et al., 2012). Party platforms and campaign rhetoric can inform voters' prospective evaluations of candidates' abilities to address economic challenges (Born, van Eck, and Johannesson, 2018; Elinder, Jordahl, and Poutvaara, 2015), including deindustrialization. Incumbents facing opponents who promise *reindustrialization* may be the most vulnerable to economic voting—particularly in localities where manufacturing losses have exerted a greater toll.

Voters have particular reasons to be sensitive to a declining manufacturing sector. Perhaps the most direct channel involves the lost wages associated with plant layoffs. Manufacturing jobs pay more than those in the services sector for workers with comparable skills and education (Krueger and Summers, 1988).[4] As plants shut down, workers who lose manufacturing jobs tend to earn less afterwards. Therefore, workers who are displaced from manufacturing tend to suffer greater relative economic harm compared to those laid off from the service sector. Furthermore, the plant closures that often precipitate layoffs in manufacturing tend to be well documented. As manufactured goods have historically signaled a nation's level of economic sophistication (Porter, 2011), deindustrialization may be particularly disquieting. Abandoned factories do not just disappear; their shells often linger as relics of bygone industrial prowess.

[3] Wright (2012) questions whether unemployment decreases incumbent vote share of both parties. He finds that unemployment is a partisan issue for voters: higher levels of unemployment increase the vote shares of Democratic (but not Republican) gubernatorial and presidential candidates.

[4] Jensen, Quinn, and Weymouth (2017) estimate an average annual wage premium of over $9,000 among manufacturing workers in industries in which fewer than 20% of employees had college degrees.

As plants close and manufacturing jobs vanish, workers in defunct firms are directly affected, but distress reverberates outside the shuttered facilities. When a factory closes, associated businesses including suppliers and downstream firms often experience lost jobs and wages as well (Acemoglu, Autor, Dorn et al., 2016). The ensuing decrease in local demand for retail, dining, and other services creates a vicious cycle that results in a localized economic downturn. Factory closures and manufacturing job losses can also trigger social challenges that do not show up in employment and wage statistics. A decline in manufacturing can decimate local government budgets and hinder the provision of public goods (Feler and Senses, 2017). Affected regions also experience increases in local crime rates (Che, Xu, and Zhang, 2018), spikes in mortality rates (Sullivan and Von Wachter, 2009), and higher incidences of opioid addiction and overdose (Pierce and Schott, 2016). Individuals' views of the national economy are often based on the conditions facing their communities, regardless of personal economic circumstances (Ansolabehere, Meredith, and Snowberg, 2014; Broz, Frieden, and Weymouth, forthcoming).

While the logic of economic voting in the context of deindustrialization is relatively straightforward, it may be insufficient to explain voting in recent elections for at least three reasons. First, our discipline's understanding of the ways in which local economic shocks such as unemployment (Healy, Persson, and Snowberg, 2017; Wright, 2012) or trade exposure (Colantone and Stanig, 2017; Margalit, 2011; Jensen, Quinn, and Weymouth, 2017) affect voting is limited; there remains considerable skepticism regarding whether localized economic hardship has a discernible effect on support for incumbents (Hall, Yoder, and Karandikar, 2017; Margalit, 2019).[5] Much of the literature on economic voting shows that voters tend to base their decisions on national-level conditions, rather than local or personal economic experiences (Lewis-Beck, 1986; Jardina, 2019).[6] If the national economy remains strong, local job losses may not significantly affect how people vote. Second, voting decisions during economic shocks will be based on the policy positions taken by political parties and candidates (Hernández and Kriesi, 2016; Wright, 2012). Challengers who are most effective at exploiting the concerns of disaffected voters may be more likely to shift support from incumbents.

[5]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.

[6]See, however, Healy, Persson, and Snowberg (2017), who show that personal economic conditions influence vote choice.

Third, distributional economics alone may be inadequate to explain the political consequences of economic distress. Voters may respond politically to downturns in different ways, depending on their social standing and the effects of job losses in their localities. For some groups of voters, economic decline may activate anxieties about their social status. If so, political behavior must be assessed in the context of voters' identities and the policy positions of candidates and parties. In the next section, we consider how voters' responses to deindustrialization depend on group-based identity.

2.2 Localized Manufacturing Layoffs and White Identity Politics

We examine how deindustrialization and the resulting localized economic downturns may influence voting by distinct groups in different ways. We argue that the decline of manufacturing can incite a particularly acute political response among some white voters due to the threat that economic restructuring poses to notions of dominant group status that are central to white identity ("whiteness"). As Harris (1993) explains, whiteness embodies a "settled expectation" of perpetually privileged economic, political, and social circumstances. For many whites in former manufacturing hubs, the ravages of deindustrialization challenge those expectations and lead them to support candidates who they expect to defend their status.

Our argument builds on social identity theory, which holds that society consists of various groups with differing levels of power and status relative to one another (Tajfel, Turner, Austin et al., 1979; Shayo, 2009). Social identity encompasses an individual's association with, or attachment to, a particular group, and the value she places on being a part of the group (Tajfel, 1974). Individuals who are strongly affiliated with their group assess political, economic and cultural outcomes through the lens of their identity: it shapes their stances on issues and political candidates (Akerlof and Kranton, 2010; Ansolabehere and Puy, 2016; Conover, 1984; Jardina, 2019; Sides, Tesler, and Vavreck, 2018). While voters may consider the interests of others, they tend to care most about the wellbeing of those with whom they most closely identify (Bobo, 1983). In turn, they tend to favor candidates and policies that are consistent with their group's interests (Mansfield and Mutz, 2009, 2013; Mutz and Kim, 2017; Jardina, 2019; Shayo, 2009); economic hardship can solidify their political preferences (Mansfield, Mutz, and Brackbill, 2019).

The decline of manufacturing in an area can create a unique social status threat for some whites. This is because the negative economic and social consequences of deindustrialization upend the settled expectations of whiteness: they challenge whites' privileged status as the dominant group. For whites who perceive manufacturing jobs as historically important sources of employment and economic security mainly for members of their own group (Guisinger, 2017), layoffs, stagnant incomes, and localized social decay all contribute to the sense of diminished status. Put differently, deindustrialization is a source of "nostalgic deprivation," which Gest, Reny, and Mayer (2018) describe as the discrepancy between individuals' understanding of their current economic, social, and political status and perceptions about their past.[7] Furthermore, white Americans with a strong in-group identity often view themselves as prototypically American (Doane and Bonilla-Silva, 2003; Theiss-Morse, 2009), and conflate their personal economic standing with that of the US (Jardina, 2019; Mutz, 2018).[8] For individuals living in localities hit hard by deindustrialization, manufacturing layoffs embody the country's declining standing as a global industrial force, and with it, their own group's declining social and economic status.

White voter status anxiety about deindustrialization can activate white identity and a preference for conservative candidates. The political expression of heightened white identity tends toward support for policies and candidates that whites expect will uphold their privileges and preserve racial hierarchy (Abrajano and Hajnal, 2017; Jardina, 2019; Mutz, 2018; Sidanius and Pratto, 2001).[9] Prior research shows that status threats elicit 'defensive' political reactions (Jost, Glaser, Kruglanski et al., 2003); whites tend to become more conservative and more supportive of the Republican Party (Abrajano and Hajnal, 2017; Gest, Reny, and Mayer, 2018; Craig and Richeson,

[7]The deprivation that we emphasize here is temporal, based on within-group comparisons over time.

[8]Jardina (2019) argues that whites are able to preserve their dominant status in part because they are able to cast themselves as mainstream Americans.

[9]Evidence from elections in the US and Europe supports the notion that economic distress contributes to the success of far-right nationalist parties and candidates (Autor, Dorn, Hanson et al., forthcoming; Colantone and Stanig, 2018; Ballard-Rosa, Malik, Rickard et al., 2017; Dehdari, 2018; Gest, Reny, and Mayer, 2018; Funke, Schularick, and Trebesch, 2016). Examining over 800 elections from 20 countries, Funke, Schularick, and Trebesch (2016) show that far-right parties increase their vote share by 30% after a financial crisis. Autor, Dorn, Hanson et al. (forthcoming) find that US areas under pressure from Chinese manufacturing competition exhibited an increasing market share for the Fox News channel and a disproportionate rise in the likelihood of electing far-right Republicans to Congress.

2014; Mutz, 2018). As whites in distressed localities seek to maintain or reinstate the privileges and benefits diminished by deindustrialization, we expect increased support for conservative candidates and policies—particularly nationalist iterations that play to dominant group status anxieties (Jardina, 2019; Sides, Tesler, and Vavreck, 2018).

Deindustrialization also contributes to economic concerns among non-whites, but the political expression of these concerns differs across demographic lines.[10] Non-whites are less likely to experience deindustrialization as a threat to their status, and candidate appeals to white identity are unlikely to attract their support. Rather than increasing support for conservative challengers among voters of color, manufacturing job losses and localized economic distress may instead lower turnout among non-white voters (Green and McElwee, 2019).

To sum up, insights from the economic voting literature suggest that manufacturing job losses may weaken support for incumbents, irrespective of voter or candidate differences. But a consideration of the ways in which economic distress is refracted through voters' identities leads to more nuanced expectations about political behavior in the context of deindustrialization. We expect variation in voting responses based on social identity concerns in conjunction with candidates' validation of those concerns. As a dominant group status threat, deindustrialization activates white identity and increases white voter support for conservative political challengers.

Our argument has several testable implications that we examine using data from recent US presidential elections. Among whites, we expect stronger anti-incumbent voting in distressed localities, particularly when the incumbent party candidate is a Democrat and the Republican challenger plays to white identity. Our main tests of this proposition focus on the 2016 US presidential election. We expect stronger support for Donald Trump among white voters in areas with higher manufacturing layoffs.[11] Additionally, we analyze ANES survey data to probe the plausibility of

[10]Although a substantial proportion of black Americans self-identify as conservative, their support for Republicans is extremely low (Philpot, 2017). Since 1968, no Republican presidential candidate has exceeded 13% of the African-American vote, and upwards of 80% self-identify as Democrats (White and Laird, 2020). Support for the Democratic Party is also well documented among Asians (Masuoka, Han, Leung et al., 2018) and Latinos (de la Garza and Cortina, 2007), especially Latino immigrants (Hawley, 2019; Pantoja, Ramirez, and Segura, 2001).

