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Kota Sugimoto

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106-6234 東京都港区六本木3-2-1 六本木グランドタワー34階
The Roppongi Grand Tower 34th Floor
3-2-1 Roppongi, Minato-ku, Tokyo 1066234 Japan
政策研究 Policy Research | Tel: 03-5797-8401 Fax: 03-5570-6031

Level playing field for renewable electricity investment:

Evidence from transmission network unbundling in Germany

Kota Sugimoto*

* Resource and Energy Unit, The Tokyo Foundation for Policy Research, Tokyo, 106-6234, Japan.
Email: sugimoto@tkfd.or.jp

Highlights

- I examine ownership unbundling of the transmission system operator in Germany
- Geographic quasi-experiment estimates local average treatment effect of unbundling
- The unbundling has very little impact on renewable electricity investment
- Legal unbundling with behavior regulation removes entry barriers and levels the field

Abstract

While economics reveals that insufficient internalization of negative environmental externality from non-renewable electricity generation is one of the major barriers to renewable electricity investment, the lack of a level playing field in the generation or retail market can be another serious impediment. Incumbent vertically integrated utilities face an incentive to prevent the penetration of renewable electricity when competition with entrants reduces their revenue from their own power plants. A bottleneck monopoly of power transmission network assets allows them to create several barriers to entry. The purpose of this study is to investigate this hypothesis by using a geographic quasi-experimental approach to the electricity industry in Germany. I take advantage of the fact that Germany has two transmission system operators (TSOs) that were ownership unbundled (separated) and two other TSOs that chose legal unbundling. I estimate the local average treatment effect of ownership unbundling of the transmission system operator on renewable electricity investment. The result indicates that installed capacity of solar, onshore wind power, and biomass power plants is not increased by the vertical separation even though the effect is likely to be overestimated by generation divestiture effects. This evidence suggests that the generation market in Germany is competitive without ownership unbundling. In other words, legal unbundling with behavior regulation can create a level playing field as ownership unbundling can.

JEL classification: L16; L43; L94; Q42; Q48; Q55

Keywords: barrier to entry, vertical separation, transmission network unbundling, renewable electricity

investment, geographic quasi-experiment

1. Introduction

While economics reveals that insufficient internalization of negative environmental externality from non-renewable electricity generation is one of the major barriers for renewable electricity investment (Hu et al., 2018a; Neuhoff, 2005; Newbery et al., 2018; Owen, 2006), the lack of a level playing field in the generation or retail market can be another serious impediment (Hu et al., 2018b). Not only incumbent vertically integrated utilities but also independent generation and supply firms are expected to play a major role in investing in renewable electricity capacity after market liberalization; however, the incumbent utilities have an incentive to prevent the penetration of renewable electricity when competition with entrants declines their revenue from their own power plants (Jacobsson and Bergek, 2004; Sovacool, 2009). Furthermore, incumbents' bottleneck monopoly of power transmission network assets can allow them to build several barriers to entry, such as high costs for connection or delaying necessary administrative procedure of new competitors' generators to start operation (Joskow, 1997; Van Koten and Ortmann, 2008). Such behavior is known as non-tariff discrimination or sabotage in the industrial organization literature (Economides, 1998; Höffler and Kranz, 2011). This conflict of interest within vertically integrated utilities has motivated the European Commission to encourage member states to implement ownership unbundling of the transmission system operator (TSO) (European Commission, 2010).

This article evaluates the causal effect of ownership unbundling of a transmission company from one of the largest vertically integrated electric utilities in Europe. Among European countries, Germany provides an important case study because it is one of the most progressive countries in diffusing renewable electricity investment, as well as having completed restructuring of the industry to induce competition. My "geographic quasi-experiment" approach exploits the fact that two privately-owned TSOs in Germany (E.ON and Vattenfall) have undergone ownership unbundling in 2010, while the remaining two TSOs (RWE and EnBW) chose legal unbundling. This situation within the country creates a geographic boundary creating the "treatment area," where a renewable electricity investor receives connection and system operation services from the ownership-unbundled (separated) TSOs, and the "control area," where the legally unbundled TSOs provide them. My identification strategy is based on two facts: that treatment assignment depends discretely on the geographic location of power plants and that relevant covariates between the two areas become well-balanced once I focus on municipalities located very close to the boundary. This allows me to use the exogenous variation created by the geographical boundary of TSO's operational area to identify the local average treatment effect (LATE) of ownership unbundling, accounting for differences in the renewable resource endowment, socio-economic characteristics, and national-level support policies. Local linear difference-in-difference (DID) regression and panel Tobit random-effects model estimate LATE. To overcome the assumptions that normally distributed and homoscedastic error Tobit model impose, I adopt censored quintile regression and Poisson regression as robustness checks. Finally, I add the ownership structure of distribution system operator to which renewable power plants connect to investigate the potential mechanism of ownership unbundling.

The contribution of this paper is to provide causal evidence on how removing a barrier for competition can facilitate renewable energy development through vertical separation. Although countries choose different arrangements for TSO unbundling, there is little ex post empirical analysis regarding the effectiveness of the unbundling for renewable electricity investment (Chawla and Pollitt, 2013). The effects of restructuring and market competition on renewable electricity investment are paid less attention than the effects of direct support policies for renewable energy, such as the feed-in tariff and renewable portfolio standard (Haas et al., 2011). However, as Hitaj (2013) reveals in her research about the impact of functional unbundling on wind power investment in the United States, transmission network unbundling can be a more cost-effective measure than financial or tax incentives; thus, it is particularly informative for policymakers in countries aiming to decarbonize the power sector under financial constraints. To my knowledge, this is the first study to adopt a quasi-experimental approach using geographic information to identify the causal impact of transmission network unbundling on renewable electricity investment.

The reminder of the paper is organized as follows. Section 2 discusses the background of the vertical separation of the electricity industry in Europe and Germany’s renewable development. Section 3 reviews the existing literature in this field. Section 4 describes my identification strategy, followed by model specification and data description. Section 5 reports the results, Section 6 performs several robustness checks, Section 7 discusses the interpretation of the results, and Section 7 concludes.

