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

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Introduction

What led to Donald Trump's surprising 2016 election victory? This paper examines the potential contribution of deindustrialization. Counties differ by exposure to manufacturing, which we use in an instrumental-variable 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.

Base paper: Baccini and Weymouth 2021, "Gone For Good: Deindustrialization, White Voter Backlash, and US Presidential Voting." *APSR*.

Outline

Framing story To do: Qualitative description of the trajectory of XYZ county that swung from Obama to Trump and suffered big manufacturing layoffs. This will establish the stakes and connect this to the broader conversation.

Substantive importance

Why did Trump win in 2016? There is a longstanding debate about relative importance of race and economic factors. Complicated by the interaction of the two. We hope to identify the importance of manufacturing job losses, both in aggregate and for different racial groups. Eventually we think that people should stop asking "race or economics" when the answer is likely both.

Empirical strategy

Differential manufacturing exposure across counties allows for identification of the causal effect of deindustrialization on change in Dem vote share. Further differences in racial exposure to mfg layoffs allows for identification of the interaction between race and deindustrialization.

Data and methods

Data is Census Quarterly Workforce Indicators, which break down county employment by industry, race and ethnicity. Augmented with public data on vote shares, employment, etc.

We look at total employment and manufacturing employment (NAICS 31-33, see extensions below). We then compute net change in mfg jobs (long term job loss) from 2004 to 2015, relative to employment in 2004.

We might be worried about endogeneity for manufacturing job losses. So we use a shift-share instrument: we predict net job losses per worker with county-level manufacturing as a share of total employment, plus controls.

Controls: unemployment in 2015, college educated share of population, male share of population, layoffs in service sector, white share of population (to control for demographic trends). We want to know if there's something singular about manufacturing jobs.

Extension Relative to Baccini and Weymoth (2021)

In their main model, Baccini and Weymouth looked at the effect of gross manufacturing job losses from 2012 to 2015 on the change in Democratic vote share in the 2016 presidential election.

Our key extension of Baccini and Weymouth's analysis is changing the quantity of interest from **gross** manufacturing job losses to **net** manufacturing job losses. For example, in Baccini and Weymouth's model, if a county lost 400 manufacturing jobs from 2012-2015 and also gained 400 manufacturing jobs over the same period, they would count 400 overall layoffs. Using our measure of *net* manufacturing job losses, we would consider this example a 0 net change in manufacturing employment. Given that job destruction and creation is a natural dynamic within the economy (i.e. seasonal employment, creative destruction), we think that *net* job losses is a more meaningful measure.

Using *net* manufacturing job losses as our outcome, we replicate Baccini and Weymouth's main model, which uses 2012-2015 manufacturing (gross) job losses to explain the change in Democratic vote share in 2016. Using their specifications, we find totally opposite results - that a *net* increase in white manufacturing jobs *increased* Democratic vote share, while a *net* increase in non-white manufacturing jobs *decreased* Democratic vote share. (See Table 3)

However, we don't think this is capturing the important dynamic at play. From 2012 to 2015, the national economy experienced a net increase in manufacturing jobs following the

2008 recession (See Figure 1). During this time of recovery, counties that experienced the most pronounced manufacturing job losses in prior years were also likely to experience the most pronounced recovery. Because of this v-shaped recovery, focusing only on 2012-2015 job losses/gains paints a distorted picture. [To DO: Empirically show negative correlation described here]

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).]

Key Findings

We find that, in aggregate, manufacturing job losses were a driver of change in Democratic vote share in the 2016 election. Breaking it down by race, we see that [TO DO: complete thought]. Using our main results from regression 3 in Table 4, we simulate a counterfactual scenario to demonstrate the practical signifcance of our estimates. Specifically, we generate a counterfactual democratic vote share assuming that all counties experienced manufacturing job losses equivalent to the county at the 25th national percentile. In Figure 3, we show the difference between the counterfactual democratic vote share and the model-predicted democratic vote share. We highlight states in purple if the difference between the counterfactual and model-predicted democratic vote shares exceeded Trump's vote share margin. Figure 3 shows that the effect sizes from our analysis suggest that, but for manufacturing layoffs from 2004-2015, Trump may not have one the 2016 presidential election.

