Replication Paper

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Outline

- Framing story: the trajectory of XYZ county that swung from O to T and suffered big manufacturing layoffs
- 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 can tease out
- Empirical strategy: Differential manuf. 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: census Quarterly Workforce Indicators, which break down employment by industry, race and ethnicity. Compute net change in mfg (long term job loss)

Findings

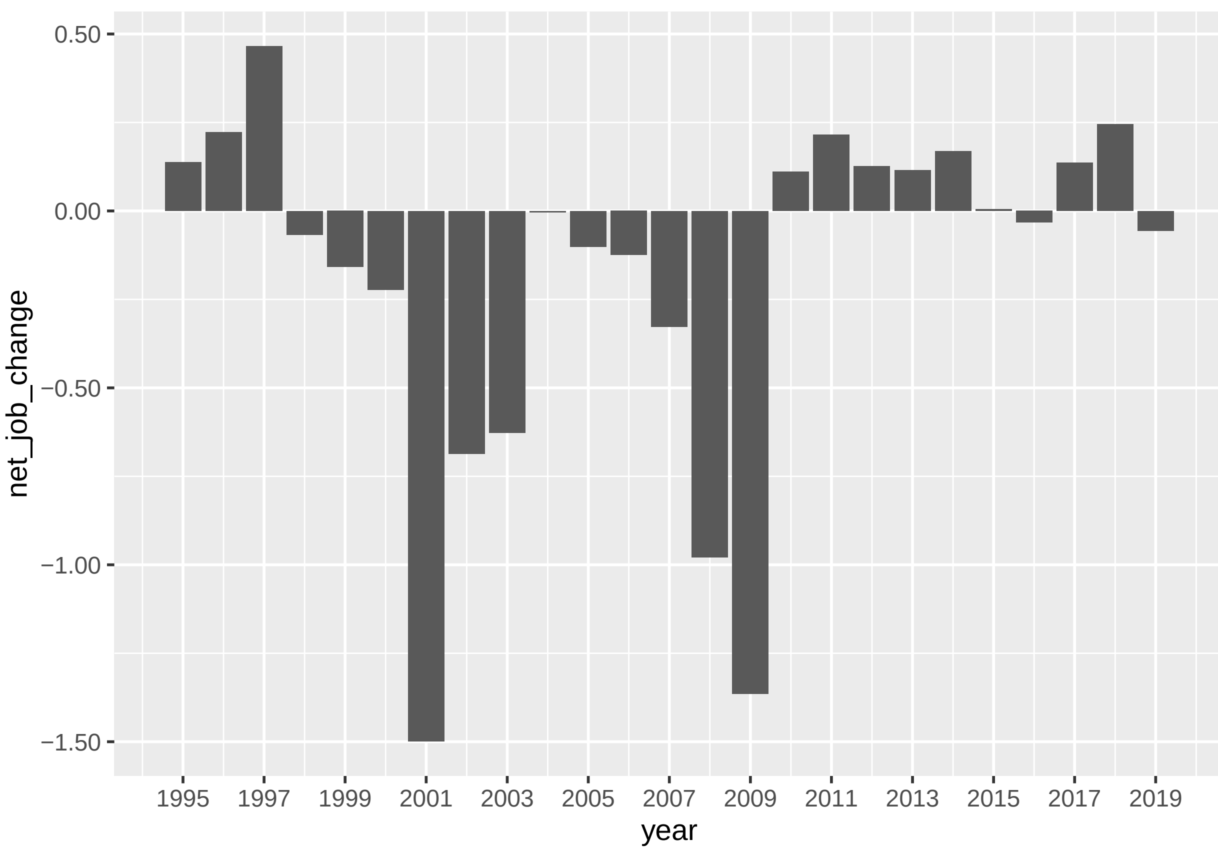
```
# manufacturing layoffs overtime

national_ts <- read_xlsx("../data/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% | |======== | 12% | |========== | 15% | |============= |
19% | |================ | 22% | |=================== | 27% |
|==================== | 29% | |===================== | 30% |
|======================== | 34% | |==========================
| 37% | |=========================== | 39% | |==========================
| 42% | |=============================== | 44% | |======================
| 45% | |=================================== | 49% | |==================
| 52% | |== | 57%
| |== | 60% |
|=== | 64% |

|=== | 67% |
|== |
71% | |===
| 72% | |==
| 75% | |==
| 79% | |==
| 82% | |==
| 87% | |==
| 90% | |==
| 94% | |==
| 97% | |==
100%

Figure X:
Net Change in Manufacturing Employment from 2004 to 2015
Normalized by 2004 Overall Employment Levels

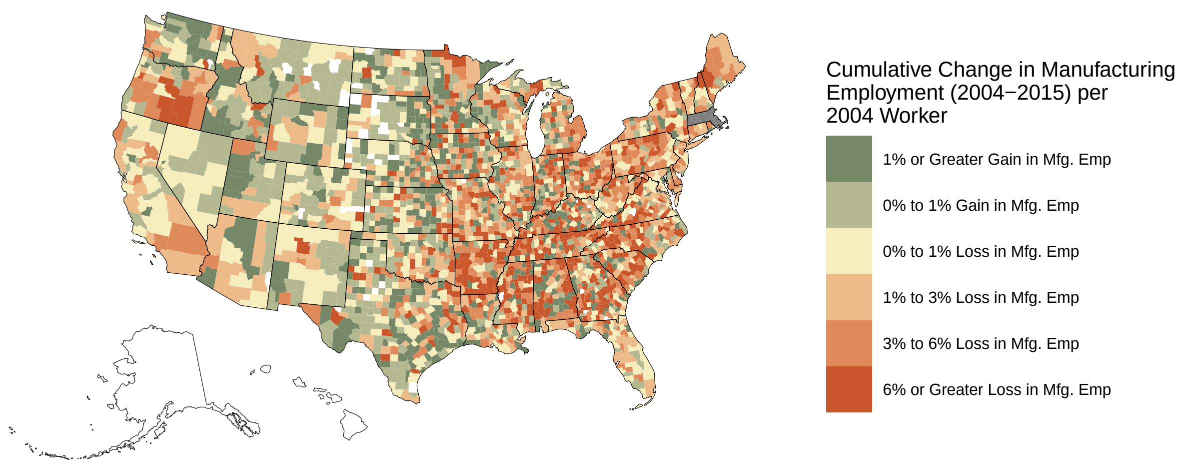


Table 1: Manufacturing Job Changes 2012-2015

