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David Castells-Quintana
Department of Applied Economics, Universitat Autònoma de Barcelona

Alvaro Domínguez
Asian Growth Research Institute

Felipe Santos-Marquez
Technische Universität Dresden

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David Castells-Quintana[1], Alvaro Domínguez[2], and Felipe Santos-Marquez[3]

[1]Department of Applied Economics, Universitat Autònoma de Barcelona. *
[2]Asian Growth Research Institute. †
[3]Technische Universität Dresden. ‡

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Abstract

We study the diffusion of adoptions of green technologies in Japan after the 2011 Fukushima incident. We find that, on average, municipalities within a 120 km radius of a given nuclear power plant adopted green technology at a higher rate than those outside that radius. We then rely on a network diffusion model to analyze the direction, speed, and order in which municipalities adopted said technology. Next, we perform a counterfactual analysis by targeting key spreaders to alter the diffusion process. Finally, we propose a novel targeting method accounting for possible "bottlenecks" preventing the propagation process in the network.

Keywords: Energy Transition, Networks, Technology Diffusion
JEL classification: C15, O33, P11, P18, Q42

1 Introduction

Given the increasing threat of climate change, energy transitions from carbon and fossil-based sources to greener and renewable ones have become a major

*E-mail: david.castells.quintana@uab.cat
†E-mail: alvdom123@gmail.com
‡E-mail: felipe.santos@tu-dresden.de

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, therefore, 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 panel dataset combining gridded data on lights, population, vegetation greenness, and pollution, aggregated at the municipal level and matched with the location of wind farms and nuclear plants. 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 considering the network structure, we are able to identify bottlenecks 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, different energy sources, including fossil

[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.

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 find that, on average, municipalities within a 120 km radius of a given nuclear power plant adopted green technology at a higher rate than those outside that radius. This work fits in the discourse surrounding the local and global policy agenda on carbon neutrality.[2]

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.

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 adop-

[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. 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).

tion. 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: 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 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. 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 role (Caragliu and Graziano, 2022).

□ 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 interactions and decisions, propagate a particular behavior in a network (e.g., green energy usage). In our case, this allows us to learn how local interactions and coordination among municipalities can create agglomeration effects and thus have a 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' distances from 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 propose a different targeting method considering "bottlenecks" that may arise in a network, preventing the spread of a technology usage. 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. Conversely, we consider a unified population and seek ways a planner can propagate green energy adoption within it.

□ **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 disaster 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 1711 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 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.

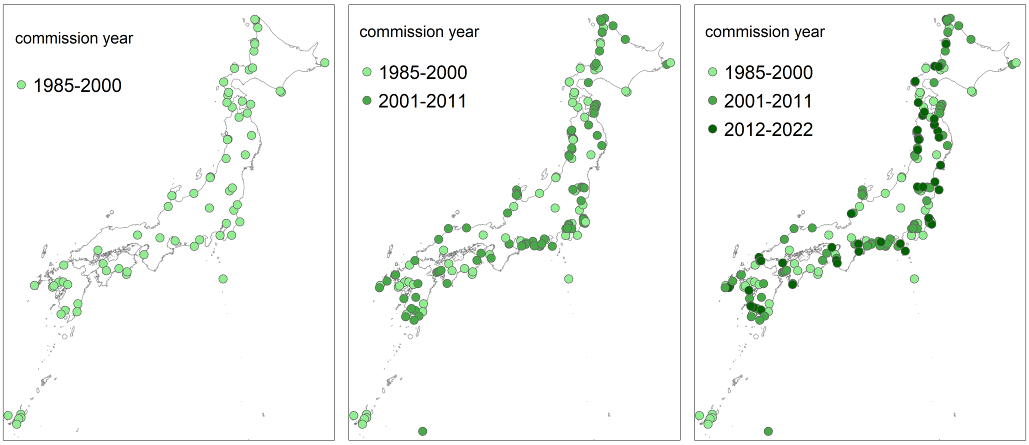
Table A.1 in the Appendix provides definitions and sources from the different variables considered, while Table A.2 provides descriptive statistics for our main variables of interest. In the rest of this section, we highlight stylized facts for our key variables.

