Causal effects of **R**enewable **P**ortfolio **S**tandards on renewable investments and generation

The role of heterogeneity and dynamics

Olivier Deschenes[1] Christopher Malloy[2] Gavin McDonald[1]

[1]University of California, Santa Barbara

[2]University of Oklahoma

Presenter: Chen FANG

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Background

U.S. decarbonization goals

- 100% carbon-free electricity by 2035
- decarbonization of the electricity generation sector by expanding renewable resources

Renewable Portfolio Standards (RPS)

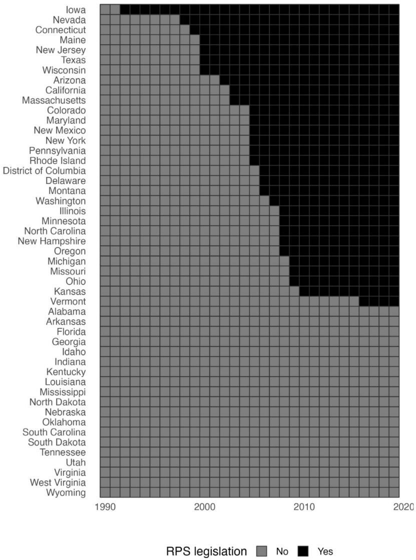
- **state-level** policy from 1991 (Iowa) Fig1 Map
- 30 states and Washington D.C (most 2000-2009)
- 70% of the US population & 64% of total generation capacity (2019)
- apply to 58% of total retail electricity sales
- more than 70 proposals for a national portfolio standard (2020)

Renewable Energy Credit (REC)

- 1 MWh of electricity generates from renewable source = 1 REC
- **Interstate Sales**: purchase electricity or **"unbundled"** RECs
- **Spillover**: incentive investments in renewables outside of the regulated state An Example

RPS Status by State

Background Data



More Details about RPS

Basic Mandate

- retail electricity suppliers should provide a minimum percentage or amount of their retail load using eligible renewable electricity generation sources

Different Designs across states

- **Time-varying targets (minimum percentages)**: in magnitudes and time frames Fig2
  - dynamics: annual percentage requirement increases gradually (until reaches mandated goal)
  - exemptions for publicly owned utilities, enforcement mechanisms, compliance tracking systems...
- **Effective Standard**: much lower (allow existing renewable generation to qualify for compliance)
- **Sources**: wind and solar ✔, hydroelectric and nuclear ✔ ✗
- **Encourage Strategy**: charges and financial penalties
- **Monitor by RECs**: issued by regional authorities that encompass multiple states (trade mostly within a region)

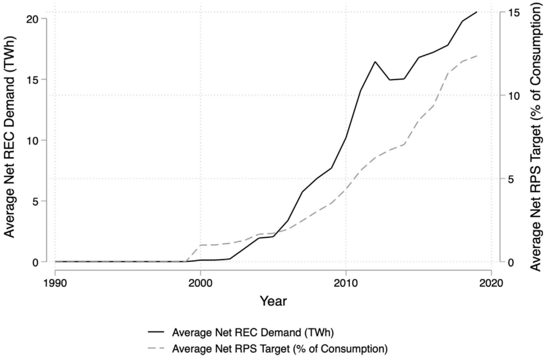
More Details about RPS

Examples

- California's RPS mandates that 60% of retail electricity sales come from renewable generation sources by 2030 and has interim targets of 44% by 2024 and 52% by 2027.
- Although California's standard was 20% of total retail electricity sales in 2010, its effective standard was approximately 17% of sales after accounting for eligible existing generation.
- some states such as California exempt publicly owned utilities from the RPS standard, while others such as Colorado set separate, lower standards for publicly owned utilities.
- Delaware enforce RPS policies by charging a fee ("Alternative Compliance Payment") for each unit of renewable generation, while other states such as California allow regulators to levy financial penalties on non-compliant utilities.

Stringency of RPS over time

details



- **Net RPS Target**: measure the percent of applicable retail electricity sales required to be generated by renewable sources
- **Net REC Demand** (= total renewable capacity mandated - existing supply of RECs): measure regulatory stringency

Literature Review

RPSs on renewable generation capacity investments, carbon emissions, and electricity prices

- **TWFE: staggered-DD**
  - positive on renewable electricity generation (Shrimali et al., 2015), (Yin and Powers, 2010)
  - little or no evidence on the deployment of renewable generating capacity (Greenstone and Nath, 2020)
- **Other Reduced-Form**
  - **IV** (Interstate sales of wholesale electricity markets): RPSs induce out-of-state emissions reductions through RECs (Feldman and Levinson, 2023), (Hollingsworth and Rudik, 2019)
  - **Synthetic Control Method**: ambiguous impact on renewables investments (Upton Jr and Snyder, 2017)
- **General Equilibrium Model**
  - deliver large resource booms or large emissions savings but not both (Bento et al., 2018)
  - effect on renewable capacity investments depends on transmission costs and natural endowments (Fullerton and Ta, 2022)

Research Question

How RPS affects the deployment of renewable electricity generation sources?