2. Background

2.1. European Commission’s direction for transmission network unbundling

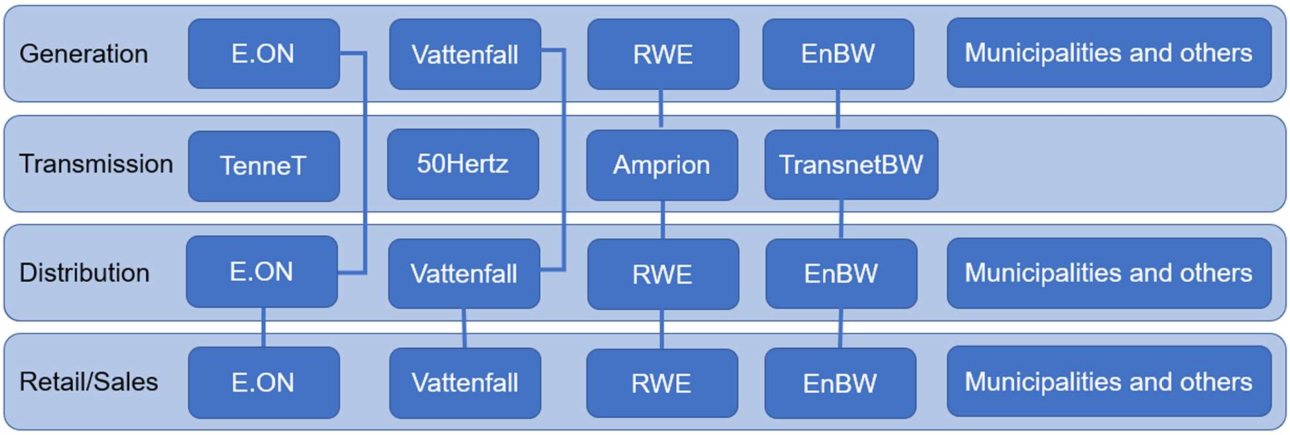
In Europe, Directive 2003/54/EC in the second legislation in the field of European Union’s energy market required vertically integrated electricity utilities to legally separate transmission companies. However, a subsequent sector inquiry conducted by the European Commission’s Directorate General for Competition in 2005 found that discriminatory practices by vertically integrated utilities using transmission grids against competitors led to problems for new entrants and hindered renewable energy penetration (Eikeland, 2011; European Commission, 2007). The European Commission's draft directive for the third energy legislation package initially aimed to enforce ownership unbundling and solve conflicts of interest. In response to opposition by Germany and several member states, the European Commission could not require vertically integrated utilities to unbundle ownership of the TSO; instead, Directive 2009/72/EC in the third energy legislation package required vertically integrated utilities to choose and implement among the following options: ownership unbundling, functional unbundling (ISO model), or strengthening behavior regulation on existing legally separated TSOs (ITO model) (European Commission, 2010). What is the difference between the legal unbundling set out in the second directive and the ITO model that appeared as a compromise in the third directive? Under the ITO model, the parent company (a former vertically integrated company) and its subsidiary companies are required to comply with stronger behavior regulations than before. These regulations are expected to prevent vertically integrated utilities from discriminating against non-affiliate market participants (Herrera Anchustegui, 2018).

According to the status review of the third energy package issued by the Council of European Energy Regulators (CEER) in 2016, about 70% of transmission companies in the EU has implemented ownership unbundling (CEER, 2016), and only a few countries had adopted functional unbundling. European Commission (2014) evaluated the ITO model and found that stakeholders testified that the ITO model had worked well so far and it was too early to proceed further with the separation, though only 2 years had passed since the ITO implementation. Brunekreeft et al. (2014) agree with the effectiveness of the ITO model, because under that model the parent company simply owns the TSO as an asset and cannot influence the TSO strategically. On the other hand, Lowe et al. (2007) and Barrett (2016) argue that the ITO model cannot eliminate the potential for fundamental conflicts of interest in vertically integrated utilities, that national regulators are likely to suffer from regulatory capture by information asymmetry, and that separation of ownership or functions is necessary because it is virtually impossible to observe and punish anti-competitive behavior of vertically integrated utilities. This debate shows that the degree of effectiveness of TSO unbundling is still controversial. A similar dispute also exists in Japan, where privately owned vertically integrated utilities implemented legal unbundling in 2020 (Ito, 2013).

2.2. German electricity industry

The German electricity industry is characterized by four large vertically integrated utilities called the "Big 4." Figure 1 shows that E.ON, Vattenfall, RWE, and EnBW dominate the generation, transmission, distribution, and retail market.

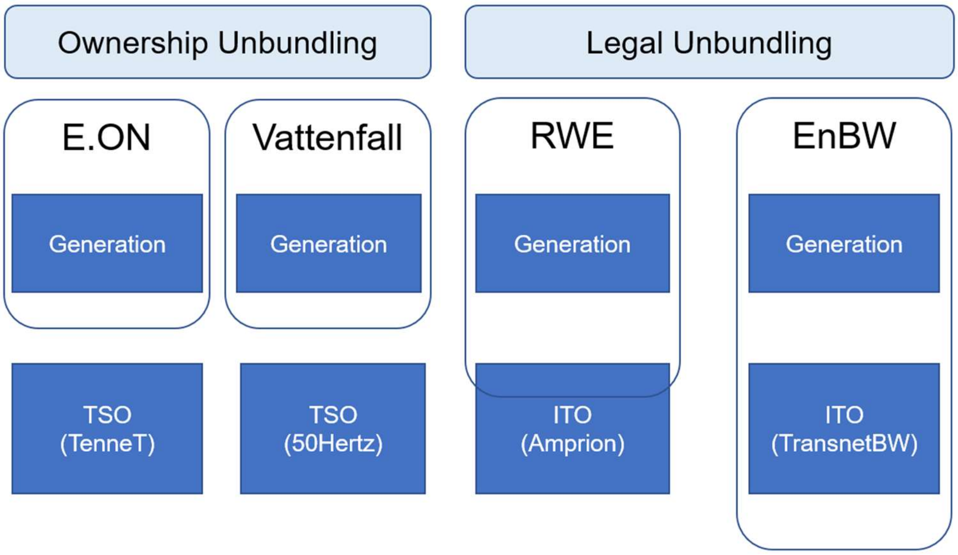
Figure 1. Electricity industry structure in Germany during 2010-2016



(Source: RAP (2015): Report on the German power system. Version 1.2 Study commissioned by Agora Energiewende.)

Two of the vertically integrated utilities ended up splitting ownership of the TSO. E.ON was suspected of anti-competitive behavior by the kroon's Directorate-General for Competition (European Commission, 2008). After investigation, E.ON announced in February 2008 that it would divest its subsidiary's transmission company E.ON Netz (Deutsche Welle, 2008a). In November 2009, E.ON announced that it would sell E.ON Netz to the Dutch state-owned company TenneT. E-ON completed the ownership unbundling in February 2010 (Duso et al., 2020). Vattenfall, a Swedish state-owned vertically integrated utility, sold its transmission company to a Belgian private company TSO Elia and an Australian infrastructure fund in March 2010; the transmission company was renamed 50Hertz. The other two vertically integrated utilities chose the ITO model (Brunekreeft et al., 2014). RWE announced in July 2011 that it would sell 74.9% of its subsidiary TSO Amprion to a consortium of German institutional investors, including insurance company Commerz Real and a pension fund, in September of that year. This is not regarded as ownership unbundling, because RWE has not completely given up ownership. EnBW continues to own TransnetBW as a wholly owned subsidiary TSO. Figures 2 summarizes how the two vertically integrated utilities in eastern Germany have separated their ownership and the two other companies, in western Germany, have switched to ITO. In this study, I focus on the east–west boundary (i.e. TenneT and 50Hertz vs. Amprion and TransnetBW operating areas) where the status of ownership unbundling of transmission companies changes discontinuously.