[11]Analyzing Trump's rhetoric during the 2016 campaign, Smith and King (2020) contend that his speeches depicted the nation's past as unequivocally great, and signaled that he would protect whites from "unjust" treatment.

various theoretical channels. We then compare the 2016 election to the two previous elections for which we have complete data, which allows us to examine support for incumbents when: 1) the Republican challenger is less reactionary (as was the case in 2012), and 2) when the incumbent party candidate is a Republican (as was the case in 2008).

3 Data and Empirical Strategy

3.1 Localized Manufacturing Layoffs

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. Technology expands labor productivity, which means fewer workers are needed to meet consumer demand.[12]

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).[13] Therefore, we are able to observe manufacturing job losses by worker age, sex, educational attainment, and

[12]It is extraordinarily difficult to establish which channel (globalization or technology) has had a greater effect on US manufacturing job losses, particularly since 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; thus, 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. 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).

[13]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.

race/ethnicity. This allows us to disaggregate job losses by demographic characteristics, for instance layoffs of white vs. 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.[14]

Using the Census Bureau application programming interface (API),[15] we queried the QWI data to obtain yearly manufacturing job loss counts at the county level for all 50 states from 2004 to 2016.[16] This process was repeated for all major disaggregations of the QWI data—sex, age, education, and race/ethnicity.[17] 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.[18]

Our study is partly motivated by the fact that the decline of manufacturing 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 2004 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 a 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

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

[15]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`.

[16]We restricted this query to the manufacturing industry (QWI Industry Codes 31–33) and all private sector firms (QWI Owner Code A05).

[17]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`.

[18]US Census Bureau. (2018). Quarterly Workforce Indicators (1998–2016). Washington, DC: US 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-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 demographic groups by summing all job loss variables for each 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.

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 2016 presidential election.[19] Following standard practice, we compute the county-level two-party vote shares of the Democratic and Republican candidates. In its most extended form, we use the following model to estimate the change in the Democratic candidate vote share:

$$\Delta Dem\ Vote\ Share_c = \alpha_0 + \beta_1 Manufacturing\ Layoffs_c + \mathbf{X_c}\zeta^{'} + \delta_s + \epsilon_c, \tag{1}$$

where $\Delta Dem\ Vote\ Share_c$ measures the change in the Democratic candidate's percentage of the two-party vote in county c in the 2016 presidential election compared to the 2012 election. We use the change rather than the *level* of the Democratic candidate's vote share, since there is a great deal of path dependence in US county-level voting behavior (e.g., the Democratic vote share in a given election correlates with the Democratic vote share in the previous election).[20] While not accounting for this temporal dependence could bias our results, our findings are not sensitive to this modeling choice. The variable $Manufacturing\ Layoffs_c$ measures manufacturing layoffs per worker in county c from 2012 through 2015 (total layoffs in the county divided by the number of workers in the county in 2011).[21] In some models, we break down manufacturing layoffs by race to explore the differential effect of white vs. non-white workers' layoffs.[22]

The vector $\mathbf{X_c}$ includes our county-level controls. First, to capture sectoral variation, we include $Service\ Layoffs_c$, which measures service layoffs per worker in county c, using the same method as for $Manufacturing\ Layoffs_c$. Second, to distinguish manufacturing layoffs from broader employment conditions, we include the average level of unemployment in county c over the previous

[19] We obtained the election data from Dave Leip's *Atlas of US Presidential Elections (2018)*, available at `https://uselectionatlas.org/BOTTOM/store_data.php`.

[20] For a similar approach, see Margalit (2011) and Jensen, Quinn, and Weymouth (2017).

[21] We lagged the denominator by five years, since layoffs affect the number of workers in each county. Data on county-level worker totals from QWI.

[22] White layoffs are measured as manufacturing job losses categorized as non-Hispanic white workers.

four years ($Unemployment_c$).[23] We note that the correlation between *Manufacturing Layoffs* and unemployment is quite low, $\rho = 0.2$.[24] Third, we also control for two potential confounders as a share of the county population: college educated and male, which we label *Demography Controls*.[25] Fourth, in some estimates, we include the white share of the total population in each county to isolate the effect of layoffs from political trends associated with demographic differences.[26]

Furthermore, δ_s denotes state fixed effects, which net out time-invariant differences across states. In some estimates, we include district fixed effects to account for possible confounders that may vary within states. β_1 and ζ are the estimated coefficients, whereas α_0 and ϵ_c are the constant and the residuals, respectively. We estimate robust standard errors, clustered at the district level.

One concern with this model specification is that because layoffs do not occur randomly, they may be systematically correlated with a county's partisan orientation. In an 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.[27] 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). Specifically, we use the following measure:

$$Bartik\ instrument_c^j = \frac{Manufacturing\ Employment_c^j}{Total\ Employment_c^j} \times \frac{Manufacturing\ Layoffs_{-c}^j}{Total\ Employment_{-c}^j} \tag{2}$$

where $Bartik\ instrument_c^j$ is the Bartik instrument for social group $j = \{total, white, non\text{-}white\}$ in county c between 2012 and 2015. $Manufacturing\ Employment_c^j$ is the number of manufacturing workers from social group j in county c in 2011, and $Total\ Employment_c^j$ is the total employment

[23] The unemployment data come from the Local Area Unemployment Statistics (LAUS) database (`https://www.bls.gov/lau/lauov.htm`).

[24] Figure A5 in Appendix A shows the scatterplot of unemployment and manufacturing job losses, highlighting the difference between these two variables.

[25] These variables are taken from the US Census and County Business Patterns. We use pre-2012 values for these controls, since we are concerned that layoffs may affect these variables.

[26] Figure A6 in Appendix A shows the geographical distribution of *White Population Share* across US counties.

[27] See Bartik (1991).

in county c in 2011. *Manufacturing Layoffs*$^{j}_{-c}$ is the number of manufacturing layoffs from social group j in the US, excluding county c between 2012 and 2015, whereas *Total Employment*$^{j}_{-c}$ is the total number of workers from social group j in the US, excluding county c in 2011. This measure captures the number of manufacturing layoffs within social group j in county c as predicted by national shifts and the sectoral composition in county c, and is unrelated to the impact of local factors.[28]

We estimate the following first-stage model:

$$Manufacturing\ Layoffs^{j}_{c} = \alpha_0 + \gamma_1 Bartik\ instrument^{j}_{c} + \mathbf{X_c}\eta^{'} + \delta_s + \epsilon_c \tag{3}$$

We plug the instrumented variable (i.e. *Manufacturing Layoffs*, the endogenous variation of which has been pruned in the first stage) into equation 1 and run the second stage with the exogenous regressor.[29] More formally, we modify equation 1 and estimate the following:

$$\Delta Dem\ Vote\ Share_c = \alpha_0 + \beta_1 \widehat{Manufacturing}\ Layoffs_c + \mathbf{X_c}\zeta^{'} + \delta_s + \epsilon_c, \tag{4}$$

The identifying variance is the initial sectoral composition of each county. In order for the Bartik instrument to facilitate a causal interpretation, the sectoral composition must only affect the outcome through its effect on layoffs. Recall that we 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 white population shares) in addition to state fixed effects.[30]

[28] 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.

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

[30] Table A1 in Appendix A 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 that is in line with Goldsmith-Pinkham, Sorkin, and Swift (2018).

3.3 Individual-Level Models

To also 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 *after* the 2016 election. Our analysis uses the full, nationally representative, stratified sample of (up to) 63,605 respondents in (up to) 2,233 counties. This dataset identifies each respondent's county of residence, which allows us to match their answers to county-level layoff data.

We estimate the effects of layoffs on individual-level voting for the Democratic candidate using the following model in its most extended form:

$$\begin{aligned} Pr(Dem\ Vote_{ic} = 1) = \alpha_1 + \beta_1 White_i + \beta_2 \textit{Manufacturing Layoffs}_c \times White_i \\ + (\mathbf{X_c} \times White_i^{'})\zeta + \mathbf{Z_i}\eta^{'} + (\mathbf{Z_i} \times White_i^{'})\theta + \delta_c + \epsilon_{ic}, \end{aligned} \tag{5}$$

where $Dem\ Vote_{ic}$ is a dummy variable scoring one if respondent i in county c voted for Hillary Clinton in the 2016 election. The variable $\textit{Manufacturing Layoffs}_c$ measures the total manufacturing layoffs per worker in county c between 2012 and 2015. This variable is interacted with $White_i$, which takes a value of one if respondent i in county c is white, and zero otherwise.[31] Moreover, we include the vector $\mathbf{X_c}$ with county-level controls interacted with the dummy $White_i$. Note that respondents are geo-coded at the level of the county, for which we have variation of manufacturing layoffs.

Furthermore, a vector $\mathbf{Z_i}$ captures individual-level controls, which we include along with their interactions with $White_i$.[32] In addition, we interact *White Population Share* with *White* and the same county-level controls as in equation 1. The individual-level model includes county fixed effects (δ_c), which net out time-invariant differences across counties. In doing so, we are unable to estimate the coefficients of *Manufacturing Layoffs* and $\mathbf{X_c}$ alone, as these get absorbed by county fixed effects. α_1 is the constant, whereas β_1, β_2, ζ, η, and θ are the coefficients. ϵ_{ic} accounts for all residual determinants of the outcome variable.

[31] We do not use *White Manufacturing Layoffs*, since we can observe voter demographics in the individual-level data. We use layoffs as a proxy for localized manufacturing decline.

[32] As individual controls we include age, education, gender, employment, and senator approval.