- **Motivation**
  - one of the most prominent policies to incentivize decarbonization of the electricity sector
  - many proposed federal policies mimic RPS
  - remain controversial and debates
- **Empirical Challenges**
  - RPS policies are **not randomly** assigned across states (Lyon, 2016)
  - **Dynamic** and **Heterogeneous** effects across states (policy design & renewable resource endowments)
- **Contribution**
  - recent data up to 2019 (latter 2010s period is critical)
  - seperate wind and solar: differences in declining cost trends and innovation (Wiser et al., 2023)
  - dynamic impacts in longer-term (11 year)
  - **leverages robust estimator (Callaway and Sant'Anna, 2021)**

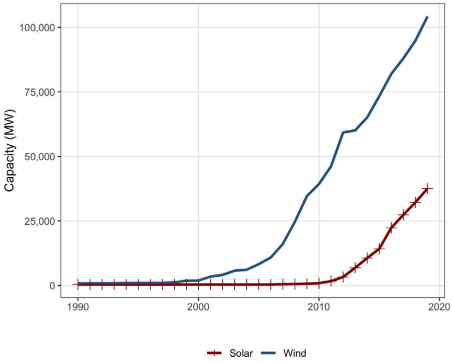
Data Source

A state-level panel data (1990-2019) set on the relevant outcomes, policy variables, and predictors of renewable investments

- RPS policy adoption (primary treatment indicator)
  - 27 states enacted, Iowa (1992), Vermont (2015) Fig1
  - large degree of autocorrelation in the treatment status (cluster-robust)
- Operating Capacity by Source
  - Energy Information Administration (EIA) Form 860
  - generator-level information at electric power plants (>1MW)
  - total cumulative installed capacity over time by source (wind, solar, coal and gas)
- Actual Generation of Electricity by Source
  - EIA Form 906
  - annual data on generation at the power plant level

Trends in renewable electricity generation capacity (MW)

solar ATT



- similar pattern, roughly linear (wind: early 2000s, solar: 2010)
- **localized** incentives for diffusion
  - reduction in levelized costs of operation
  - federal and state-level production tax credits

Data Source & Main Variables

Variable	Units	Source
Transmission lines	km per km^2	Homeland Infrastructure Foundation-Level Data (HIFLD)
Wind speed	meters per second	NREL Wind Integration National Dataset (WIND)
Solar irradiance	kWh / m^2 /year	NREL Physical Solar Model version 3 Global Horizontal Irradiance Multi-year Annual Average
Installed capacity	MW	EIA Form EIA-860
Generation	GWh	EIA Form EIA-906
GDP per capita	$ per person	Bureau of Economic Analysis (BEA) dataset SAGDP2N
Electricity price	all end-use, $ / kWh	EIA State Energy Data System (SEDS)
Electricity consumption	Bil. kWh	EIA State Energy Data System (SEDS)
House LCV score	Scale $[0, 100]$	League of Conservation Voters (LCV) Scorecard
Senate LCV score	Scale $[0, 100]$	League of Conservation Voters (LCV) Scorecard
Fraction counties non-attainment	Share $[0, 1]$	Environmental Protection Agency (EPA) Greenbook

- RPSs are more likely to be adopted in states that scored higher in the League of Conservation Voters (LCV) score index.

Summary Statistics (1990)

	RPS states	Non RPS states	Difference
A. Infrastructure & Endowments			
Transmission lines (km per km^2)	0.16	0.14	0.02
Wind speed (meter per second)	6.3	6.1	0.2
Solar irradiance (kWh / m^2 /year)	4.3	4.6	-0.2
B. Installed Capacity (MW)			
Wind	26.0	0.0	26.0
Solar	13.4	0.0	13.4
Coal	5,500.6	7,164.8	-1,664.2
Gas	4,182.7	2,873.30	1,309.4
Total	15,694.1	14,394.0	1,300.10
C. Generation (GWh)			
Wind	183	0	183
Solar	24	0	24
Coal	58,930	74,690	-15,761
Gas	18,468	9,714	8,754
Total	64,289	57,571	6,718
D. Other Predictors			
GDP per capita	42,278	34,145	8,132***
Electricity price (all end-use, $ / kWh)	0.12	0.10	0.02***
Electricity consumption (Bil. kWh)	59.6	46.3	13.4
House LCV score	62.1	41.7	20.4***
Senate LCV score	62.3	34.4	27.9***
Observations	30	19	