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

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.

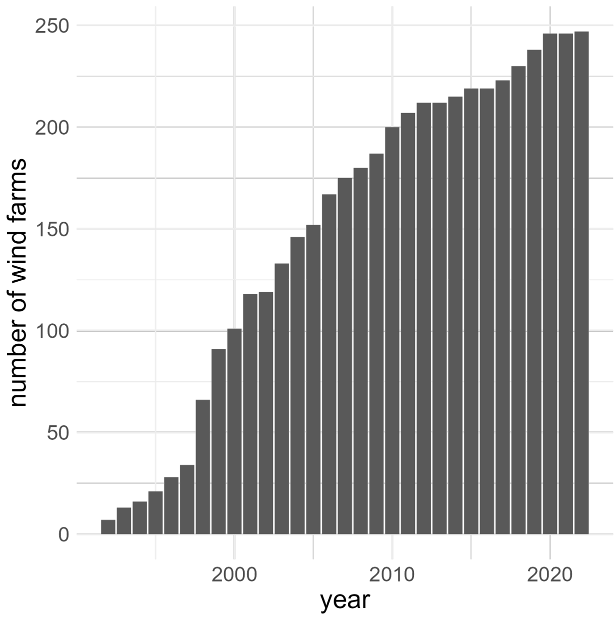
3.2 Nuclear plants

Figure 3 shows the location of the 16 Japanese nuclear power plants. 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.

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

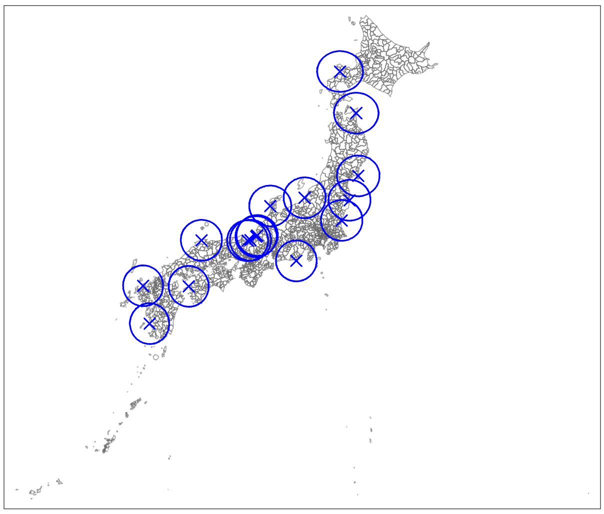
In this section, we use our panel data set to explore the connection between the proximity to nuclear power plants and the spread of adoption of Wind

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.

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.

Energy Technology (WET). We do this relying on econometric analysis and benefiting from the exogenous shock that the Fukushima incident in 2011 represented.

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 country-specific fixed effects, our panel-data specification exploits the within-countries 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. Results in Table 1 show the regressions estimated based on Equation 1 for three different models. 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 0.01. Lastly, including the full set of controls in column (3) yields a point estimate that remains statistically significant with a value of approximately 1.2%.

Table 1: Regression estimates of the Difference-in-Differences model

Dependent Variable:	log(wind_farms+1)		
Model:	(1)	(2)	(3)
Variables			
treat2	0.0214***	0.0104**	0.0119**
	(0.0031)	(0.0049)	(0.0050)
ozone			-0.0070***
			(0.0019)
pm2.5			-0.0008
			(0.0006)
pop			5.7×10^{-8}
			(4.78×10^{-7})
log(lights+1)			0.0023
			(0.0026)
lights_pc			-0.0073**
			(0.0032)
ndvi_mean			-2.3×10^{-6}
			(1.84×10^{-6})
Fixed-effects			
asdf_id	Yes	Yes	Yes
year		Yes	Yes
Fit statistics			
R^2	0.90594	0.90673	0.90719

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

Note: this table reports the regressions estimates based on Equation (1).