We employ a similar identification strategy as in the county-level analysis, using our shift-share manufacturing layoffs instrument. In this case, we endogenize *Manufacturing Layoffs* $\times$ *White* using the instrument described in Equation 2 in interaction with *White*. We estimate instrumental variable regressions with robust standard errors clustered by county.

4 Results: The 2016 US Presidential Election

4.1 County-Level Estimates

Table 1 reports the results of the county-level election models, starting with our baseline model.[33] The coefficient for manufacturing layoffs is negative and significant in Models 1–3. The effect holds when we include *White Population Share* and *Service Layoffs*. These findings indicate that Democratic vote shares decline in counties with more manufacturing job losses.[34]

Next we investigate the effects of layoffs disaggregated by race (Models 4–6). We include white and non-white manufacturing layoff variables on the right-hand side of the model. In all models *White Manufacturing Layoffs* enters negative and significant, whereas *Non-White Manufacturing Layoffs* is positive and significant. Taken together, the results suggest that manufacturing job losses may lead to different voting behavior across demographic lines. We will further investigate this possibility in individual-level analysis.

Two additional findings are worth mentioning. First, the inclusion of the variable *White Population Share* reduces the magnitude of the coefficient on *White Manufacturing Layoffs* by roughly 25%, likely due to the fact that these variables are highly correlated. Second, the coefficient of *Service Layoffs* is never significant in any of the model specifications.

[33] Table A2 in Appendix B reports the results of ordinary least squares (OLS) models as benchmarks.

[34] Table A3 Appendix B reports the first stage of Models 1 and 4. 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 two-stage least-squares (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.

The magnitude of the estimated effect of job losses on voting is nontrivial. Indeed, with our estimates in hand, we can calculate the percentage lost in Democratic vote share that is attributable to white manufacturing layoffs. First, we estimate the predicted change in the Democratic vote share from Model 5, which is our most conservative estimate, as a benchmark. Second, we set *White Manufacturing Layoffs* equal to 0.02, which corresponds to the 25^{th} percentile, in order to simulate a counterfactual scenario in which deindustrialization has a relatively low impact.[35] Then, we predict the change in the Democratic vote share that we would have observed if all counties had experienced manufacturing layoffs at the 25^{th} percentile. Finally, we compare the predicted vote share changes from our counterfactual with the benchmark predicted vote share changes. The Democratic vote share would have been 3.6% higher nationally in this counterfactual scenario.[36]

We perform a number of additional tests, the results of which are reported and discussed in Appendix B and summarized here. First, we run our models with different outcome variables, which we report in Table A5. We show that our results are similar if we use: (a) *levels* rather than *changes* in Democratic candidates' percentages and (b) overall Democratic vote shares (rather than two-party) to operationalize our outcome variable. Moreover, we show that our results hold if we include potential confounders: layoffs broken down by education level, age, and gender, as well as the localized effects of Chinese import surges, the *China Shock* concept developed by Autor, Dorn, and Hanson (2013) (Table A6). In addition, the results are virtually the same if we include district fixed effects, which allow us to account for characteristics that vary within each state (Table A7). Finally, our results are similar if we use the cumulative number of manufacturing layoffs between 2004 and 2015 in each county (divided by the total number of workers in 2003). This test examines the longer-term consequences of deindustrialization, relying on the most extensive available data (Table A8). Finally, we show that our results hold if we use commuting zone (CZ), rather than county, as the unit of analysis (Table A9).

[35] There are 766 counties in the lower quartile of the *Manufacturing Layoffs* distribution.

[36] Appendix Table A4 summarizes these effects. It also includes the effects across four states, which had an actual vote margin in favor of Trump in the 2016 election that is smaller than our aggregate estimated effect (i.e. less than 3.6%). Three of these four states experienced manufacturing job losses that were significantly higher than the national average. Our counterfactual exercise indicates that manufacturing layoffs were a decisive factor in Trump's victory in these states, which ultimately decided the election.

Table 1: Manufacturing Layoffs and the 2016 Presidential Election, County Level

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS					
	Change of Democratic Vote Share					
Manufacturing Layoffs	-0.066**	-0.044*	-0.043*			
	(0.019)	(0.018)	(0.019)			
White Manufacturing Layoffs				-0.234**	-0.145**	-0.151**
				(0.033)	(0.035)	(0.036)
Non-white Manufacturing Layoffs				0.185**	0.131**	0.132**
				(0.034)	(0.032)	(0.032)
Observations	3,068	3,066	3,065	2,767	2,766	2,765
R-squared	0.500	0.539	0.539	0.564	0.589	0.589
Underidentification test	323.11**	318.80**	294.13**	267.80**	237.76**	239.53**
Weak identification test	535.22**	526.16**	468.62**	234.47**	205.82**	195.223**
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes
White Population Share	No	Yes	Yes	No	Yes	Yes
Sevice Layoffs	No	No	Yes	No	No	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Note: 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is county. The outcome variable is the change in the Democratic candidate's two-party vote share in county c in the 2016 presidential election. The key independent variables are manufacturing layoffs per worker broken down by race. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

4.2 Individual-Level Results

We have shown that manufacturing job losses in general, and white worker layoffs in particular, significantly reduced incumbent party vote shares in 2016. In this section, we further explore the impact of layoffs on the 2016 presidential election using individual-level data, which allow us to overcome three shortcomings of the previous analysis. First and most importantly, we are able to identify the race of the respondents. This allows us to examine whether manufacturing layoffs led to greater support for Trump among white voters. Second, we can control for a set of potentially confounding individual-level characteristics. Third, since the data track variation across individuals, we can include county fixed effects to control for time-invariant characteristics at the county level.

Our main results are reported in Table 2. In Model 1, we estimate our baseline model, whereas Models 2 and 3 add *White Population Share* and Model 3 also includes *Service Layoffs*.[37] The coefficient of the interaction between layoffs and white respondents is always negative and significant. This indicates that whites were less likely than non-whites to vote for Clinton in counties that had experienced more manufacturing layoffs.

In Model 4 we examine the impact of manufacturing job losses on voter turnout. This outcome scores one if the respondent voted in the 2016 presidential election. The coefficient of the interaction between *White* and *Manufacturing Layoffs* is positive and significant. This result indicates that manufacturing layoffs depressed the turnout of voters of color relative to white voters.

We report the full results of additional robustness tests in Appendix B and briefly discuss the main findings here. The main results are similar if we interact white manufacturing layoffs rather than total layoffs with *White* (Table A11). Furthermore, our results are unchanged when we include the *China Shock* variable (Table A12). Moreover, our results are similar if we use cumulative manufacturing layoffs (total layoffs since 2004) instead of manufacturing layoffs (Table A13). Finally, our results are similar if we use layoffs per worker in CZs rather than counties (Table A14).

[37]The first stage of Model 3 is reported in Table A10 in Appendix B. The first stages of the other models show similar estimates (available upon request). Standard diagnostic tests raise no concerns of under-identification or weak identification.

Table 2: Manufacturing Layoffs and the 2016 Presidential Election, Individual Level

	(1)	(2)	(3)	(4)
	2SLS			
	Pr(Voting for the Democratic Candidate=1)			Pr(Voting=1)
White	0.18***	-0.32**	-0.33**	0.20***
	(0.030)	(0.074)	(0.074)	(0.031)
White*Manufacturing Layoffs	-0.64***	-0.67**	-0.51*	0.71***
	(0.213)	(0.244)	(0.257)	(0.222)
Number of counties	2,233	2,232	2,231	2,232
Observations	63,605	63,591	63,582	63,605
R-squared	0.165	0.166	0.166	0.151
Underidentification test	2138.09**	2309.30**	2016.10**	2309.30**
Weak identification test	7551.14**	6602.32**	5675.69**	6602.32**
Unemployment Control	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Demography Controls	No	Yes	Yes	No
White Population Share	No	Yes	Yes	No
Service Layoffs	No	No	Yes	No
County fixed effects	Yes	Yes	Yes	Yes

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

Note: 2SLS regressions with robust standard errors clustered by county in parentheses. The unit of observation is individual-county. The outcome variables are a dummy scored one if the respondent voted for the Democratic candidate in the 2016 election (Models 1–3) and a dummy scored one if the respondent voted in the 2016 election (Model 4). The key independent variable is manufacturing layoffs per worker interacted with a dummy that takes a value of one if the respondent is white. Sources: QWI (2018), CCES (2018), LAUS (2018).

4.3 Exploring Possible Mechanisms

We have shown that manufacturing layoffs influenced the voting patterns of whites and non-whites differently in the 2016 election. In this section, we explore four possible mechanisms that may be driving this result. First, we focus on a question related to the status of the US: Is the US economy improving?[38]. Second, we explore a question on the status of the country more generally: Is the country on the "right track"?[39] Third, we include a question concerning individual upward mobility: How much opportunity is there to get ahead?[40] Fourth, we explore the pocketbook economic channel: "Are you better off financially than you were a year ago?"[41]

We use data from the 2016 wave of the ANES survey, which was administered *before* the election. 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.[42] We use the same estimation strategy as in equation 5, but employ an additional set of individual-level controls following Jardina (2019), including dummies for: Democrat, gender, unemployed, college degree, and trade union membership, as well as an ordinal variable capturing the respondent's ideology.[43]

Table 3 reports the results of the 2SLS regressions.[44] Model 1 demonstrates that white respondents who live in districts hit by greater job losses are significantly more likely to believe the economy is worsening. In Model 2, the coefficient of the interaction between *White* and *Layoffs*

[38]The exact wording is: "Now thinking about the economy in the country as a whole, would you say that over the past year the nation's economy has gotten better, stayed about the same, or gotten worse?" We created a dummy equal to 1 if the respondent indicates "gotten better."

[39]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 direction."

[40]The exact wording is "How much opportunity is there in America today for the average person to get ahead?". We create a dummy equal to 1 if the respondent indicates "A great deal" or "A lot".