- marked differences between states adopting RPSs and states never adopting them

causal effect on Deployment and Generation

Canonical Equation

Difference-in-differences design with a TWFE estimator Dynamic TWFE

$$y_{it} = \beta RPS_{it} + X_{it}'\theta + \gamma_i + \delta_t + \varepsilon_{it}$$

- y_{it} denotes utility-scale wind or solar electric capacity installed (or generation)
- X_{it} is a vector of state-specific time varying control variables
- γ_i: state fixed effects
- δ_t: the year fixed effects
- β: the **average treatment effect on the treated (ATT)** of an RPS policy on the outcomes (utility-scale wind and solar capacity and generation)
- β not guaranteed to recover an interpretable causal parameter

(Rios-Avila et al., 2022)

causal effect on Deployment and Generation

A robust ATT estimator (Callaway and Sant'Anna, 2021) Details

well suited to staggered adoption research designs with a binary treatment indicator as in our setting

$$ATT_{g,t} = \mathbb{E}\left[\frac{G_g}{\mathbb{E}[G_g]}(Y_t - Y_{g-1} - \mathbb{E}[Y_t - Y_{g-1}|X, G_g = 0])\right]$$

- G_g: equal to one if a state first implemented an RPS at period g
- Y_t: potential outcome at event-time period t
- Y_{g-1}: the potential outcome in period $g-1$
- $ATT_{g,t}$: **compare** the differential outcomes of states in adoption cohort g between t and the period prior to RPS **to** the same differential in states which are not yet treated by g

impacts of RPS intensity

Binary Indicator ⇒ continuous measure of treatment

Measure RPS intensity by calculating the total demand for RECs in each state (Feldman and Levinson, 2023) Schematic

$$Net - RPS_{it} = \max\left(0, RPS_{it} - EligibleRenewables_{i,\tau i-1}\right)$$

$$Net - Out - of - State - REC - Demand_{it} = \sum_{j \in TP_i} \max\left(0, RPS_{jt} - Renewables_{jt}\right)$$

- Net in-state demand = gross statutory RPS requirement less eligible renewable generation produced in the year before RPS
- Net out-of-state demand for RECs = the sum of the RPS goal where state i can sell RECs to, less those states' contemporaneous renewables generation (Hollingsworth and Rudik, 2019)
- total demand for RECs = in-state + out-of-state demand (binarize to 1 when exceeds sample average level)

Estimated ATT (wind)

	(1)	(2)	(3)
Panel A: Capacity (MW)			
Overall ATT (cohort)	652	475	1220**
	(405)	(389)	(410)
Overall ATT (year)	394	306	713*
	(219)	(222)	(278)
1-5 years post	241*	158	241
	(113)	(119)	(149)
6-11 years post	575	469	1210**
	(353)	(352)	(452)
Panel B: Generation (GWh)			
Overall ATT (cohort)	3260	2250	6950**
	(2240)	(2110)	(2270)
Overall ATT (year)	1740	1330	3720*
	(1140)	(1070)	(1500)
1-5 years post	1090*	680	1110
	(534)	(569)	(695)
6-11 years post	2550	2070	6490*
	(1850)	(1720)	(2580)
Controls			
Endowments		Yes	Yes
Sociopolitical			Yes
Observations	1380	1380	1380

- **column (3)**: full set of natural endowments and socioeconomic controls
- RPS policy increases installed wind capacity by 1220 MW on average
  - 44% of the average installed wind capacity (among RPS states, 2019)
- larger impact for 6–11 years after RPS (than 1-5)
- 1% increase in the RPS target implies the share of capacity increases by 0.41%
- e.g. 6490 GWh
  - 176% of mean wind generation
  - 20% of mean coal generation (among RPS states, 2019)

- $***p < 0.001$, $**p < 0.01$, $*p < 0.05$.
- Standard errors are computed using a multiplier bootstrap method, clustering at the state level.

