The geography of energy transitions: a network approach for post-Fukushima Japan

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Motivation I

Given the increasing threat of climate change, **energy transitions from traditional sources to greener and renewable ones have become a major global need and goal**.

However, energy transitions are costly and require time:

- **Renewables** still represent **less than 30 per cent of all global electricity generation** and only around **11 per cent of global primary energy**.
- **Wind electricity** generation has shown one of the highest increases among all renewable power technologies but represents only **around 7 per cent of electricity generation worldwide**.
- At this pace of transition, we are far from meeting the goal of global Net Zero Emissions by 2050 (International Energy Association, 2023)

Motivation II

Energy transitions are occurring at different speeds across world regions and sectors:

- Some countries doing really well, while others show no progress, with **important technological and economic obstacles** to be overcome.
- Within countries, **the adoption and spread of renewable energy sources is very uneven in space**.

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4. Using panel-data econometric techniques, to **explore the connection between the proximity to nuclear power plants and the spread of the adoption of Wind Energy Technology** (WET).

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5. and **modelling and simulating the diffusion of WET through a network approach**.

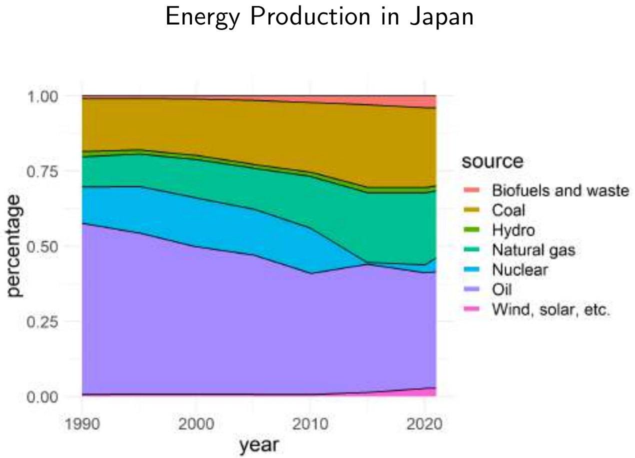
Why Japan

1. FNI works as **a natural experiment**, enabling us to identify the causal effects of phasing out nuclear technology on WET diffusion:
   - After FNI, more than 90% of nuclear power plants in Japan were shut down.

2. **In Japan different energy sources coexist**:
   - Including fossil fuels, nuclear, and renewables, all having been extensively adopted with leading global technologies.

3. Availability of **rich, fine-grained geo-located data** of WET adoption along with other factors for Japan for over 20 years.

Energy Production in Japan



Note: Figures created with data on power production from IEA

Related Literature

Energy transitions, especially to those papers analyzing local adoption of greener technologies:

- Hall and Helmers (2013), Popp et al. (2011), Rode and Weber (2016).

Network diffusion of new technologies:

- Acemoglu et al., 2011; Beaman et al., 2021
- especially in the energy sector (Halleck-Vega et al. (2018)).

Energy consequences of exogenous shocks:

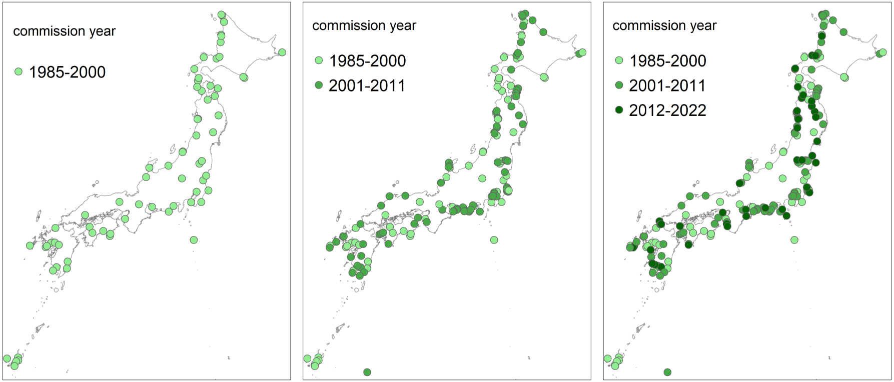
- in particular, the Fukushima event in Japan in 2011 (Kawashima and Takeda (2012), Rehdanz et al. (2017) Okubo et al. (2020)).