Figure 2. Transmission network unbundling in German vertically integrated utilities

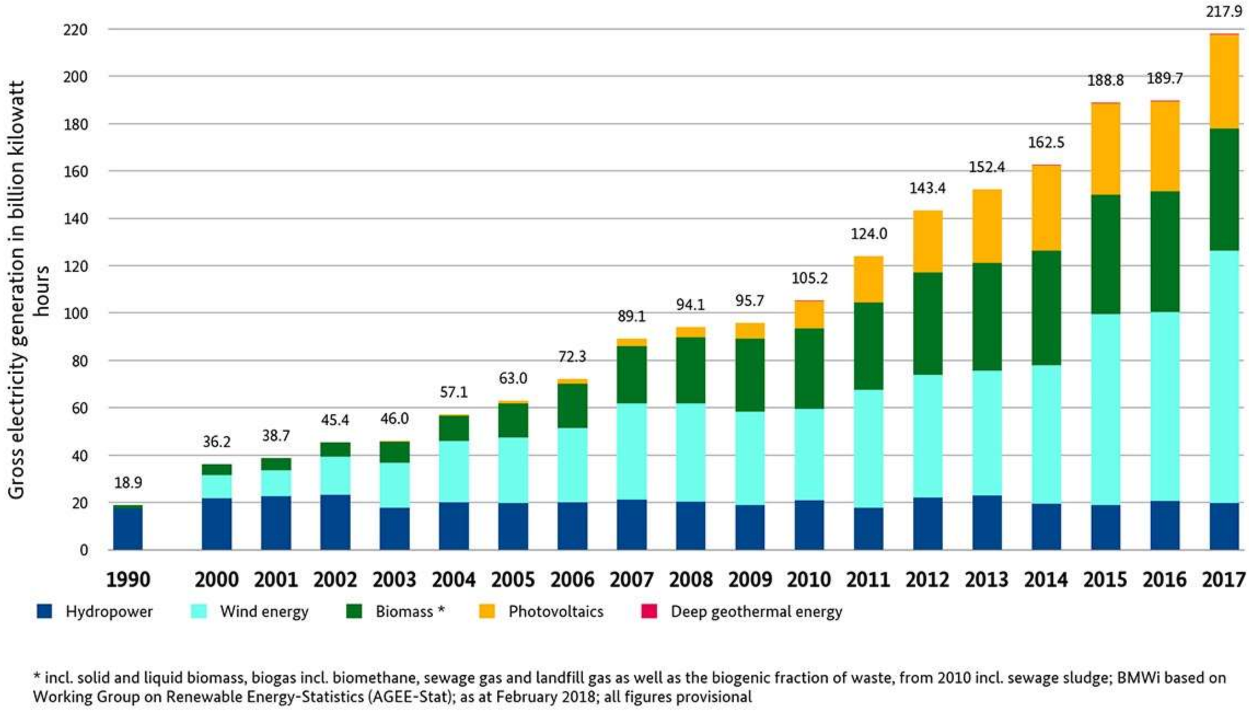


2.3. German renewable electricity investment

Figure 3 shows that the amount of electricity generated from renewable resources in Germany has continued to increase over the last decades. There has been remarkable growth of solar PV, onshore wind power generation, and biomass power generation[1] in recent years. An interesting feature of the generation market in Germany is the participation of third-party producers. Toke et al. (2008) shows that more than 5 GW of wind power plant is owned by local farmers and citizen participating in co-operatives, which was the largest amount among European countries at the time. In 2013, 30% of solar PV and onshore wind power capacity was installed by households and co-operatives (Brunekreeft et al., 2016). By contrast, existing utilities owned only 12% of renewable power in 2013. Hence, it is important to explain why these third-party producers could play the large role in investing renewable electricity generation capacity. Unbundling the transmission sector from power generation and retail sectors may explain the increase of renewable electricity development by influencing connection to the transmission or distribution grid, system operation, and investment in transmission lines. If these are implemented by transmission companies in a discriminatory manner, there will be barriers to entry for independent renewable power producers. If sufficient separation were implemented, both potential conflicts of interest and concerns about anti-competitive behaviors would be eliminated, and renewable electricity investment would be accelerated.

Figure 3. Electricity generated by renewable energy in Germany

[1] The main energy resource of biomass power generation in Germany is biogas. Biogas is a gaseous mix of methane and carbon dioxide, which is produced by mixing organic waste, such as livestock manure and energy grains (e.g., corn), and fermenting it with the aid of bacteria.



Source: BMWi, 2018.

3. Literature review

Pros and cons of vertical separation in electricity industry have been widely discussed (Brunekreeft, 2008, 2015; Meyer, 2012a, 2012b; Pollitt, 2008). Previous econometric literature on TSO unbundling mainly focuses on the positive effect on retail price (Fiorio and Florio, 2013; Nagayama, 2007, 2009). On the other hand, Gugler et al. (2013) analyze the impact of ownership separation of the TSO on the total amount of power generation, transmission, and distribution investment in European countries. Gugler et al. (2017) estimate the extent to which TSO unbundling erodes the cost savings realized by vertical integration in Europe. Other studies focus on DSO unbundling; for example, Nikogosian and Veith (2012) find that ownership unbundling of DSO is associated with a lower retail price in Germany than vertically integrated utility or legally bundled DSO. The authors discuss that incentives for the DSO to engage in non-price discrimination might not have been removed under the legal unbundling. Heim et al. (2018) estimate that legal separation of DSO results in a 5% to 9% decrease of transmission tariff in Germany. However, there is little empirical evidence regarding the effect of TSO unbundling on renewable electricity investment.

Other strands of econometric literature investigate the determinants of renewable energy development.

Schaffer and Brun (2015) and Dharshing (2017) use spatial econometric methods to identify the determinants of the level of residential solar PV installation in Germany and find that it is correlated not only with the area-specific solar radiation level and expected rate of return for investment but also with local housing density, income, education, and low unemployment. Interestingly, both studies show that the concentration of residential rooftop solar PV installations in Germany can be explained by the imitation effect. Hitaj and Löschel (2019) is a seminal work that demonstrates the impact of German feed-in tariffs on onshore wind power installation. The authors estimate that grid density, measured as the ratio of the length of a transmission line to district area, is positively correlated with wind power capacity only for the period 1996–1999, and not afterwards. They attribute this result to the Renewable Energy Act (Erneuerbare Energien-Gesetz) amended in 2000, which guaranteed the priority connection for renewables and mandated TSOs to bear the necessary grid expansion costs. In other words, connection cost has no longer been burdened by developers in deciding where to locate onshore wind power plant since 2000. Goetzke and Rave (2016) and Lauf et al. (2019) also estimate the determinants of wind power deployment in Germany using district-level data, and find that land availability, the expected profitability of wind projects, and wind resource are important factors in explaining the development pattern.

Again, however, none of these studies explicitly include TSO unbundling as an important explanatory variable. With regard to onshore wind power, Hitaj and Löschel (2019) assume that the TSO just follows developers' requests for connection and bear costs in compliance with the Renewable Energy Act provisions. However, a legally unbundled TSO, a subsidiary of the vertically integrated utility, may be reluctant to connect or manage renewable electricity provided by other non-affiliate companies. If a TSO is completely separated from a vertically integrated utility' influence, potential conflicts of interest might disappear and the TSO may obtain more freedom for independent decision-making about connection and system operation, which may increase renewable electricity investment. In fact, Sugimoto (2019) finds that functional unbundling of the TSO in the United States is correlated with onshore wind power investment by independent power producers, implying that improved connection and system operation by independent TSOs matter for renewables.

4. Research design and data

4.1. Identification strategy

Figure 4 shows the geographic boundary where a renewable power plant receives connection and system operation from TSOs in Germany. Panel A displays each TSO's system operation area, and Panel B shows where the red border intersects each of six states: Lower Saxony (Niedersachsen), North Rhine Westphalia (Nordrhein-Westfalen), Rhineland-Palatinate (Rheinland-Pfalz), Hesse

(Hessen), Baden-Württemberg, and Bavaria (Bayern). I call this border as “treatment assignment boundary.” This boundary line does not overlap with significant geographic obstacles, such as the Rhine river, the Alps, the autobahn, or railways except in the southern part of Hesse. I exploit the fact that TenneT experienced ownership unbundling from E.ON in 2010 while western TSOs such as Amprion and TransnetBW, remained in the state of legal unbundling. This generated a sharp discontinuity in the treatment assignment (received system operation by the ownership-unbundled TSO: TenneT) as a function of location. 50hertz is another TSO that separated its ownership from Vattenfall, but I do not use it in my analysis because it is far from the boundary of Amprion and TransnetBW’s system operation areas (i.e. the control area).

