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

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Abstract

Given the increasing threat of climate change, energy transitions from traditional sources to greener and renewable ones has become a major need and goal worldwide. However, energy transitions are costly and usually slow. In this paper, we empirically study the adoption and spatial spread of energy transitions from nuclear to wind triggered by the Fukushima incident in Japan in 2011. We build a novel panel dataset for 1741 municipalities combining detailed gridded data on the location of wind farms and nuclear plants, merged with data on lights, population, vegetation greenness, and pollution, from 2001 to 2020. Using panel-data econometric techniques (including difference-in-differences and event study estimates), we explore the connection between the proximity to nuclear power plants and the adoption of Wind Energy Technology (WET). We then simulate through a network diffusion model the possible speed and order in which municipalities adopted WET after 2011. Finally, we perform a counterfactual analysis by targeting key spreaders to alter the diffusion process, allowing policymakers to propose policies to accelerate said diffusion in optimal scenarios.

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1 Introduction

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. The need for more sustainable energy is recognized by the Sustainable Development Goals 7, on affordable and clean energy, and 11, on sustainable cities and communities. However, energy transitions are costly and require time. While the capacity of renewable energy sources has increased substantially in recent years, renewables still represent less than 30% of all global electricity generation and only around 11% of global primary energy. Wind electricity generation, in particular, has shown one of the highest increases among all renewable power technologies but represents only around 7% of electricity generation worldwide. At this pace of transition, we are still far from meeting the goal of global Net Zero Emissions by 2050, with only 3 of 50 components evaluated as fully on track (International Energy Association, 2023).[1] Furthermore, energy transitions are occurring at different speeds across world regions and sectors, with some countries showing no progress and with important technological and economic obstacles to be overcome. In this regard, a better understanding of the local pace and diffusion in the adoption of renewable energy sources can be of great value to improve policy design that fosters and accelerates needed energy transitions worldwide.

This paper empirically studies the spatial spread of green energy transitions at the local level. We focus on Japan and explore nuclear-to-wind energy transitions triggered by the Fukushima Nuclear Incident (FNI) in 2011. To do so, we build a novel dataset combining detailed gridded data on the location of wind farms and nuclear plants, merged with data on lights, population, vegetation greenness, and pollution. Our dataset includes 1742 municipalities with observations from 2001 to 2020. Using panel-data econometric techniques, we explore the connection between the proximity to nuclear power plants and the spread of the adoption of Wind Energy Technology (WET). We then model and simulate the diffusion of WET through a network, taking into account how adoption coordination at the local (municipal) level may impact at a higher level (i.e., regional or national). By explicitly

[1] Solar, electric vehicles, and lighting are the only components evaluated as on track. By country, poorer regions of the globe are clearly lagging behind. See the full report on https://www.iea.org/topics/tracking-clean-energy-progress.

considering the network structure, we are able to identify nodes that may hinder the diffusion process and thus inform policy design.

We look at post-Fukushima Japan for various reasons. First, because the FNI works as a natural experiment, enabling us to identify the causal effects of phasing out nuclear technology on WET diffusion. Second, due to the relevance of the Japanese case, where different energy sources, including fossil fuels, nuclear, and renewables, have been extensively adopted with leading global technologies. Finally, due to the availability of rich, fine-grained geo-located data of WET adoption along with other factors for Japan for over 20 years.

We argue that proximity matters in the adoption and diffusion of greener technologies. In this line, first we find that, on average, municipalities closer to a nuclear power plant adopted wind technology at a higher rate than those further away. Second, we show that diffusion also depends on proximity to other municipalities that have adopted wind technology.

Our paper relates to several strands in the literature. First, we relate to the increasing literature on energy transitions, especially to those papers analyzing local adoption of greener technologies (Hall and Helmers, 2013; Popp et al., 2011; Rode and Weber, 2016). Second, we relate to the literature studying network diffusion of new technologies (Acemoglu et al., 2011; Beaman et al., 2021), especially in the energy sector (Halleck-Vega et al., 2018). Finally, we relate to papers studying the energy consequences of exogenous shocks, in particular, the Fukushima event in Japan in 2011 (Okubo et al., 2020; Rehdanz et al., 2017; Kawashima and Takeda, 2012).

We contribute to the literature through diverse avenues. First, by empirically analyzing a specific energy transition (nuclear to wind), exploiting rich fine-grained data in Japan, and benefiting from the natural experiment that the Fukushima incident provided. Differently from other papers analyzing this incident, we employ causal inference methods to study the effect of this incident on the adoption of wind energy technology. Second, we benefit from our detailed data by integrating two complementary methodologies, namely Difference-in-Differences (Diff-in-Diff) and network analysis. This allows us to first capture the effect of an exogenous shock (i.e., the FNI) on the adoption of wind energy to then study the subsequent diffusion mechanism. Finally, by better understanding the structure of progressive adoption of newer technologies, we provide insights that might improve policy design in the allocation of resources to foster the diffusion of these technologies. Therefore, we speak to the local and global policy agenda on carbon neutrality.[2]

[2]For instance, according to the Ministry of Economy, Trade and Industry of Japan (METI): "In October 2020, Japan declared that it aims to achieve carbon neutrality by 2050.

The rest of the paper is structured as follows. In Section 2, we review the literature. In Section 3, we provide some insights about the Japanese context, describe our data, and derive stylized facts. In Section 4, we perform regression analysis to estimate the causal impact of the FNI on WET adoption. In Section 5, we implement a network model to explain the diffusion of WET in Japan. Finally, section 6 concludes and derives policy implications.

2 The spatial diffusion of energy transitions: conceptual framework and literature review

□ Energy transitions: pace and determinants

One key dimension of climate change mitigation is that of energy transition. In this regard, there is an increasing branch of the literature focusing on the pace and determinants of energy transitions (see for instance Hall and Helmers (2013); Popp et al. (2011); Rode and Weber (2016); Halleck-Vega et al. (2018)). While some papers have taken a country-level perspective, others have delved into subnational dynamics, analyzing energy transitions at a more local level (see for instance Blanchet (2015), for Berlin; Bayulgen (2020), for the US; Oudes and Stremke (2018), for Italy; Balta-Ozkan et al. (2021), for the UK). This literature has highlighted the relevance of several contextual factors, including civil preferences and demands, as well as policy designs to foster the spread of greener energy sources.

Regarding the type of energy transition, earlier studies tended to focus on solar energy. But, in contrast to solar, wind energy is not on track to meet the Net Zero Emissions target by 2050; productivity has to rise, costs have to go down, and the average annual generation growth rate needs to increase to about 17% (International Energy Association, 2023). Some studies have focused on the deployment of wind sources at the local level (see for instance, Frantál and Nováková (2019), for the Czech Republic; Kiunke et al. (2022), for Germany).

Most of the studies mentioned above have implicitly analyzed energy transitions by analyzing the deployment of renewable sources but have not explicitly looked at actual transitions from one energy source to another (i.e., fossil to nuclear, fossil to renewables, nuclear to renewables, including solar and/or wind). And few papers have actually focused on nuclear-to-wind

Carbon neutrality by 2050 cannot be realized through ordinary efforts. It is necessary to significantly accelerate efforts toward structural changes in the energy and industrial sectors and undertake bold investment for innovation." https://www.meti.go.jp/english/policy/energy_environment/global_warming/ggs2050/ (Accessed September 20, 2023).

transitions (Hong et al. (2018), for Sweden; Cherp et al. (2017), comparing Germany and Japan).

Finally, a fundamental aspect of energy transition is not only the adoption of greener technologies but also their diffusion in space. Agglomeration economies due to proximity have for long been shown to be fundamental in the diffusion of new technologies and ideas; labor market pooling, input sharing, and knowledge spillovers have been identified as three main sources of these external economies of scale (Rosenthal and Strange, 2004). In this regard, recent papers in regional science have put the focus on the spatial process of energy transitions, where spatial distances and proximities play a pivotal rol. As highlighted by (Caragliu and Graziano, 2022), the complexity of scattered local energy initiatives cannot ignore the subtle and intricate network of commonalities that may on the one hand enhance cooperative behavior and the successful adoption of energy efficient technologies, while, on the other hand, cause the failure of technologically superior options.

□ Networks in the spatial diffusion of green technologies

One way to study the spatial diffusion of energy transitions, especially at local levels, is by analyzing the role of networks. Networks allow us to model the structure of relations or interactions through which certain behaviors spread. In this regard, we can study diffusion processes by modeling how agents, through their interplay and decisions, propagate a particular action in a network (e.g., green energy usage). In our case, this allows us to learn how local interconnections and coordination among municipalities can create agglomeration effects and thus have a more global impact on the adoption and spread of renewable energies.

The classical work of Morris (2000) formalizes how, through a network, two alternative actions can be played in equilibrium. Our model builds upon some of Morris's definitions and expands on them to analyze other questions. Other authors, such as Acemoglu et al. (2011), study the adoption of technologies using a similar model. In our case, we do so, too, but considering weights on the network's links to capture spatial influence from players' proximity to each other. Cabrales et al. (2011) present a model that simultaneously explores network formation and productive efforts. Paired agents create spillovers, which are multiplicative in both agents' efforts. This differs from our study since we do not consider paired players resulting from a network formation process as a condition for diffusion to take place. Instead, we work with a fixed network where diffusion occurs from the coordination of actions due to the incentives that agents derive from neighboring agents' actions.

A related but different strand of the literature studies how such diffusion may be altered/maximized through the proper "targeting" of influential or important nodes, given their relative position in the network. Works such as Kempe et al. (2003), Banerjee et al. (2013), Tsakas (2017), Galeotti et al. (2020), Beaman et al. (2021), Alexander et al. (2022), and Jackson and Storms (2023) study this issue and propose various alternatives for targeting such agents. In this work, we employ a different targeting method, and focus on nodes that may prevent the spread of a technology. Galeotti and Rogers (2013) investigate the dynamics of a harmful state in a population split in two. Their study derives conditions under which a planner can suppress this state contingent on the level of group interaction. In contrast, we consider a unified population and seek ways a planner can propagate green energy adoption within it.