Data

Variable	Available Years	Data Type	Source
Ozone concentration	1995, 2000, 2005, 2010-13.	average	Goodman et al. (2019)
PM2.5 Concentration	1990, 1995, 2000, 2005, 2010-12	average	Goodman et al. (2019)
Population GHSL	1990, 2000, 2015	count	Goodman et al. (2019)
NDVI	1990-2020	average	Goodman et al. (2019)
Lights	1992-2020	count	Li et al. (2020)
Wind farms	1985-2022	count	Wind Power database (2022)

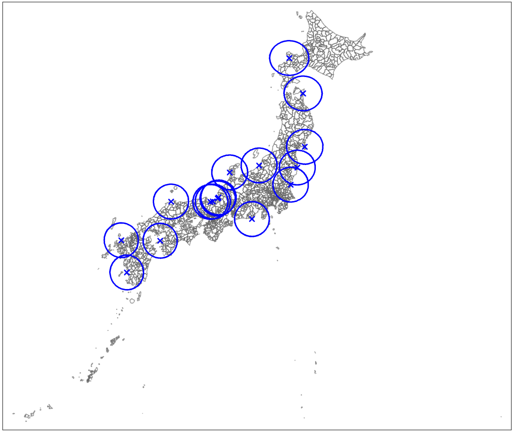
Note: We construct a balanced panel for 1992-2020. Missing data are replaced with linear interpolation estimates.

The expansion of WET over time



Source: created with data from the Wind Power database and GeoQuery Goodman et al. (2019)

Nuclear power plants in Japan



Source: created with data from the Global Power Plant Database v1.3.0 and Goodman et al. (2019)

Summary Statistics 2001, 2011 & 2020

	2001		2011		2020	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
wind_farms	0.061	0.36	0.11	0.54	0.14	0.6
ozone	58	3.1	59	3.7	60	3.9
pm2.5	15	4.8	14	3.7	14	4
pop	72401	178056	72731	182222	72864	183986
lights_pc	0.21	0.36	0.18	0.29	0.18	0.29
ndvi_mean	5351	1425	5232	1410	4407	1256
log_lights	8	1.1	7.9	1.1	7.7	1.1

Summary Statistics 2001-2020

	Unique (#)	Missing (%)	Mean	SD	Min	Median	Max
unit	1711	0	868	503	0	869	1741
year	20	0	2010	5.8	2001	2010	2020
wind_farms	8	0	0.1	0.51	0	0	7
ozone	21862	0	59	3.6	44	60	65
pm2.5	21948	0	14	4.1	5.2	14	37
pop	25665	0	72 690	181 684	22	25 641	3 665 297
lights_pc	33961	0	0.2	0.33	0	0.1	8.2
ndvi_mean	34200	0	5237	1406	122	5605	7661
log_lights	10955	0	7.9	1.1	0	7.9	11

The post-Fukushima adoption of wind energy: a Difference-in-Differences approach

To assess to what extent the 2011 Fukushima incident translated into an increase in the adoption WET in areas surrounding nuclear power plants, we estimate the following difference-in-differences specification:

$$log(WF)_{rt} = \alpha_r + \alpha_t + \beta T_{rt} + \delta X_{rt} + \varepsilon_{rt},$$

- WF is the number of wind farms in municipality r at time t
- α_r are municipality fixed effects and α_t year fixed effects
- T is a treatment dummy which takes the value of 1 if municipality r is at a distance lower than 120 kilometers from any nuclear reactor for all years after 2011
- X_{rt} is a vector of controls
- ε_{rt} is an idiosyncratic error term

And the following event-study design:

$$log(WF)_{rt} = \alpha_r + \alpha_t + \sum_{\tau=-q}^{-2} \gamma_\tau D^\tau_{rt} + \sum_{\tau=0}^{m} \delta_\tau D^\tau_{rt} + \delta X_{rt} + \varepsilon_{rt}$$