Figure 4. TSOs’ operation areas, state borders, and treatment assignment boundary

Panel A. TSOs’ operation areas Panel B. State borders and the treatment assignment boundary

Note: The red line in Panel B illustrates the treatment assignment boundary between treatment area (i.e. TenneT’s system operation area) and control area (i.e. Amprion’s and TransnetBW’s system operation area)

In this setting, geographic regression discontinuity design (RDD) is applicable if disaggregated locational data, such as household address and house address, are available (Keele and Titiunik, 2015, 2016). Unfortunately, location data for renewable power plants in Germany is not available due to data protection reasons; therefore, I apply a geographic quasi-experiment (GQE) approach suggested by Keele et al. (2017).

In this approach, outcome variable Y_{it} is renewable electricity generation capacity installed in municipality *i* in the year *t* that it starts operation. Renewable power sources include solar power, onshore wind power, and biomass power plants. I adopt the potential outcome framework and denote Y_{it0} as the potential outcome of municipality *i* in the absence of treatment T_i=0 and Y_{it1} as that with treatment T_i=1. Treatment is defined as receiving connection and system operation from the ownership-unbundled TSO (TenneT). Thus, the observed outcome is written as follows: $Y_{it} = T_i Y_{it1} - (1 - T_i) Y_{it0}$. I define the centroid of municipality *i* based on the coordinate system of longitude and latitude and denote it as $C_i = (longitude_i, latitude_i)$. The location point C_i determines treatment status T_i across a geographic boundary in a discrete manner, and so T_i is a discrete function of the municipality's location $T_i = f(C_i)$. The treatment is defined by the following dummy variable:

$$T_i = \begin{cases} 1 & \text{if } C_i \in \text{treatment area} \\ 0 & \text{if } C_i \in \text{control area.} \end{cases}$$

Let b_i^* be a point on the treatment assignment boundary that is closest to C_i. Then, I can calculate the Euclidean distance d_i^* between b_i^* and C_i: $d_i^*=d(b_i^*, C_i)$.[2] Next, X'_{it} represents exogenous covariates such as renewable resource potential and population density. The GQE requires "conditional geographic mean independence" for identification:

$$E[Y_{it1} \mid d_i^* < D, X'_{it}, T_i] = E[Y_{it1} \mid d_i^* < D, X'_{it}]$$
$$E[Y_{it0} \mid d_i^* < D, X'_{it}, T_i] = E[Y_{it0} \mid d_i^* < D, X'_{it}]$$

This assumption requires the potential outcomes Y_{it0} and Y_{it1} to be conditionally mean independent of the treatment assignment T_i within a buffer *D* around the boundary. Before performing the main estimation, two falsification tests are conducted to check the validity of the assumption. The first test checks the balance of observable covariates focusing on the narrow regions within 30 km, 20 km, and 10 km from each side of the boundary (total bandwidth 60 km, 40 km, 20 km, respectively). The second test regresses pretreatment outcome in 2007 on the covariates in 2008 to investigate whether there are enough observable covariates to remove differences in the pre-treatment outcomes (Keele et al., 2017).

Any GQE becomes invalid if individuals can precisely manipulate the treatment assignment variable (Lee and Lemieux, 2010). Such a sorting (i.e. self-selection) process may occur in my case if some renewable power developers can precisely select the location for renewable power plant installation, expecting to receive better services from more independent TSO. However, I assume this is not likely to occur in my empirical example for three reasons. First, the balance test presented in the Results section shows that geographic and demographic covariates are mostly balanced across the boundary within 10 km, indicating that systematic sorting based on these covariates is unlikely to have occurred (Table 2). Second, the density test in the section 5 shows that renewable power plants located within 10 km from the boundary are distributed continuously before and after the unbundling (Figure 6).

[2] I use World Geodetic System 1984 as a geographic coordinate reference system and Universal Transverse Mercator zone 33 N as a projected coordinate reference system (EPSG:32632).

Third, renewable electricity investors would not know the ownership unbundling of E.ON until 2008. The announcement of ownership unbundling by E.ON in February 2008 surprised even the German government (Deutsche Welle, 2008a). E.ON and the government had opposed the mandatory TSO ownership unbundling suggested by the European Commission and discussed a joint holdings option as a compromise (Deutsche Welle, 2008b). However, E.ON chose ownership unbundling to settle down the negotiation with European Commission about illegal cartel agreements (Brunekreeft et al., 2014). This process shows that it was impossible for renewable electricity investors to strategically locate their plants in the treatment area at least until 2008. In the case of such selective sorting across the treatment assignment boundary occurring after 2008, the robustness check in the section 6 restricts dataset to those power plants that started operation in or before 2010. Because it takes developers usually more than three years from initial planning to start operating a renewable power plant (Bauwens et al., 2016; Sovacool et al., 2020), I believe the possible anticipation effect initiated by the E.ON's announcement in 2008 cannot cause capacity addition at least until 2010. The robustness check confirms that such a sorting problem seems not to exist (Table 6). Still, to the extent that unobservable covariates determine the location of renewable power plants, the sorting could bring some bias to the estimated effect of the unbundling.

Compound treatments are another obstacle for identifying local average treatment effect of interest in GQE (Keele et al., 2017; Keele and Titiunik, 2015). Compound treatment means there are multiple treatments affecting potential outcomes. In my empirical application, there are three possible compound treatments. First, the Renewable Energy Act was revised in 2016 to set the upper limit for new onshore wind power generation in only the north area. I restrict my dataset to 2016 to isolate a compound treatment of this law. Second, federal states are probably offering compounding treatments because each state has several ways to induce renewable electricity investment, such as allocating specific areas for renewable power plants and setting targets for future renewable electricity investment (Ohlhorst, 2015). It is likely that renewable electricity generation capacity installation level differs between states. Among the five states where the geographic boundary crosses, Baden-Württemberg belongs to only the control area and Bavaria belongs to only the treatment area, while Lower Saxony, North Rhine Westphalia and Hesse are common to both areas. Thus, a potential compound treatment may be a concern in the two states in the south region. I include state dummies to separately estimate the unbundling effect. Finally, the sale of large scale power plants by E.ON in the treatment area may compound potential outcomes. As a settlement with the European Commission against anti-competitive behaviors, E.ON sold 5000 megawatts (MW) of non-renewable power plants between January 2009 and May 2010 (Duso et al., 2020). Most divested power plants are located in TenneT's area. This event may have increased competition in the generation market only in the treatment area and weakened the incentive of TenneT to exercise discriminatory behavior against renewable electricity investment by non-affiliate developers. If so, it would lead to overestimation of the effect of ownership unbundling of the TSO on renewable electricity generation capacity. A robustness check by limiting the data up to 2010 can partly avoid this compound treatment, because power plants installed up to 2010 are most likely not to be affected by the divestiture. The result confirms that the threat is not the case (Table 6).