□ Evidence of energy transitions in Japan

Japan is a good case study to analyze energy transitions. As mentioned already, Japan is a leading country in terms of energy technologies, where several energy sources, from fossil-fuel-based to nuclear to renewables, have been extensively deployed. Thus, several papers have empirically analyzed the Japanese case (Fraser, 2019). Some studies have already analyzed the impact of the FNI on Japan's energy markets and energy transition (Okubo et al., 2020; Rehdanz et al., 2017; Kawashima and Takeda, 2012). Some of these studies consider the role of spatial factors, such as the distance to the Fukushima nuclear power plant and other plants has also been taken into account. For instance, Okubo et al. (2020) report that individuals living up to 30 km from a Nuclear power plant run by Tokyo Electric Power Company (TEPCO) have a higher preference for renewables in the energy mix. Additionally, Rehdanz et al. (2017) report that the willingness to pay (WTP) for renewables increases with the proximity to Fukushima, while for the nuclear share, the WTP decreases for municipalities close to Fukushima. Close to what we do, Mochizuki and Chang (2017) have empirically shown how the Fukushima nuclear accident was an opportunity for the diffusion of solar energy across Japanese communities.

However, compared to previous studies, we empirically analyze the intensity and geographical extent of energy transitions given the exogenous shock of the FNI. We also study why some municipalities transit and others do not. And by doing so, relying on network analysis, we provide insights on how to better design policy interventions that optimize and accelerate the adoption and diffusion of renewable energy sources.

3 Energy production and transition in Japan: context and data

In Japan, coal and oil have been used to produce over 65% of its energy needs for over 30 years. Although there had been a decreasing trend in the usage of fossil fuels, this was reversed after the 2011 Fukushima Nuclear Incident (FNI). Before the incident, the government projected that about 40% of the energy mix would come from nuclear sources by 2030. Nevertheless, as of 2020, projections stand at about 20% and thus show a 20% decline in pre-disaster planning (Hughes, 2021).

In terms of renewable energy, there has been a recent rise in its share in Japan's electricity mix. Such a rise has been mainly dominated by the installation of solar photovoltaic (PV) units. The deployment of solar PVs at higher rates than other renewable energy sources may be explained by technical and nontechnical components (Hughes, 2021), and is in line with a lower global adoption of wind vs solar. In Japan, technical components are related to the high capital and maintenance costs associated with WET deployment in a country with such a mountainous geography. Non-technical reasons can be associated with the lobbying power of the PV industry, as suggested by Li et al. (2019). Despite the growth of the installed capacity of renewables, fossil fuels continue to have the largest importance in energy generation. In fact, from 2010 to 2015, the share of electricity generated from thermal coal increased from 21 to 31 percent (Hughes, 2021).

To explore the effect of the FNI on the expansion of adoption of wind farms, we build a detailed panel dataset combining gridded data on night-time lights, population, normalized difference vegetation index, and pollution, matched with the location of nuclear plants and wind farms. Our dataset includes information for 1742 Japanese municipalities from 2001 to 2020.

For energy production data, we rely on the "Wind Power" database for Japan[3]. This dataset contains information on the geolocation of wind farms. It also includes other information, such as the year the wind farms were commissioned and the number of turbines in each farm. Using this data, we calculate the number of wind farms per municipality from 2001 to 2020. For nuclear, we rely on the Global Power Plant Database (2018). This database includes the geolocation (longitude-latitude) of each plant. Appendix A provides more information on the construction of energy variables.

We match our data on wind farms and nuclear plants with other data aggregated at the municipal level. For air pollution, we obtain data for

[3]Data available from http://www.thewindpower.net/ .

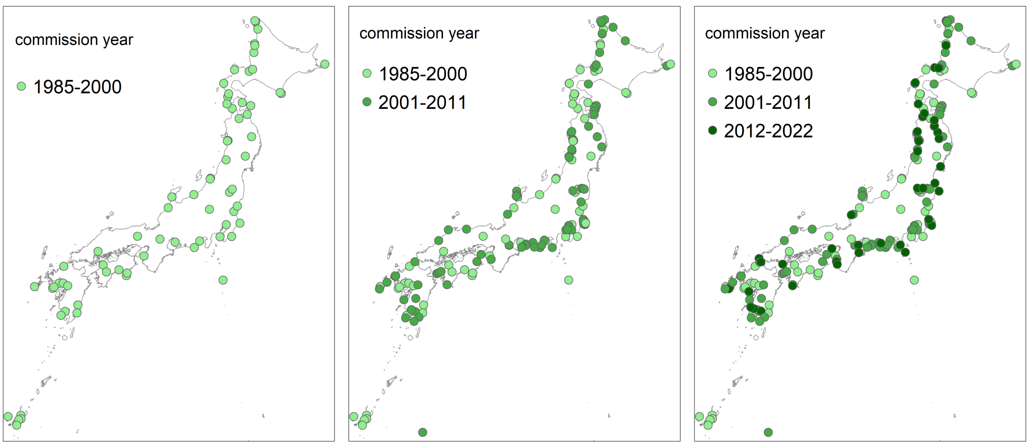
ozone concentration and $PM_{2.5}$ concentration. This data comes from Brauer et al. (2016) and was obtained via GeoQuery (Goodman et al., 2019). For population, we rely on GHS population grid multitemporal estimates, and for green cover, we use the normalized difference vegetation index, both from GeoQuery (Goodman et al., 2019). We also use data on night-time lights from Li et al. (2020). This dataset provides a harmonization between the DSMP and VIIRS time series, allowing us to have data from 1992 to 2020.

Table A1 in the Appendix provides definitions and sources from the different variables considered, while Tables A2 and A3 provide descriptive statistics for our main variables of interest. In the rest of this section, we highlight stylized facts for our key variables.

3.1 Wind energy production and diffusion

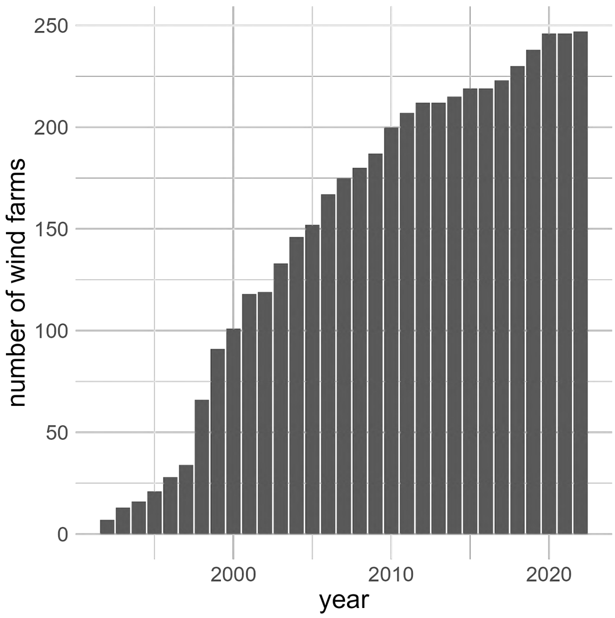
Figure 1 shows a map with the location of all wind farms in the database for which both commission year and geolocation are available. The figure shows that wind farms are mostly located in coastal areas and in the four largest islands of Hokkaido, Honshu, Shikoku, and Kyushu. Coastal areas seem the most appropriate for the development of onshore wind farms, given the mountainous geography of the largest islands. Figure 2 provides a barplot showing the evolution in the total number of wind farms over time. This plot shows how the adoption of wind farm technology followed a rapid growth up to the year 2000, slowing down afterward until the early 2010s and then rising again rapidly.

Figure 1: Location of wind farms and commission years



Note: Maps were created using data from the "Wind Power" database for Japan. Only wind farms for which geolocation and commissioned years are available are considered.

Figure 2: Evolution in the number of wind farms

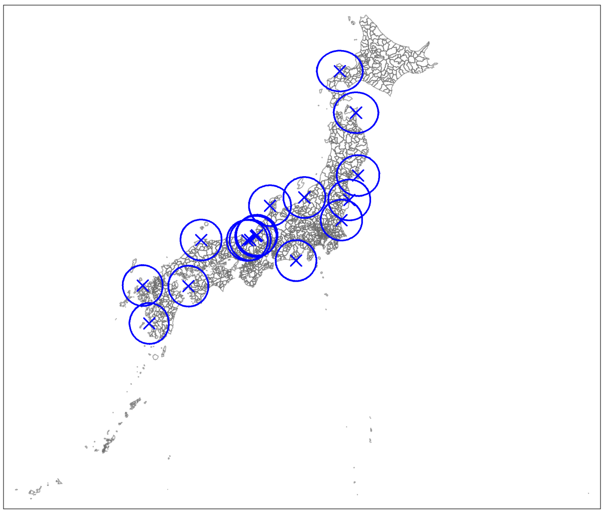


Note: The figure was created with data from the "Wind Power" database for Japan. Only wind farms for which geolocation and commissioned years are available are considered.

3.2 Nuclear power plants

Figure 3 shows the location of the sixteen nuclear power plants located in Japan. As we are interested in spatial patterns of substitution of energy sources, the figure also shows buffers of a 100 km radius surrounding all plants. In Appendix A, we show the timeline of oppening and closure of all these 16 nuclear plants.

Figure 3: Location of nuclear plants in Japan



Note: Location of 16 Japanese nuclear power plants. Geolocation data was taken from the Global Power Plant Database. The circles represent 100 km radius buffers surrounding each nuclear power plant.

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

In this section, we use our panel data set to explore the connection between the proximity to nuclear power plants and the spread of adoption of Wind Energy Technology (WET). We do this relying on econometric analysis and benefiting from the exogenous shock that the Fukushima incident in 2011 represented. Figure A1 presents a timeline of the operation of nuclear power reactors in Japan. It is shown that the shock affected all 16 power plants, and all reactors were shut down after the incident, with the last reactor being shut in may 2012.