Additionally, we find that, given the evolution of the business cycle, considering only recent job losses can paint a misleading picture of the relationship between manufacturing job losses and changes in vote share. In fact, we find that net manufacturing job losses from 2004 to 2011 are crucial to explaining Trump's 2016 win. This finding suggests that economic changes, like manufacturing layoffs, can have lagged and variable political consequence.

We find that, in aggregate, manufacturing job losses were associated with loss of Democratic vote share in the 2016 election. 10 manufacturing job losses per worker in a county since 2004 corresponded to a 3.8 % loss in vote share, plus or minus 3.3 %. Breaking it down by race, we see that white

Potential Future Work

- Temporal: Finding a better way to characterize the potentially lagged effect of manufacturing job losses on Democratic votes. Incorporating study of the 2008, 2012, 2020 elections.
- Disaggregation: Instead of instrumenting by manufacturing share, perhaps we can look at layoffs by industry in each county. While aggregate manufacturing employment may be endogenous, there's less reason to believe that specific industries would be (cf. Autor, Dorn and Hanson). This may also allow us to get further away from ecological inference problems.
- Trend-cycle estimation: There are techniques from econometrics and other places that could potentially be used to decompose gross layoffs into seasonal and non-seasonal components.
- Mechanisms: survey work to examine where the racial difference in economic voting behavior comes from. Is it expressive? Is it because information is transmitted along racially segregated networks?

Tables and Figures

Manufacturing Layoffs Over Time

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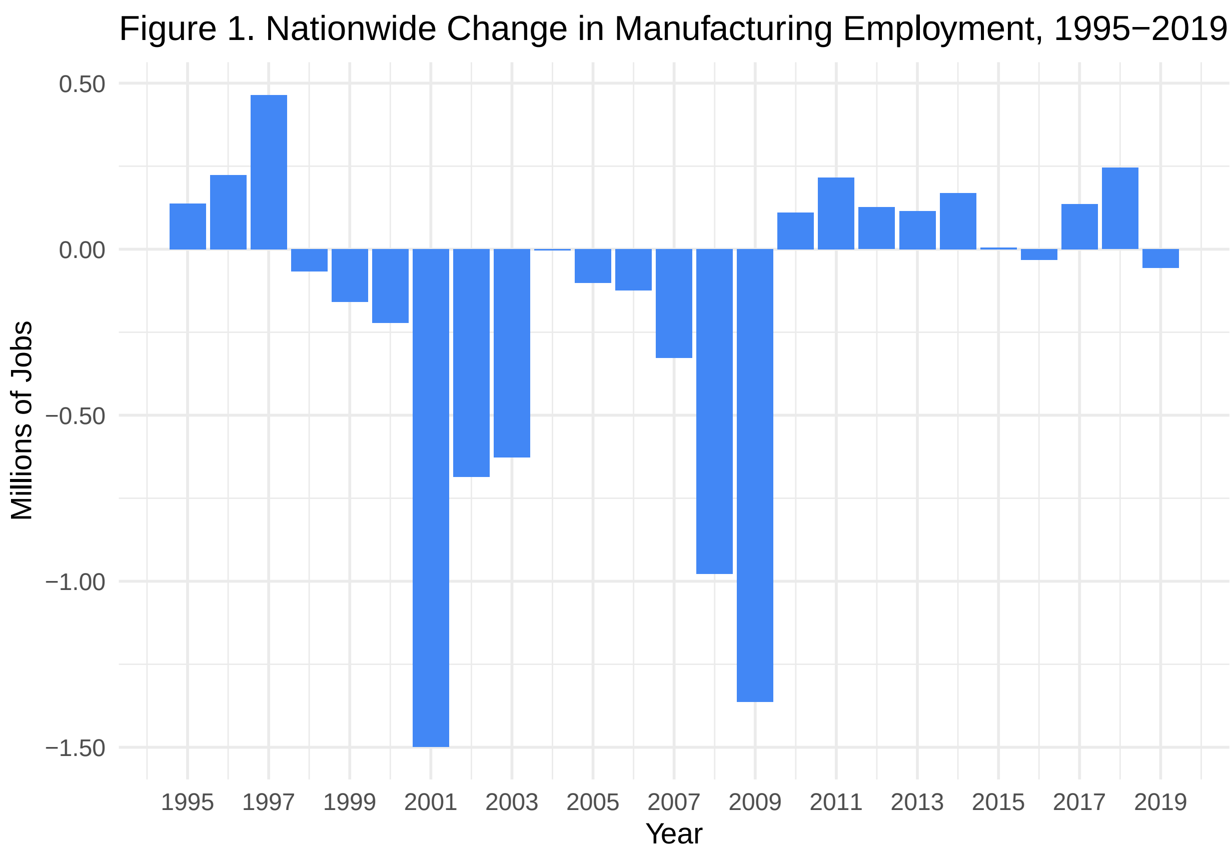
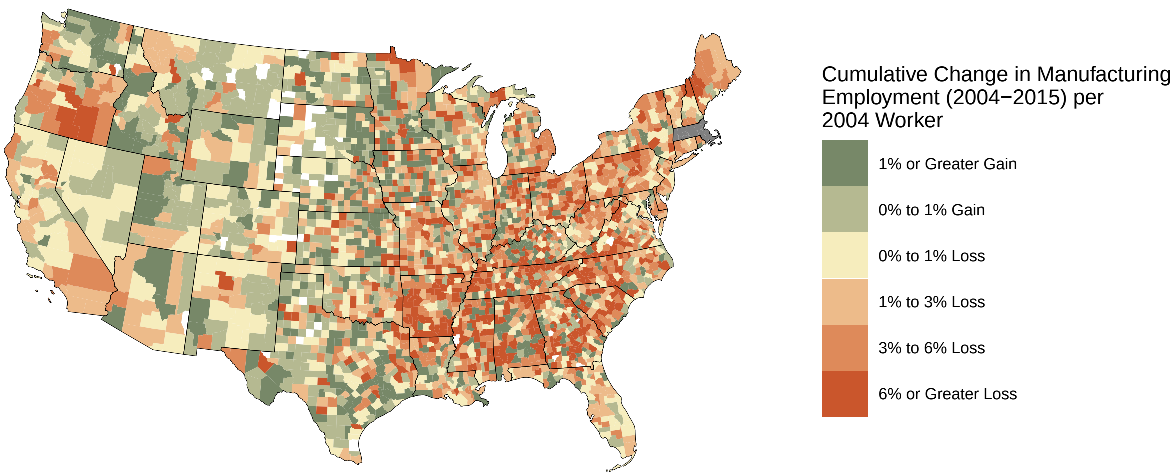