4.2. Model specifications

The following linear regression functions are used for the estimation:

$$Y_{it}=c+\beta_1 T_i+\beta_2 Post_t+\beta_3 T_i \times Post_t+\beta_4 X'_{it} + \alpha_i + Year_t+\varepsilon_{it.}$$

This is the standard panel data fixed-effects model. β_3 is the main parameter of interest, representing the local average treatment effect. X'_{it} denotes a vector of exogenous covariates and $Year_t$ includes year dummies. Note that I restrict the estimation to the areas within 30 km from each side of the boundary (total 60 km). This local linear DID regression may produce inconsistent estimates in the presence of a serious “corner solution”: observed zero values for the nontrivial fraction of the outcome variable (Wooldridge, 2010). Actually, many municipalities have zero renewable electricity capacity installed during the study period.

To address the corner solution problem, I use panel Tobit random-effects model. Since the panel Tobit fixed-effects model suffers from an incidental parameters problem under the small T compared to the number of observations (Neyman and Scott, 1948) and leads to inconsistent estimates, I rely on a random-effects model. This non-linear model is first proposed by Tobin (1958) using the maximum likelihood estimator. The Tobit model is specified as:

$$Y^*_{it}=c+\beta_1 T_i+\beta_2 Post_t+\beta_3 T_i \times Post_t+\beta_4 f(C_i)+\beta_5 X'_{it} + \alpha_i + State_i + Year_t+\varepsilon_{it}$$

$$Y_{it}=\max(0, Y^*_{it})$$

$$\alpha_i|X_{it} \sim \mathrm{Normal}(0, \sigma_\alpha^2),$$

$$\varepsilon_{it}|X_{it} \sim \mathrm{Normal}(0, \sigma_\varepsilon^2)$$

Y* is modeled as a latent variable, as opposed to the actually observed outcome Y. Accordingly, when Y*>0, Y is observed and otherwise Y is 0. $f(C_i)$ is a function of municipality’s location. The functional form of $f(C_i)$ is unknown and thus I approximate by two forms of polynomial regarding the municipality’s location, which aims to control smooth functions of locations. In line with Dell (2010), I use a cubic polynomial of distance from the municipality to the boundary, as well as a cubic polynomial of longitude and latitude. Appendix reports the estimation of the quadratic and quartic of distance to the boundary and the results are virtually unchanged. Random effect α_i and idiosyncratic error term ε_{it} is assumed to follow the normal distribution and have the homoscedastic variance as well as being independent with the observable covariates X'_{it}. Since this model still may produce inconsistent estimates under the non-normal or heteroskedastic error term, robustness checks in section 6 adopt several robust models to address the potential violation of these assumptions.

4.3. Data

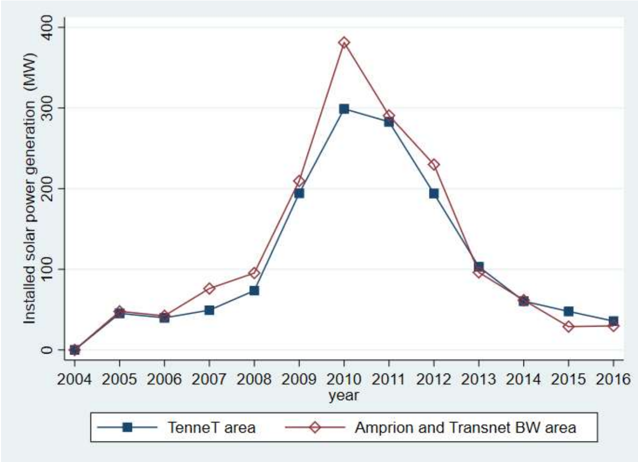
I use solar, onshore wind, and biomass power generation capacity measured in MW installed as outcome variables (2008–2016). Plant-level data are available from four TSOs in Germany (Netztransparenz.de, 2019). The dataset contains plant capacity size, operation start date, which TSO the plant is managed by, to which DSO it is connected, voltage level, the municipality where it is located, and so on. Unfortunately, it does not contain comprehensive address information within a municipality due to privacy protection. Therefore, I merge the plant capacity data to the municipality's centroid where the power plant is located. The location data are used to calculate the Euclidean distance from the municipality to the boundary of the transmission system operation area between TenneT (treatment area) and Amprion or TransnetBW (control area). The total sample consists of 11,082 municipalities in Germany. Note that the dataset includes urban districts (*kreisfrei Städtes*) and city states (*Stadtstaaten*), such as Berlin and Hamburg. Data after 2017 are available but excluded from the analysis, because the Renewable Energy Act was revised in 2016 to limit onshore wind deployment in the north area to stop grid congestion (BMWi, 2020).

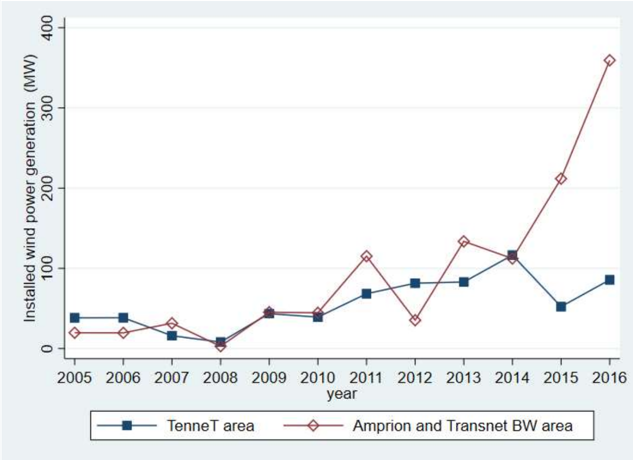
Figure 5 shows the annual capacity addition of renewable power plants during 2004–2016 at municipalities located within 10 km of the geographic boundary. Panel A displays that solar power plants development peaked in 2010. Panel B shows that the onshore wind power capacity development stagnates until 2010 but records an increasing trend after 2010. Panel C shows that most biomass power plants are installed by 2011; all outcomes seem to have parallel pre-trends between treated and control areas before 2010, which supports the required assumption for the DID regression.

Figure 5. Renewable electricity generation capacity addition by municipality with 10 km from the boundary