[41]The exact wording is: "We are interested in how people are getting along financially these days. Would you say that you are [much better off financially, somewhat better off, about the same, somewhat worse off, or much worse off] than you were a year ago?" We create a dummy equal to 1 if the respondent indicates "much better" or "somewhat better".

[42]The results are virtually the same if we weight manufacturing layoffs by county population in 2000.

[43]All estimates are weighted on pre-election weight (Web sample).

[44]The first stage of Model 1 is reported in Table A15 in Appendix B. The first stages of the other models show similar estimates (available upon request). Diagnostic tests raise no concerns about weak or under-identification.

Table 3: Exploring the Mechanisms with Individual Survey Data

	(1)	(2)	(3)	(4)
	2SLS			
	US Economy Better than Previous Years	Things in the US on the Right Track	Opportunity in the US to Get Ahead	You and Your Family Better Financially than Previous Years
White	0.13	0.07	0.15	0.79
	(0.088)	(0.098)	(0.103)	(1.404)
White*Manufacturing Layoffs	-3.73***	-2.83*	-3.97**	0.05
	(1.435)	(1.678)	(1.693)	(0.084)
Observations	1,686	1,685	1,449	1,686
R-squared	0.119	0.168	0.044	0.085
Underidentification test	115.60***	114.45***	96.12***	115.60***
Weak identification test	277.09***	273.14***	186.55***	277.10***
Individual Controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes

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

Note: 2SLS regressions with robust standard errors in parentheses. The unit of observation is individual-district-election. The outcome variables capture (1) Is the US economy worse than in previous years? (2) Is the US on the right track? (3) How much opportunity is there in the US to get ahead? (4) Are you better off financially? The key independent variable is manufacturing layoffs per worker interacted with a dummy scoring one if the respondent is white. Estimates are weighted on pre-election weight (Web sample). Sources: QWI (2018), ANES (2018), LAUS (2018).

is negative and significant, indicating that white respondents in districts affected by layoffs are more likely than non-white respondents to believe the country is on the wrong track. In Model 3, white respondents in harder-hit districts report fewer opportunities to get ahead than non-white respondents living in the same districts. In Model 4, we find no evidence that high layoffs operate strictly as a pocketbook economic issue for white respondents. Rather, the results suggest that white respondents in hard-hit districts have grimmer assessments of the US economic trajectory and individual opportunity than non-whites in the same districts, regardless of personal economic circumstances.

In sum, these results indicate that whites experience deindustrialization differently than non-whites, as our theory anticipates. Localized manufacturing job losses appear to invoke concerns among white voters about American economic decline and the current course of the country. Job losses also appear to lead whites to question the prospects of upward mobility at the individual level, for the "average" American. These results suggest that localized manufacturing decline heightens economic anxiety among whites in particular. In conjunction with the voting results indicating a strong preference for Trump among white voters in localities with higher manufacturing job losses, one possible interpretation of the survey analysis is that some whites perceive deindustrialization as a status threat.

5 Evidence from Previous Presidential Elections

Here we extend the analysis to previous US presidential elections, which allows us to explore some of the scope conditions of our argument. Data from the 2012 election allow us to examine the effects of manufacturing job losses on support for the Democratic incumbent against a challenger, Mitt Romney, whose campaign made fewer efforts to stoke white identity compared to the 2016 Trump campaign. Data from 2008 allow us to examine the response to layoffs when the incumbent party candidate is a Republican rather than a Democrat.

5.1 Model Specification

In line with the previous analysis, we use the following baseline model to estimate changes in Democratic candidate vote share:

$$\begin{aligned}\Delta Dem\ Vote\ Share_{ct} = \alpha_0 + \beta_1 Manufacturing\ Layoffs_{c\tau} + \beta_2 Manufacturing\ Layoffs_{c\tau} \times \\ Dem\ Inc_t + \beta_3 Unemployment_{c\tau} + \beta_4 Unemployment_{c\tau} \times Dem\ Inc_t \\ + \beta_5 White\ Population\ Share_{c\tau} + \beta_6 White\ Population\ Share_{c\tau} \times Dem\ Inc_t \\ + \mathbf{Demography\ Controls_c} \times Dem\ Inc_t^{'}\zeta + \delta_c + \delta_{st} + \epsilon_{ct},\end{aligned} \tag{6}$$

where all variables are as described in the previous section. Note that τ denotes the four years preceding the election.[45] Given that we have time-varying variables for different waves of elections, the model in equation 6 uses a standard difference-in-differences (DID) design. 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. Our approach also allows us to test whether white voters punish Democrats more than Republicans for manufacturing layoffs.

Furthermore, δ_c and δ_{st} denote county fixed effects 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. Moreover, we include $Unemployment_{c\tau}$ and $White\ Population\ Share_{c\tau}$ and their interaction with $Dem\ Inc_t$. Furthermore, we use baseline values of demography controls (i.e. pre-2008 time-invariant values) interacted with $Dem\ Inc_t$. We use baseline values, since we are concerned that the demographic composition of counties is potentially a function of layoffs. The coefficient of these baseline controls can be estimated because they are interacted with a time-varying dummy. α_0 is the constant, whereas β_1, β_2, ..., β_6, and ζ are the coefficients. The error term ϵ_{ct} accounts for all residual determinants of the outcome variable.

Four additional considerations are necessary. First, since we do not use first differences of the right-hand-side variables, we can include county fixed effects. Second, the constitutive term

[45] We use total layoffs over the previous four years, whereas we take the average value over the previous four years for the other controls.

Dem Inc_t is omitted because its coefficient is absorbed by state-election fixed effects. Third, a key difference from standard DID methods is that *Manufacturing* $Layoffs_{c\tau}$ is a continuous rather than dichotomous variable, which implies that our "treated" units receive heterogeneous treatments of differing intensities. Fourth, since we are concerned about the possible endogeneity of layoffs, we rely on the same identification strategy as outlined in the previous section. Our approach is an instrumented DID design with the exogenous source of variation provided by the Bartik instrument, since layoffs are not randomly assigned.[46]

5.2 Results

Table 4 reports the results of the pooled models, along with those from the 2008 and 2012 elections in isolation. The coefficient of the interaction between *Manufacturing Layoffs* and *Dem Inc* is negative and significant in Model 1, indicating that counties hit by more layoffs are less likely to vote for the Democratic candidate when the president is a Democrat. In Model 2, 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*. The estimates show that while the interaction between *White Manufacturing Layoffs* and *Dem Inc* is negative and significant, the interaction between *Non-white Manufacturing Layoffs* and *Dem Inc* is not significant. Note that the coefficients of *Manufacturing Layoffs* and *White Manufacturing Layoffs* alone are both positive and significant, indicating greater support for Democrats in 2008 (when a Republican was the incumbent) in counties that had experienced more layoffs. Taken together, the results suggest that whites may respond to layoffs differently than non-whites, a proposition that we will probe further with the individual-level data.[47]

Models 3 and 4 of Table 4 report the estimates from the 2008 and 2012 elections in isolation. The coefficient of white layoffs is negative but not significant in the 2008 election, whereas it is negative and significant in 2012. The estimated effect is less than half the size in 2012 compared to 2016 (see Table 1, Model 4). The 2016 election stands out in our period of study in ways we

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

[47] The first stage of Model 1 is reported in Table A16 in Appendix C. 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). Standard diagnostic tests raise no concerns of under-identification or weak identification.

Table 4: Manufacturing Layoffs and Presidential Elections, County Level, 2008–2016

	(1)	(2)	(3)	(4)
	2SLS			
	Change of Democratic Vote Share			
	2008-2016		2008	2012
Manufacturing Layoffs	0.147**			
	(0.037)			
White Manufacturing Layoffs		0.260**	-0.018	-0.102**
		(0.053)	(0.024)	(0.019)
Non-white Manufacturing Layoffs		-0.151**	0.092**	0.103**
		(0.035)	(0.022)	(0.017)
Manufacturing Layoffs*Dem Inc.	-0.040*			
	(0.020)			
White Manufacturing Layoffs*Dem Inc.		-0.071*		
		(0.036)		
Non-white Manufacturing Layoffs*Dem Inc.		0.031		
		(0.023)		
Number of counties	3,055	2,753	2,700	2,763
Observations	9,120	8,103	2,700	2,763
R-squared	0.014	0.014	0.087	0.073
Underidentification test	155.65**	176.81**	285.28**	363.32**
Weak identification test	78.91**	67.73**	509.26**	526.29**
Unemployment Control	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes
White Population Share	Yes	Yes	No	No
State fixed effects	No	No	Yes	Yes
County fixed effects	Yes	Yes	No	No
State-election fixed effects	Yes	Yes	No	No

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

Note: 2SLS regressions with robust standard errors clustered by county in parentheses. The unit of observation is county-election (Models 1 and 2) and county (Models 3 and 4). The outcome variable is the change in the Democratic candidate's vote share in county c in the 2008-2016 presidential elections. The key independent variables are manufacturing layoffs per worker broken down by race interacted with a dummy that scores one if the incumbent is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Table 5: Manufacturing Layoffs and Presidential Elections, Individual Level, 2008–2016

	(1)	(2)	(3)
	2SLS		
	Pr(Voting for the Democratic Candidate=1)		
	2008-2016	2008	2012
White	-0.38**	0.00	0.21**
	(0.045)	(0.053)	(0.036)
White*Manufacturing Layoffs	-0.49**	-0.41	-0.39*
	(0.154)	(0.243)	(0.178)
Number of counties	2,545	1,968	2,200
Observations	146,117	30,500	52,055
R-squared	0.153	0.139	0.161
Underidentification test	398.77**	552.84**	1732.89**
Weak identification test	2478.27**	1951.96**	120000**
Unemployment Control	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes
Demography Controls	Yes	No	No
White Population Share	Yes	No	No
Service Layoffs	Yes	No	No
County fixed effects	No	Yes	Yes
County-election fixed effects	Yes	No	No

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

Note: OLS and 2SLS regressions with robust standard errors in parentheses. The unit of observation is individual-election (Model 1) and individual-county (Models 2 and 3). 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 manufacturing layoffs per worker interacted with a dummy that takes a value of one if the respondent is white. Sources: QWI (2018), CCES (2018), LAUS (2018).

would expect. White voters in deindustrializing localities favored Trump, who explicitly cultivated status threats related to white identity and promised to revive US manufacturing.

