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 effects of deindustrialization in a localized way. Deindustrialization - the transition of the U.S. economy away from manufacturing - has led to widespread job loss and created knock-on adverse effects in many formerly industrial areas. Along with Baccini and Weymouth (2021), we find evidence that the experience of deindustrialization 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 loss swung towards Donald Trump in 2016, and that this occurred more when those losing jobs were white.

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 XXXXXXXXXXXXXX FIGURE XXXXXXXXXXXXXXX, the bulk of U.S. manufacturing job loss took place

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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 XXXXXXXXXXXXXXX FIGURE XXXXXXXXXXXXX. 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.

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.

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.

XXXXXXXXXXXXXXXXX sources of other data

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 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. 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

D. Conclusion

If we expand our measure of net manufacturing job losses to include the 2004 to 2011 period - which covers most of the period when the U.S. manufacturing economy was hit most intensely (See Figure 1) – we get a result that corroborates the core intuition of Baccini and Weymouth (See Table 4). That is, we find that net white manufacturing job losses decreased Democratic vote share, while net non-white manufacturing job losses increased Democratic vote share.

It is important to highlight the substantive importance of the *timing* of manufacturing layoffs on political outcomes. Whereas Baccini and Weymouth's analysis suggests that economic changes lead to immediate political consequences, our analysis shows that economic changes can have lagged and variable effects on political outcomes. The mechanisms of these lagged effects merit further study.

[Note: to demonstrate our point about **variable** effects, In our next iteration of the analysis, we will show that manufacturing job losses had little explanatory effect on changes in Democratic vote share in other elections (2012 and 2020).]

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