Brother, can you spare a manufacturing job? White Voters' reaction 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 O to T 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? 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.

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

Findings

We find that, in aggregate, manufacturing job losses are a driver of change in Democratic vote share.

Breaking it down by race, we see that

Findings

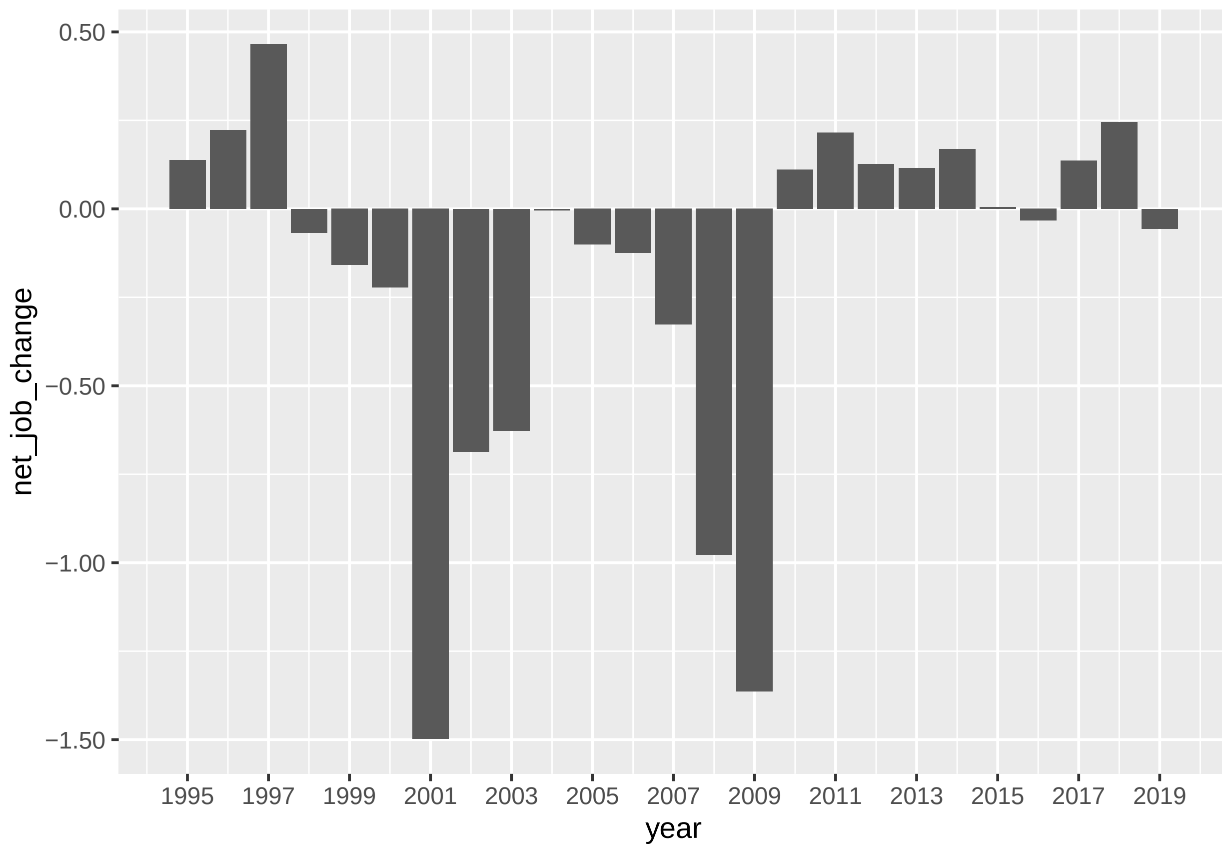
```
# manufacturing layoffs overtime

national_ts <- read_xlsx("../National_Data_TS.xlsx")
```

```
## New names:
## * `` -> ...1
```

```
national_ts <- national_ts %>%
  rename(year = 1,
         net_job_change = 2) %>%
  dplyr::select(year, net_job_change) %>%
  mutate(
    year = as.numeric(year),
    net_job_change = net_job_change*4) %>% group_by()
```

```r
ggplot(data = national_ts %>% filter(year >= 1995), aes(x = year, y = net_job_change)) +
  geom_col() + scale_x_continuous(breaks=seq(1995,2019,2)) +
    scale_y_continuous(labels = label_number(suffix = "", scale = 1e-6))
```

```
## Warning: Removed 2 rows containing missing values (position_stack).
```