With the important caveat that we are examining a small number of elections, some notable inferences emerge when we compare the county-level results. First, while the pooled county-level analysis indicates that manufacturing layoffs induce anti-incumbent voting regardless of which party is in power, the 2008 results in isolation do not reveal a statistically significant decline in Republican support. Second, the anti-incumbent effects on manufacturing layoffs are stronger and more robust when Democrats are the incumbents.

A similar story emerges in the individual-level models reported in Table 5. In Model 1, we show the results of the pooled analysis.[48] The estimated interaction between *White* and *Manufacturing Layoffs* is negative and significant, indicating lower support for Democratic incumbents among whites where manufacturing layoffs are high. Note that we include county-election year fixed effects in this model, which acount for time-varying characterestics at the county level. For this reasons, we unable to estimate *Manufacturing Layoffs*, whose coefficient gets absorbed by county-election year fixed effects.

Models 2 and 3 are similar to the results at the county level. There is no evidence that manufacturing layoffs affect the probability of voting for the Democratic candidate in 2008 (when the incumbent is a Republican) among white respondents, whereas the interaction between *Manufacturing Layoffs* and *White* is negative and significant in 2012 (when the incumbent is a Democrat). That is to say that anti-incumbent effects are not generic, but rather appear to depend on the party in power. In particular, we do not find robust evidence that manufacturing job losses contribute to increases in anti-incumbent voting among whites when the incumbent is a Republican. Consistent with our theoretical expectations, manufacturing job losses appear to harm Democratic incumbents more than Republican ones.[49] Finally, we note that the estimated effect of the interaction term is substantively smaller in 2012 than it is in 2016. We find that Trump's reactionary campaign particularly appealed to white voters in deindustrializing localities.

[48]In this model we omit the interaction with the dummy for incumbency to ease the interpretation of the results, which would be problematic with the triple interaction term.

[49]Again, we note that this inference comes with the caveat that it is based on a small number of elections.

As with the 2016 election analysis, we implement numerous robustness checks, which we detail in Appendix C. Our results remain unchanged.

6 Conclusion

Deindustrialization has profoundly altered the American economic and social landscape, yielding dramatic political effects. Manufacturing job losses cause changes in voting behavior for different groups in contrasting ways. We argue that deindustrialization threatens dominant group status, leading white voters in affected areas to favor candidates who they believe will address economic distress and defend racial hierarchy. Examining county- and individual-level data from three recent US presidential elections, we found that manufacturing layoffs weakened white voter support for Democratic incumbents, especially in 2016. In their responses to survey questions, whites associated local manufacturing job losses with obstacles to individual upward mobility, and with broader American economic decline. US deindustrialization appears to be central to the white voter backlash that culminated in the surprising election of Donald Trump. Due to globalization and automation, most lost US manufacturing jobs are gone for good. But the impact of deindustrialization on US politics will resonate for years to come.

Our more general takeaway is that the political consequences of economic change are heterogeneous across places and people. Within nations, political reactions to economic shocks will vary, since they affect communities in different ways depending on their industrial composition and consequent exposure (Rickard, 2020). Yet such reactions also depend on how voters in affected communities interpret their local conditions. Individuals' associations with particular groups provide one such interpretive lens. We have shown that localized shocks can roil politics: manufacturing job losses perpetuated status anxieties and produced a reactionary political response among some whites, defined in part by in-group solidarity and out-group negativity. While often viewed as discrete, we conclude that economic interests and social identities may be more fruitfully understood as integrated sources of political behavior.

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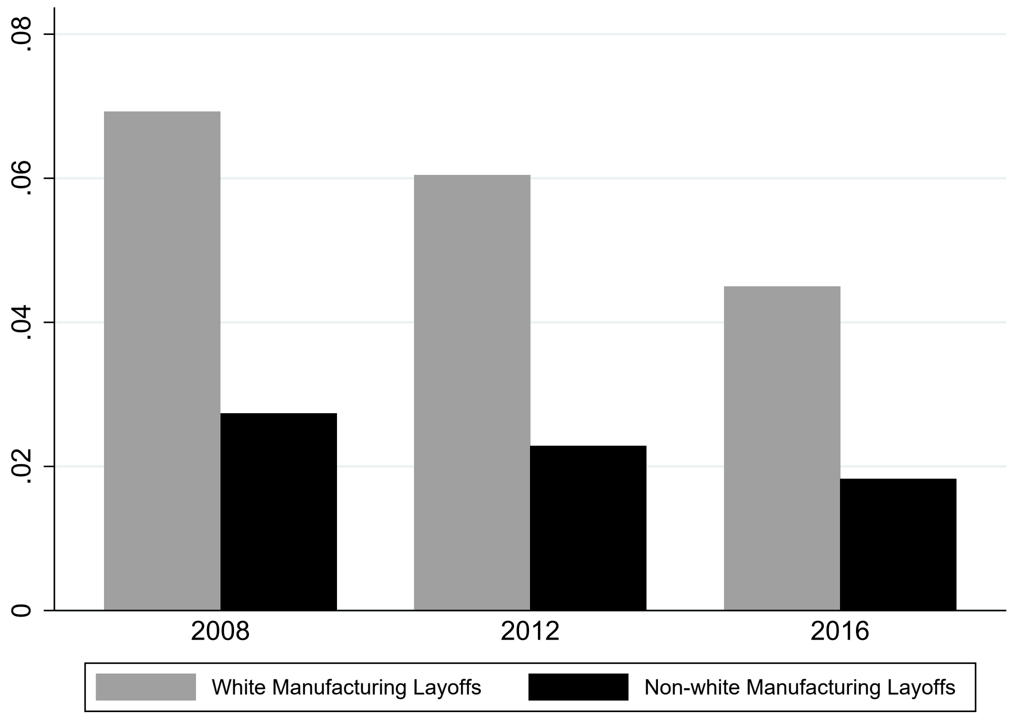
Appendix A

