

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

Descriptive Statistics

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

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 - 12:28:54 AM

Table 3: Effect of Manufacturing Layoffs on Democratic Vote Share

	<i>Dependent variable:</i>			
	Change in Share (2012-2016)			
	(1)	(2)	(3)	(4)
Manufacturing Layoffs	0.36*** (0.12)	0.21** (0.10)		
White Manufacturing Layoffs			6.39*** (1.21)	1.57*** (0.57)
Nonwhite Manufacturing Layoffs			-3.92*** (0.74)	-0.95*** (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

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

	<i>Dependent variable:</i>			
	Change in Share (2016-2012)			
	(1)	(2)	(3)	(4)
Manufacturing Layoffs	-0.31*** (0.10)	-0.31* (0.17)		
White Manufacturing Layoffs			-0.24*** (0.05)	-0.20*** (0.07)
Nonwhite Manufacturing Layoffs			0.17*** (0.03)	0.13*** (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

Counterfactual assessment of election

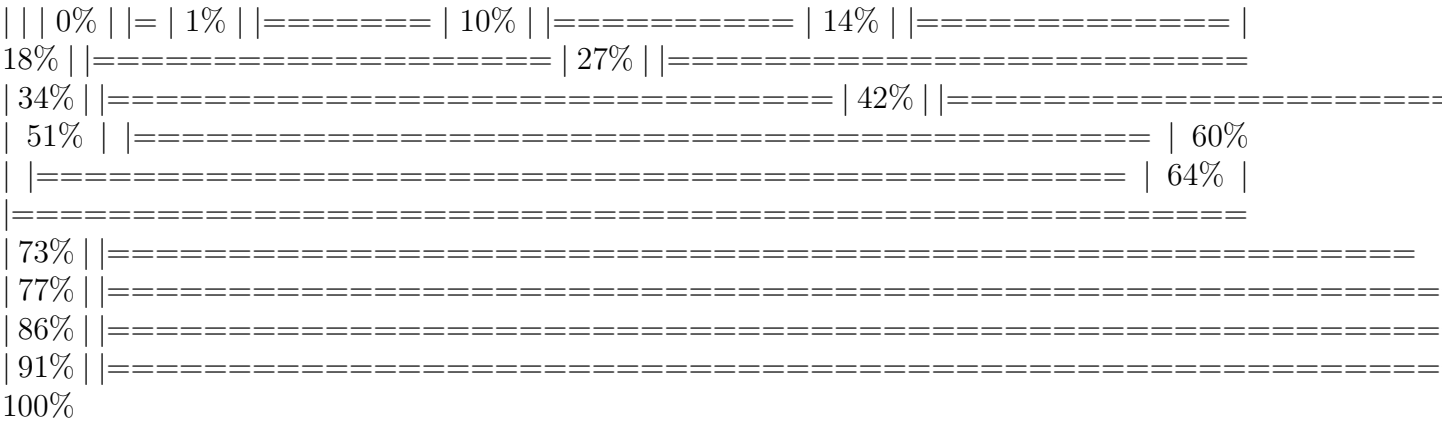
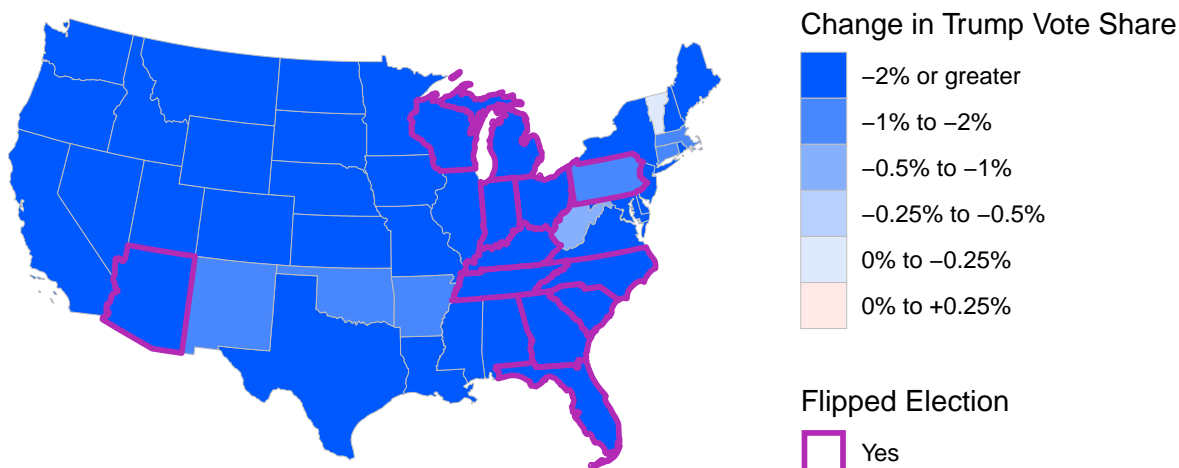


Figure X:
Manufacturing Layoffs Led Trump to 2016 Victory
Change in Trump Vote Share Assuming Counterfactual Manufacturing Layoffs (25th Percentile)



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 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.

Appendix