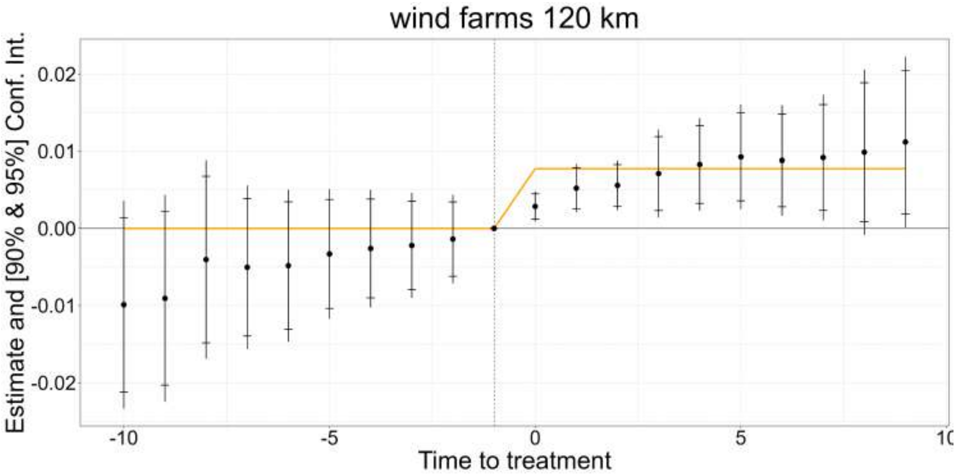
DiD regression estimates

Table: Regression estimates of the Difference-in-Differences model

Dependent Variable:	log(wind_farms+1)		
Model:	(1)	(2)	(3)
Variables			
treatment	0.0214***	0.0104**	0.0119**
	(0.0031)	(0.0049)	(0.0050)
Fixed-effects			
municipality	Yes	Yes	Yes
year		Yes	Yes
Controls			Yes
Fit statistics			
R^2	0.90594	0.90673	0.90719

Notes: Clustered (municipality) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. This table reports the regressions estimates based on Equation (1). When specified in the model, we control for ozone concentration, $PM_{2.5}$ concentration, population, the normalized difference vegetation index, and night-time lights.

Event study plot - controls included in regression



Heterogeneity analysis - distance

Dependent Variables:	log(total_power+1)		log(wind_farms+1)	
Model:	(1)	(2)	(3)	(4)
Variables				
treatment	0.1089**	0.4702***	0.0119**	0.0513***
	(0.0543)	(0.1293)	(0.0050)	(0.0138)
treatment × min		-0.0049***		-0.0005***
		(0.0014)		(0.0002)
Fixed-effects				
unit	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	34,220	34,220	34,220	34,220
R^2	0.84844	0.84946	0.90719	0.90805

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Robustness checks

Our main results are robust to:

- Excluding Tokyo's 23 wards
- Excluding municipaities close to Fukushima Daiichi nuclear power plant
- Permutation tests
- Using alternative wind outcomes (extensive and intensive margines and total power)

We also find higher point estimates as we use smaller distance thresholds:

- Different treatment assignment for distance $<=120$
- ES estimation for treatment assignment for distances $<=150$

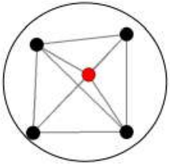
But smaller (and mostly insignificant) as we use larger distance thresholds:

- Different treatment assignment for distances $>=120$

WET adoption: the role of neighbors

Dep Variable:	log(wind_farms+1)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
treat	0.0125**	0.0107**	0.0124**	0.0072	0.0119**	0.0015
	(0.0050)	(0.0051)	(0.0051)	(0.0052)	(0.0050)	(0.0051)
WET in 20km	0.0278**	0.0245**				
	(0.0116)	(0.0110)				
treat × WET in 20km		0.0079				
		(0.0072)				
WET in 30km			0.0225**	0.0181*		
			(0.0093)	(0.0093)		
treat × WET in 30km				0.0123**		
				(0.0062)		
WET in 40km					-0.0014	-0.0064
					(0.0060)	(0.0065)
treat × WET in 40km						0.0174***
						(0.0058)
Fixed-effects						
asdf_id	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	34,220	34,220	34,220	34,220	34,220	34,220
R^2	0.90742	0.90745	0.90742	0.90753	0.90719	0.90742

Network analysis: the underlying network of municiplaities as nuclear plants shutdown



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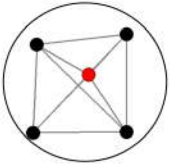