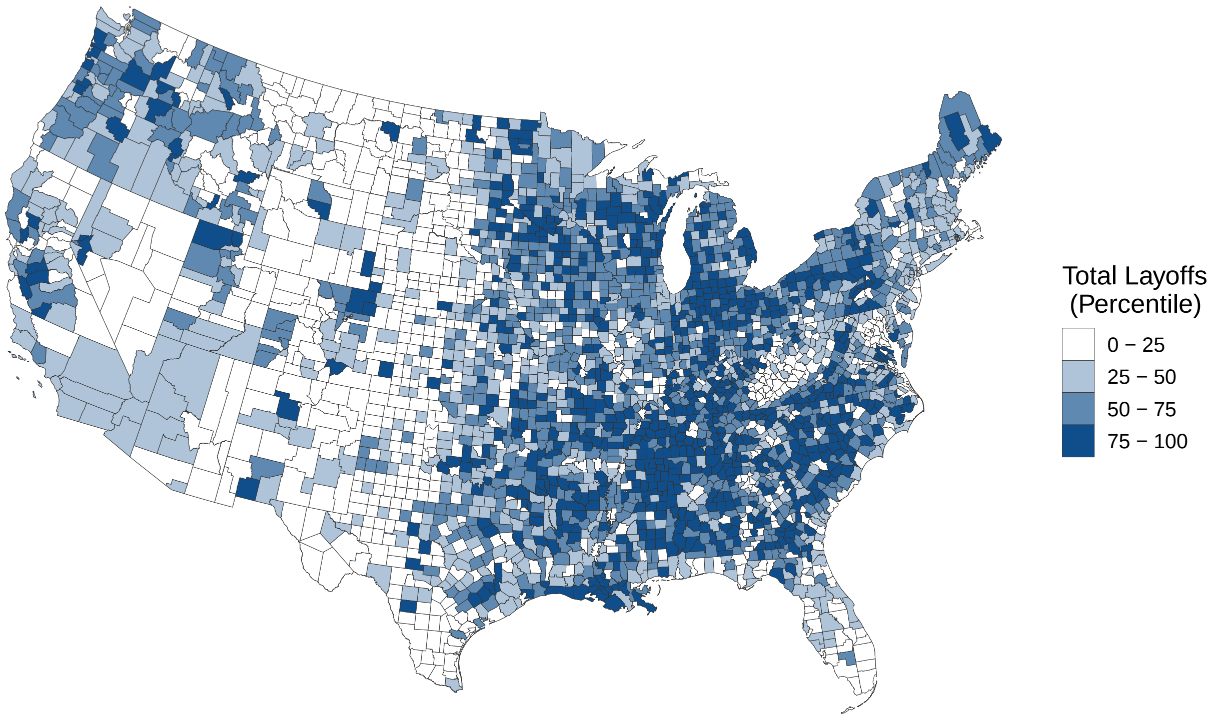
Descriptive Statistics

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



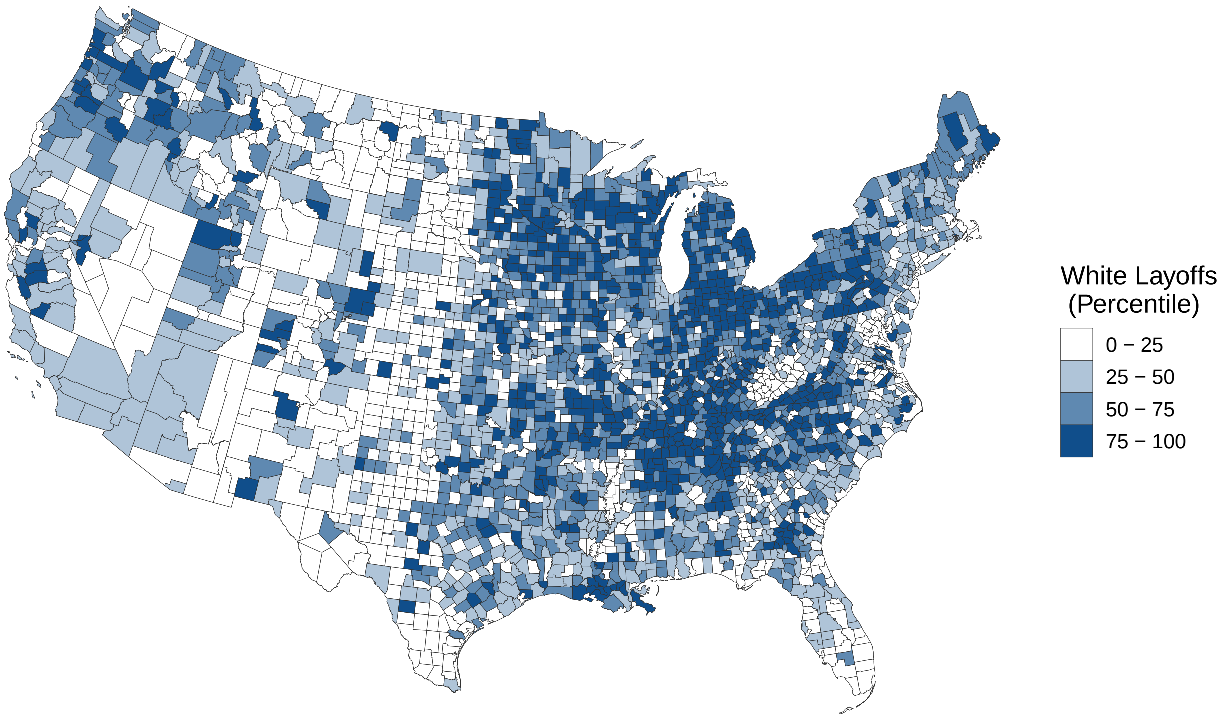
Note: *White Manufacturing Layoffs* and *Non-white Manufacturing Layoffs* are the mean of manufacturing layoffs per worker broken down by race. Source: QWI (2018).

Figure A2: Manufacturing Layoffs by US County



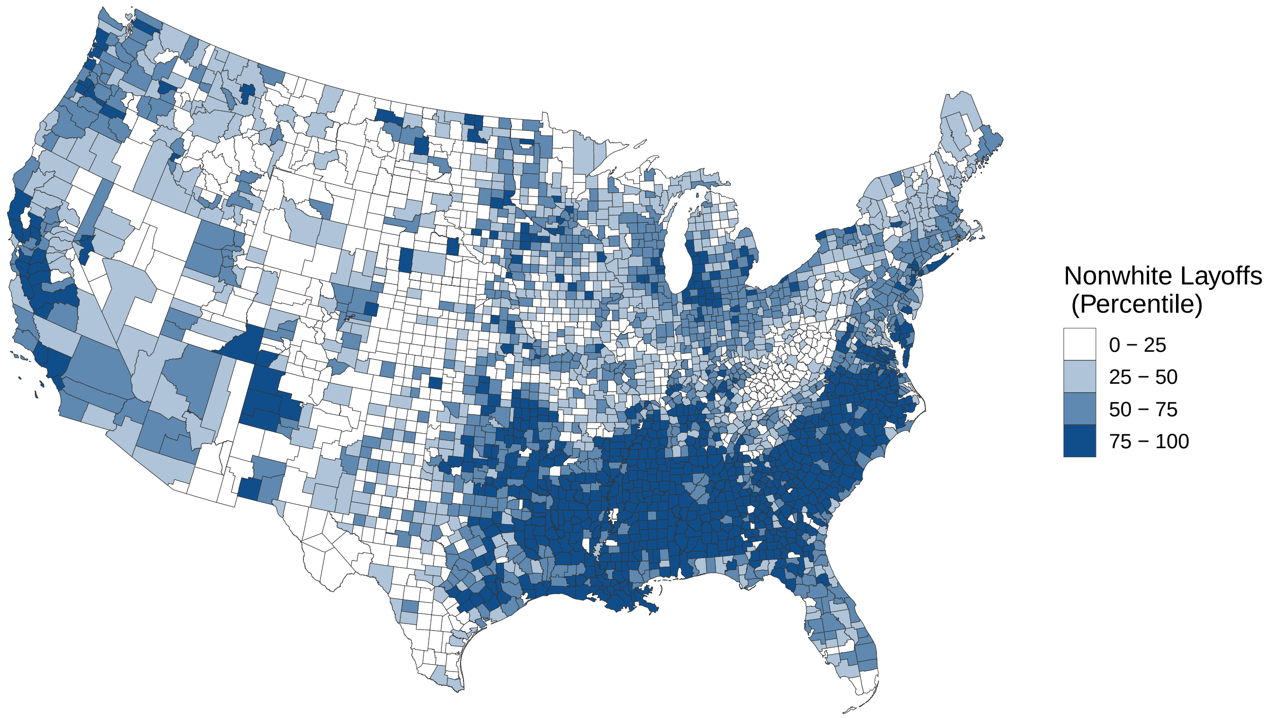
Note: Manufacturing Layoffs is the mean of manufacturing layoffs per worker from 2004 through 2016. Source: Quarterly Workforce Indicators.

Figure A3: White Manufacturing Worker Layoffs by US County



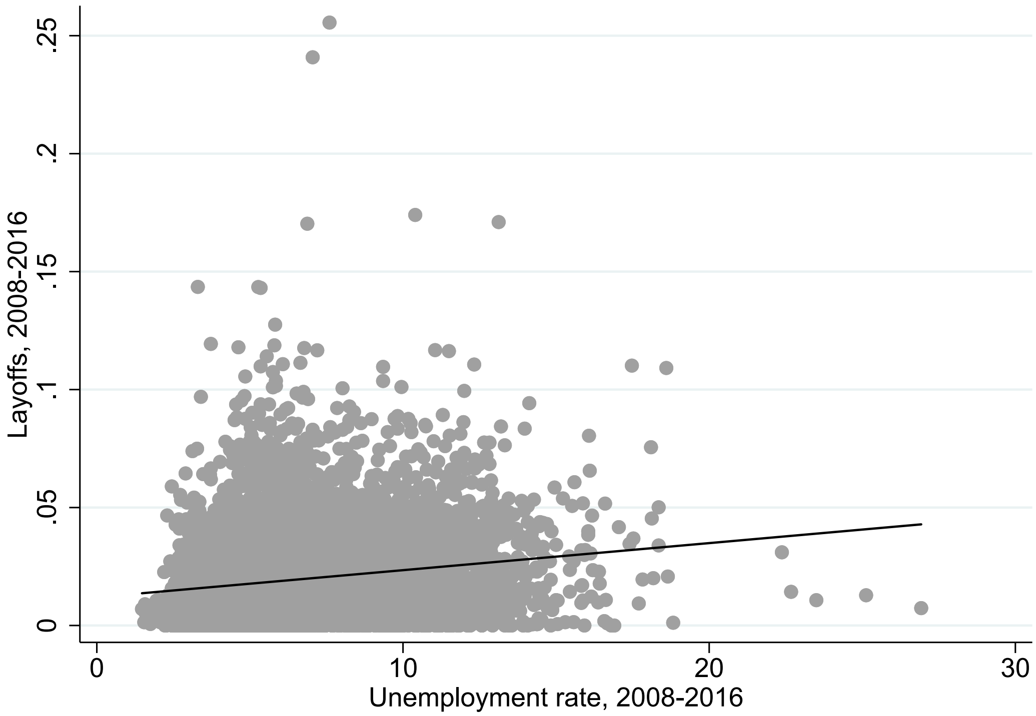
Note: White Manufacturing Layoffs is the mean white manufacturing layoffs per worker from 2004 through 2016. Source: Quarterly Workforce Indicators.

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



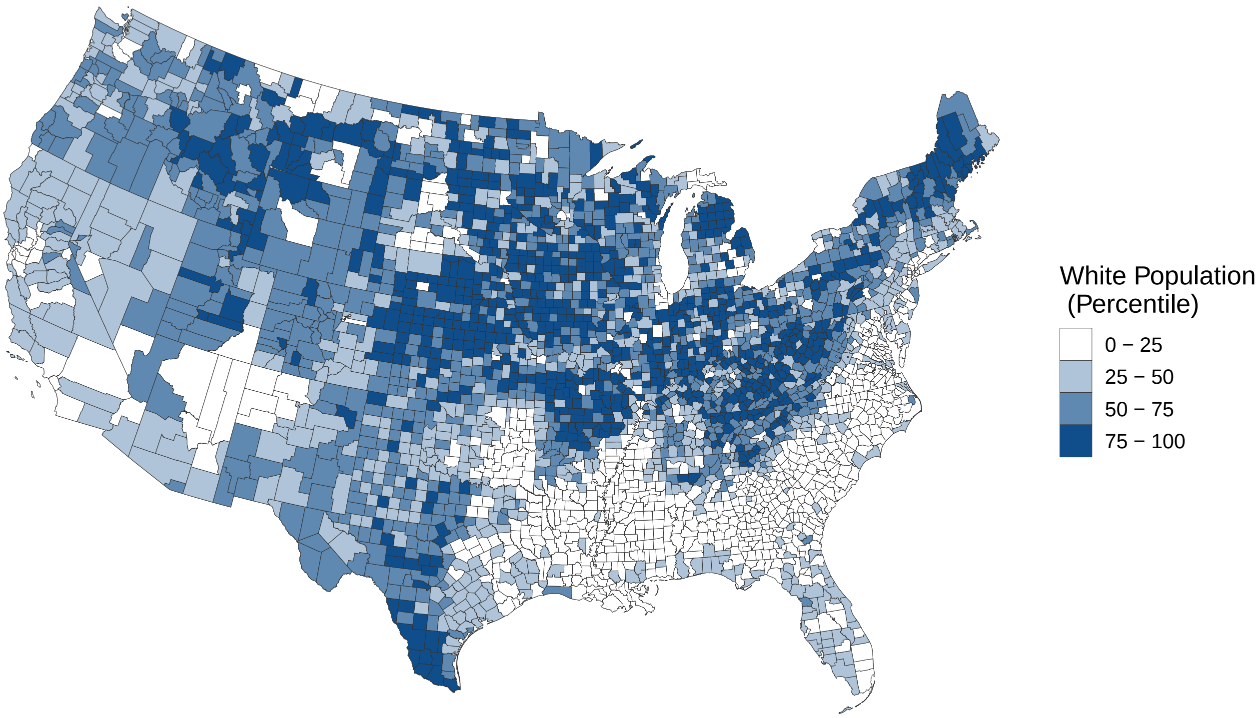
Note: Non-white Manufacturing Layoffs is the mean of non-white manufacturing layoffs per worker from 2004 through 2016. Source: Quarterly Workforce Indicators.

