Brother, Can You Spare a Manufacturing Job? How Voters React to Deindustrialization

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What led to Donald Trump's surprising 2016 election victory? This paper examines the potential contribution of deindustrialization. We use an instrumental-variable approach and a covariate-balancing approach to identify the effect of manufacturing job loss on change in Democratic vote share. We find that Democratic vote share falls in counties with high manufacturing job loss since 2004. Disaggregating this result by race shows that the Democratic vote share fell where layoffs affected white populations, and rose where layoffs affected nonwhites. This suggests a racial component to how voters process economic hardship.

This paper analyzes the relationship between deindustrialization, race, and the election of Donald Trump in 2016. Previous analysis has frequently focused on racial animus, trade, or the conjunction of the two (Autor et al. (2020); Che et al. (2016); Ballard-Rosa, Jensen and Scheve (2021)). We extend the analysis of Baccini and Weymouth (2021), one of the first papers to examine the political effects of deindustrialization while considering race and localization. Deindustrialization - the transition of the U.S. economy away from manufacturing - has led to widespread job loss and created adverse knock-on effects for a wide swath of Americans. This incorporates job losses due to trade with China and others (see Acemoglu et al. (2016)); it also includes job losses due to automation, demand changes, and other factors. The experience of deindustrialization has not been uniform; rather, it has been concentrated in certain areas of the country that were previously economically reliant on manufacturing XXXXXXXXXXXX MAP FIGURE XXXXXXXXXXX. We believe the localized nature of this analysis highlights the uneven and concentrated harms of deindustrialization.

Along with Baccini and Weymouth (2021), we find evidence that the experience of deindustralization was associated with support for Donald Trump, particularly among whites. However, we find that the related effects in the 2016 election are not associated with recent manufacturing job loss; rather, the opposite. Counties with manufacturing job losses from 2012-2015 tended to become more Democratic. We extend the analysis to the 2004-2015 period, to capture the long-term effects of deindustrialization on a region. Doing so, we find that regions experiencing more manufacturing job losses swung towards Donald Trump in 2016, and that this occurred more when those losing jobs were white.

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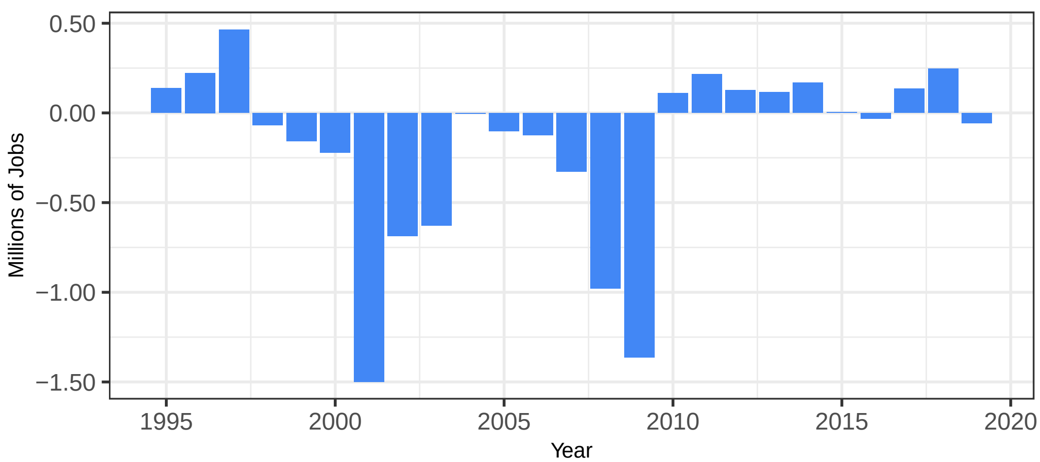
Our analysis extends Baccini and Weymouth (2021) in several ways. First, we change focus from a measure of gross losses in manufacturing jobs to net losses. As discussed in I.A, we believe this to be a more accurate measure of deindustrialization. Second, we change the temporal focus. Rather than focusing on manufacturing job loss in 2012-2015, we extend our analysis back to 2004. This is an important change. As shown in Figure , the bulk of U.S. manufacturing job loss took place prior to 2012; in fact, the 2012-2015 period was characterized by a slight rebound in manufacturing jobs. During this rebound, counties that experienced the most pronounced manufacturing job losses in prior years were also likely to experience the most pronounced recovery, as described in Figure . Because of this v-shaped recovery, focusing only on 2012-2015 job losses/gains paints a distorted picture. Finally, we augment the instrumental-variable approach with one based on covariate balancing, which produces similar results.

Figure 1. Nationwide Change in Manufacturing Employment, 1995-2019



Note: Gain or loss of national manufacturing jobs, divided by total national workforce.

