

# The Population Health Impact of the Right-to-Work Laws

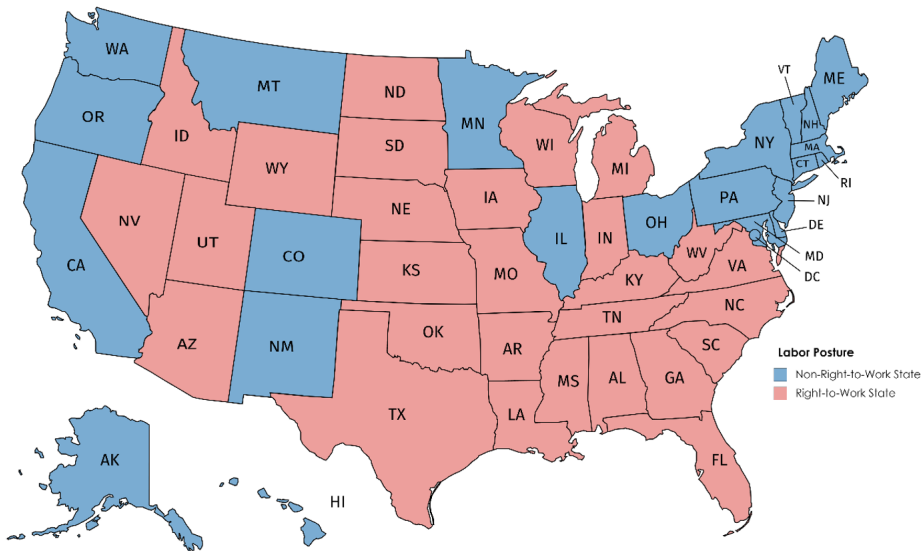
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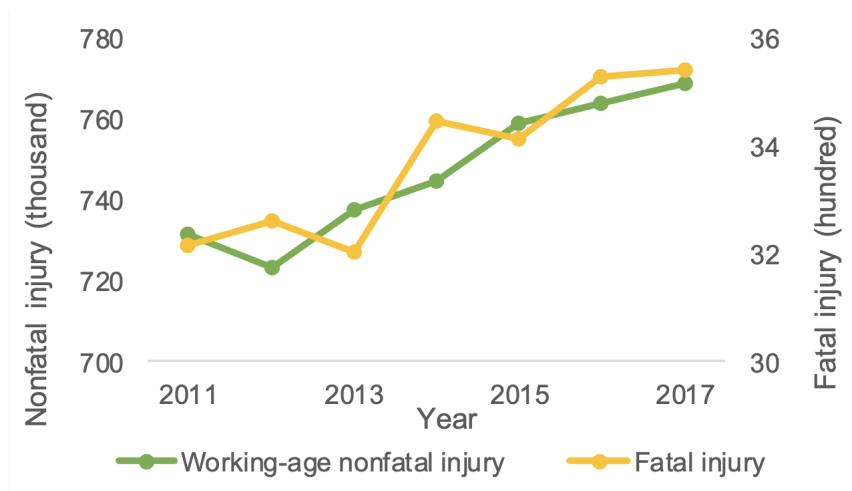
PAA Annual Meeting  
April 8, 2022

## Prevalence of State Right-to-Work Laws



Data Source: National Right to Work Foundation

## Increasing trend of fatal and nonfatal occupational injuries



Source: The U.S. Bureau of Labor Statistics

“Deaths of despair” on the rise in the US (Case & Deaton, 2015, 2017)

## Research Question

- ▶ What is the causal impact of the Right-to-Work (RTW) legislation on population health?

## Existing Literature

- ▶ Studies on the economic effects of RTW laws have produced mixed results, but a substantial literature agrees that they tend to weaken union bargaining power (Holmes 1998; Chava et al. 2020; Kalenkoski & Lacombe 2006; Vedder & Robe 2014; Carroll 1983; Ellwood & Fine 1987; Eren & Ozbeklik 2016; Garofalo & Malhotra 1992; Lumsden & Petersen 1975)
- ▶ The health impacts of RTW laws remain understudied (Gould & Shierholz 2011; Zullo 2011; Zoorob 2018)
- ▶ Existing literature suffers from important methodological limitations (Borusyak et al. 2021; Callaway & Sant'Anna 2021; De Chaisemartin & D'Haultfoeuille 2020; Goodman-Bacon 2021; Baker et al. 2021; Sun & Abraham 2021)

### Two key contributions:

1. widen the literature on the link between RTW laws and health
2. address the methodological issues