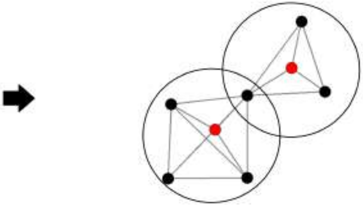

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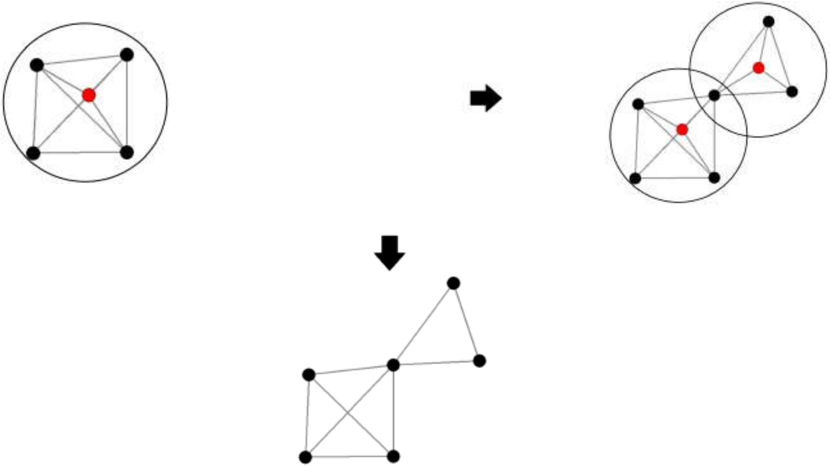


Network analysis: subnetworks

From the definition of the network we identify 3 subnetworks:

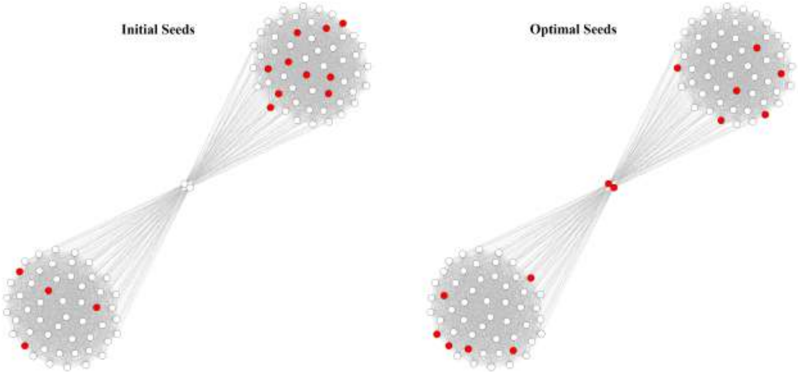
- The first with 798 municipalities (mostly central Japan), the second with 109 (north), and the third one with 259 (south).

To simulate diffusion, we set thresholds as follows:

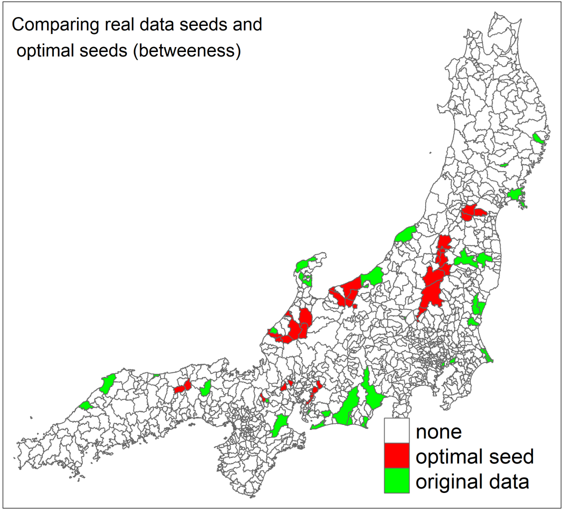
- Find a q_i (i.e., proportion of neighbours that adopted for a given municipality to consider adoption) such that if we add ϵ to it, there is no diffusion.
- Multiply q_i by 0.25, 0.5, and 0.75 and obtain its Q1, Q2, Q3 & Q4.
- We use these four threshold values in simulating the diffusion process though different targeting strategies.

Early adopters ("Seeds first period")