4.1 Did Fukushima increase the adoption of greener energy sources?

We begin by assessing to what extent the 2011 Fukushima incident translated into an increase in the adoption of green technologies (namely wind) in areas surrounding nuclear power plants. To do so, we rely on Difference-in-Differences (Diff-in-Diff) approach, as specified in equation 1:

$$log(WF)_{rt} = \beta T_{rt} + \delta X_{rt} + \gamma_t + \theta_r + \varepsilon_{rt}, \tag{1}$$

where $(WF)_{rt}$ is the number of wind farms in municipality r at time t, and T_{rt} is our treatment dummy, which takes a value of 1 if municipality r is at a distance below a given threshold (i.e., 60, 90 or 120 km) from any nuclear reactor for all years after 2011 (the year of the Fukushima incident). X_{rt} is a vector of controls. γ_t are time-specific fixed effects, while θ_t are municipality-specific fixed effects. As we include unit-specific fixed effects, our panel-data specification exploits the within-municipality evolution over time, controlling for time-specific fixed effects.

Our identification of β rests on the natural experiment that the Fukushima accident represented. The assumption is that after the Fukushima incident, municipalities closer to nuclear power plants had higher incentives for energy transition away from nuclear sources. Public confidence in nuclear energy generation plummeted after the Fukushima incident, and the authorities responded by shutting down most of the country's 50 operational power reactors. We also expect that as reactors have slowly resumed operation, the effect that we measure may also show a decreasing trend. In any case, our ability to identify a causal effect depends on whether the parallel trends assumption holds for the trend of wind farm development in treated and non-treated municipalities. We argue that such an assumption holds as we conduct event study analysis and compare pre-treatment trends for treatment and control groups.

Table 1 presents the results of the Diff-in-Diff specification based on Equation 1. Column (1) shows the estimates for a model in which only the treatment dummy is considered and controlling for municipality-fixed effects. The coefficient estimate suggests that treated municipalities have, on average, a 2% higher number of wind farms. To control for yearly shocks that affect all municipalities, time-fixed effects are included in column (2). The point estimate in (2) with the full set of two-way fixed effects is halved from the value in (1) to 1%. Lastly, in column (3) we include a several controls, yieling a point estimate that remains statistically significant with a value of approximately 1.2%.

In Appendix B we present a set of robustness checks for the differennce-in-differences regression estimates. We first show that the point estimate remains statistically significant at around 1.2% even excluding the 23 special wards in Tokyo (Table B1). Second, the coefficient also holds when we remove municipalities that are closer than three cut-off distances from the Fukushima Daichii nuclear power plant: 50, 150, and 229 km, which removes 25% of all municipalities (Table B2). This shows that the effect is not only driven by the municipalities close to the Fukushima Daichii nuclear power plant. Third, we estimate our model for samples in which the treatment assignment varies for radii from 30 to 210 km (Tables B3 and B4). It is of particular interest

Table 1: 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.

that the point estimates for treatment assignments increase as the threshold distances decrease, as shown in Table B3. For instance, for a threshold of 30 km the treatment coefficient is about 6.5%, which represents a five-fold increase from the baseline estimate of 1.2% for 120 km, suggesting the relevance of proximity to nuclear reactors in the adoption of wind energy post-Fukushima incident. Finally, we also show that after running a permutation test our baseline estimate of 0.0119 remains significant at a 5% confidence level (Figure B1).

4.2 Heterogeneity Analysis

As explained before, we assign treatment to municipalities based on the distance to any nuclear power plant. In this subsection, we present heterogeneity results in which we include an interaction term in Equation 1. Results are presented in Table 2. We further consider an additional outcome variable, total power, measuring the power generated in kW using wind turbines. As shown in column (1), treated units have, on average, 11 percent higher generated power. Including the interaction term with the minimum distance increases considerably the point estimate for the treatment variable. The coefficients sugget that for municipalities where a nuclear power plant was located (min=0km), we see 47% higher wind-power generation post-Fukushima (see column 2). As the distance to any nuclear plant increases by one kilometer, the power generated by wind farms post Fukushima is 0.5 percentage points lower. Similar results, although at a different scale, are also shown in columns (3) and (4) when using the number of wind farms as the outcome variable. These results in Table 2 reinforce the idea that municipalities in the vicinity of nuclear reactors had, on average, a higher post-Fukushima adoption of WET.

Table 2: Distance heterogeneity estimates

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

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. The variable min is the minimum distance to a nuclear power plant.

4.3 Event study

The Difference-in-Difference estimation provides the average treatment effect. Nevertheless, it is possible that the effect becomes less or more pronounced over time, or that it takes some time for the effect to kick in. For these reasons, we perform a simple event study to capture dynamic treatment effects. This is done using the model in Equation 2:

$$\log(WF)_{rt} = \sum_{\tau=-q}^{-2} \gamma_\tau D_{rt}^{\tau} + \sum_{\tau=0}^{m} \delta_\tau D_{rt}^{\tau} + \delta X_{rt} + \gamma_t + \theta_r + \epsilon_{rt} \tag{2}$$

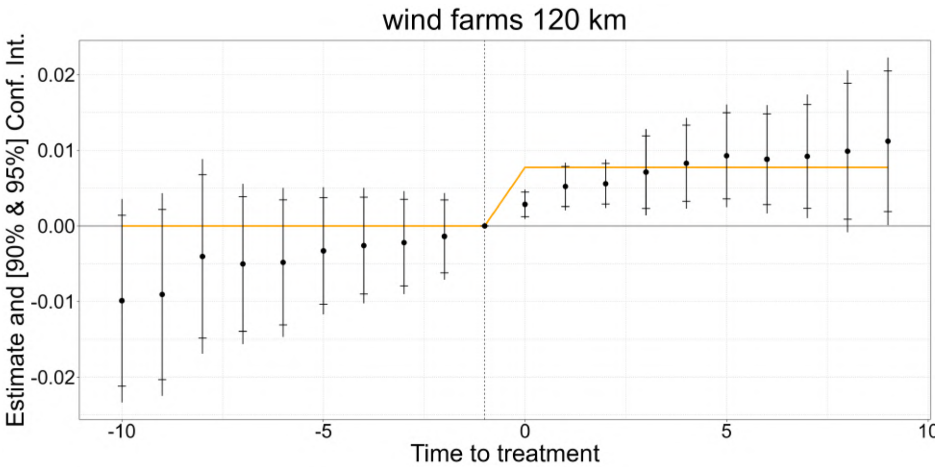
Where γ_τ are the coefficients for the years before treatment, also known as leads, and δ_τ are the after-treatment coefficients, also known as lags. The coefficient for one year before treatment is omitted, which makes it the reference year. X_{rt} is a vector of controls, γ_t are time-specific fixed effects, and θ_r are municipality-specific fixed effects.

The estimates of the coefficients for the leads and lags for municipalities treated in a radius of 120 km are shown in Figure 4. Figures B2 and B3 in the Appendix show the estimates for treatment groups defined by 90 and 150 km radius around all nuclear power plants. All the pre-treatment coefficients shown in Figure 2 are not statistically different from zero, suggesting that control and treatment groups exhibit parallel trends before the FNI. In contrast, during the treatment period, municipalities in the vicinity of nuclear reactors had, on average, a higher number of wind farms for most post-treatment years; point estimates are close to the 1% reported using the diff-in-diff estimator. Nevertheless, the coefficient estimates for 9 and 10 years after the FNI are not statistically different from zero at conventional significance levels. The insignificant levels for later years suggest that, as nuclear reactors have been reactivated, municipalities in proximity to nuclear plants have not developed more wind farms compared to control municipalities. This change in later years may also reflect that not only incentives to build turbines have spread through the country in line with national-level policies aimed at reaching carbon neutrality but also that larger investments may be flowing to offshore turbines in line with the underlying higher capacity in offshore areas in Japan.

In addition to our baseline event-study results for the number of wind farms, we also show robustness to the selection of alternative measures of WET adoption. In Figure B4, the outcome variable is a dummy variable that takes the value of one if the technology is present in a given municipality, while Figure B5 shows the estimates when total generated wind power is used as outcome variables. Lastly, Figure B6 considers as outcome variable the number of wind turbines.

As an extra robustness check we also provide an event study estimation of a staggered treatment design in Figure B7. For this design, the time of treatment is not necessarily the year of Fukushima nuclear accident (2011), but the year in which for a given treated municipality the last reactor of the closest nuclear power plant was temporarily shut down. In most cases, such year continues to be 2011 but for the municipalities closer to name the plants and years the year is 2012.

Figure 4: Event study estimates



Note: this figure shows the point estimates for the leads and lags based on equation (2). The treatment status is based on the distance from the centroid of a municipality to the closest nuclear power plant. Municipalities at distances lower than 120 km are assigned to the treatment group. We control for ozone concentration, $PM_{2.5}$ concentration, population, the normalized difference vegetation index, and night-time lights.

4.4 WET adoption: the role of neighbors

So far we have shown that municipalities near nuclear reactors had, on average, a higher post-Fukushima adoption of WET. But not only the vicinity to closing nuclear plants could trigger WET adoption. As discussed in Section 2, spatial distances and proximity in adoption play a crucial role in the diffusion of greener technologies. In this regard, it is expected that adoption of WET will be higher when nearby municipalities also adopt WET. We test this in Table 3. First, we find that having WET in a neighbouring municipality (i.e., in a radius below 20 or 30km) significantly increases the number of wind farms. Second, we find that it is indeed the interaction between being close to a (closing) nuclear plant *and* having a neighbouring municipality with WET which significantly increases the number of wind farms post-Fukushima at the municipality level.

Table 3: Regression estimates including neighbor effect

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)
n 20km	0.0278**	0.0245**				
	(0.0116)	(0.0110)				
treat × n 20km		0.0079				
		(0.0072)				
n 30km			0.0225**	0.0181*		
			(0.0093)	(0.0093)		
treat × n 30km				0.0123**		
				(0.0062)		
n 40km					-0.0014	-0.0064
					(0.0060)	(0.0065)
treat × n 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

Notes: Clustered (municipality) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Regression estimates including a neighbor dummy and interaction. **n 10km** dummy is one if any neighbor at a distance lower or equal to 10km has adopted the technology, other variables defined in a similar manner. We control for ozone concentration, $PM_{2.5}$ concentration, population, the normalized difference vegetation index, and night-time lights.