4.2 Event study

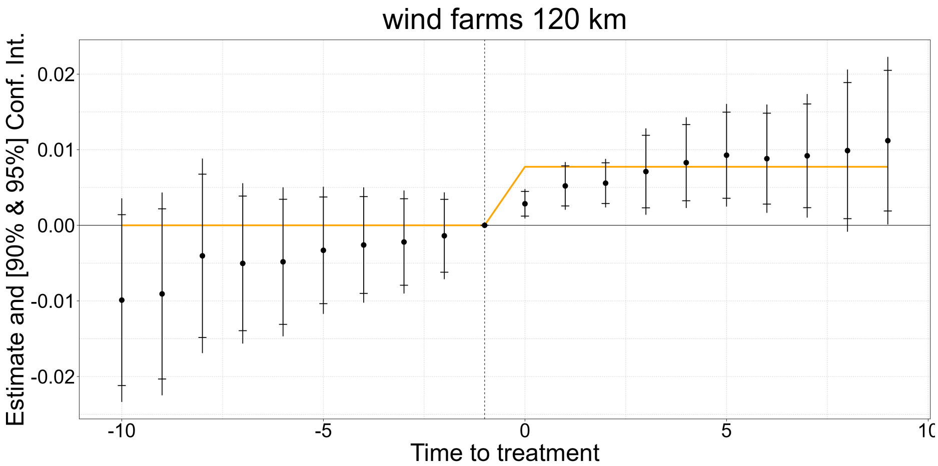
The Difference-in-Difference estimation provides the average treatment effect. Nevertheless, it is possible that the effect becomes less or more pronounced over time, or that it takes some time for the effect to kick in. For these reasons, we perform a simple event study to capture dynamic treatment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

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

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 2. Figures XX and XX 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.

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.

5 Network diffusion of wind energy adoption in Japan

5.1 Network inference

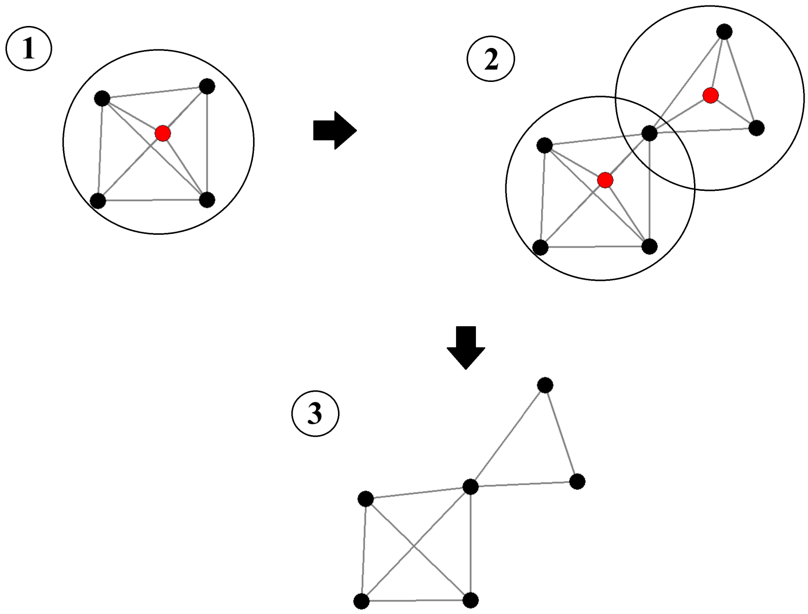
To model the diffusion of adoptions of energy within the network where municipalities are interconnected, we first need to establish its structure. Since we lack prior knowledge of the network topology, we use the following approach to infer it. First, we define a radius of 120 kilometers from a given 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, symbolizing the nuclear power plants, from the network, reflecting the scenario where these power plants have ceased operations. The remaining graph, which includes only munici-

[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.

palities, becomes the central focus of our analysis. This approach allows us to account for the shut down of nuclear power plants and concentrate exclusively on the underlying network of interactions between municipalities, which is critical for our simulations.