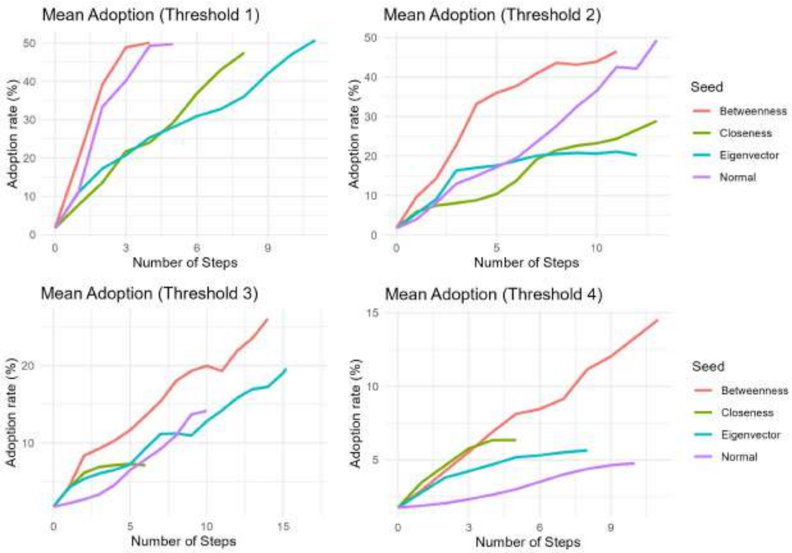
Initial seeds vs Optimal seeding:



Seeds in the first network (Central Japan - 798 municipalities)



Cumulative adoption rate for the first subnetwork



Network analysis: takeaway

Policymakers could accelerate WET adoption by targeting central connectors that link densely populated areas.

- By focusing resources and generating incentives at these key nodes, they can enhance the geographical diffusion of WET.
- In this particular case, the "Betweenness" approach (i.e., targeting municiplaities that are in the shortests paths in the network between other municipalities) shows faster capacity for geographical diffusion.

Conclusions

Using novel panel data, we have shown how the exogenous shock of **Fukushima incident of 2011 led to an increase in the adoption of wind farms**.

This happened unevenly in space, with **municipalities close to i) nuclear plants, and ii) adopting neighbours, being more likely to transit to WET**.

Using a network diffusion model, we have analysed this geographical spread of WET, identifying policy interventions with the potential to foster the pace of adoption.

Thank You!

Link or QR code to the working paper

https://tud.link/z8wypx

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Sample without Tokyo's wards

Table: Sample without Tokyo's wards

Dependent Variable:	log(wind_farms+1)	
Model:	(1)	(2)
Variables		
treatment	0.0106**	0.0115**
	(0.0050)	(0.0050)
Fixed-effects		
municipality	Yes	Yes
year	Yes	Yes
Controls		Yes
Fit statistics		
Observations	33,760	33,760
R^2	0.90689	0.90739

Notes: Clustered (municipality) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Estimates for the sample of all municipalities except the Tokyo's 23 special wards.

Back to robustness checks

Subsample: distance to Fukushima Daiichi nuclear power plant

Dependent Variable:	log(wind_farms+1)			
Model:	baseline	50 km	150 km	229 km
Variables				
treatment	0.0119**	0.0107**	0.0120**	0.0146***
	(0.0050)	(0.0049)	(0.0051)	(0.0056)
Fixed-effects				
municipality	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	34,220	33,740	30,900	25,640
R^2	0.90719	0.91292	0.91445	0.91029

Notes: Clustered (municipality) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Regression estimates for the sample in which municipalities are at a distance larger than a given threshold from the Fukushima Daiichi nuclear power plant. 229 km represents the distance at which 25% of municipalities are removed from the sample.

Back to robustness checks

Treatment assignment for distances <= 120

Dependent Variable:	log(wind_farms+1)			
Model:	30 km	60 km	90 km	120 km (baseline)
Variables				
treatment	0.0653***	0.0267***	0.0189***	0.0119**
	(0.0202)	(0.0082)	(0.0051)	(0.0050)
Fixed-effects				
municipality	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	34,220	34,220	34,220	34,220
R^2	0.90841	0.90762	0.90746	0.90719

Notes: Clustered (municipality) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Regression estimates for samples in which the treatment varies according to the distance from any nuclear power plant.

Back to robustness checks

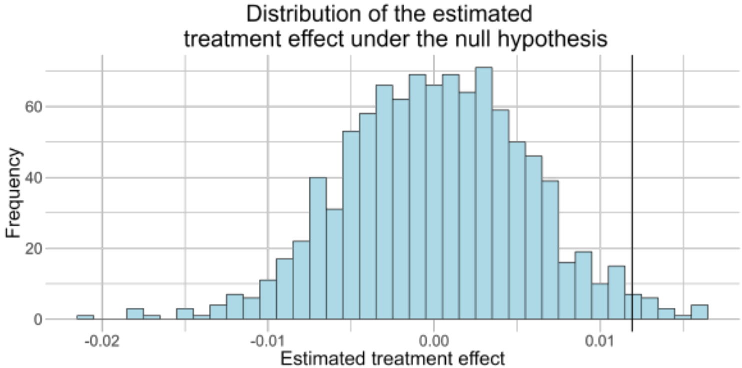
Treatment assignment for distances $>= 120$