Dynamic Effects (wind)

- subset for which have 11 years of (pre-) & (post-) RPS
  - point ⇒ event time-specific treatment effect
  - length of tickers ⇒ 95% CI
- **long-lasting** change (to the electricity sector)
  - **pre**: parallel trends (credible ATT)
  - **post**: significant only 5–7 years, roughly linear treatment effects, no sign of reverting back

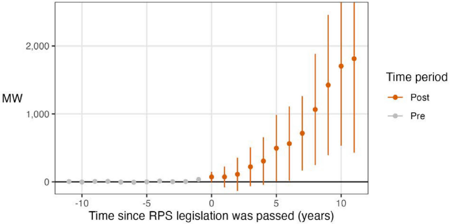


Figure: installed wind capacity

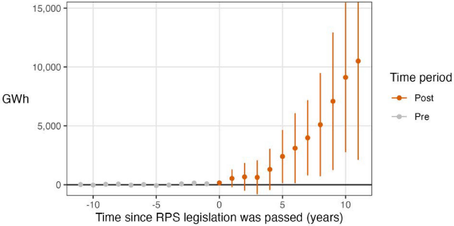


Figure: wind electricity generation

Estimated ATT (solar)

	(1)	(2)	(3)
Panel A: Capacity (MW)			
Overall ATT (cohort)	201*	235**	155
	(92.8)	(85.9)	(106)
Overall ATT (year)	50.1	71.1	43.0
	(53.7)	(51.4)	(51.3)
1-5 years post	2.14	3.65*	1.51
	(1.92)	(1.68)	(1.93)
6-11 years post	98.3	139	84.7
	(101)	(100)	(99.2)
Panel B: Generation (GWh)			
Overall ATT (cohort)	762*	902*	676
	(375)	(354)	(409)
Overall ATT (year)	119	195	114
	(145)	(139)	(139)
1-5 years post	2.38	8.61*	1.78
	(5.40)	(4.13)	(5.57)
6-11 years post	236	382	227
	(275)	(273)	(273)
Controls			
Endowments		Yes	Yes
Sociopolitical			Yes
Observations	1380	1380	1380

- **positive but insignificant**
  - smaller estimates than their wind counterparts
  - vary in statistical precision across specifications
  - much occur between 6-11 years
- 1% increase in the RPS target implies the share of capacity increases by 0.02%
- Lagged Investment Trends
  - **wind**: occurred since 2000 (economically attractive and lower risk than solar) (Wiser et al., 2011)
  - **solar**: similar accumulation since 2010

- $***p < 0.001$, $**p < 0.01$, $*p < 0.05$.
- Standard errors are computed using a multiplier bootstrap method, clustering at the state level.

Dynamic Effects (solar)

- subset for which have 11 years of (pre-) & (post-) RPS
  - point ⇒ event time-specific treatment effect
  - length of tickers ⇒ 95% CI
- **Very small** change (to the electricity sector)
  - **pre**: parallel trends (credible ATT)
  - **post**: small and indistinguishable from zero

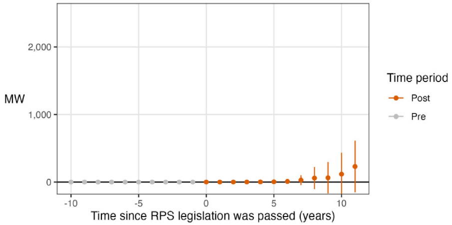


Figure: installed solar capacity

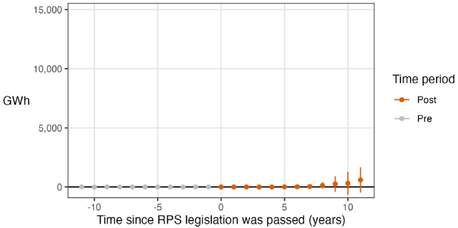


Figure: solar electricity generation

Robustness Check

- **Alternative Control Groups**
  - never treated states vs. never and not yet treated
- **Sample**
  - balanced vs. not balanced (for 11 pre- and post- periods)
- **Treatment Definitions**
  - (net REC demand) above the sample average vs. being positive

Dependent variable	Balanced	Control	Independent variable	Solar	Wind
Capacity (MW)	**Yes**	**NYT**	**RPS Legislation**	**43 (51.3)**	**713* (278)**
Generation (GWh)	**Yes**	**NYT**	**RPS Legislation**	**114 (139)**	**3720* (1500)**
Capacity (MW)	Yes	NT	RPS Legislation	43 (51.3)	739** (278)
Capacity (MW)	No	NYT	RPS Legislation	284 (243)	1980* (869)
Capacity (MW)	Yes	NYT	Net REC demand (average)	353 (454)	1120* (543)
Capacity (MW)	Yes	NYT	Net REC demand (positive)	114 (97.8)	671* (323)
Generation (GWh)	Yes	NT	RPS Legislation	114 (139)	3830* (1510)
Generation (GWh)	No	NYT	RPS Legislation	1400 (1090)	11700* (5060)
Generation (GWh)	Yes	NYT	Net REC demand (average)	1410 (1800)	5620* (2830)
Generation (GWh)	Yes	NYT	Net REC demand (positive)	369 (351)	3480 (1800)

Robustness Check (Cont'd)