Figure 2.

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I. Data and Methods

A. Data

Following Baccini and Weymouth (2021), our unit of analysis is the county. This allows us to capture not only the direct effects of deindustrialization on laid-off manufacturing workers, but also on the local economy. The primary outcome variable is the county's change in Democratic vote share between 2012 and 2016. We obtain this from XXXXXXXXX

We want to measure the causal relationship between deindustrialization and the change in vote share. As a measure of deindustrialization, we use the loss of manufacturing jobs as a share of the total beginning-of-period employment in each county. Suppose at the beginning of our period there were 2000 manufacturing workers in a county, and 8000 non-manufacturing workers. At the end there are only 1500 manufacturing workers. This is a loss of $500/10000 = 5\%$.

In this choice we diverge from Baccini and Weymouth (2021), which uses **gross** manufacturing job losses. For example, if a county lost 450 manufacturing jobs from 2012-2015 and also gained 400 manufacturing jobs over the same period, this would be 450 **gross** job losses, but only 50 **net** job losses. The **gross** measure captures several dynamics unrelated to deindustrialization - for example, seasonal unemployment in a food-manufacturing region, or workers moving between jobs. Thus we believe the **net** job losses over a period are the more accurate measure. It can be argued that the non-seasonal or non-structural components of gross job losses are a useful covariate. Basic notions of prospect theory suggest that the loss of a job and subsequent regaining of another identical job may still create substantial discontent. Constructing a better measure of gross job losses is an area for further methodological and substantive research.

Data on job gains and losses are obtained, using an API, from the Census Bureau's Quarterly Workforce Indicators (U.S. Census Bureau (2020)), which contains (among other things) information about employment by industry and county. These statistics are further disaggregated by race and ethnicity. The Census Bureau obtains this data from a combination of sources, such as administrative tax data and the U.S. Census.

XXXXXXXXXXXXXXXX sources of other data

Basic descriptive statistics of job losses and other key covariates can be seen in Table 1.

B. Methods

We conduct two related tests of our hypothesis. Our first test involves an instrumental-variable approach. A regression of change in Democratic vote share on manufacturing job losses risks endogeneity, in case counties with manufacturing job losses were otherwise predisposed to turn towards Trump (a singular candidate, after all). To mitigate these risks, Baccini and Weymouth (2021) uses

Table 1—Manufacturing Job Changes 2004-2015

	Mean	Std Dev	25th Pctile	Median	75th Pctile
Mfg Share of Emp	0.20	0.15	0.09	0.17	0.29
Mfg Share of Emp (White)	0.16	0.13	0.06	0.13	0.22
Mfg Share of Emp (Nonwhite)	0.05	0.07	0.01	0.02	0.06
Change in Mfg Jobs/ Worker	0.04	0.09	-0.01	0.02	0.06
Change in Mfg Jobs/ Worker (W)	0.03	0.07	0.00	0.02	0.06
Change in Mfg Jobs/ Worker (NW)	0.00	0.04	-0.01	0.00	0.01

a Bartik instrument, which we adapt (see Bartik (1991)). This instrument essentially uses the cross-county distribution of manufacturing employment as a source of exogenous variation.

$$b_{j,c} = \frac{\text{Manufacturing Employment}_{j,c} \text{ at } t_0}{\text{Total Employment}_c \text{ at } t_0} * \frac{\text{National Manufacturing Job Change}_{j,c}}{\text{Total National Employment at } t_0}$$

Using this instrument, we then conduct a two stage regression. First we estimate manufacturing job loss with the Bartik Instrument and a set of county-level controls; then we use the estimated values of job losses to predict Democratic vote share. In these regressions we control for unemployment, service layoffs, the share of college-educated voters, and the share of male voters. For some estimates, we also control for the white share of the population. We also apply state fixed effects to account for a wide variety of state-level changes from 2012-2016 (such as voter suppression tactics). These controls are similar to those of Baccini and Weymouth (2021).

Our second approach involves attempting to balance the covariates of the deindustrialization treatment. We use the same covariates as are used in controls above, as well as manufacturing as share of the population and total population. We apply the method of Covariate Balancing Propensity Scores, as developed by Imai and Ratkovic (2014); this method generates weights to reduce the correlation between covariates and treatment, while addressing several of the issues with propensity score weights. Given covariate-balancing weights, we then conduct a single-stage weighted regression of change in Democratic vote share on manufacturing job loss, using the same controls as above.