Figure A5: Manufacturing Layoffs and Unemployment



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

Figure A6: White Population Shares



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

Table A1: Correlations between Bartik Instrument and Potential Confounders

	Unemployment	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 *Manufacturingl Layoffs* as for equation 2. Sources: QWI (2018) and LAUS (2018).

Appendix B

County-level evidence

Table A2 shows the results of the reduced-form models.

Table A2: Manufacturing Layoffs and 2016 Presidential Election, County Level

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

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

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

Table A3 shows the results of the first stage of Models 1 and 4 of Table 1.

Table A3: Manufacturing Layoffs and 2016 Presidential Election, County Level (First Stage)

	2SLS	
	Change of Democratic Vote Share	
	(1)	(2)
	Manufacturing Layoffs	*White Manufacturing Layoffs*
Bartik instrument (total)	106.62***	
	(4.61)	
Bartik instrument (white)		108.20***
		(7.06)
Observations	3,068	2,767
R-squared	0.500	0.564
Unemployment Control	Yes	Yes
Demography Controls	Yes	Yes
White Population Share	No	No
Sevice Layoffs	No	No
State fixed effects	Yes	Yes

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

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

Table A4 reports the magnitude of the effects of manufacturing layoffs.

Table A4: Counterfactual Outcomes in the US and in Closely Contested States

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

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

Robustness checks. We perform several tests to corroborate the validity of our findings. We re-run our main models with three different outcome variables. First, we recalculate our main models using levels rather than *changes* in Democratic candidates' percentages. Table A5 (Models 1–2) reports the results, which are similar to those discussed above. Second, our results are similar if we use Democratic votes as a share of all votes as the operationalization of our outcome variable (Table A5, Models 3–4). Third, we examine the relationship between layoffs and turnout. One possible interpretation of our results is that manufacturing layoffs reduce the turnout of non-white voters; we find suggestive evidence that this might be the case (Table A5, Models 5–6). Note that we do not have turnout data broken down by partisanship or race.

Moreover, we include potential confounders in our main model specification to check whether our results are driven by omitted variable bias. First, we include worker layoffs, broken down by education level, age, and gender (Table A6, Models 1–2), which could be potential confounders of *White Layoffs*. All of these variables enter with statistically significant coefficients.[50]

The second additional covariate is the 'China shock' measure developed by Autor, Dorn, and Hanson (2013) to capture the localized effect of Chinese imports to the US (*China shock*).[51] Our main results hold even after including this potential confounder (see Table A6, Models 3–4).[52] In Models 5–6, we also instrument for the China shock using the same identification strategy as in Autor, Dorn and Hanson (2013). Our main results remain unchanged.

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

We also explore the effect of cumulative manufacturing layoffs on the 2016 presidential election, which confirms our main findings (Table A8).

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): workers with similar economic interests who are in close geographic proximity—even if spread across adjoining counties—could 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

[50] 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.

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

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

area's local economy. This is potentially problematic for our 2SLS analysis, since commuters who live and work in different counties represent a threat to the exclusion restriction. To address this issue, we re-run our main DID and 2SLS models using CZ as the unit of analysis. The results are virtually the same as those reported above (see Tables A9). If anything, the results are even stronger than the county-level findings, suggesting that any bias works against our key findings.

Table A5: Manufacturing Layoffs and 2016 Presidential Election, County Level (Other Outcomes)

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

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

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

Table A6: Manufacturing Layoffs and 2016 Presidential Election, County Level (Including Confounders)

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

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

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

Table A7: Manufacturing Layoffs and 2016 Presidential Election, County Level (with District Fixed Effects)

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

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

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

Table A8: Manufacturing Layoffs and 2016 Presidential Election, County Level (Cumulative Manufacturing Layoffs, 2004-2015)

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

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

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

Table A9: Manufacturing Layoffs and 2016 Presidential Election, County Level (CZ as the Unit of Analysis)

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS					
	Change of Democratic Vote Share					
Manufacturing Layoffs	-0.142***	-0.117***	-0.098**			
	(0.043)	(0.043)	(0.045)			
White Manufacturing Layoffs				-0.377***	-0.329***	-0.308***
				(0.070)	(0.078)	(0.080)
Non-white Manufacturing Layoffs				0.242***	0.205***	0.210***
				(0.053)	(0.054)	(0.054)
Observations	721	721	720	688	688	687
R-squared	0.360	0.383	0.383	0.414	0.421	0.420
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes
White Population Share	No	Yes	Yes	No	Yes	Yes
Sevice Layoffs	No	No	Yes	No	No	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

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

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

Individual-Level Evidence

Table A10 shows the results of the first stage of Model 1 of Table 2.

Table A10: Manufacturing Layoffs and 2016 Presidential Election, Individual Level (First Stage)

	2SLS
	Change of Democratic Vote Share
	(1)
	*Manufacturing Layoffs*White*
Bartik instrument (total)*White	451.420***
	(13.00)
Observations	63,964
Number of district	2,592
R-squared	0.109
Unemployment Control	Yes
Individual Controls	Yes
Demography Controls	No
White Population Share	No
Sevice Layoffs	No
County fixed effects	Yes

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

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

Robustness checks. We perform several robustness checks in line with the county-level analysis. First, we replace *Manufacturing Layoffs* with *White Manufacturing Layoffs* and its interaction with *White* (Table A11) and the results are similar to those reported in 2.

Second, we include in our models *China shock*, along with its interaction with *White*. Table A12 shows that our results hold even when we include this potential confounder.[53]

Third, we explore the effect of cumulative manufacturing layoffs on the 2016 presidential election at the individual level. Even in this case, the estimates confirm our main findings (Table A13).

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

Finally, our results are similar if we use layoffs per worker in CZs rather than counties (Table A14). The concern is that there is a relatively low number of respondents in each county. On the contrary, there are many respondents in each CZ, since the number of counties is more than three times the number of CZs. In these models, we use CZ fixed effects and cluster standard errors at the level of CZ.

Table A11: Manufacturing Layoffs and the 2016 Presidential Election, Individual Level

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

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

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

Table A12: Manufacturing Layoffs and the 2016 Presidential Election, Individual Level (Including *China Shock)*

	(1)	(2)
	2SLS	
	Pr(Voting for the Democratic Candidate=1)	
White	-0.04	-0.26***
	(0.046)	(0.046)
White*Manufacturing Layoffs	-0.56**	-0.480*
	(0.256)	(0.257)
White*China Shock	-0.99***	-1.28***
	(0.358)	(0.370)
Observations	62,642	62,642
R-squared	0.166	0.166
Unemployment Control	Yes	Yes
Individual Controls	Yes	Yes
Demography Controls	Yes	Yes
White Counties	Yes	Yes
Service Layoffs	Yes	Yes
County FE	Yes	Yes

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

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

Table A13: Manufacturing Layoffs and the 2016 Presidential Election, Individual Level (Cumulative Manufacturing Layoffs, 2004-2015)

	(1)	(2)	(3)	(4)
	2SLS			
	Pr(Voting for the Democratic Candidate=1)			Pr(Voting=1)
White	0.24***	-0.27***	-0.28***	0.15*
	(0.033)	(0.076)	(0.076)	(0.081)
White*Manufacturing Layoffs (cumulative)	-0.15***	-0.16***	-0.14***	0.08
	(0.040)	(0.045)	(0.047)	(0.047)
Observations	58,060	58,046	58,037	58,046
R-squared	0.166	0.167	0.168	0.153
Unemployment Control	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Demography Controls	No	Yes	Yes	No
White Population Share	No	Yes	Yes	No
Service Layoffs	No	No	Yes	No
County fixed effects	Yes	Yes	Yes	Yes

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

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

Table A14: Manufacturing Layoffs and the 2016 Presidential Election, Individual Level (CZ as the Unit of Analysis)

	(1)	(2)	(3)	(4)
	2SLS			
	Pr(Voting for the Democratic Candidate=1)			Pr(Voting=1)
White	0.16***	0.04	0.03	0.27***
	(0.027)	(0.049)	(0.050)	(0.052)
White*Manufacturing Layoffs	-0.86***	-0.50***	-0.54***	0.04
	(0.109)	(0.124)	(0.130)	(0.137)
Observations	63,908	63,894	63,894	63,894
R-squared	0.137	0.139	0.139	0.124
Unemployment Control	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Demography Controls	No	Yes	Yes	No
White Population Share	No	Yes	Yes	No
Service Layoffs	No	No	Yes	No
CZ fixed effects	Yes	Yes	Yes	Yes

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

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

Table A15 shows the results of the first stage of Model 1 of Table 3.

Table A15: Manufacturing Layoffs and Individual Attitudes in the 2016 Presidential Election (First Stage)

	2SLS
	Change of Democratic Vote Share
	(1)
	*Manufacturing Layoffs*White*
Bartik instrument (total)*White	451.420***
	(13.00)
Observations	63,964
Number of district	2,592
R-squared	0.109
Unemployment Control	Yes
Individual Controls	Yes
Demography Controls	No
White Population Share	No
Sevice Layoffs	No
County fixed effects	Yes

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

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

Appendix C

County-Level Evidence

Table A16 shows the results of the first stage of Model 1 of Table 4.