- 2 years of **Anticipation Effects** details
- **Sample Construction** (consider "irreversible" assumption)
  - drop RPS states where net demand for RECs is 0 after RPS
- **Alternative Treatment Adoption Cohort Groups**
  - group states into 3-year adoption cohorts (before: 1 year)
- **Estimator**
  - TWFE regression using OLS (net REC demand & binary RPS)

Dependent variable	Anticipation	Drop states	Cohort Group	Method	Independent Variable	Solar	Wind
Capacity (MW)	**No**	**No**	**1-Year**	**C+S**	**RPS Legislation**	**43 (51.3)**	**713* (278)**
Generation (GWh)	**No**	**No**	**1-Year**	**C+S**	**RPS Legislation**	**114 (139)**	**3720* (1500)**
Capacity (MW)	Yes	No	1-Year	C+S	RPS Legislation	43 (51.3)	809** (301)
Capacity (MW)	No	Yes	1-Year	C+S	RPS Legislation	43 (94.2)	681 (479)
Capacity (MW)	No	No	3-Year	C+S	RPS Legislation	145 (122)	1220** (467)
Capacity (MW)	No	No	-	TWFE	Net REC demand (TWh)	2.4 (1.67)	14.1 (18.3)
Capacity (MW)	No	No	-	TWFE	RPS Legislation	-5.85 (3.31)	90.9* (39.1)
Generation (GWh)	Yes	No	1-Year	C+S	RPS Legislation	118 (137)	4190* (1660)
Generation (GWh)	No	Yes	1-Year	C+S	RPS Legislation	106 (247)	4860 (2910)
Generation (GWh)	No	No	3-Year	C+S	RPS Legislation	633 (500)	6900* (2690)
Generation (GWh)	No	No	-	TWFE	Net REC demand (TWh)	5.74 (3.37)	59.5 (99.5)
Generation (GWh)	No	No	-	TWFE	RPS Legislation	-14.4 (7.73)	536* (211)

Discussion

Estimation of the contribution of RPS

- ATT on wind capacity approximately $\approx$ 1000 MW (11 years post RPS)
- 29×1000MW $\approx$ 29GW, almost 30% of current aggregate wind capacity

Policy Implications

- Clean Energy Standard proposed by Biden (2021) shares many features with RPSs
  - may promote investments in wind & solar production capacity and generation
- whether investments sufficient?
  - for energy sector to reach zero emissions by 2035

CES: a technology-neutral portfolio standard that requires that a certain percentage of utility sales be met through "clean" zero- or low-carbon resources, such as renewables, nuclear energy, coal or natural gas fitted with carbon capture, and other technologies.
As with an RPS, eligible technologies are awarded credits per MWh of generation that can be traded, which provides an efficient, market-based solution to meet a standard. (Source: RFF)

Potential Caveats

Main Results

- RPS dramatically increased wind capacity investments and generation
  - this increase persists up to 11 years
- RPS takes time to affect renewable capacity installations and generation (6–11 years)
- no evidence on solar capacity

Potential Caveats?

- More heterogeneity in policy design Map
- data can't be well-suited for solar investments (timing) Trend
- Be careful of interpretation of different DiD estimators Misinterpretation

Takeaways

For Research

- Heterogeneity and Dynamic Effects are really important!
- In China: revisit some "Pilot" Policies
  - ETS? Water Right Trading? Low-Carbon City?
  - "Green" Credits (REC) in China

For Researchers

- Possible to make correct identification using limited, coarse observations (1380 here)
- Refer to "cutting-edge" econometrics strategies!
  - Causal Inference framework matters
- Re-evaluate some Policies in China.
  - `R` package for `did` estimation: click here!