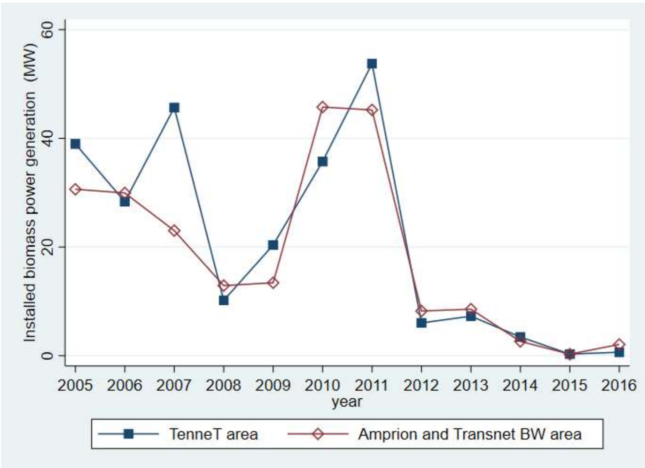
Panel A. Solar power capacity

Panel B. Wind power capacity





Panel C. Biomass power capacity



The vector data of German map is obtained from GADM (GADM, 2018). Geographic covariates include elevation, slope, solar power potential, wind power potential, and agricultural land area. Elevation (unit: meter) and slope (unit: degree) data are extracted from a digital terrain model of Germany based on NASA's Shuttle Radar Topography Mission (OpenDEMData.info, 2020). Solar power potential is derived from solar radiation data of "Yearly average global irradiance on a horizontal surface (W/m^2), period 2005–2015" from the Climate Monitoring Satellite Application Facility Solar Radiation Data (European Commission, 2020). I spatially average raster values by municipality and multiply them by 8760 h / 1000 to obtain annual solar power resource potential (kW/year). Wind power potential is wind power density per municipality (kW/m^2). The German Meteorological Service calculates 200 m × 200 m gridded Weibull parameters (scale parameter c and shape parameter k) assuming a hub height of 80 m based on 218 quality-controlled ground stations during 1981–2000 (German Meteorological Service, 2020). Following Pishgar-Komleh et al. (2015), I calculate average wind power density per municipality using the Weibull parameters, assuming that air density is 1.225 (kg / m^3).[3] Agricultural land area measured in hectares is a proxy for biomass resource potential. These three variables are proxies for renewable resource potential, which is probably one of the most important factors for renewable electricity investment (Fleiß et al. 2017; Krohn et al. 2009). Other covariates include GDP per capita (€), population density, and property tax rate determined by municipality (Grundsteuer B). These covariates are published by the Federal Statistical Office (2020).

Table 1 presents descriptive statistics. The first three columns show observations, means, and standard deviations of all variables for the full sample. The next three columns summarize the same statics using the sample within 10 km from the boundary between TenneT and Amprion/TransnetBW. It is important to note that all outcome variables have nonnegative values and means smaller than the standard deviations, implying a long right tail distribution with corner solution. The dataset is an unbalanced panel because GDP per capita is only observable in 2008, 2010, 2013, 2014, and 2015.

Table 1. Descriptive statistics during 2008-2016

	Full dataset			Sub-sample dataset (within 10 km)		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Solar power capacity	81,000	0.43	1.67	4,653	0.58	1.27
Wind power capacity	81,000	0.29	2.55	4,653	0.35	3.40
Biomass power capacity	81,000	0.04	0.26	4,653	0.06	0.28
Solar power potential	80,946	125.19	4.33	4,653	125.56	3.92
Wind power potential	80,946	203.23	84.59	4,653	182.54	53.62
Agricultural land (biomass power potential)	78,291	1912.32	2008.71	4,581	2355.96	2239.65
Elevation	80,946	268.02	233.88	4,653	358.15	230.15

[3] The wind power density per swept area of turbine for (kW/m^2) is calculated as: $\frac{1}{2} * \text{air density} * c^3 * \Gamma\left(\frac{k+3}{k}\right) * \frac{1}{1000}$.

Slope	80,946	3.46	3.04	4,653	4.07	2.91
Population density	74,154	201.42	304.61	4,580	239.53	344.21
GDP per capita	40,386	16237.88	4760.59	2,543	17650.48	4106.89
Property tax rate	73,993	344.69	61.36	4,581	341.87	64.26

5. Results

Before estimating LATE, I conduct three falsification tests. First, I simply regress each pretreatment covariate as a placebo outcome on the treatment variable to find the bandwidth where pretreatment covariates balance within 30 km from each side of the boundary. In this way, I hope the statistically insignificant treatment effects will be estimated by narrowing the distance to the boundary.

Table 2 contains the result of the balance test. A robust standard error is in the bracket, and Conley's standard error robust to spatial correlation is in the parentheses (Conley, 1999). Conley's standard error tends to be larger than the robust standard error. Most covariates (all except agricultural land area and slope) become insignificant as the municipality's distance to the boundary approaches 10 km, indicating that covariate balancing improves as distance narrows. This suggests that the data sample within 10 km from the treatment assignment boundary are the most suitable for analysis, neutralizing the role of unobservable factors. As Keele and Titinuk (2015) note, it is known that narrowing distance does not necessarily remove all the imbalances of covariates. Note that I exclude all municipalities in Rhineland-Palatinate that are located mostly in the control area, to accomplish covariate balancing. Thus, municipalities located within 10 km from the boundary in five states are used for the following analysis.[4] Municipalities in the treatment area within 10 km from the boundary still have on average less agricultural land by 640 hectares and steeper land than the control area by about one degree. Although estimating the treatment effect on solar and wind power generation capacities is less likely to suffer from confounding covariates, the effect of ownership unbundling on biomass power capacity may be underestimated, since agricultural land should be positively correlated with biomass power plant installation.

Table 2. Balance test

Solar power potential (kW)	Wind power potential (kW)
30 km	30 km

[4] The online appendix reports the results of the main analysis including all municipalities in Rhineland-Palatinate and confirms that the results are virtually unchanged.

Treatment	Control	Std.Err.	Treatment	Control	Std.Err.
125.326	126.161	[0.22]***	177.459	188.054	[3.14]***
		(1.002)			(10.833)
20 km			20 km		
Treatment	Control	Std.Err.	Treatment	Control	Std.Err.
125.415	126.033	[0.26]**	177.28	188.27	[3.58]***
		(0.798)			(9.398)
10 km			10 km		
Treatment	Control	Std.Err.	Treatment	Control	Std.Err.
125.381	125.748	[0.35]	179.732	187.364	[4.83]
		(0.533)			(6.835)
Agricultural land (ha)			Elevation (m)		
30 km			30 km		
Treatment	Control	Std.Err.	Treatment	Control	Std.Err.
2107.124	2432.442	[116.49]***	332.15	384.591	[12.92]***
		(353.537)			(59.686)
20 km			20 km		
Treatment	Control	Std.Err.	Treatment	Control	Std.Err.
2070.789	2487.115	[139.53]***	335.334	380.168	[15.20]***
		(369.419)			(50.911)
10 km			10 km		
Treatment	Control	Std.Err.	Treatment	Control	Std.Err.
2065.594	2705.394	[202.22]***	345.421	370.158	[20.76]
		(354.555)			(32.337)
Slope (degree)			Population density		
30 km			30 km		
Treatment	Control	Std.Err.	Treatment	Control	Std.Err.
4.077	4.055	[0.17]	219.266	248.96	[17.12]***
		(0.547)			(52.111)
20 km			20 km		
Treatment	Control	Std.Err.	Treatment	Control	Std.Err.
4.101	3.749	[0.19]*	214.235	263.188	[20.56]**
		(0.468)			(52.779)
10 km			10 km		