Figure 5: Inference of the Network



In the following section, we describe the network model we use to study the diffusion process of technology adoption. The idea is that this spread results from coordinated efforts between different municipalities at the local level, which in turn have a global impact. This phenomenon is related to the fact that the network's defining factor is the geographical proximity to nuclear power plants. The presence of these may have contributed to the clustering of economic and social activities in their vicinity. This clustering could be attributed to various factors, such as job opportunities, infrastructure, or other elements associated with the presence of power plants.

5.2 The Model

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

- $N = \{1, 2, \ldots, n\}$ is the set of agents or nodes[5] in the network.

[5] In this paper we will refer to agents, nodes, and municipalities interchangeably.

- 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 $N_i(G) = \{j \,|\, ij \in E\}$. An important measure in weighted networks is the strength of node i, defined as:

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

where w_{ij} represents the weight or distance between nodes i and j in the network. A weight of 0 indicates the absence of a connection between nodes. This measure gives the influence that node i receives from its neighbors within the network based on the weights of its connections. Meanwhile, let $\bar{S}_i = \frac{S_i}{|N_i(G)|}$ denote the average strength of node i, where $|N_i(G)|$ represents the degree or number of (unweighted) connections of node i.[6]

5.3 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.

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 a fraction $q \in (0, 1]$ of her neighbors is in the seed set:

$$\frac{\sum_j (\Psi(0) \cap D_{ij}(G))}{\sum_j D_{ij}(G)} \geq q \Rightarrow i \in \Psi(1) \tag{3}$$

where $D_{ij}(G) = \frac{1}{w_{ij}} \cdot \bar{S}_i$ represents 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. Equation 1 tells us that agent i will contemplate whether to adopt the new technology if at least a fraction q of her neighbors is within the seed set at $k = 0$. If an agent rejects adoption in period k, she will have the opportunity to reconsider in period $k + 1$. This will

[6]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.

continue until she decides to adopt. This mechanism will work in delaying the diffusion process.

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	
		Adopt Tech	*Do not Adopt*
Agent i	*Adopt Tech*	a, a	b, c
	Do not Adopt	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 adopts the behavior, then the agent's best response is to also choose to do so. 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 adopts a behavior if exactly q of their neighbors follow it.

For $k \geq 0$, we generalize the condition for adopting technology as:

$$\frac{\sum_j(\{\bigcup_{t=0}^{k-1} \Psi(t)\} \cap D_{ij}(G))}{\sum_j D_{ij}(G)} \geq q \Rightarrow i \in \Psi(k). \tag{4}$$

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:

$$\frac{\sum_j(\mathcal{H} \cap D_{ij}(G))}{\sum_j D_{ij}(G)} > 1 - q, \quad \forall i \in \mathcal{H}. \tag{5}$$

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 the threshold q.

5.4 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-nit community not accepting anything coming from "the outside"). Therefore, members of a cohesive set $\mathcal{H}$ cannot satisfy Equation 4 unless there exists (at least) an individual inside $\mathcal{H}$ who has previously adopted the innovation.

5.5 Results

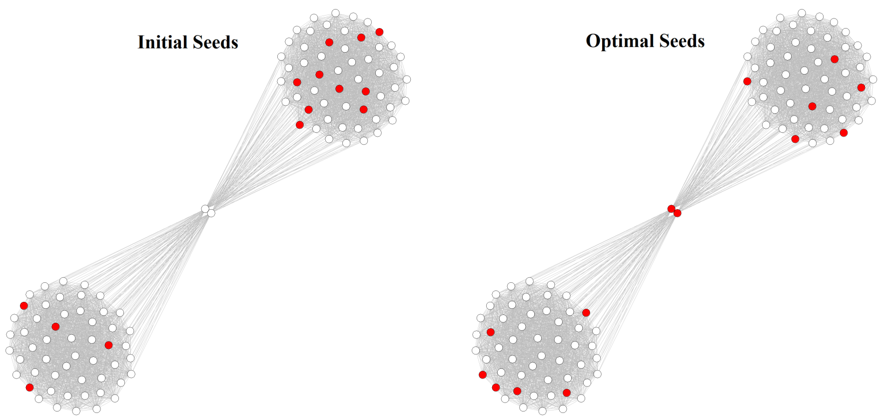
Relying on the definition to infer networks from subsection 6.1, we obtain three sub-networks or components: The first with 798 municipalities, the second with 109, and the third with 259. The first component contains mostly municipalities from the central area of Japan (island of Honshu), the second from the north, Hokkaido, and the third from the south, Kyushu. The structure of the networks is because of the geographic position of nuclear power plants within these islands. Due to, in some instances, power plants being located at distances above 120 km from others in different islands, components do not have connections between them.