Dependent Variable:	log(wind_farms+1)			
Model:	120 km (baseline)	150 km	180 km	210 km
Variables				
treatment	0.0119**	0.0097	0.0152*	0.0144
	(0.0050)	(0.0074)	(0.0078)	(0.0093)
Fixed-effects				
municipality	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	34,220	34,220	34,220	34,220
R^2	0.90719	0.90711	0.90714	0.90712

Notes: Clustered (municipality) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Regression estimates for samples in which the treatment varies according to the distance from any nuclear power plant. We control for ozone concentration, $PM_{2.5}$ concentration, population, the normalized difference vegetation index, and night-time lights.

Back to robustness checks

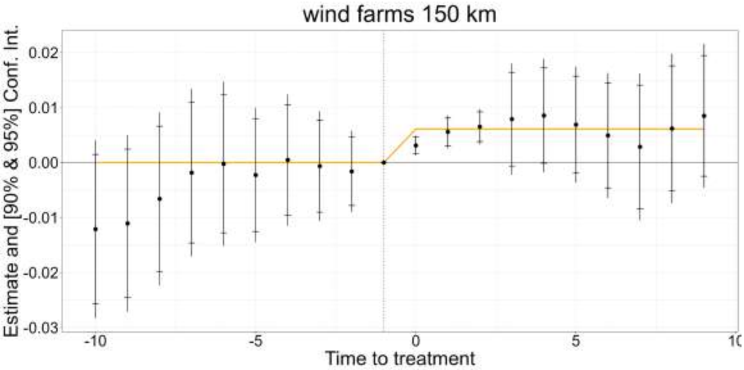
Permutation test



Note: this figure shows the distribution of the point estimates for the DiD treatment effect based on equation (1). The treatment status is assigned randomly to 1263 municipalities based on 999 draws. The black line represents our baseline estimate. Once the 1000 estimates, 999 from the draws and our baseline, are ranked, the baseline estimate ranks 982 which may be interpreted as a p-value with a significance level below 5%.