Figure 1. Nationwide Change in Manufacturing Employment, 1995−2019
0.50
0.00
−0.50
−1.00
−1.50
Millions of Jobs
1995
1997
1999
2001
2003
2005
2007
2009
2011
2013
2015
2017
2019
Year

Geographic Concentration of Layoffs

Figure 2: Net Change in Manufacturing Employment from 2004 to 2015

Normalized by 2004 Overall Employment Levels



Descriptive Statistics

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

Table 2: Manufacturing Job Changes 2012-2015

	Mean	Std Dev	25th Pctile	Median	75th Pctile
Change in Dem Vote Share	-0.06	0.05	-0.10	-0.05	-0.03
Mfg Share of Emp	0.20	0.16	0.08	0.16	0.28
Mfg Share of Emp (White)	0.15	0.13	0.06	0.12	0.22
Mfg Share of Emp (Nonwhite)	0.05	0.07	0.01	0.03	0.06
Change in Mfg Jobs/ Worker	-0.01	0.05	-0.02	0.00	0.01
Change in Mfg Jobs/ Worker (W)	0.00	0.03	-0.01	0.00	0.01
Change in Mfg Jobs/ Worker (NW)	0.00	0.02	-0.01	0.00	0.00

Regression Results (Using 2004-2015 Net Manu Job Change)

Table 3: Effect of Manufacturing Layoffs on Democratic Vote Share (since 2004)

	Dependent variable:			
	Change in 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)
Controls For White Share/Service Layoffs	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:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Regression Results (Using 2012-2015 Net Manu Job Change)

Table 4: Effect of Manufacturing Layoffs on Democratic Vote Share

	Dependent variable:			
	Change in Share (2012-2016)			
	(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)
Controls For White Share/Service Layoffs	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			

Counterfactual assessment of election (Using 2004-2015 Layoffs)

Figure 3: Impact of Manufacturing Job Lossess on Democratic Vote Share

Change in Democratic Vote Share Assuming 25th Percentile of Manufacturing Job Losses