## This Paper

- ▶ Investigate the impact of RTW laws on four critical health outcomes
  1. all-cause mortality
  2. mortality among White and Black workers without college degrees
  3. mortality related to “deaths of despair”
  4. occupational fatal injuries
  
- ▶ Construct a unique state-year-level dataset for the years 1992-2016 from multiple data sources
  
- ▶ Apply the innovative [interactive fixed effects counterfactual \(IFect\)](#) estimator to investigate the dynamic treatment effects

## Theoretical Framework

- ▶ Restrict the functions of unions, less likely to receive employer-sponsored health insurance
- ▶ Worse workplace safety
- ▶ Restrict health promotion, worse psychosocial influences on health (e.g., job instability and no sense of belonging)

# Data

## State-year panel dataset of 50 states from 1992-2016

### ▶ Dependent variables:

1. workers' age-adjusted (25-64) mortality from CDC and SEER
2. all-cause mortality rates for White and Black workers without college degrees separately
3. "deaths of despair" mortality: drug overdose, suicide, and alcohol-related diseases
4. fatal occupational injuries from BLS

### ▶ Key independent variables:

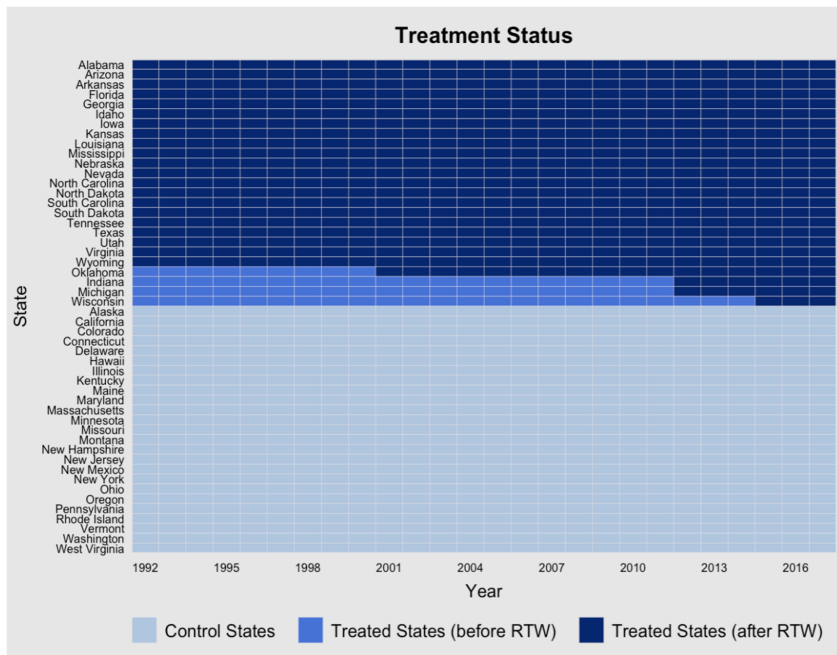
1. enactment of RTW laws - four treatment units: Oklahoma, Michigan, Indiana, and Wisconsin

### ▶ Control variables:

1. several time-varying state characteristics similarly as Zoorob (2018) and Caughey and Warshaw (2016)



## The dynamic “roll out” of RTW laws



## Traditional TWFE Approach

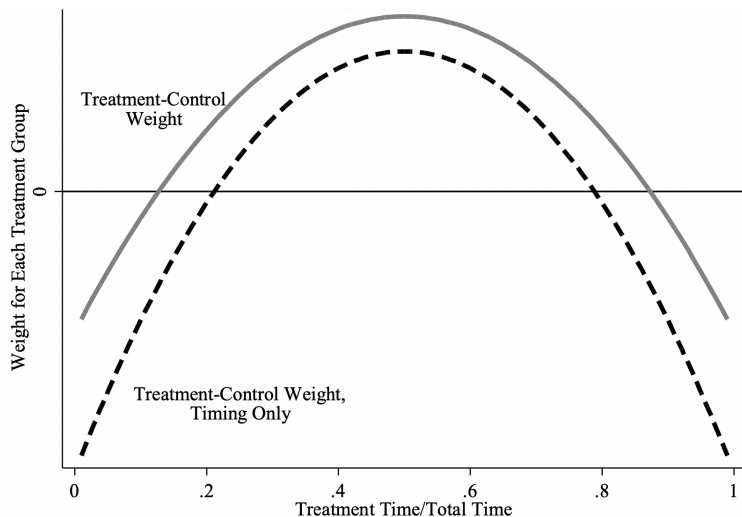
$$y_{it} = \alpha_i + \alpha_t + \delta D_{it} + \epsilon_{it}$$