All our results so far point towards the relevance of proximity in the diffusion of WET. Higher adoption seems to depend on the location of phasing technologies (i.e., nuclear) as well as on neighbours also adopting WET. Clearly, the increase and spread of wind farms is not random in space. In the next section we rely on network analysis to study the spatial patterns of WET adoption.

5 Network diffusion of wind energy adoption in Japan

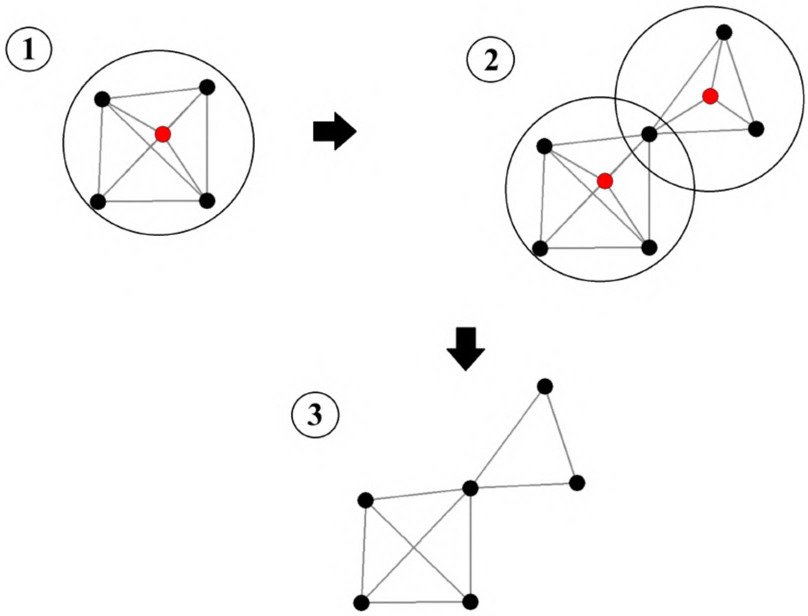
5.1 Network inference

To model the diffusion of adoptions of energy generation technologies within the network where municipalities are interconnected, we first need to establish its structure. Since we lack prior knowledge of the network topology, we use the following approach to infer it. First, we define a radius of 120 kilometers from a given nuclear power plant. Any municipality within this distance is considered connected to the respective power plant. If two or more municipalities are connected to the same power plant, they are also linked to one another in the network. We show these connections in the first graph of Figure 5, where power plants are depicted as red nodes and municipalities as black nodes.[4] Similarly, if a municipality is positioned within 120 kilometers of two or more power plants, it is connected to all of them.

Subsequently, we remove the red nodes from the network, which represent the nuclear power plants, since the diffusion occurs only through municipalities. The remaining graph then becomes the central focus of our analysis. This approach allows us to account for the shutdown of nuclear power plants and concentrate exclusively on the underlying network of interactions between municipalities, which is critical for our simulations.

[4]The links do not necessarily represent functional or operational connections between municipalities and power plants, but rather the spatial proximity or influence of the power plant on the nearby municipalities in a geographical context.

Figure 5: Inference of the Network



In Appendix C, we detail the network model we use to study the diffusion process of energy adoption. Intuitively, the model describes the technology diffusion process within a network, represented as a graph, where nodes symbolize municipalities connected by weighted links indicating distance. The diffusion starts with a subset of nodes serving as seeds, representing the initial adopters (e.g., the municipalities with wind turbines in the initial period). In subsequent iterations, each node has a 50% probability of adopting the technology based on a threshold related to the proportion of adopting neighbors in the seed set. This decision-making process reflects the influence of interconnected agents and their likelihood to adopt based on neighbor behavior. Equilibrium is achieved when the initial seed set fails to propagate the innovation further through the network. Another potential obstacle to diffusion arises when non-adopting agents are interconnected in a way that hinders spread, characterized by a weighted proportion of neighbors exceeding a threshold, depicting a collective resistance to technology adoption, particularly in cohesive groups.

Moreover, the diffusion dynamics are tied to coordinated efforts among municipal governments at the local level, yielding a global impact. This phenomenon is linked to the network's defining factor – geographical proximity to nuclear power plants. The presence of these plants potentially contributes to the clustering of economic and social activities in their vicinity, driven by factors like job opportunities and infrastructure associated with the presence of power plants. This clustering effect underscores the global repercussions of localized decisions within the network, highlighting the interconnected nature of technology diffusion and its broader socioeconomic implications.

5.2 Results

Relying on the definition to infer networks from subsection 5.1, we obtain three subnetworks: the first with 798 municipalities, the second with 109, and the third with 259. The first subnetwork contains mostly municipalities from central Japan (Honshu), the second from the north (Hokkaido), and the third from the south (Kyushu). The network structure is influenced by the geographic positions of nuclear power plants within these islands. Due to the significant distances between islands, often separated by large bodies of water, diffusion of influence through local interaction is highly unlikely. All this, coupled with the fact that power plants are located at distances above 120 km from others in different islands, results in subnetworks that do not have connections between them.

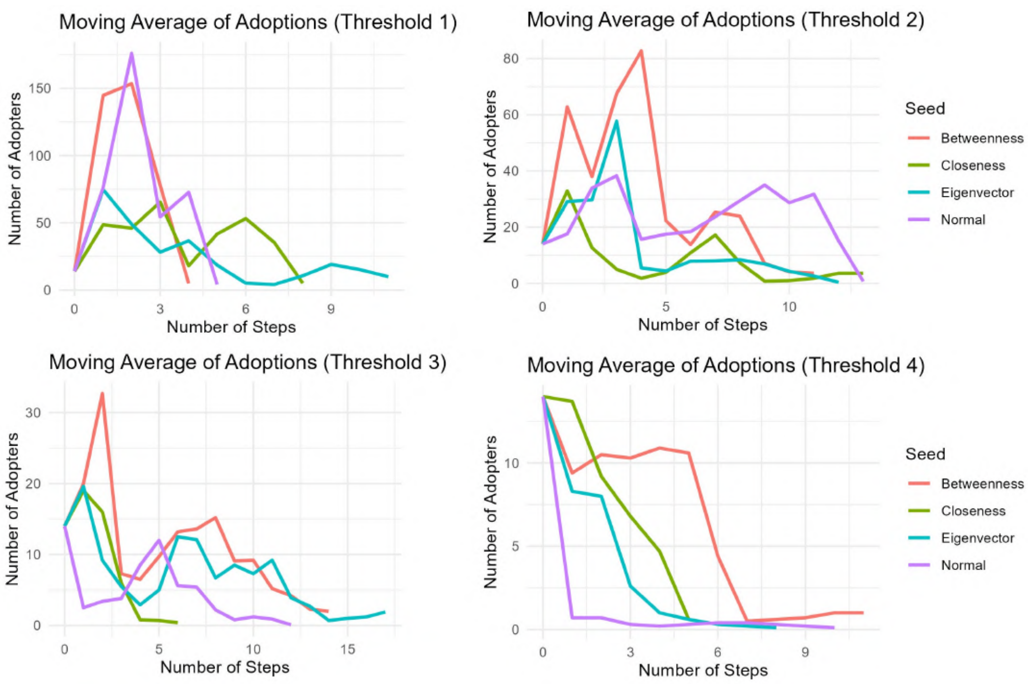
Consequently, we focus our analysis on the first subnetwork, which is not only the largest and most representative but also contains the majority of municipalities. Moreover, the first subnetwork presents a more complex and interconnected structure, making it ideal for studying diffusion processes. Additionally, we remove the red nodes representing the nuclear power plants, as diffusion occurs exclusively through municipalities.

To run the simulations, we need to obtain threshold values, q, where higher values imply a more stringent condition for diffusion. We find a high enough q such that if we add $\epsilon > 0$ to it, no diffusion occurs (i.e., the maximum value at which diffusion still happens, with any slight increase preventing further diffusion). We then multiply this q by 0.25, 0.5, and 0.75 to obtain three additional thresholds, resulting in four thresholds in total: Thresholds 1, 2, 3, and 4. These values allow us to assess the speed and extent of diffusion at different stringency levels.

Additionally, we may ask how to maximize the spread of an event of interest (in our case, the adoption of green technologies). To achieve this, different methods of "targeting" have been proposed. Some of the most common ones involve allocating the initial seeds based on various centrality measures such as closeness, betweenness, and eigenvector centrality. By using these centrality measures, the central planner can identify the best positions in the network to maximize diffusion. This is illustrated in Figure C1 in Appendix C, where we see the connection between initial seeds in an "optimal" allocation. Given the network structure, we redistribute the same number of seeds to positions that enhance their potential to diffuse the technology effectively.

We proceed to run simulations using the criteria for thresholds mentioned above. Also, we run these simulations using the original seeds (i.e., the municipalities that first adopted the technologies in the real world) and alternative ones given by seeds allocated through different centrality measures.[5] Figure 6 below presents the results after 100 runs. The "normal" seeds correspond to the original adopters in these graphs. We can see that as we move from the first threshold to the third one, the runs take, on average, more time to end. Further, each curve shifts to the right and fluctuates more. With the first threshold, the number of adoptions peaks almost at the beginning, but higher values of q delay (and even reduce) the number of adoptions at each simulation step. Finally, in the fourth threshold, each curve declines almost immediately due to the stringency of the conditions for diffusion.