In order to run the simulations, we need to obtain threshold values, q, with higher values implying a more stringent condition for diffusion to occur. We proceed by finding a q such that if we add $\epsilon > 0$ to it, there is no diffusion (i.e., the maximum value at which diffusion still happens, with any slight increase beyond this point preventing any further diffusion). Then, we multiply the obtained q by 0.25, 0.5, and 0.75. This way, we obtain three additional thresholds along with the original q: Thresholds 1, 2, 3, and 4.

These four values allow us to assess the speed and extent of the 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 do this, different methods of "targeting" have been proposed. Some of the most common ones consist of optimally allocating the initial seeds based on different centrality measures such as Closeness, Betweenness, and Eigenvector. By using some centrality, the central planner can find the best positions in the network for the diffusion to be maximized. We can observe this in Figure 6. In it, we see that if the initial seeds are as those of the graph to the left, then an "optimal" allocation would be that in the graph to the right. Given the network structure, we redistribute the same number of seeds so that they are better positioned to diffuse the technology.

Figure 6: Seeding in a Network

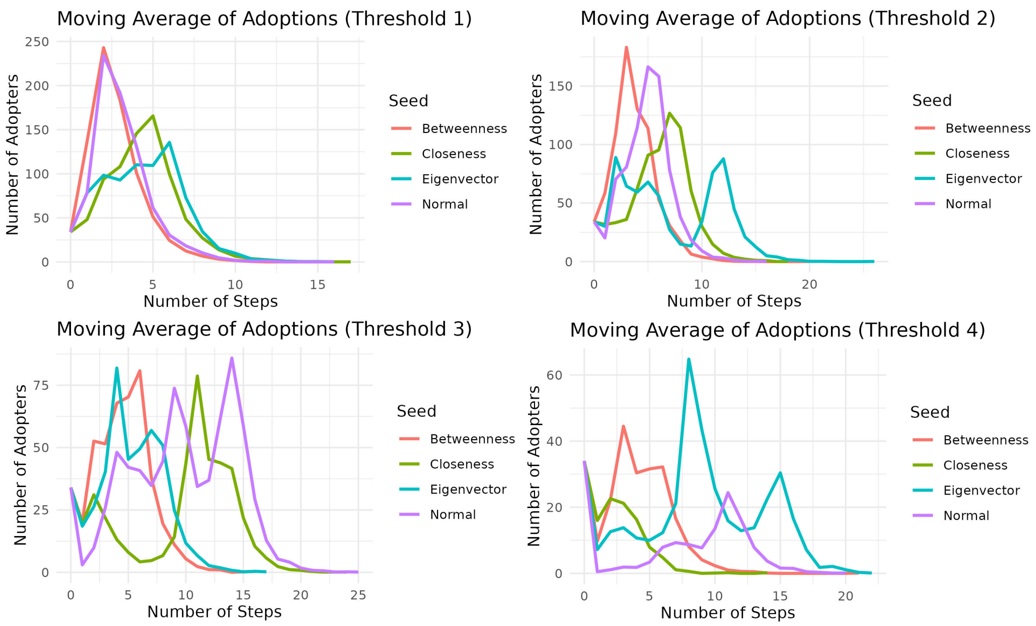


We proceed to run simulations for each of the components utilizing the criteria for thresholds mentioned above. Also, we run these simulations using the original seeds (i.e., the municipalities that adopted the technologies in the real world first) and alternative ones given by seeds allocated through different centrality measures.[7] Figure 7 below presents the results after 100 runs for the first component. In these graphs, the "Normal" seeds correspond to the real original adopters. We can see that as we move from the first threshold to the fourth one, the runs take, on average, more time to end. Further, each seeding curve shifts to the right and becomes more variable. With the first threshold, the number of adoptions peaks almost at the beginning, but

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

higher values of q delay (and even reduce) the number of adoptions at each step of the simulation. The results for the other components are shown in Appendix B.