Appendix: the Distribution of RPS

Background

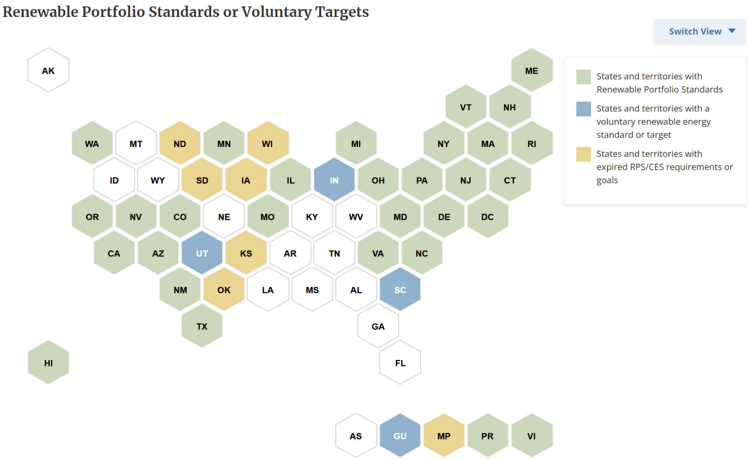


Figure: Renewable Portfolio Standards or Voluntary Targets

Source: National Conference of State Legislatures

Appendix: Emissions savings versus resource booms

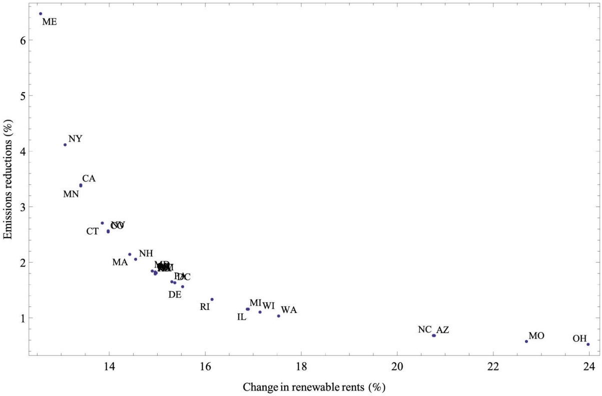
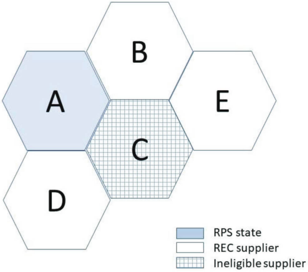


Figure: Change in emission savings and renewable rents by state due to 10% increase in RPS

Source: (Bento et al., 2018)

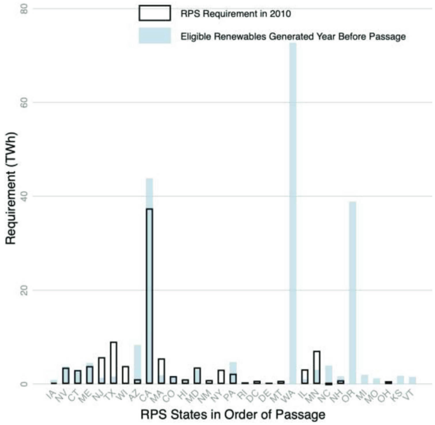
Appendix: A Schematic of REC Market (Feldman and Levinson, 2023)

RPS intensity



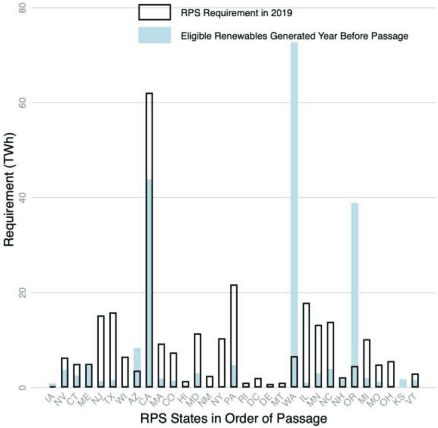
- **Left**: A purchase RECs from B, D, and E
- **Right**: B purchase RECs from A, C, and E
- eg: when calculating D's net out-of-state REC demand, we include A's requirement but not B's.

Appendix: Net in-state demand (2010) (Feldman and Levinson, 2023)



- most states' RPS goals were already being met by the renewables they were generating before enactment

Appendix: Net in-state demand (2019) (Feldman and Levinson, 2023)



- most states' RPSs required some new renewables, at least relative to their original levels.

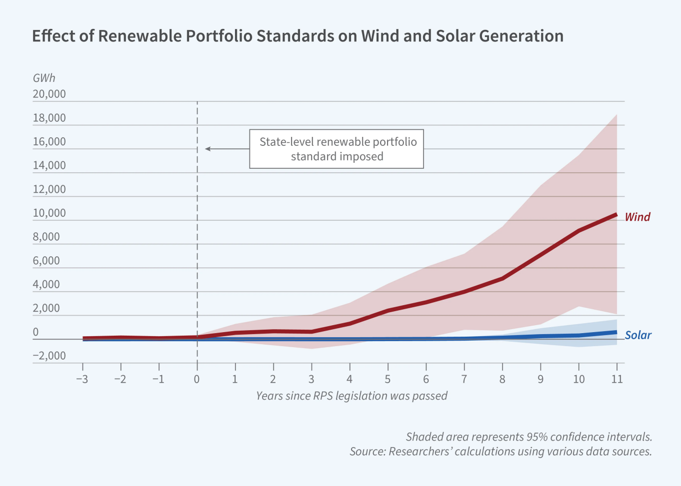
Appendix: Endogenous Nonadditionality (Feldman and Levinson, 2023)