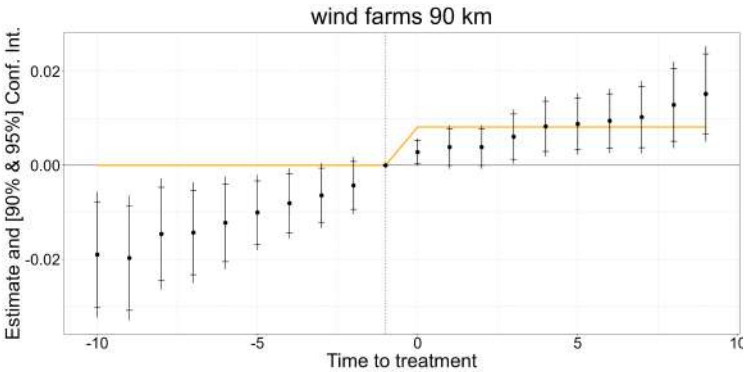
Back to robustness checks

Event study plot - with controls



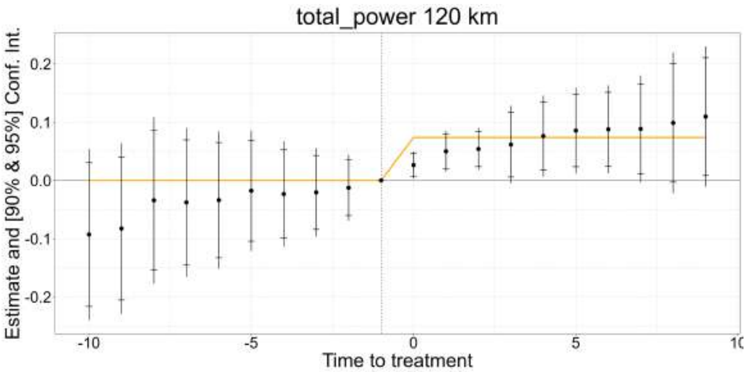
Back to robustness checks

Event study plot - with controls



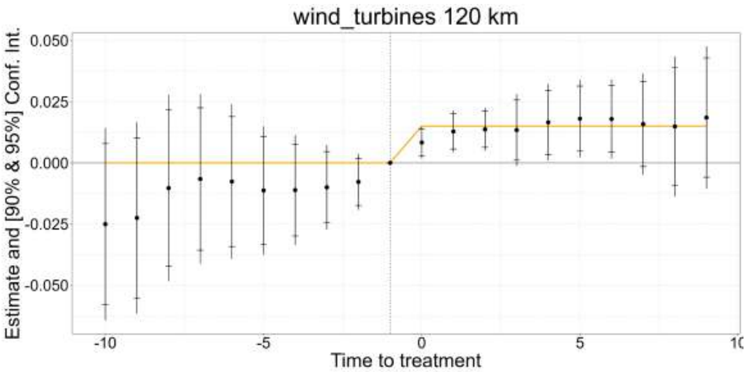
Back to robustness checks

Alternative wind farm outcomes



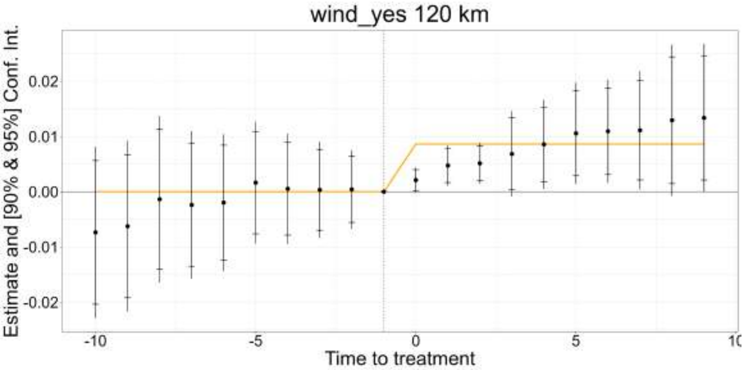
Back to robustness checks

Alternative wind farm outcomes



Back to robustness checks

Alternative wind farm outcomes



Back to robustness checks

The Model I

Set of agents $N = \{1, ..., n\}$ in a network, represented through a graph $G = (N, E)$.

E is the set of edges connecting different agents, with no self-loops.

We say that an edge $ij \in E$ connects i to j, and the network is undirected, thus $ij = ji$.

The set of neighbors of agent $i \in N$ is defined as $i \in N$ as $N_i(G) = \{j \,|\, ij \in E\}$.

We assume that at iteration $k = 0$, a subset of individuals $\Psi(0) \subseteq N$ is selected as seeds.

At the next iteration, an individual $i \in N \setminus \Psi(0)$ will ***consider*** adopting the innovation if at least $q_i \in (0, 1]$ fraction of neighbors are in seed set:

$$\frac{|\Psi(0) \cap N_i(G)|}{|N_i(G)|} \geq q_i \Rightarrow i \in \Psi(1). \tag{1}$$

The Model II

For $k \geq 0$ we generalize this as:

A node $i \in N \setminus \bigcup_{t=0}^{k-1} \Psi(t)$ will consider adoption of a new technology at k if

$$\frac{|\{\bigcup_{t=0}^{k-1} \Psi(t)\} \cap N_i(G)|}{|N_i(G)|} \geq q_i \Rightarrow i \in \Psi(k). \tag{2}$$

The Model II

For $k \geq 0$ we generalize this as:

A node $i \in N \setminus \bigcup_{t=0}^{k-1} \Psi(t)$ will consider adoption of a new technology at k if

$$\frac{|\{\bigcup_{t=0}^{k-1} \Psi(t)\} \cap N_i(G)|}{|N_i(G)|} \geq q_i \Rightarrow i \in \Psi(k). \tag{2}$$

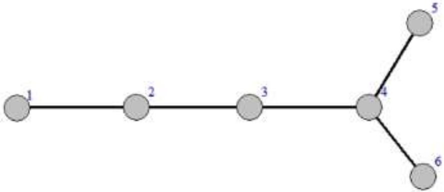
We define a subset $\mathcal{H} \subseteq N$ to be cohesive if

$$\frac{|\mathcal{H} \cap N_i(G)|}{|N_i(G)|} > 1 - q_i, \ \forall i \in \mathcal{H}. \tag{3}$$

A set of agents make a cohesive set if, for each member of the set, the proportion of neighbors in the set is strictly greater than the individual specific threshold.