Figure 6: Number of Adopters for Each Threshold



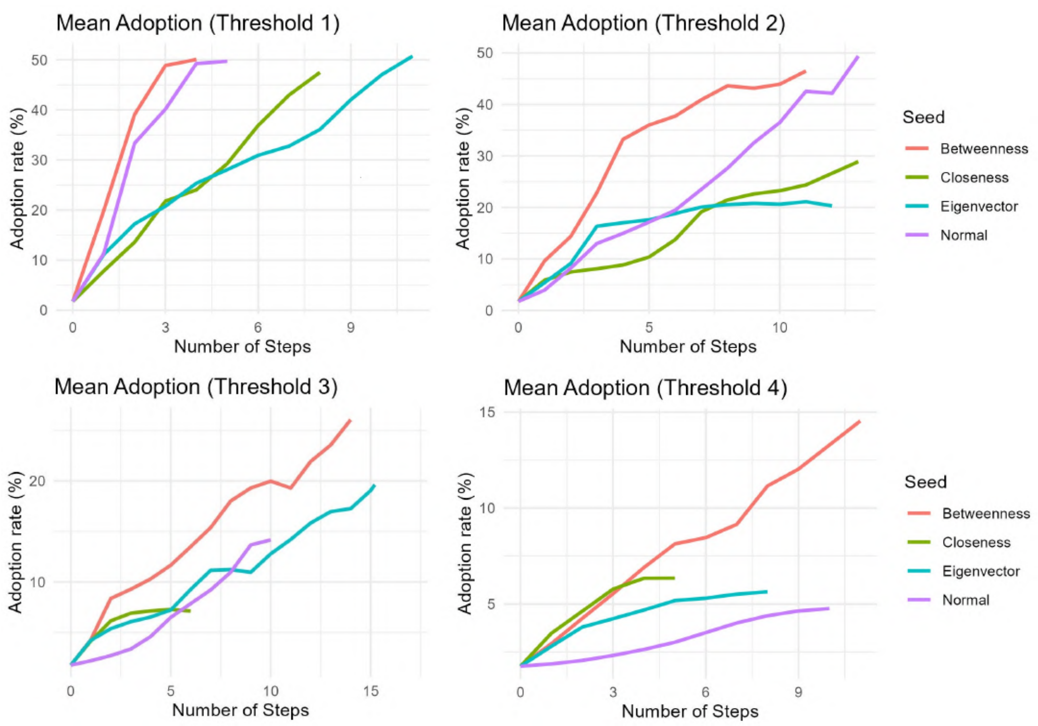
In Figure 7, we observe the cumulative mean adoption of the technologies for the first component. For the lowest values of q (threshold 1), regardless of the seeding type, we reach approximately 50% technology adoption (although at different speeds/number of steps). This outcome is due to the stochastic nature of the adoption process, with each node considering whether to adopt

[5]The idea of using these other seeds is to analyze alternative "if" or "counterfactual" scenarios to the real one.

the technology being modeled as a Bernoulli trial with a 50% probability. Running the simulations 100 times results in convergence to this percentage. When we increase the value of q to that of threshold 2, we see that the normal and betweenness seedings are the only ones that, once again, reach approximately 50% of adoption. The other seeding strategies do not cross the 30% of adoption.

When we raise q up to threshold 3, the normal seeding strategy performs decisively worse than before. Instead, the betweenness seeding strategy continues performing better than the others. Meanwhile, the eigenvector one proves to be resilient, attaining a similar percentage of adoption as in the previous threshold. Lastly, for the maximum value that q can attain before no more diffusion occurs (threshold 4), all seeding strategies take a big hit. Betweenness still remains the decidedly better seeding strategy, while normal performs the worst. Meanwhile eigenvector and closeness attain between a 5 and 7% of adoption.

Figure 7: Cumulative Mean Adoptions of Technology



Why does the betweenness seeding strategy, on average, outperform others? This can be attributed to the network structure, particularly in municipalities located between two or more nuclear power stations. These municipalities act as “gatekeepers” in the diffusion process—nodes that connect or lie between tightly knit groups on either side. As illustrated by the two central nodes in each graph depicted in Figure C1 in the Appendix, communication between different parts of the network must pass through these central nodes, which can complicate diffusion if these municipalities disrupt the propagation of technologies. Betweenness centrality accounts for this dynamic, leading to better performance.

Figure C2 illustrates the positioning of seeds in both the normal and betweenness cases. In the normal case, seeds are spread out, which can hinder diffusion by failing to meet threshold values, potentially slowing or halting the process. In contrast, the betweenness strategy places seeds more strategically, concentrating them in key areas. This concentration helps to "push over" threshold values, allowing higher levels of propagation to be achieved.

Based on this analysis, policymakers can accelerate WET adoption in different regions or parts of a country represented by networks by targeting central connectors that link densely populated areas. By focusing resources and generating incentives at these key nodes, they can enhance the diffusion of WET, facilitate quicker adoption, and overcome potential barriers that might otherwise impede progress. This approach leverages the network's structure to ensure that WET adoption policies are effective and that WET spreads efficiently throughout the regions or parts of the country in question.

6 Conclusions and policy implications

In this paper, we have empirically explored the adoption and spatial diffusion of wind energy. To do so, we have focused on Japan, building a dataset combining detailed gridded data on the location of wind farms and nuclear plants, merged with data on lights, population, vegetation greenness, and pollution, all aggregated for more than 1711 municipalities. Using panel-data econometric techniques, we have shown how the exogenous shock that the Fukushima incident of 2011 represented led to an increase in the adoption of wind farms, especially in municipalities close to nuclear plants.

Through simulations using a network diffusion model, we have demonstrated how coordination in adopting green technologies among municipalities can impact the national level. These simulations revealed various paths and timelines for adoption within the network. Utilizing betweenness centrality as a targeting strategy enables faster and broader diffusion compared to other methods, as it identifies potential gatekeepers—municipalities strategically positioned in the network that may hinder diffusion. This approach provides policymakers with a valuable tool to maximize green technology adoption while minimizing costs.

Overall, our findings highlight the role of proximity and networks. Policymakers can achieve desired outcomes more efficiently by targeting specific municipalities based on their relative position in the network. In our case, this translates into better and faster adoption of greener technologies such as WET.

Finally, given the increasing threat of climate change and the global need for mitigation, a better understand on how to foster and accelerate energy transitions is needed. We have provided some insights from nuclear-to-wind transitions in Japan. Further research on other transitions in different contexts could be of great value.

A Data overview

Table A1: Variables and data sources

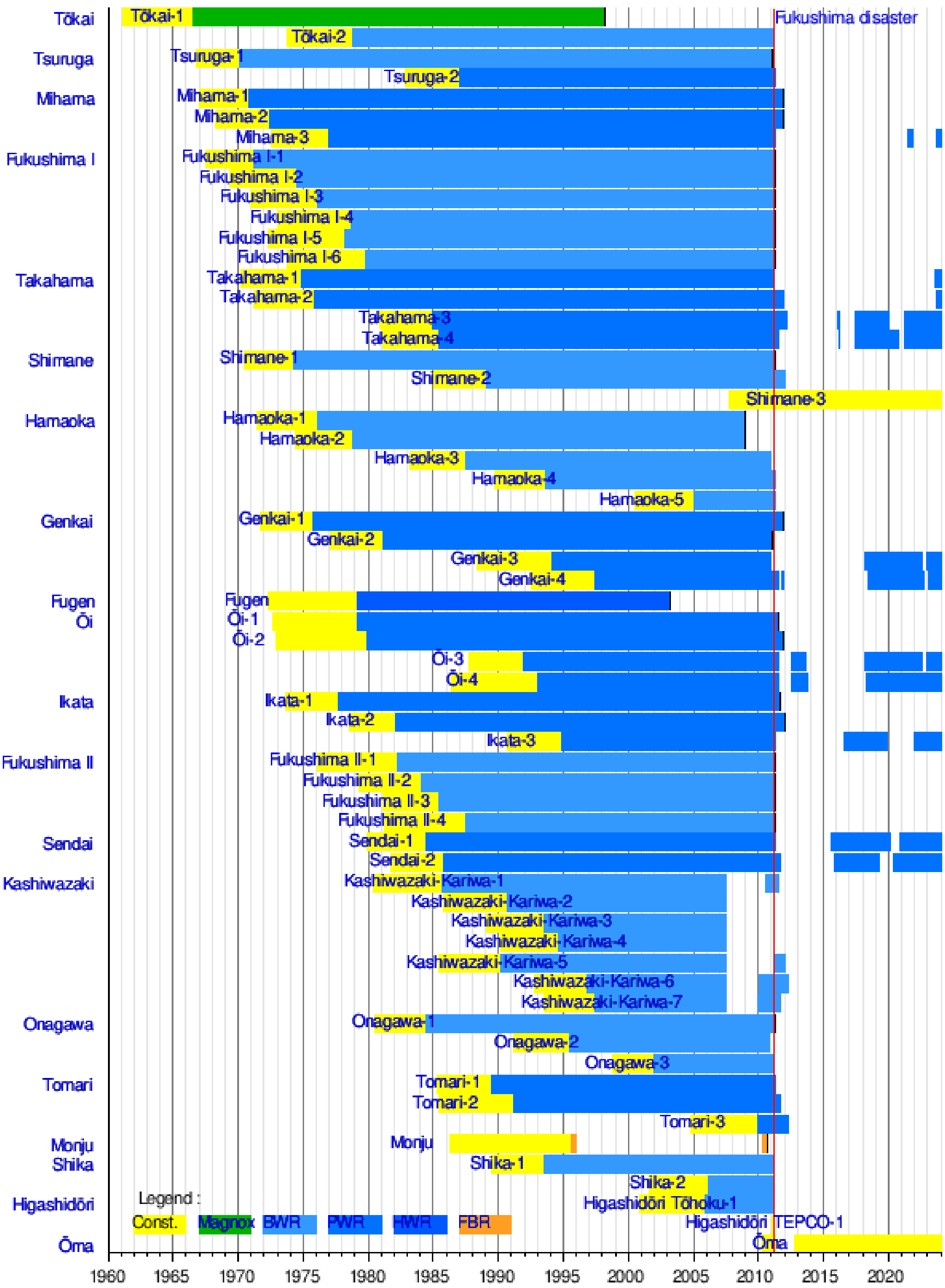
Variable	Available Years	Data Type	Source
Ozone concentration	1995, 2000,05,10-13	average	Goodman et al. (2019)
PM2.5 Concentration	1990,95, 2000,05,10-12	average	Goodman et al. (2019)
Population GHSL	1990, 2000,15	count	Goodman et al. (2019)
NDVI	1990-2020	average	Goodman et al. (2019)
Lights	1992-2020	count	Li et al. (2020)
Wind farms	1985-2022	count	Wind Power database (2022)

Table A2: Summary statistics for the years 2001,2011 and 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

We construct a balanced panel for 1992-2020 with data collected from the sources shown in Table A1. Missing data are replaced with linear interpolation estimates. The data used for the table are only for years 2001 to 2020.