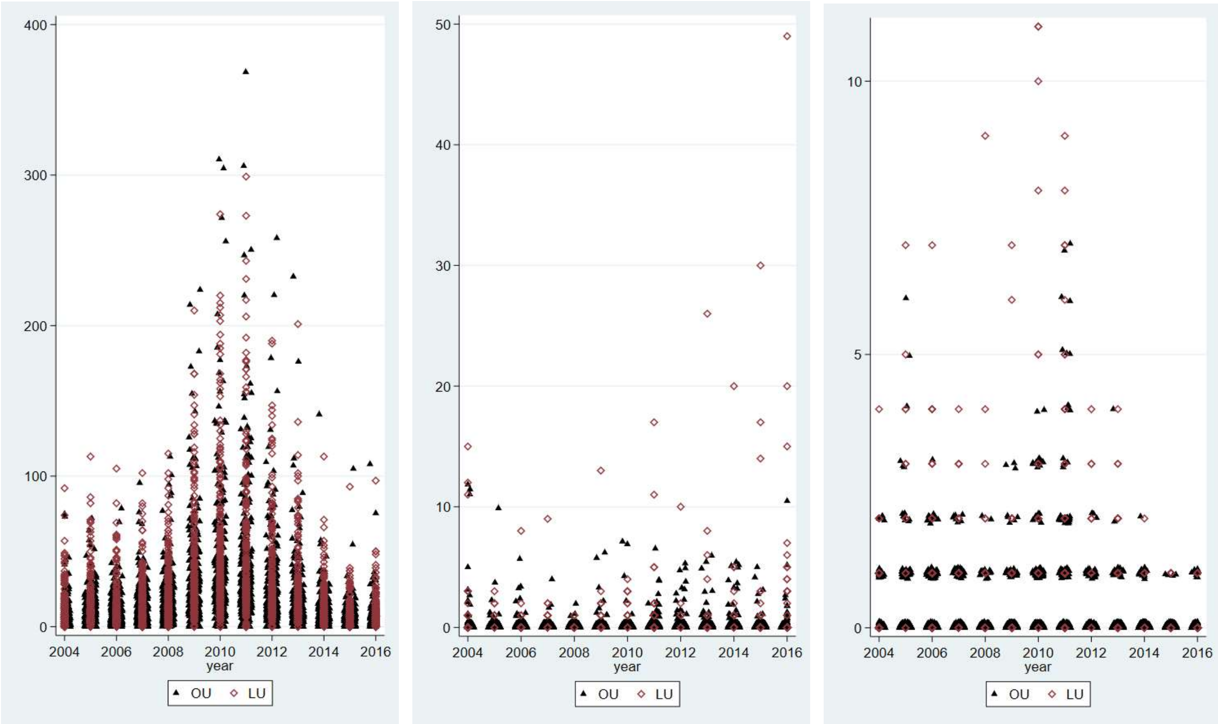
Treatment	Control	Std.Err.	Treatment	Control	Std.Err.
4.452	3.589	[0.26]***	220.693	260.716	[31.28]
		(0.438)			(58.404)
GDP per capita (euro)			Property tax rate (%)		
30 km			30 km		
Treatment	Control	Std.Err.	Treatment	Control	Std.Err.
15510.5	15549.53	[221.14]	321.636	332.234	[3.32]***
		(841.87)			(11.198)
20 km			20 km		
Treatment	Control	Std.Err.	Treatment	Control	Std.Err.
15319.96	15635.65	[240.80]	322.888	328.02	[4.02]
		(712.99)			(10.842)
10 km			10 km		
Treatment	Control	Std.Err.	Treatment	Control	Std.Err.
15347.24	15426.22	[330.22]	323.46	327.481	[5.35]
		(626.90)			(8.649)

Note: Outcomes are the municipality's covariates in 2008, except that 2007 is used for GDP per capita. The data samples used are reduced progressively from 30 km to 20 km and to 10 km from the boundary. Robust standard error is in brackets, and Conley's standard error is in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Second, Figure 6 plots the counts of installed renewable power plants per municipality in each area located within 10 km from the treatment boundary. This density test in the spirit of McCrary (2007) illustrates that there is no indication of significant sorting of the location in the treatment area after 2010.

Figure 6. Density test

Panel A. Solar power plant Panel B. Wind power plant Panel C. Biomass power plant



Notes: The plot shows the density of observations per municipality by treatment and control area located within 10 km from the treatment boundary. OU denotes the ownership-unbundled TenneT's operation area, and LU is the legally unbundled area operated by Amprion and TransnetBW.

Third, I perform the placebo test using the cross-sectional data for renewable electricity generation capacity installed in 2007 with covariates in 2008. I use the cubic polynomial of distance to the boundary as well as longitude and latitude. I expect insignificant estimates because the outcome in 2007 is not affected by the treatment, by definition. Table 3 shows that ownership unbundling has a statistically insignificant association with wind and biomass. The association with solar power plants is negative and significant at 10%. These results show no indication of the violation of the parallel pre-trend assumption and indicate that the announcement by E.ON of the TSO sale (E.ON Netz) in 2008 is not likely to induce expectation for renewable electricity developers.

Table 3. Placebo test on outcomes in 2007

Outcome	Solar		Wind		Biomass	
Cubic Polynomial	Distance	Lon/lat	Distance	Lon/lat	Distance	Lon/lat
T*Post	-0.119*	-0.123*	0.136	0.183	0.169	0.144
[Std.Err]	[0.06]	[0.07]	[0.23]	[0.23]	[0.12]	[0.14]

Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	0.037	0.028	0.05	0.049	-0.002	-0.011
Clusters	499	499	161	161	312	312
Observations	502	502	161	161	314	314

Note: Outcome is renewable electricity generation capacity installed (starting operation) in 2007. The data sample used covers the area within 10 km from the boundary. Distance to the treatment assignment boundary is specified as the cubic polynomial of distance to the boundary and longitude and latitude. Robust standard error clustered by the municipality is in brackets. Statistically significant coefficients are denoted by the following rule: * p<0.1, ** p<0.05, *** p<0.01. All estimates include state dummies.

Table 4 reports the local linear DID regression results. I repeat the estimation experimentally using the sample that contains the municipalities located within 30 km, 20 km, and 10 km from each side of the boundary. I cluster standard error at the municipality level. The result shows that the ownership unbundling by E.ON does not have a statistically or economically significant coefficient with any renewable electricity investment. The point estimates keep stable across all distances and specifications. A similar result is gained for the Tobit model in Table 5. The first three columns add the polynomial of the municipality's distance to the treatment assignment boundary, while the fourth to sixth columns use longitude and latitude as geographic location control variables. The results show that the Tobit model also estimates insignificant effects on renewables, regardless of the three bandwidths.

Table 4. Local linear DID regression estimates

Panel A. Outcome: Solar power capacity

Distance within	30 km	20 km	10 km
T*Post	0.006	0.003	0.007
[Std.Err]	[0.04]	[0.05]	[0.07]
Covariates	Yes	Yes	Yes
Adj-R^2	0.157	0.138	0.145
Clusters	1342	965	509
Observations	6703	4821	2543

Panel B. Outcome: Wind power capacity

Distance within	30 km	20 km	10 km
T*Post	-0.109	-0.099	-0.308
[Std.Err]	[0.10]	[0.12]	[0.21]

Covariates	Yes	Yes	Yes
Adj-R^2	0.003	0.004	0.004
Clusters	1342	965	509
Observations	6703	4821	2543

Panel C. Outcome: Biomass power capacity

Distance within	30km	20km	10km
T*Post	0.028	0.011	0.001
[Std.Err]	[0.02]	[0.02]	[0.03]
Covariates	Yes	Yes	Yes
Adj-R^2	0.034	0.043	0.056
Clusters	1342	965	509
Observations	6703	4821	2543

Note: Outcome is renewable electricity generation capacity installed (starting operation) per year. The data sample used is progressively reduced from 30 km to 20 km and to 10 km from the boundary. Robust standard error clustered by the municipality is in brackets. Statistically significant coefficients are denoted by the following rule: * p<0.1, ** p<0.05, *** p<0.01.