XXXXXXXXXXXXXXX BALANCE FIGURE??? XXXXXXXXXXXXXXXXXXXXXXXXXXX

C. Results

We find that counties experiencing deindustrialization from 2004-2015 are substantially more likely to vote for Trump. Further, we find that this effect is largely attributable to whites. In other words, net white manufacturing job losses decreased Democratic vote share, while net non-white manufacturing job losses increased Democratic vote share. We find the same effect when using covariate balancing, albeit of reduced size.

The results can be found in Table 2. The regression coefficient in Model 4, for instance, means that a loss of 10 manufacturing jobs per 100 workers in a county (a relatively extreme value) corresponds to a loss of 3.2% in Democratic vote share.

Table 2—Effect of Manufacturing Job Loss from 2004 to 2015

	Dependent variable:			
	Change in Dem. Share, 2016-2012			
	(1)	(2)	(3)	(4)
Manufacturing Layoffs	-0.34^{**}	-0.38^{**}		
	(0.14)	(0.17)		
White Manufacturing Layoffs			-0.23^{***}	-0.32^{***}
			(0.08)	(0.10)
Nonwhite Manufacturing Layoffs			0.15^{***}	0.20^{***}
			(0.05)	(0.06)
White Share/Svc Layoffs Control	No	Yes	No	Yes
Observations	3,049	3,049	2,750	2,750
Adjusted R^2	0.72	0.72	0.75	0.75
Note:				*p<0.1; **p<0.05; ***p<0.01

This coefficient is still somewhat difficult to interpret, and made increasingly so by the winner-take-all system by which U.S. Electoral College votes are allocated. As an alternative perspective, we examined a range of counterfactual scenarios, in which counties experienced job losses

XXXXXXXXXXXXXXXXXXXXXX EXPLAIN COUNTERFACTUAL

Timing

Restricting our analysis to only the 2012-2015 period, while continuing to use the net job loss metric, produces an effect opposite to that of Baccini and Weymouth (2021). The loss of Democratic vote share seems to be associated with a gain in manufacturing jobs, both in general and among whites. We believe this time-restricted analysis suffers from an omitted variable bias. As discussed above, the 2012-2015 period can be broadly characterized as a slight rebound from the manufacturing job losses in the 2008 financial crisis. The counties that experience job losses from 2004-2012 are more likely to have job gains in 2012-2015 (see). An apparent relationship between 2012-2015 job gains and loss of Democratic vote share in fact represents 2004-2012 job losses that may lead to both the later job gains and the loss of vote share. These results can be seen in Table 3.

Table 3—Effect of Manufacturing Job Loss from 2004 to 2015

	Dependent variable:			
	Change in Dem. Share, 2016-2012			
	(1)	(2)	(3)	(4)
Manufacturing Layoffs	0.43^{**}	0.37^{**}		
	(0.17)	(0.17)		
White Manufacturing Layoffs			6.50^{***}	2.33^{***}
			(2.20)	(0.76)
Nonwhite Manufacturing Layoffs			-3.99^{***}	-1.42^{***}
			(1.36)	(0.47)
White Share/Svc Layoffs Control	No	Yes	No	Yes
Observations	3,064	3,064	2,765	2,765
Adjusted R^2	0.73	0.73	0.75	0.75

Note: *p<0.1; **p<0.05; ***p<0.01

This result suggests an important temporal dimension to the political effects of deindustrialization - job losses in 2004-2012 make their effects felt in 2016. In some ways, this result is more plausible than if the 2012-2015 job losses were a significant covariate of voting. The effects of job loss may take some time to be felt, at both individual and community levels (see McKee-Ryan et al. (2009), Foote, Grosz and Stevens (2019)). The mechanisms of this relationship make a good topic for subsequent research.

D. Conclusion

As much research has noted, the national and global implications of American deindustrialization are only beginning to be felt - from the 2016 election to isolationism to the opioid epidemic. Previous analyses have often focused on choosing between explanations grounded in racial issues or political-economic evolutions (ex: Green and McElwee (2019), Reny, Collingwood and Valenzuela (2019)). We are joining a growing body of scholars searching for explanations at the intersection of the two. We believe that deindustrialization is fundamentally connected to particular places, and so the localized approach adopted by Baccini and Weymouth (2021) offers a great deal of promise. Further research might explore further ways in which geography has influenced the rightward turn in the U.S., for example through the use of techniques of spatial econometrics or the careful use of ethnography.

While our study is oriented towards history, deindustrialization is in no way confined to the past. The trajectory of American manufacturing employment is far from certain, with continued competition from abroad and the perennial threat of automation. We believe the case of the U.S. also offers insight that is applicable to the phenomenon of 'premature deindustrialization' in the developing world, and the concurrent growth of populist parties in Hungary, Brazil, India and elsewhere (Rodrik (2015), Castillo and Martins (2016)).

Figure 3. Caption for figure below.

Note: Figure notes without optional leadin.

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