Geographic Concentration of Layoffs

| | | 0% | |= | 2% | |=== | 4% | |==== | 6% | |===== | 7% | |====== |
9% | |======== | 11% | |========= | 12% | |========== | 14% |
|=========== | 15% | |============= | 19% | |==============
| 19% | |=============== | 22% | |================= | 24% |
|================== | 26% | |=================== | 27% |
|===================== | 30% | |====================== | 32%
| |======================== | 34% | |=========================
| 36% | |========================== | 37% | |===========================
| 39% | |============================= | 42% | |===============================
| 45% | |================================= | 47% | |==================================
| 49% | |==================================== | 51% |

|==| 52% | |====================
| 54% | |===| 57%
	==	59%
===	60%
===	64%
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71%		==
72%		===
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89%		===
90%		===
92%		===
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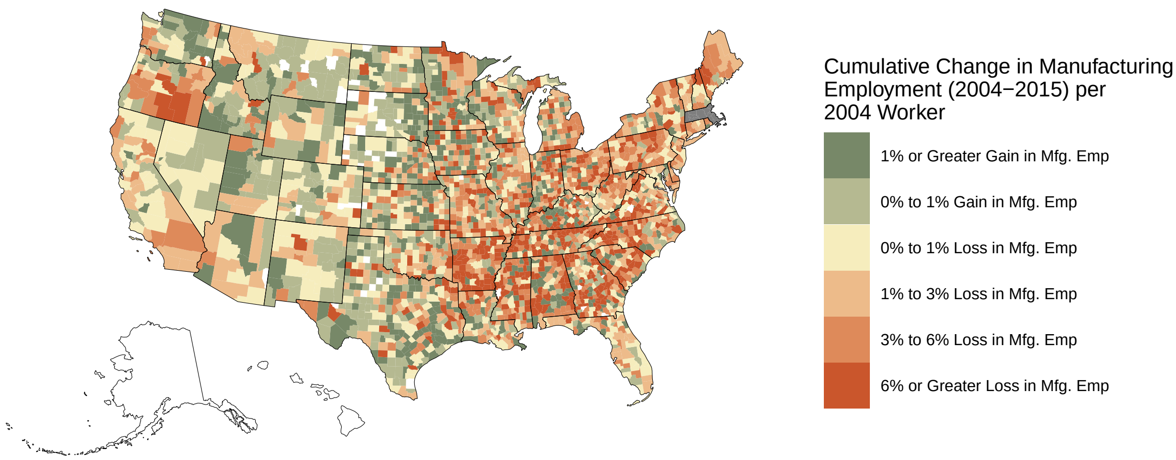
96%		===
97%		===
99%		===
100%

Figure X:
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

Figures

Example

Regression summaries

% Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu % Date and time: Mon, Nov 29, 2021 - 8:07:08 PM

Table 3: Effect of Manufacturing Layoffs on Democratic Vote Share

	Dependent variable:			
	Change in Share (2012-2016)			
	(1)	(2)	(3)	(4)
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			

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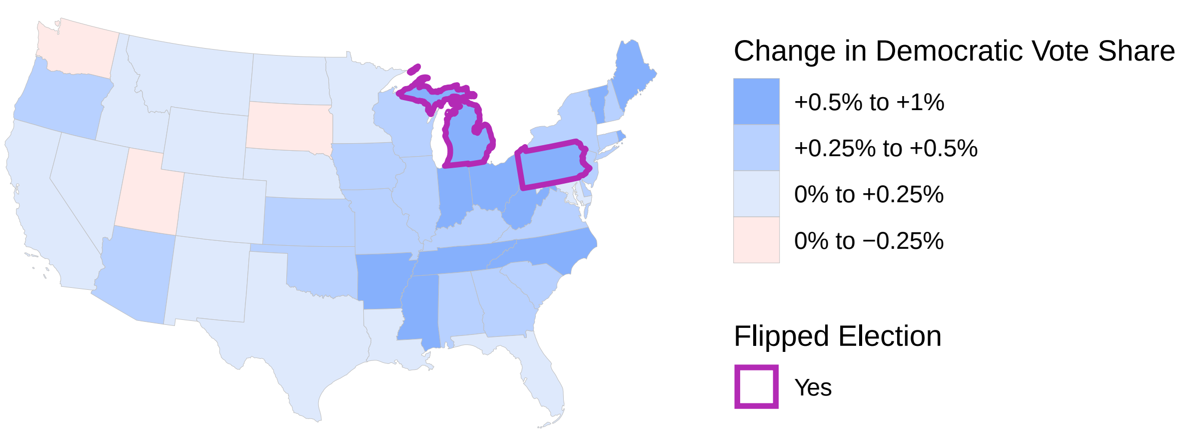
Table 4: Effect of Manufacturing Layoffs on Democratic Vote Share (since 2004)

	Dependent variable:			
	Change in Share (2016-2012)			
	(1)	(2)	(3)	(4)
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			

Counterfactual assessment of election

(Using 2004-2015 Layoffs)

Figure X:
Without Manufacturing Layoffs, Democrats Would Have Won 2016 Election
Change in Democratic Vote Share Assuming Counterfactual Manufacturing Layoffs (25th Perce



example state: Michigan

2020

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 endogeneous, 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?