Table A16: Manufacturing Layoffs and Presidential Elections, 2008-2016, County Level (first stage)

	2SLS	
	Change of Democratic Vote Share	
	(1)	
	Manufacturing Layoffs	*Manufacturing Layoffs*Dem Inc*
Bartik instrument	76.65***	-12.82***
	(5.56)	(3.91)
Bartik instrument*Dem Inc	2.68	102.73***
	(3.46)	(2.79)
Observations	9,120	
Number of counties	3,055	
Unemployment Control	Yes	
Demography Controls	Yes	
White Population Share	Yes	
Sevice Layoffs	No	
County fixed effects	Yes	
State-year fixed effects	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 year. The instrumented variable is manufacturing layoffs interacted with a dummy scoring one if the president is a Democrat. The instrument is the Bartik instrument described in 3. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Robustness checks. We perform several tests to corroborate the validity of our findings. Tables reporting the results of these tests are showed below. First, we re-run our main models with three different outcome variables: (1) levels rather than *changes* in Democratic candidates' percentages; (2) Democratic votes as a share of all votes as the operationalization of our outcome variable; 3) turnout. All these tests leave our results unchanged.

Moreover, we include potential confounders in our main model specification: 1) worker layoffs, broken down by level of education, age, and gender; 2) the 'China shock' variable. Results hold even when we include these variables.

Moreover, 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 As for the 2016 election, 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 linear-specific trends to validate the parallel-trends assumption. 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.

Table A17: Manufacturing Layoffs and Presidential Elections, 2008–2016, County Level (Other Outcomes)

	(1)	(2)	(3)
	2SLS		
	Change of Democratic Vote Share	Change of Democratic Vote Share (third party)	Change of Turnout
Manufacturing Layoffs	0.210***	0.122***	-0.010
	(0.035)	(0.036)	(0.024)
Manufacturing Layoffs*Dem Inc	-0.039***	-0.053***	0.021*
	(0.015)	(0.019)	(0.012)
Observations	9,126	9,126	9,123
R-squared	0.085	-0.000	0.002
Number of counties	3,056	3,056	3,055
Unemployment Control	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes
White Counties	No	No	No
Sevice Layoffs	No	No	No
State-year FE	Yes	Yes	Yes
Counties FE	Yes	Yes	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 year. The outcome variables are (1) the Democratic candidate's vote share (Model 1), (2) the change in the Democratic candidate's vote share including third parties (Model 2), (3) the change in turnout (Model 3). The key independent variable is manufacturing layoffs interacted with a dummy scoring one if the president is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Table A18: Manufacturing Layoffs and Presidential Elections, 2008–2016, County Level (including Confounders)

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS					
	Change of Democratic Vote Share					
Manufacturing Layoffs	0.148***		0.136***		0.141***	
	(0.037)		(0.037)		(0.037)	
White Manufacturing Layoffs		0.244***		0.242***		0.250***
		(0.051)		(0.053)		(0.054)
Non-white Manufacturing Layoffs		-0.117***		-0.114***		-0.116***
		(0.033)		(0.033)		(0.033)
Manufacturing Layoffs*Dem Inc	-0.056***		-0.056***		-0.058***	
	(0.019)		(0.020)		(0.020)	
White Manufacturing Layoffs*Dem Inc		-0.063**		-0.069**		-0.074**
		(0.032)		(0.034)		(0.034)
Non-white Manufacturing Layoffs*Dem		-0.002		0.005		0.006
		(0.022)		(0.023)		(0.023)
China Shock			-0.002	-0.081	0.189	0.001
			(0.123)	(0.126)	(0.142)	(0.147)
China Shock*Dem Inc			0.030	0.142	0.064	0.219*
			(0.095)	(0.101)	(0.110)	(0.117)
Observations	9,120	8,103	8,816	7,854	8,816	7,854
R-squared	0.012	0.012	0.013	0.008	0.010	0.005
Number of counties	3,055	2,753	3,050	2,733	3,050	2,733
Unemployment Control	Yes	Yes	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes	Yes	Yes
White Counties	Yes	Yes	Yes	Yes	Yes	Yes
Sevice Layoffs	No	No	No	No	No	No
Other Layoffs	Yes	Yes	No	No	No	No
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Note: 2SLS with robust standard errors clustered by county in parentheses. The unit of observation is county-election year. The outcome variable is the change in the Democratic candidate's vote share. The key independent variable is manufacturing layoffs interacted with a dummy scoring one if the president is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Table A19: Manufacturing Layoffs and Presidential Elections, 2008–2016, County Level (CZ as Unit of Analysis)

	(1)	(2)	(3)	(4)
	OLS			
	Change of Democratic Vote Share			
Manufacturing Layoffs	-0.011			
	(0.089)			
White Manufacturing Layoffs		-0.103	-0.037	-0.180***
		(0.158)	(0.061)	(0.050)
Non-white Manufacturing Layoffs		-0.052	0.195***	0.264***
		(0.105)	(0.057)	(0.041)
Manufacturing Layoffs*Dem Inc	-0.117**			
	(0.047)			
White Manufacturing Layoffs*Dem Inc		-0.219***		
		(0.084)		
Non-white Manufacturing Layoffs*Dem Inc		0.035		
		(0.072)		
Observations	2,142	2,036	675	688
R-squared	0.028	0.024	0.069	0.124
Number of CZs	715	686	675	688
Unemployment Control	Yes	Yes	Yes	Yes
Demography Controls	Yes	Yes	Yes	Yes
White Counties	Yes	Yes	No	No
State FE	Yes	Yes	No	No
State State-year FE	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	No	No

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

Note: 2SLS with robust standard errors clustered by CZ in parentheses. The unit of observation is CZ-election year. The outcome variable is the change in the Democratic candidate's vote share. The key independent variable is manufacturing layoffs interacted with a dummy scoring one if the president is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Table A20: Manufacturing Layoffs and Presidential Elections, 2008–2016, County Level (including Trends)

	(1)	(2)
	OLS	
	Change of Democratic Vote Share	
Manufacturing Layoffs	0.189***	
	(0.037)	
White Manufacturing Layoffs		0.283***
		(0.051)
Non-white Manufacturing Layoffs		-0.147***
		(0.034)
Manufacturing Layoffs*Dem Inc	-0.053***	
	(0.019)	
White Manufacturing Layoffs*Dem Inc		-0.059*
		(0.032)
Non-white Manufacturing Layoffs*Dem Inc		0.008
		(0.023)
Observations	9,118	8,101
R-squared	-0.011	-0.002
Number of counties	3,054	2,752
Unemployment Control	Yes	Yes
Demography Controls	Yes	Yes
White Counties	Yes	Yes
County FE	Yes	Yes
State-year FE	Yes	Yes
CZ trends	Yes	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 year. The outcome variable is the change in the Democratic candidate's vote share. The key independent variable is manufacturing layoffs interacted with a dummy scoring one if the president is a Democrat. Sources: QWI (2018), Dave Leip's *Atlas of US Presidential Elections (2018)*, LAUS (2018).

Individual-Level Evidence

Robustness checks. We perform several robustness checks in line with the county-level analysis. First, we include in our models *China shock* and its interaction with *White*. Note that county-election year fixed effects would not account for these potential confounders if race moderated their effects. Table A21 shows that our results hold even when we include this variable.[54]

Second, our results are similar if we use layoffs per worker in CZs rather than counties (Table A22). The concern is that there is a relatively low number of respondents in each county. On the contrary, there are many respondents in each CZ, since the number of counties is more than three times the number of CZs. In these models, we use CZ fixed effects and cluster the standard errors at the level of CZ.

Finally, our results hold if we include county-specific trends, indicating that the parallel-trend assumption is likely to hold in our DID models (Table A23).

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

Table A21: Manufacturing Layoffs and Presidential Elections, 2008–2016, Individual Level (including *China Shock)*

	(1)	(2)
	2SLS	
	Pr(Voting for the Democratic Candidate=1)	
White	-0.02	-0.01
	(0.032)	(0.032)
White*Manufacturing Layoffs	-0.37***	-0.35***
	(0.131)	(0.130)
White*China Shock	-0.90***	-1.16***
	(0.213)	(0.234)
Observations	114,567	114,567
R-squared	0.146	0.146
Unemployment Control	Yes	Yes
Individual Controls	Yes	Yes
Demography Controls	Yes	Yes
White Counties	Yes	Yes
Service Layoffs	Yes	Yes
County FE	Yes	Yes

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

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

Table A22: Manufacturing Layoffs and Presidential Election, 2008–2016, Individual Level (CZ as the Unit of Analysis)

	(1)	(2)	(3)
	2SLS		
	Pr(Voting for the Democratic Candidate=1)		
	2008-2016	2008	2012
White	-0.08**	-0.05	0.19***
	(0.035)	(0.046)	(0.033)
White*Manufacturing Layoffs	-0.37***	-0.63***	-0.54***
	(0.069)	(0.106)	(0.096)
Observations	147,200	30,941	52,384
R-squared	0.119	0.091	0.130
Unemployment Control	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes
Demography Controls	Yes	No	No
White Population Share	Yes	No	No
Service Layoffs	Yes	No	No
CZ FE	No	Yes	Yes
CZ-election FE	Yes	No	No

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

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

Table A23: Manufacturing Layoffs and Presidential Elections, 2008–2016, Individual Level (County Trends)

	(1)
	2SLS
	Pr(Voting for the Democratic Candidate=1)
	2008-2016
White	-0.38**
	(0.045)
White*Manufacturing Layoffs	-0.49**
	(0.154)
Observations	146,117
R-squared	0.153
Unemployment Control	Yes
Individual Controls	Yes
Demography Controls	Yes
White Population Share	Yes
Service Layoffs	Yes
County specific trends	Yes
County-election fixed effects	Yes

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

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