Example

Background

- In 2010 Nevada was requiring that 3.5 TWh of electricity sales come from renewable sources.
- But Nevada's RPS had been enacted in 1997, and the year before that, it was already producing 3.7 TWh of renewables, more than its RPS requirement in 2010. None of the renewables generated in Nevada before 2010 should be attributed to its RPS.
- some of Nevada's renewables growth before 2010 might, in theory, be attributable to RPSs in nearby states like California and Arizona.
- Nevada utilities might generate renewable energy for the purpose of selling unbundled RECs to those other states.
- **What makes policy evaluation tricky** is that Nevada's renewables growth after 2010 might be attributable both to its own RPS, which increased to 6.3 TWh by 2019, and to RPSs in nearby states.

Appendix: Combined Figure



Source: NBER Digest (Nov.2023)

Appendix: "Dynamic" Variations of the TWFE specification

$$Y_{i,t} = \alpha_i + \alpha_t + \gamma_k^{-K} D_{i,t}^{<-K} + \sum_{k=-K}^{-2} \gamma_k^{lead} D_{i,t}^{k} + \sum_{k=0}^{L} \gamma_k^{lags} D_{i,t}^{k} + \gamma_k^{L+} D_{i,t}^{>L} + \varepsilon_{i,t}$$

- with the **event study** dummies $D_{i,t}^{k} = \mathbf{1}\{t - G_i = k\}$, where G_i indicates the period unit i is first treated (Group).
- $D_{i,t}^{k}$ is an indicator for unit i being k periods away from initial treatment at time t.
- γ's cannot be rigorously interpreted as reliable measures of "dynamic treatment effects". (Sun and Abraham, 2021)

Appendix: “Beyond 2030” in the UK

拟投资5000多亿元，英国将进行史上最大电网变革

英国国家电网计划，到2035年，英国电力系统将接入86 GW的海上风电。这已超过了当前全球海上风电的装机总量。

ESO publishes “Beyond 2030” – a £58bn investment plan in the future of Britain’s energy system

Future Network Development / 19 Mar 2024 - 3 minute read

Source: ESO (Electricity System Operator for Great Britain)

Appendix: Misinterpretation of DiD estimators

Ashvin Gandhi @ashdgandhi · Jan 23

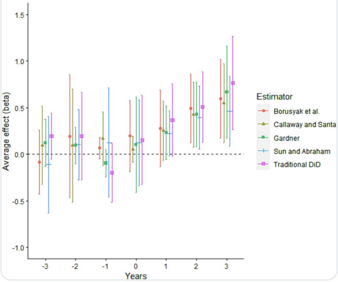
I have refereed multiple papers where the authors implemented CSDID and didn't realize that the graph actually shows clear pre-trends. In fact, I have been guilty of this misinterpretation more than once as well.

Ashvin Gandhi @ashdgandhi · 16h

Asking for more than one alternative DD estimator should immediately disqualify a reviewer.

Journal of Corporate Finance @JCorpFin · Mar 30

Wait, is that FIVE DiD estimators in one graph?😍😍😍
x.com/JCorpFin/statu...



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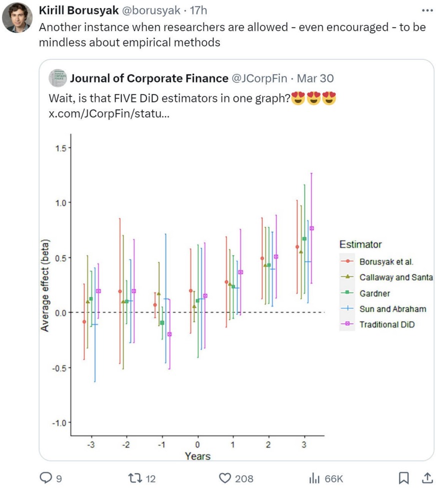
Source: Ashvin Gandhi's Twitter

Appendix: Misinterpretation of DiD estimators (Cont'd)



Source: Kirill Borusyak's Twitter

Appendix: Misinterpretation of DiD estimators (Cont'd)

Journal of Corporate Finance reposted

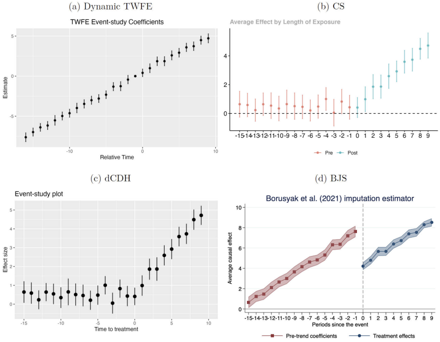
Jonathan Roth @jondr44 · 21h

Replying to @analisapackham and @JCorpFin

Tbc I'm fine with a figure with the different estimators in different panels (altho I don't think it's necessary).