Figure A1: Japan's nuclear power reactors Timeline



Note: figure taken from Nuclear power in Japan (2023)

Table A3: Summary statistics for the DiD panel

	Unique (#)	Mean	SD	Min	Median	Max
asdf_id	1711	868	503	0	869	1741
year	20	2010	5.8	2001	2010	2020
wind_farms	8	0.1	0.51	0	0	7
ozone	21862	59	3.6	44	60	65
pm2.5	21948	14	4.1	5.2	14	37
pop	25665	72690	181684	22	25641	3665297
lights_pc	33961	0.2	0.33	0	0.1	8.2
ndvi_mean	34200	5237	1406	122	5605	7661
log_lights	10955	7.9	1.1	0	7.9	11

We construct a balanced panel for 1992-2020 with data collected from the sources shown in Table A1. Missing data are replaced with linear interpolation estimates. The data used for the table are only for years 2001 to 2020.

B Additional results to Section 4

Table B1: 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
Within R^2	0.00104	0.00641

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. When specified in the model, we control for ozone concentration, $PM_{2.5}$ concentration, population, the normalized difference vegetation index, and night-time lights..

Table B2: 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
Within R^2	0.00594	0.00652	0.00771	0.01160

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. We control for ozone concentration, $PM_{2.5}$ concentration, population, the normalized difference vegetation index, and night-time lights.

Table B3: 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
Within R^2	0.01901	0.01053	0.00883	0.00594

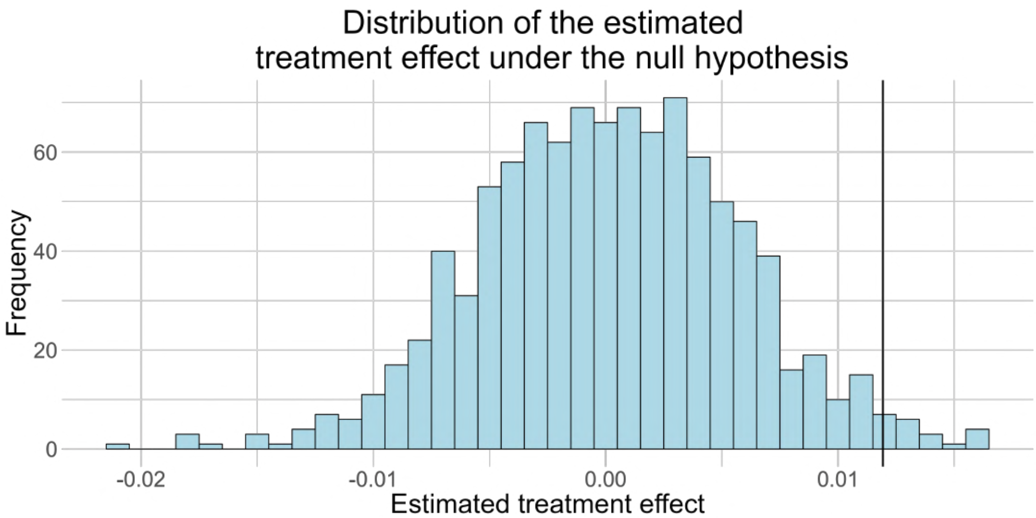
Notes: Clustered (municipality) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Regression estimates for samples in which the treatment varies according to the distance from any nuclear power plant. We control for ozone concentration, $PM_{2.5}$ concentration, population,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

Table B4: 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
Within R^2	0.00594	0.00512	0.00545	0.00517

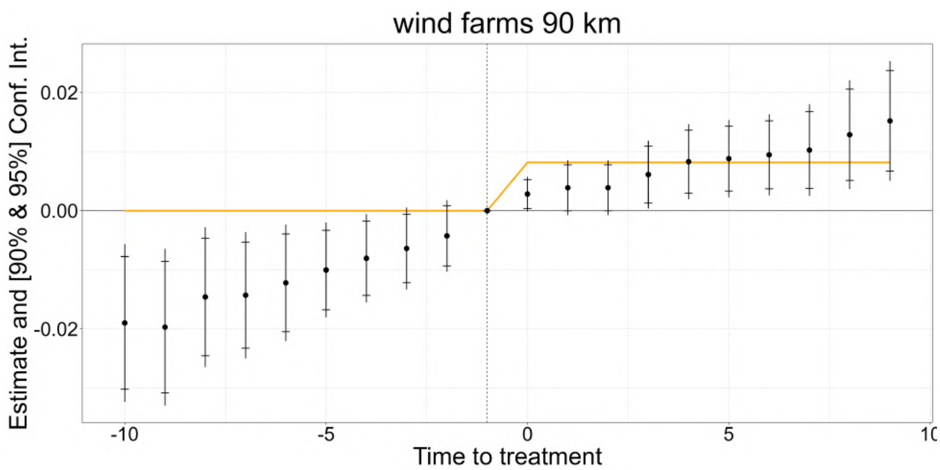
Notes: Clustered (municipality) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Regression estimates for samples in which the treatment varies according to the distance from any nuclear power plant. We control for ozone concentration, $PM_{2.5}$ concentration, population,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

Figure B1: Permutation test



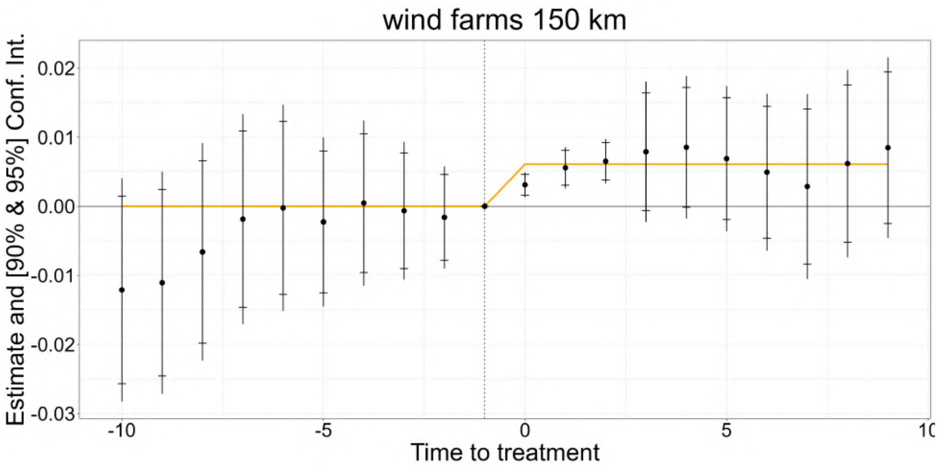
Note: this figure shows the distribution of the point estimates for the DiD treatment effect based on equation (1). The treatment status is assigned randomly to 1263 municipalities based on 999 draws. The black line represents our baseline estimate. Once the 1000 estimates, 999 from the draws and our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

Figure B2: Event study estimates



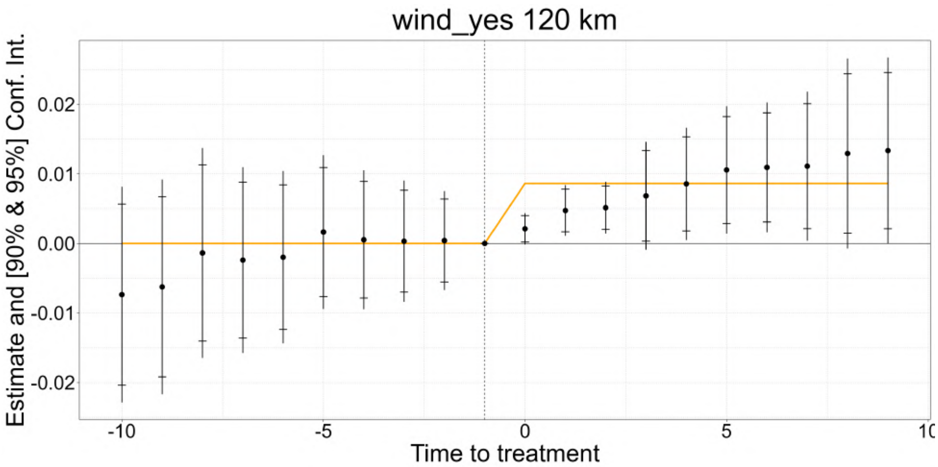
Note: this figure shows the point estimates for the leads and lags based on equation (2). The treatment status is based on the distance from the centroid of a municipality to the closest nuclear power plant. Municipalities at distances lower than 90 km are assigned to the treatment group. We control for ozone concentration, $PM_{2.5}$ concentration, population, the normalized difference vegetation index, and night-time lights.

Figure B3: Event study estimates



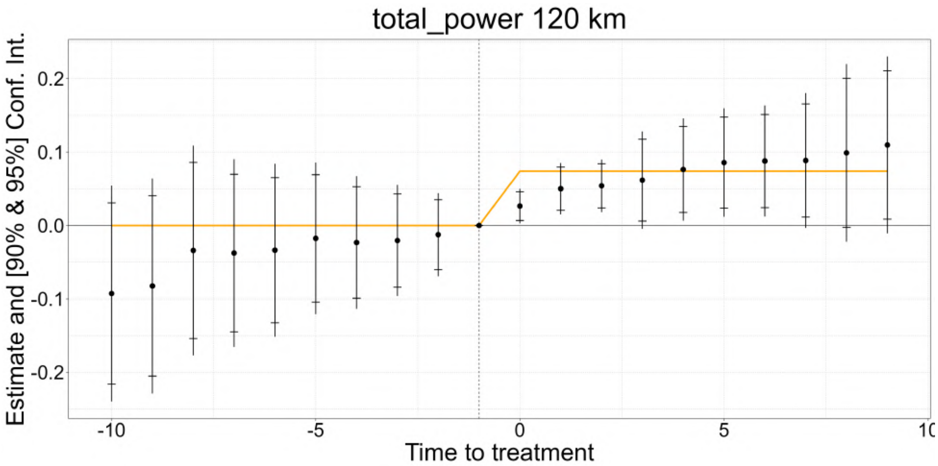
Note: this figure shows the point estimates for the leads and lags based on equation (2). The treatment status is based on the distance from the centroid of a municipality to the closest nuclear power plant. Municipalities at distances lower than 150 km are assigned to the treatment group. We control for ozone concentration, $PM_{2.5}$ concentration, population, the normalized difference vegetation index, and night-time lights.