- ▶  $\alpha_i$  and  $\alpha_t$  are unit and time fixed effects
- ▶  $D_{it}$  the unit-time indicator for treatment

Allows **only one parameter** to capture the treatment effect for all units

$\delta$  with staggered treatment timing is a *weighted average of many different treatment effects*: weights are often negative and non-intuitive

## Negative Weighting Problem



Source: Goodman-Bacon (2021)

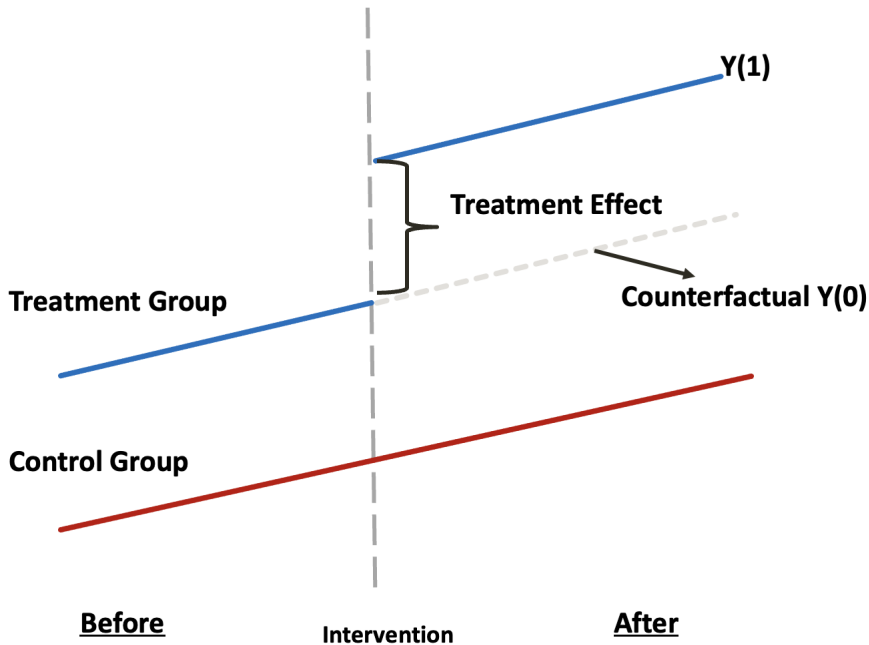
- ▶ Units treated in the middle get more weight as treated
- ▶ Units treated at the beginning or toward the ends get more weight as controls

## Why TWFE approach fails in our case?

TWFE models in the staggered policy adoption can lead to severely biased estimates of the treatment effect (Borusyak et al. 2021; Callaway & Sant'Anna 2021; De Chaisemartin & D'Haultfoeuille 2020; Goodman-Bacon 2021; Imai & Kim 2019; Sun & Abraham 2021)

- ▶ TWFE in staggered design violates:
  1. ✗ “constant treatment effect”
  2. ✗ “no carryover effect”
  3. ✗ strict exogeneity

# Counterfactual estimators



“Causal inference is a missing data problem” [more details](#)

## Intuition of IFECT method

- ▶ In a panel setting, treat  $Y(1)$  as missing data
- ▶ Predict  $Y(0)$  based on an outcome model (a factor model) (Gobillon & Magnac, 2016; Xu, 2017; Liu et al. 2021)
  - Train prediction models only with data in the control group
- ▶ Estimate ATT by averaging differences between  $Y(1)$  and  $\hat{Y}(0)$

[link to scm](#)

## The advantages of IFect method

### TWFE :

- ▶ ✗ “constant treatment effect”
- ▶ ✗ “no carryover effect”
- ▶ ✗ strict exogeneity