An example

Case 1:

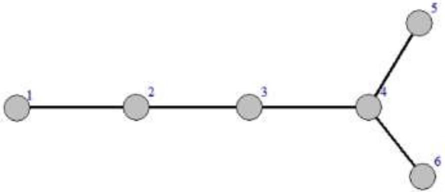


- Assume q_i is $0.5 - \epsilon$ for nodes 1, 2, and $0.5 + \epsilon$ for the rest, with $0 < \epsilon \ll 1$.
- $\mathcal{H} = \{\{3, 4, 5, 6\}, \{4, 5, 6\}, \{1, 2, 3, 4, 5\}\}$ and more!

An example

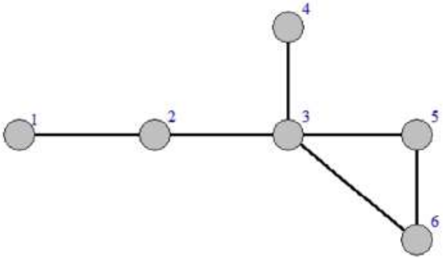
- Assume q_i is $0.5 - \epsilon$ for nodes 1, 2, and $0.5 + \epsilon$ for the rest, with $0 < \epsilon \ll 1$.
- $\mathcal{H} = \{\{3, 4, 5, 6\}, \{4, 5, 6\}, \{1, 2, 3, 4, 5\}\}$ and more!

Case 1:



- Assume q_i is $0.5 - \epsilon$ for all nodes, with $0 < \epsilon \ll 1$.
- If we strategically target nodes 3, 5, or 6, we can obtain a complete diffusion.
- This shows the importance of targeting specific nodes in the network.

Case 2:



Equilibrium I

We say that for a given graph and threshold values, a nonempty set Ψ^* will be a fixed point of the threshold model if

$$\Psi(0) = \Psi^* \Rightarrow \Psi(k) = \emptyset, \ \forall k > 0. \tag{4}$$

Equation 4 says that a nonempty set is a fixed point if an innovation initiated at that particular set can not propagate through the rest of the network.

We say that for a graph G with thresholds $\{q_i\}_{i \in N}$ an adopter set Ψ^* is a fixed point $\Leftrightarrow (\Psi^*)^c = N \setminus \Psi^*$ is a cohesive set.

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Lemma 1 (Acemoglu et al. 2011):

For a given graph G and threshold values $\{q_i\}_{i \in N}$, an adopter set Ψ^* is a fixed point $\Leftrightarrow$ $(\Psi^*)^c = N \setminus \Psi^*$ is a cohesive set.

Equilibrium II

This proof is based on Morris [Proposition 1]: Members of a cohesive set $\mathcal{H}$ cannot satisfy Eq. (2) unless there exists an individual inside $\mathcal{H}$ who has previously adopted the innovation.

Therefore, if one initializes an innovation from a set Ψ^* whose complement is a cohesive set, the innovation will not be adopted by the members of the complement set.

In the previous examples, we observe several fixed points:

- $\Psi^* = \{\{1,2\},\{1,2,3\},\{6\}\}$ for case 1.
- $\Psi^* = \{\{1,2\},\{4\},\{1,2,4\}\}$ for case 2.

Additionally, the universal set $\{1,2,3,4,5,6\}$ is also a fixed point.

Eq

Equilibrium III

Lemma 2 (Acemoglu et al. 2011):

For a given graph G, threshold values $\{q_i\}_{i \in N}$ and seed set $\Psi(0)$, denote $\{\Psi_t^*\}_{t=1}^{K}$, $K \geq 1$ as the set of fixed points for which $\Psi(0) \subseteq \Psi_t^*$ holds. Then,

$$\Psi^* = \bigcap_{t=1}^{K} \Psi_t^* \tag{5}$$

is the set of final adopters.

Equilibrium IV

Corollary 1:

Given a graph G, with threshold values $\{q_i\}_{i \in N}$ and seed set $\Psi(0)$, denote $\{\mathcal{H}_t\}_{t=1}^{K}$, $K \geq 1$ as the set of cohesive subsets of N for which $\Psi(0) \cap \mathcal{H}_t = \emptyset$ holds. Then,

$$\Psi^* = \left(\bigcup_{t=1}^{K} \mathcal{H}_t \right)^c \tag{6}$$

is the set of final adopters.

Number of adoptions for the first subnetwork