Figure B4: Event study estimates



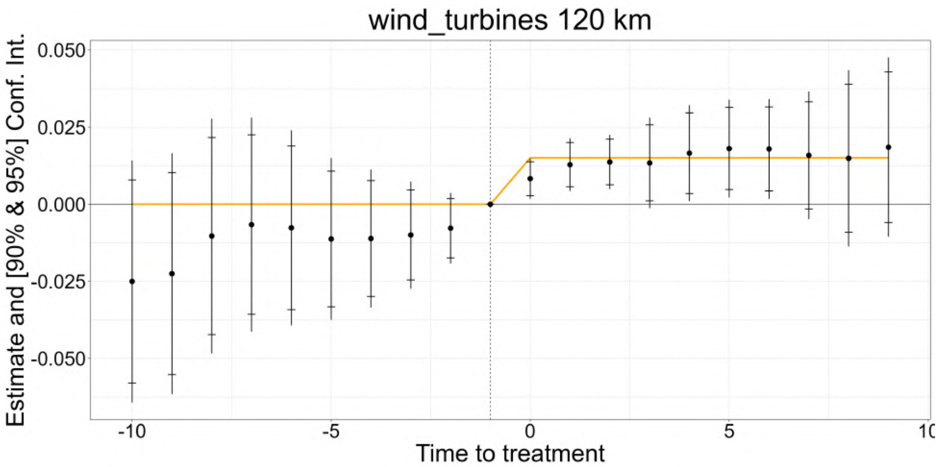
Note: this figure shows the point estimates for the leads and lags based on equation (2). The treatment status is based on the distance from the centroid of a municipality to the closest nuclear power plant. Municipalities at distances lower than 120 km are assigned to the treatment group. We control for ozone concentration, $PM_{2.5}$ concentration, population, the normalized difference vegetation index, and night-time lights.

Figure B5: Event study estimates



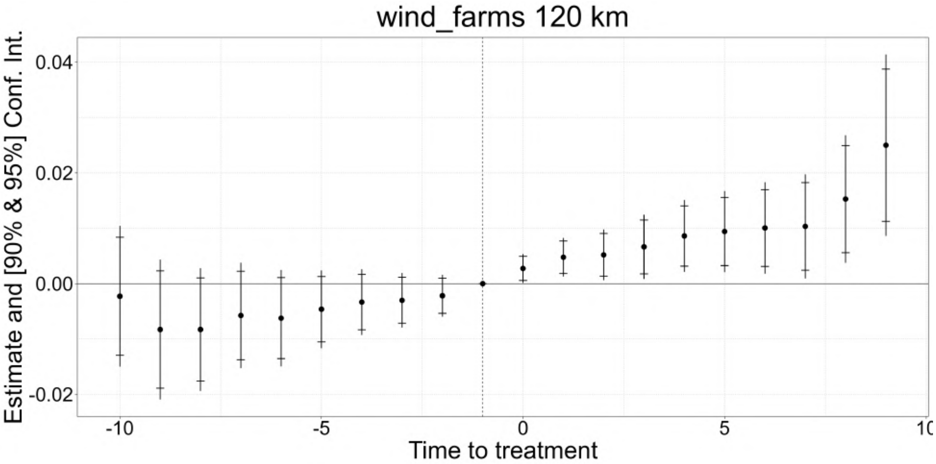
Note: this figure shows the point estimates for the leads and lags based on equation (2). The treatment status is based on the distance from the centroid of a municipality to the closest nuclear power plant. Municipalities at distances lower than 120 km are assigned to the treatment group. We control for ozone concentration, $PM_{2.5}$ concentration, population, the normalized difference vegetation index, and night-time lights.

Figure B6: Event study estimates



Note: this figure shows the point estimates for the leads and lags based on equation (2). The treatment status is based on the distance from the centroid of a municipality to the closest nuclear power plant. Municipalities at distances lower than 120 km are assigned to the treatment group. We control for ozone concentration, $PM_{2.5}$ concentration, population, the normalized difference vegetation index, and night-time lights.

Figure B7: Event study estimates



Note: this figure shows the point estimates for the leads and lags based on equation (2). The treatment status is based on the distance from the centroid of a municipality to the closest nuclear power plant. Municipalities at distances lower than 120 km are assigned to the treatment group. For a municipality in the treatment group, the time of treatment is the year in which the last reactor was stopped at the closest nuclear power plant after the Fukushima nuclear accident. We control for ozone concentration, $PM_{2.5}$ concentration, population, the normalized difference vegetation index, and night-time lights.

C Additional info to Section 5

In this section we explain in more detail the network diffusion model used in this paper. Aditionally, we present some of the results obtained in section 5.2.

C.1 The Model

We consider a weighted network represented as a graph $G = (N, E, w)$, where:

- $N = \{1, 2, \dots, n\}$ is the set of agents or nodes in the network.[6]
- E is the set of edges connecting different agents, with no self-loops. More specifically, we denote $ij \in E$ as the existence of an edge or link between nodes i and j. Additionally, the network is undirected, i.e., $ij = ji$, $\forall ij \in E$.
- w is a function that assigns weights to the edges, $w : E \to \mathbb{R}^+ \cup \{0\}$. In other words, w assigns a non-negative real number to each edge $ij \in E$.

We define the set of neighbors of agent $i \in N$ as $N_i(G) = \{j \,|\, ij \in E\}$. Additionally, we say that the total geographic distance from node i to its neighbors is given by:

$$S_i = \sum_{j \in N_i(G)} w_{ij}$$

where w_{ij} represents the distance between nodes i and j in the network. A weight of 0 indicates the absence of a connection or distance between nodes. Also, let $\bar{S}_i = \frac{S_i}{|N_i(G)|}$ denote the average geographic distance of node i, where $|N_i(G)|$ represents the degree or number of (unweighted) connections of node i.[7] Finally, let $D_{ij}(G) = \frac{1}{w_{ij}} \cdot \bar{S}_i$ represent the spatial influence of node i's neighborhood, so that closer neighbors, captured through $\frac{1}{w_{ij}}$, will have a stronger influence than those farther away.

C.2 Seed Set & Thresholds

At the initial iteration ($k = 0$), a subset of individuals $\Psi(0) \subseteq N$ is selected as the seeds. These represent the set of agents initially activated (i.e. those who adopted the green technology) at this time.

[6] In this paper we refer to agents, nodes, and municipal governments interchangeably.

[7] While S_i and $|N_i(G)|$ may both represent the weighted degree of a node, we distinguish them to represent the weighted and unweighted versions of degree, respectively.

At the next iteration, a node $i \in N$ will *consider*, with equal probability, the adoption of a new technology (i.e., determined through a 50% Bernoulli trial) if at least a fraction $q \in (0, 1]$ of her neighbors is in the seed set:

$$\frac{\sum_{j \in \Psi(0)} D_{ij}(G)}{\sum_{j \in N_i(G)} D_{ij}(G)} \geq q \tag{3}$$

If this condition is met, there is a 50% probability that agent i will adopt the technology and join $\Psi(1)$. If instead an agent rejects, we move on to the next agent. An agent who rejected, never considers adopting again and, thus, does not join the seed set.

Following Morris (2000), we can interpret this model as agents playing a coordination game. Their payoffs come from whether or not they match behavior with each of their neighbors:

		Agent j	
		Consider	*Not Consider*
Agent i	*Consider*	a, a	b, c
	Not Consider	c, b	d, d

with $a > c$ and $d > b$, thus coordinating is better than not doing so. In this game, a specific threshold exists, such that if at least a proportion $q = \frac{d-b}{a-c+d-b}$ of an agent's neighbors present a behavior, then the agent's best response is to also replicate it. At this precise threshold, the agent remains indifferent, while in all other cases, it has a clearly defined best response. Usually, it is unlikely for the threshold to be precisely met. Nevertheless, certain rational thresholds, say $q = 1/2$, are discussed in the literature. For example, individuals might tend to conform to most of their friends' actions, making room for these rational thresholds. Unless specified otherwise, when there is a tie, we will assume that an agent imitates a behavior if exactly q of their neighbors follow it.

For $k \geq 0$, we generalize equation 3 as:

$$\frac{\sum_{j \in \bigcup_{t=0}^{k-1} \Psi(t)} D_{ij}(G)}{\sum_{j \in N_i(G)} D_{ij}(G)} \geq q \tag{4}$$

This general condition ensures that for any period k, agent i will consider adopting the new technology if the weighted proportion of neighbors within the union of seed sets up to that period exceeds or equals q for that agent.

Additionally, we define a subset $\mathcal{H} \subseteq N$ to be cohesive if:

$$\frac{\sum_{j \in \mathcal{H}} D_{ij}(G)}{\sum_{j \in N_i(G)} D_{ij}(G)} > 1 - q. \tag{5}$$

Equation 5 says that a set of agents makes a cohesive set $\mathcal{H}$ if, for each member of the set, the weighted proportion of neighbors in $\mathcal{H}$ is strictly greater than threshold $1 - q$.

C.3 Equilibrium

A non-empty seed set Ψ^* is considered a fixed point (an equilibrium) of the threshold model if:

$$\Psi(0) = \Psi^* \Rightarrow \Psi(k) = \emptyset, \ \forall k > 0. \tag{6}$$

Equation 6 states that if the initial seed set $\Psi(0)$ is equal to Ψ^*, then the set of activated agents will become empty ($\Psi(k) = \emptyset$) for all subsequent iterations ($k > 0$). In other words, an innovation initiated at Ψ^* cannot propagate further through the network.