But putting them all on one panel (a) makes it seem like the estimates are comparable, and (b) makes it visually hard to follow

1 4 25 3.3K



Source: Jonathan Roth's Twitter (Roth, 2024) Caveats

Appendix: Details from (Callaway and Sant'Anna, 2021)

Treatment Effects in DiD Designs with Multiple Periods ATT

Framework

- focus on a panel data case.
- consider a **random** sample (iid):

$$\{(Y_{i,1}, Y_{i,2}, ..., Y_{i,\tau}, D_{i,1}, D_{i,2}, ..., D_{i,\tau}, X_i)\}_{i=1}^{n}$$

  where $D_{i,t} = 1$ if unit i is treated in period t and 0 otherwise.
- $G_{i,g} = 1$ if unit i is first treated at time g, and zero otherwise ("Treatment starting-time" / "Cohort dummies")
- $C = 1$ is a "never-treated" cimparison group (not required, though)
- **Staggerd treatment adoption**: $D_{i,t} = 1 \Rightarrow D_{i,t+1} = 1$, for $t = 1, 2, ..., \tau$. (**Irreversibility**, or units do not "forget" about the treatment experience)

Appendix: Details from (Callaway and Sant'Anna, 2021)

Framework (Cont'd)

- **Potential outcomes**:

$$Y_{i,t} = Y_{i,t}(0) + \sum_{g=2}^{T} \left(Y_{i,t}(g) - Y_{i,t}(0) \right) \cdot G_{i,g}$$

  - $Y_{i,t}(0)$: unit i's untreated potential outcome at time t if they remain untreated through time period $\mathcal{T}$
  - $Y_{i,t}(g)$: potential outcome that unit i would experience at time t if they were to first become treated in time period g

- **Parameter of interest**:

$$ATT(g,t) = \mathbb{E}[Y_t(g) - Y_t(0) | G_g = 1], \text{ for } t \geqslant g$$

  - Average treatment effect for the group of units first treated at time period g, in calendar time t

Appendix: Details from (Callaway and Sant'Anna, 2021)

Framework (Cont'd) Robust

- **Limited Treatment Anticipation**: there is a known $\delta \geqslant 0$ s.t.

$$\mathbb{E}[Y_t(g)|X, G_g = 1] = \mathbb{E}[Y_t(0)|X, G_g = 1] \quad a.s.$$

for all $g \in \mathcal{G}$, $t \in 1, ..., \mathcal{T}$ such that $\underbrace{t < g - \delta}_{\text{"before effective starting date"}}$.

- For simplicity, let's take $\delta = 0$, which is arguably the norm in the literature.
- If units anticipate treatment by two period, this assumption would hold with $\delta = 2$.
- Generalized propensity score uniformly bounded away from 1:

$$p_{g,t}(X) = P(G_g = 1|X, G_g + (1 - D_t)(1 - G_g) = 1) \leqslant 1 - \epsilon \quad a.s.$$

Appendix: Details from (Callaway and Sant'Anna, 2021)

Framework (Cont'd)

- **Parallel Trend Assumption (based on a "never-treated" group)**: For each $t \in \{2, ..., \tau\}$, $g \in G$ such that $t \geqslant g$,

$$\mathbb{E}[Y_t(0) - Y_{t-1}(0)|X, G_g = 1] = \mathbb{E}[Y_t(0) - Y_{t-1}(0)|X, C = 1] \;\; a.s.$$

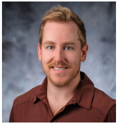
- **Parallel Trend Assumption (based on "Not-Yet-Treated" Groups)**: For each $(s, t) \in \{2, ..., \tau\} \times \{2, ..., \tau\}$, $g \in G$ such that $t \geqslant g$, $s \geqslant t$.

$$\begin{aligned}&\mathbb{E}[Y_t(0) - Y_{t-1}(0)|X, G_g = 1] \\ &\qquad = \mathbb{E}[Y_t(0) - Y_{t-1}(0)|X, D_s = 0, G_g = 0] \quad a.s.\end{aligned}$$

Appendix: About the Researchers

Olivier Deschenes

- "My recent research is focused on estimating the impacts of climate change on human health and economic productivity in the U.S. and around the world using historical data."



Christopher Malloy

- "In my current work, I use applied empirical methods and causal inference to understand the effect of assigning liability for low probability, high severity events on firm precaution to prevent such events."

Gavin McDonald

- "The tools he uses include ... program impact evaluation and econometrics, decision support tool web app development, and big data and machine learning."

Thank You!

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