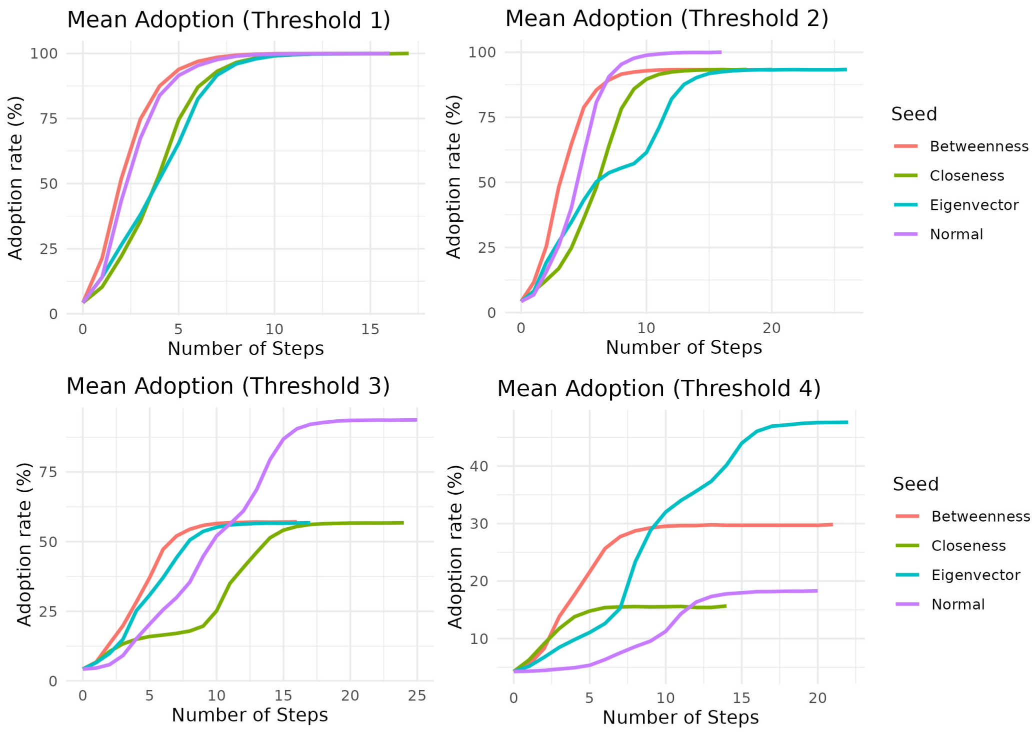
Figure 7: Number of Adopters for Each Threshold (First Component)



In Figure 8 below, we can 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 full adoption of the technology (although at different speeds/number of steps). When we increase the value of q to that of threshold 2, the Normal seeding is the only one that attains full adoption. The other seeding strategies reach approximately 92.5% of adoption. This same situation repeats when we raise q again, as shown in the graph for threshold 3. Interestingly, for the maximum value that q can attain before no more diffusion occurs (threshold 4), the Normal seeding experiences a noticeable drop to below 20%, whereas the Eigenvector seeding strategy is more successful, achieving above 50% adoption.