For a graph G with threshold value q, an adopter set Ψ^* is considered a fixed point if and only if its complement, $(\Psi^*)^c = N \setminus \Psi^*$, forms a cohesive set:

$$\text{Fixed Point: } \Psi^* \Leftrightarrow (\Psi^*)^c \text{ is cohesive.}$$

This means that a set Ψ^* is a fixed point if, when it adopts the innovation, its complement $(\Psi^*)^c$ (the non-adopting agents) forms a cohesive set. In other words, the non-adopting agents are interconnected in a way that prevents further adoption of the innovation (think of a closed village or a tightly-knit community not accepting anything coming from "the outside"). Therefore, if $(\Psi^*)^c$ forms a cohesive set, then further adoption beyond Ψ^* cannot occur because the influence from outside the cohesive set is insufficient.

C.4 Network Figures

Figure C1: Seeding in a Network

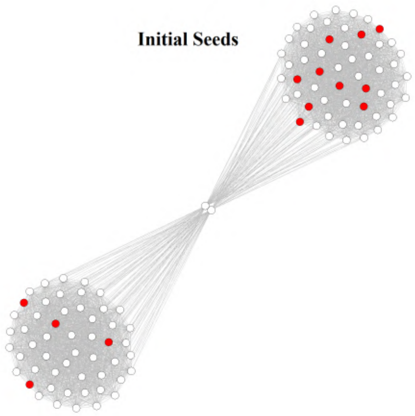
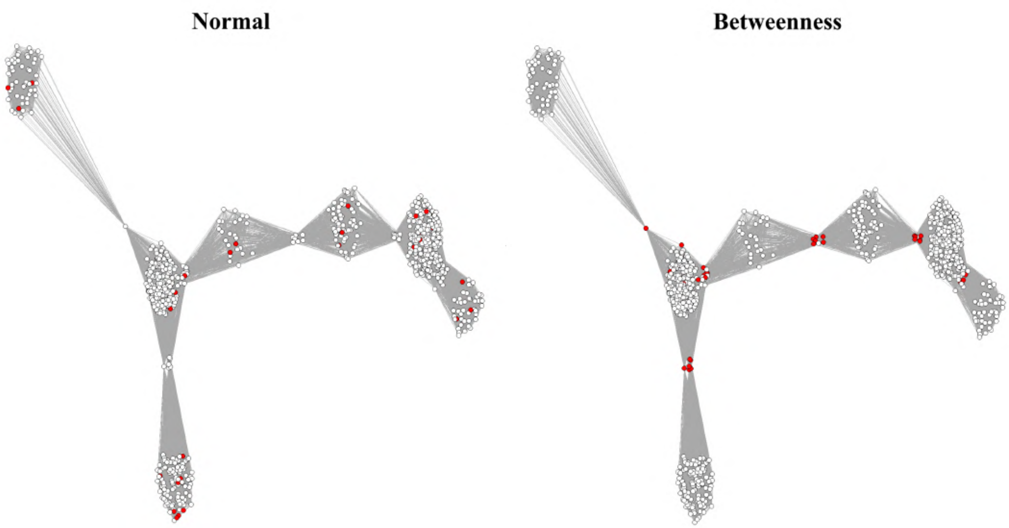


Figure C2: Seeding in First Subnetwork



References

Acemoglu, D., Ozdaglar, A., and Yildiz, E. (2011). Diffusion of innovations in social networks. In *IEEE Conference on Decision and Control and European Control Conference*, pages 2329–2334, Orlando, FL, USA. IEEE.

Alexander, M., Forastiere, L., Gupta, S., and Christakis, N. A. (2022). Algorithms for seeding social networks can enhance the adoption of a public health intervention in urban india. *Proceedings of the National Academy of Sciences*, 119(30):e2120742119.

Balta-Ozkan, N., Yildirim, J., Connor, P. M., Truckell, I., and Hart, P. (2021). Energy transition at local level: Analyzing the role of peer effects and socio-economic factors on uk solar photovoltaic deployment. *Energy Policy*, 148:112004.

Banerjee, A., Chandrasekhar, A. G., Duflo, E., and Jackson, M. O. (2013). The Diffusion of Microfinance. *Science*, 341(6144):1236498.

Bayulgen, O. (2020). Localizing the energy transition: Town-level political and socio-economic drivers of clean energy in the united states. *Energy Research & Social Science*, 62:101376.

Beaman, L., BenYishay, A., Magruder, J., and Mobarak, A. M. (2021). Can Network Theory-Based Targeting Increase Technology Adoption? *American Economic Review*, 111(6):1918–1943.

Blanchet, T. (2015). Struggle over energy transition in berlin: How do grassroots initiatives affect local energy policy-making? *Energy Policy*, 78:246–254.

Brauer, M., Freedman, G., Frostad, J., Van Donkelaar, A., Martin, R. V., Dentener, F., Dingenen, R. V., Estep, K., Amini, H., Apte, J. S., Balakrishnan, K., Barregard, L., Broday, D., Feigin, V., Ghosh, S., Hopke, P. K., Knibbs, L. D., Kokubo, Y., Liu, Y., Ma, S., Morawska, L., Sangrador, J. L. T., Shaddick, G., Anderson, H. R., Vos, T., Forouzanfar, M. H., Burnett, R. T., and Cohen, A. (2016). Ambient Air Pollution Exposure Estimation for the Global Burden of Disease 2013. *Environmental Science & Technology*, 50(1):79–88.

Cabrales, A., Calvó-Armengol, A., and Zenou, Y. (2011). Social interactions and spillovers. *Games and Economic Behavior*, 72(2):339–360.

Caragliu, A. and Graziano, M. (2022). The spatial dimension of energy transition policies, practices and technologies. *Energy Policy*, 168:113154.

Cherp, A., Vinichenko, V., Jewell, J., Suzuki, M., and Antal, M. (2017). Comparing electricity transitions: A historical analysis of nuclear, wind and solar power in germany and japan. *Energy Policy*, 101:612–628.

Frantál, B. and Nováková, E. (2019). On the spatial differentiation of energy transitions: Exploring determinants of uneven wind energy developments in the czech republic. *Moravian Geographical Reports*, 27(2):79–91.

Fraser, T. (2019). Japan's resilient, renewable cities: how socioeconomics and local policy drive japan's renewable energy transition. *Environmental Politics*.

Galeotti, A., Golub, B., and Goyal, S. (2020). Targeting Interventions in Networks. *Econometrica*, 88(6):2445–2471.

Galeotti, A. and Rogers, B. W. (2013). Strategic immunization and group structure. *American Economic Journal: Microeconomics*, 5(2):1–32.

Goodman, S., BenYishay, A., Lv, Z., and Runfola, D. (2019). GeoQuery: Integrating HPC systems and public web-based geospatial data tools. *Computers & Geosciences*, 122:103–112.

Hall, B. H. and Helmers, C. (2013). Innovation and diffusion of clean/green technology: Can patent commons help? *Journal of Environmental Economics and Management*, 66(1):33–51.

Halleck-Vega, S., Mandel, A., and Millock, K. (2018). Accelerating diffusion of climate-friendly technologies: A network perspective. *Ecological Economics*, 152:235–245.

Hong, S., Qvist, S., and Brook, B. W. (2018). Economic and environmental costs of replacing nuclear fission with solar and wind energy in sweden. *Energy Policy*, 112:56–66.

Hughes, L. (2021). Energy Policy in Japan: Revisiting Radical Incrementalism. In Pekkanen, R. J. and Pekkanen, S. M., editors, *The Oxford Handbook of Japanese Politics*, pages 376–394. Oxford University Press, 1 edition.

Jackson, M. O. and Storms, E. C. (2023). Behavioral communities and the atomic structure of networks. *arXiv preprint at arXiv:1710.04656.*

Kawashima, S. and Takeda, F. (2012). The effect of the Fukushima nuclear accident on stock prices of electric power utilities in Japan. *Energy Economics*, 34(6):2029–2038.

Kempe, D., Kleinberg, J., and Tardos, É. (2003). Maximizing the spread of influence through a social network. In *Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 137–146.

Kiunke, T., Gemignani, N., Malheiro, P., and Brudermann, T. (2022). Key factors influencing onshore wind energy development: A case study from the german north sea region. *Energy Policy*, 165:112962.

Li, A., Xu, Y., and Shiroyama, H. (2019). Solar lobby and energy transition in Japan. *Energy Policy*, 134:110950.

Li, X., Zhou, Y., Zhao, M., and Zhao, X. (2020). A harmonized global nighttime light dataset 1992–2018. *Scientific Data*, 7(1):168.

Mochizuki, J. and Chang, S. E. (2017). Disasters as opportunity for change: Tsunami recovery and energy transition in japan. *International journal of disaster risk reduction*, 21:331–339.

Morris, S. (2000). Contagion. *The Review of Economic Studies*, 67(1):57–78.

Nuclear power in Japan (2023). Nuclear power in japan — Wikipedia, the free encyclopedia. [Online; accessed 26-January-2023].

Okubo, T., Narita, D., Rehdanz, K., and Schroeder, C. (2020). Preferences for Nuclear Power in Post-Fukushima Japan: Evidence from a Large Nationwide Household Survey. *Energies*, 13(11):2938.

Oudes, D. and Stremke, S. (2018). Spatial transition analysis: Spatially explicit and evidence-based targets for sustainable energy transition at the local and regional scale. *Landscape and Urban Planning*, 169:1–11.

Popp, D., Hascic, I., and Medhi, N. (2011). Technology and the diffusion of renewable energy. *Energy Economics*, 33(4):648–662.

Rehdanz, K., Schröder, C., Narita, D., and Okubo, T. (2017). Public preferences for alternative electricity mixes in post-Fukushima Japan. *Energy Economics*, 65:262–270.

Rode, J. and Weber, A. (2016). Does localized imitation drive technology adoption? A case study on rooftop photovoltaic systems in Germany. *Journal of Environmental Economics and Management*, 78:38–48.

Rosenthal, S. and Strange, W. (2004). Evidence on the nature and sources of agglomeration economies. *HandBook of Urban and Regional Economics*, 4:2119.

Tsakas, N. (2017). Diffusion by imitation: The importance of targeting agents. *Journal of Economic Behavior & Organization*, 139:118–151.