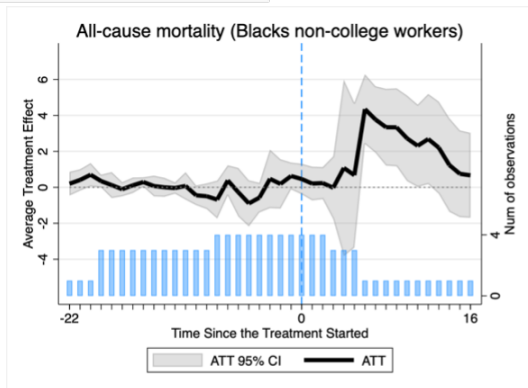
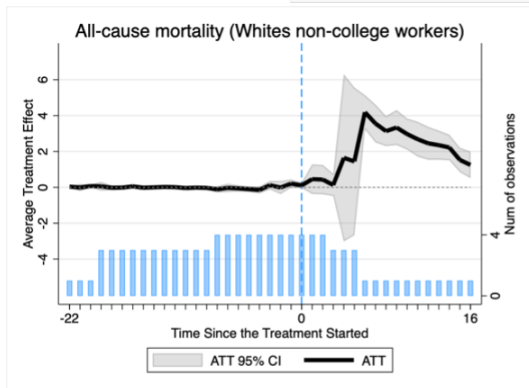
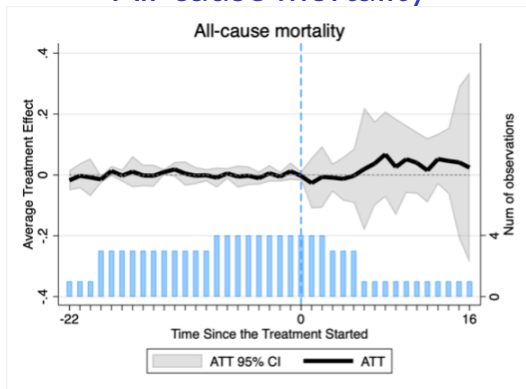
### IFect :

- ▶ ✓ heterogeneous treatment effects
- ▶ ✓ dynamic & carryover effects
- ▶ ✓ Account for certain unobserved time-varying confounders
  - Rely on the factor-augmented models to relax the strict exogeneity assumption

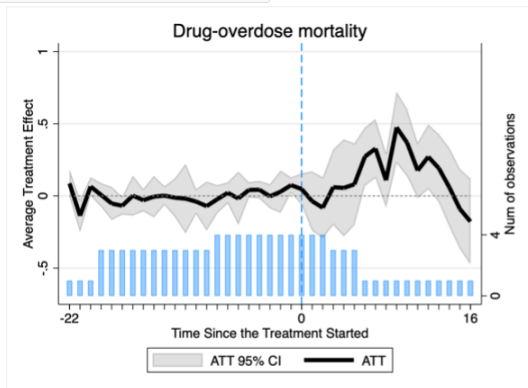
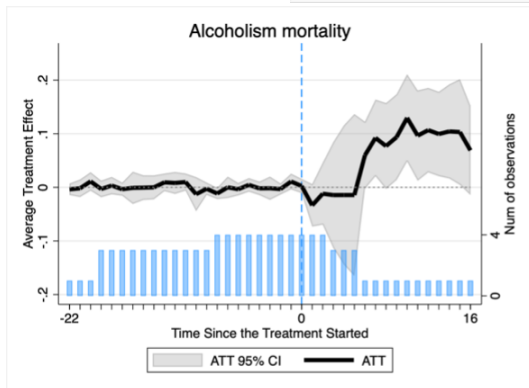
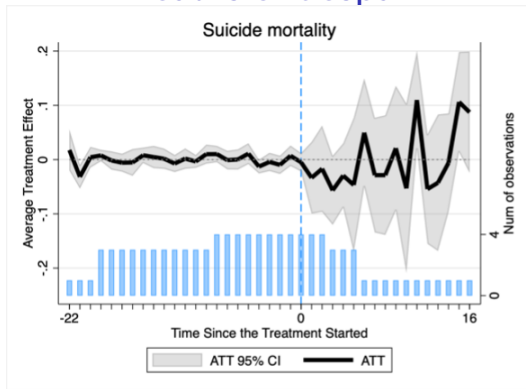
# The Dynamic Treatment Effects of RTW