Why does the Normal seeding strategy generally outperform the other ones? This can be attributed to the network structure, where within each component, there are municipalities situated between two or more nuclear power stations. An illustrative example can be seen in the two central nodes in each graph depicted in Figure 6. These municipalities essentially act as "gatekeepers" for the diffusion process. In simpler terms, if one side of the network wants to communicate with the other, it must do so through these

Figure 8: Cumulative Mean Adoptions of Technology (First Component)



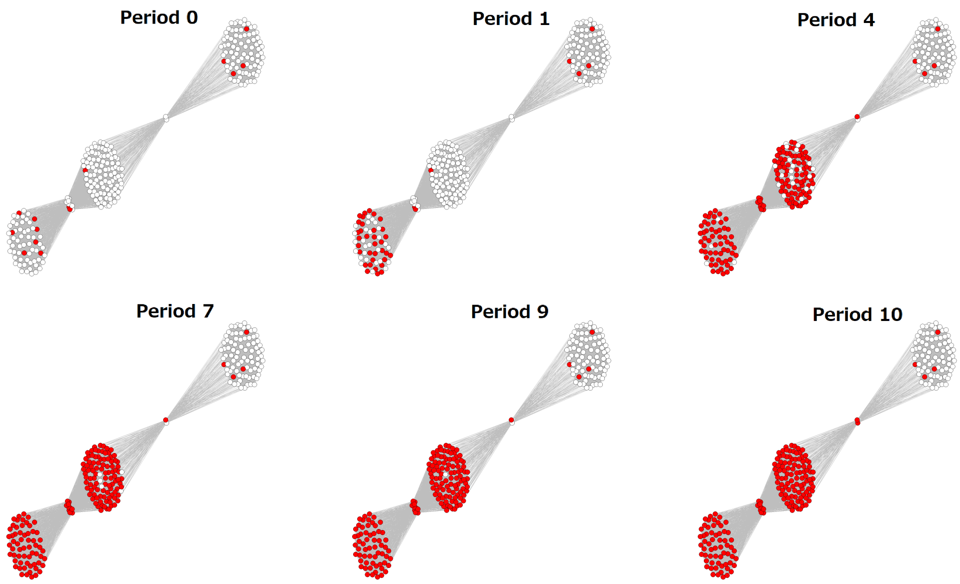
central nodes.

The situation described above can lead to complications in the diffusion process, as these municipalities may serve as bottlenecks that disrupt the propagation of technologies. For instance, if a municipality requires more than eight neighbors to adopt to decide to do so itself, the diffusion process on the left side of the graph in Figure 6 will be partial or incomplete. Furthermore, in the case of the "Optimal" seeding on the right side of the graph, diffusion will not occur at all!

When running simulations for the first component of the network (shown in Figure 9), we encounter the same issue. In this scenario, we have fourteen initial seeds for the Normal case. Throughout each run or period, we observe the diffusion process continue until it halts by the end of period 10. Notably, this diffusion remains partial, as the upper right side of the network retains its original state – only the initial seeds have adopted the technology, with no other nodes changing their statuses. This observation confirms that the two municipalities connecting this large cluster of municipalities to the rest of the network inhibit the diffusion process.

To solve this kind of problem, we propose an alternative type of seeding method. We define this targeting and show its results in Appendix B.

Figure 9: Bottlenecks in First Component



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 lights, population, vegetation greenness, and pollution, aggregated at the municipal level and matched with the location of wind farms and nuclear plants for more than 1711 municipalities in over the 1990-2020 period. 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.

By relying on a network diffusion model, we show how the coordination of adoptions of green technologies through the local interaction of municipalities has impacts at the national level. By running simulations, we are able to analyze the alternative diffusion paths and timings of said adoption in the network. Naturally, one would be inclined to ask if we can change the outcomes of the spread of technology by targeting specific municipalities, given their position in the network. When we apply traditional targeting methods, we observe that these do not provide any improvement due to the existence of specific municipalities that work as bottlenecks in the propagation of technologies. We then propose a new type of targeting that takes these bottlenecks into consideration. Our results show that not only does it allow for a faster diffusion, but it also relies on fewer seeds or starting points, thus solving an essential economic problem: maximizing outcomes while minimizing costs.

Our findings suggest that considering the network of influences of municipalities and targeting specific ones based on their relative positions can help policymakers attain desired outcomes more efficiently. In our case, this translates into better and faster adoption of greener technologies such as WET.

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