	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

Table 2: 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

Descriptive Statistics

Figures

Example

Regression summaries

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% 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 - 5:56:54 PM

Table 3: Effect of Manufacturing Layoffs on Democratic Vote Share

	Dependent variable:			
	Change in Share (2012-2016)			
	(1)	(2)	(3)	(4)
Manufacturing Layoffs	0.36***	0.21**		
	(0.12)	(0.10)		
White Manufacturing Layoffs			6.39***	1.57***
			(1.21)	(0.57)
Nonwhite Manufacturing Layoffs			−3.92***	−0.95***
			(0.74)	(0.35)
Controls For White Share/Service Layoffs	No	Yes	No	Yes
Observations	2,930	2,930	2,707	2,707
Adjusted R^2	0.72	0.74	0.73	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

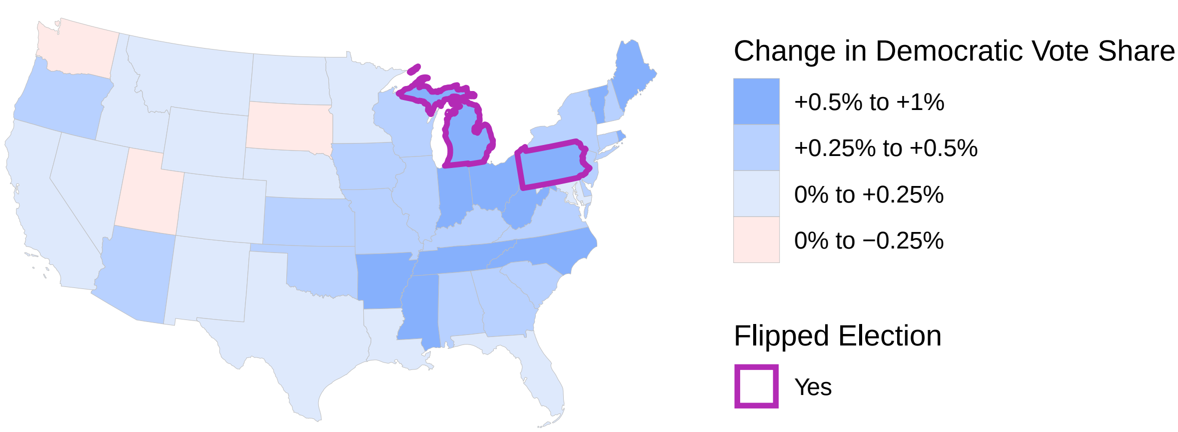

Table 4: Effect of Manufacturing Layoffs on Democratic Vote Share (since 2004)

	Dependent variable:			
	Change in Share (2016-2012)			
	(1)	(2)	(3)	(4)
Manufacturing Layoffs	-0.31^{***}	-0.31^{*}		
	(0.10)	(0.17)		
White Manufacturing Layoffs			-0.24^{***}	-0.20^{***}
			(0.05)	(0.07)
Nonwhite Manufacturing Layoffs			0.17^{***}	0.13^{***}
			(0.03)	(0.04)
Controls For White Share/Service Layoffs	No	Yes	No	Yes
Observations	2,966	2,966	2,720	2,720
Adjusted R^2	0.71	0.73	0.73	0.75
Note:	*p<0.1; **p<0.05; ***p<0.01			

example state: Michigan

2020

Potential Future Work

- 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.

Appendix