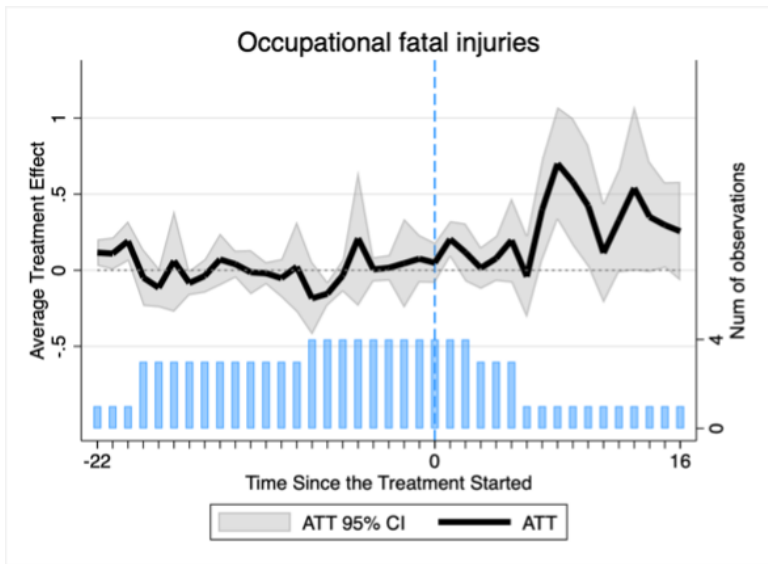
# All-cause mortality



# “Deaths of despair”



## Fatal injuries



## Other Results

### ▶ Diagnostic tests

- Placebo test: Statistically indistinguishable from zero, except for drug-overdose mortality and mortality for White workers without college degrees
- Wald test for no pre-treatment trend: The  $p$ -values are all greater than 0.1, thus fail to reject the null hypothesis that there is no pre-treatment trend

### ▶ Effects by treatment cohort: Oklahoma experienced a particularly strong effect

## Conclusion

- ▶ This study examines the effects of RTW legislation on population health outcomes
  - We apply the **innovate IFect approach** to overcome pitfalls of the TWFE method
  - The passage of RTW laws has led to **increased** mortality
  - A **greater** impact on early adopter – Oklahoma, important to uncover the heterogeneity of treatment effects

## Policy Implication

- ▶ Policy makers should focus their attention on how changes in labor and industrial policy “spill over” to health impacts
  - Factor in these risks and their costs for policy evaluation
  - Use correct methods to quantify the effects
  
- ▶ States that choose to pass RTW laws should consider “safeguards” to reduce negative effects on workers’ health, especially those without college degrees

*Thank You!*

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# Appendix



## Right-to-work Laws

- ▶ Ban on contracts requiring all employees to join and pay dues to a union
  
- ▶ Arguments for:
  - Liberty of contract
  - Freedom of association
  
- ▶ Arguments against:
  - Free-riding

## Link with synthetic control

- ▶ Recall that ADH (2010) use a factor-augmented model to motivate the synthetic control method:

$$Y_{it}(0) = \theta'_t Z_i + \xi_t + \lambda'_i f_t + \varepsilon_{it}$$

- ▶ What if we actually estimate the model using observations under the control condition only?
- ▶ Xu (2017) imports the so-called interactive fixed-effect (IFE) model to a DiD setting:

$$Y_{it}(0) = X'_{it} \beta + \alpha_i + \xi_t + \lambda'_i f_t + \varepsilon_{it}$$

- ▶ Athey et al. (2021) extend it and introduce the matrix completion method
- ▶ Liu et al. (2021) put these methods in a general framework – “the counterfactual estimators”
- ▶ No negative weighting!

## Model-based counterfactual estimators

A model-based counterfactual estimator proceeds in the following steps:

- ▶ Step 1: Train the model using observations under the control condition ( $D_{it} = 0$ ).
- ▶ Step 2. Predict the counterfactual outcome  $\hat{Y}_{it}(0)$  for each observation under the treatment condition ( $D_{it} = 1$ ) and obtain an estimate of the individual treatment effect:  $\hat{\tau}_{it} = Y_{it} - \hat{Y}_{it}(0)$
- ▶ Step 3. Generate estimates for the causal quantities of interest

$$ATT = \mathbb{E}[\tau_{it} \mid D_{it} = 1, \forall i \in \mathcal{T}, \forall t], \quad \text{or}$$
$$ATT_s = \mathbb{E}[\tau_{it} \mid D_{i,t-s} = 0, \underbrace{D_{i,t-s+1} = D_{i,t-s+2} = \dots = D_{it} = 1}_{s \text{ periods}}, \forall i \in \mathcal{T}].$$

## TWFE vs. IFect

	(1)	(2)
	Two-Way Fixed Effects (TWFE)	Interactive Fixed Effects Counter- factual Estimates (IFect)
<i>Panel A: All-cause mortality</i>		
All-cause mortality	0.03 (0.02)	0.01 (0.04)
All-cause mortality (Whites non-college workers)	1.21 (0.72)	1.53 (1.60)
All-cause mortality (Blacks non-college workers)	1.15 (0.97)	1.23 (1.78)
<i>Panel B: Mortality Related to "Deaths-of-Despair"</i>		
Drug-overdose mortality	0.20* (0.08)	0.07 (0.13)
Alcohol-related mortality	0.03 (0.03)	0.03 (0.08)
Suicide mortality	0 (0.02)	-0.02 (0.04)
<i>Panel C: Fatal injuries</i>		
Occupational fatal injuries	0.18** (0.06)	0.22* (0.12)
Observations	1250	1250
# Units	28	28