Table 5. Tobit random-effects model estimates

Panel A. Outcome: Solar power capacity

Outcome	Solar					
Cubic Polynomial	Distance to Boundary			Longitude and Latitude		
Distance within	30 km	20 km	10 km	30 km	20 km	10 km
T*Post	0.0089	0.0043	-0.0183	0.0090	0.0041	-0.0168
[Std.Err]	[0.04]	[0.05]	[0.07]	[0.04]	[0.05]	[0.07]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6703	4821	2543	6703	4821	2543

Panel B. Outcome: Wind power capacity

Outcome	Wind					
Cubic Polynomial	Distance to Boundary			Longitude and Latitude		
Distance within	30 km	20 km	10 km	30 km	20 km	10 km
T*Post	0.0060	-0.0463	-0.3046	-0.00003	-0.0513	-0.3061
[Std.Err]	[0.12]	[0.15]	[0.31]	[0.12]	[0.15]	[0.31]

Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6703	4821	2543	6703	4821	2543

Panel C. Outcome: Biomass power capacity

Outcome	Biomass					
Cubic Polynomial	Distance to Boundary			Longitude and Latitude		
Distance within	30km	20km	10km	30km	20km	10km
T*Post	0.0118	0.0035	0.0062	0.0130	0.0046	0.0066
[Std.Err]	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.02]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6703	4821	2543	6703	4821	2543

Note: Outcome is renewable electricity generation capacity installed (starting operation) per year. The data sample used is reduced progressively from 30 km to 20 km and to 10 km from the boundary. Columns 1–3 use the cubic polynomial of distance to the treatment assignment boundary and columns 4–6 use that of longitude and latitude. Average marginal effect is reported. Statistically significant coefficients are denoted by the following rule: * p<0.1, ** p<0.05, *** p<0.01. All estimates contain year dummies and time-invariant covariates such as solar potential, wind power potential, agricultural land, elevation, slope, and state dummies.

6. Robustness checks

I perform several robustness checks to confirm the sensitivity of the main estimation result. All robustness checks except the local linear DID model use cubic polynomial of the distance to the boundary. Appendix reports the estimation results using that of longitude and latitude. All robustness checks report the results for a 10 km buffer.

First, I restrict the data sample to 2008–2010 to avoid the possible contamination by sorting and the compound treatment of the generator divestiture by E.ON. If the selective sorting occurs in the treatment area, more renewable power plant should be installed latter periods rather than just after implementation. Table 6 reports that most coefficients are negative but insignificant and similar in magnitude to the estimation in the previous section.

Table 6. Robustness checks when data sample is 2008–2010

Outcome	Solar		Wind		Biomass	
Model	DID	Tobit	DID	Tobit	DID	Tobit

T*Post	-0.432*	-0.296**	-0.056	-0.108	-0.045	0.026
[Std.Err]	[0.24]	[0.14]	[0.12]	[0.11]	[0.05]	[0.04]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	0.157		0.012		0.048	
Clusters	509		509		509	
Observations	1018	1018	1018	1018	1018	1018

Note: Outcome is renewable electricity generation capacity installed (starting operation) per year. The data sample used covers within 10 km from the boundary. Distance to the treatment assignment boundary is specified as the cubic polynomials. Robust standard error is clustered by municipality in brackets for the local linear DID. Statistically significant coefficients are denoted by the following rule: * p<0.1, ** p<0.05, *** p<0.01. All Tobit random-effect estimates contain year dummies and time-invariant covariates such as solar potential, wind power potential, agricultural land, elevation, slope, and state dummies.

Second, I use the censored quintile regression (CQR). While both local linear DID regression and Tobit model estimate conditional mean E[Y|X], CQR suggested first by Powell (1986) estimates conditional τ-quintile $Q_\tau[Y_i|X_i]$, taking censoring[5] or corner solution into account. Unlike the Tobit model, the CQR allows the error term to be non-normal and heteroskedastic, and robust to outliers. Chernozhukov and Hong (2002) invents a three-step algorithm for Powell's CQR estimator. In the first step, a set of observations that are unlikely to be at a corner are preserved through the logit or probit estimation. In the second step, the standard quantile regression is conducted. Third, based on the estimated value of conditional quantiles of the outcome, a larger set of observations are preserved for another quantile regression.[6] For computational reason, I cannot analyze wind and biomass data, which have more than 90% zero observations. Since this method only allows cross-section data, I adapt the CCR to solar power capacity outcome in 2008, 2010, 2013, 2014, and 2015 and report the average corner marginal effect at median. Standard error is computed by the weighted bootstrap method, repeating 100 times. Table 7 shows that the average corner marginal effect of ownership unbundling at median of solar power capacity is mostly positive but is statistically and economically insignificant.

Table 7. Censored quintile regression estimates

Year	2008	2010	2013	2014	2015
T	0.0006	-0.0965	0.0277	0.0066	0.0013
[Std.Err]	[0.042]	[0.194]	[0.028]	[0.018]	[0.009]

[5] While censoring means some observations are not observed at certain values, however, corner solution outcomes are actually observable as zeroes.

[6] Refer to Chernozhukov et al. (2019, 2015) for details and implementation in Stata.

Covariates	Yes	Yes	Yes	Yes	Yes
Observations	517	517	517	517	517

Note: Outcome is solar power generation capacity installed (starting operation) per year. The data sample used covers within 10 km from the boundary. Distance to the treatment assignment boundary is specified as the cubic polynomials. Standard error is in brackets. Statistically significant coefficients are denoted by the following rule: * p<0.1, ** p<0.05, *** p<0.01. All estimates contain time-invariant covariates such as solar potential, elevation, slope, and state dummies. A logit model is used in the first stage.

Third, I conduct Poisson regression, transforming outcome variables into count data. The Poisson regression is also suited to analyze the corner solution outcome, because a nonnegative outcome is guaranteed by modeling the conditional mean function in exponential form: $\mathrm{E}[\mathrm{Y_{it}}|\mathrm{X_{it}}] = \alpha_i \exp(c + \beta_1 \mathrm{T_i} + \beta_2 \mathrm{Post_t} + \beta_3 \mathrm{T_i} \times \mathrm{Post_t} + \beta_4\, f(\mathrm{C_i}) + \beta_5 \mathrm{X'_{it}} + \mathrm{State_i} + \mathrm{Year_t} + \varepsilon_{it})$. Another advantage of the Poisson model is that the panel data unobserved- (fixed-) effects model is exceptionally tractable, unlike other nonlinear models such as the Tobit model. The fixed-effects Poisson estimator is consistent without assuming the distribution of Y_{it} given (x_i, c_i) and independence between Y_{it} and Y_{ir}, $t \neq r$ (Wooldridge, 2010). For these properties, this alternative model serves as an additional robust check to the main specifications. The outcome variable is transformed into the number of annual renewable power plants built in a municipality. Note that the fixed-effects model loses the observations for which the municipality has a zero outcome during all periods in the estimation. I present the result for both random- and fixed-effects models. Table 8 shows that both models have the similar scale of insignificant coefficients, indicating ownership unbundling does not increase the number of renewable power plant installation.

Table 8. Poisson regression estimates

Outcome	Solar		Wind		Biomass	
Model	RE	FE	RE	FE	RE	FE
T*Post	0.065	0.058	-1.222	-1.317	0.329	0.314
[Std.Err]	[0.05]	[0.05]	[0.93]	[0.93]	[0.42]	[0.43]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-9672.63	-6883.19	-689.22	-334.63	-787.27	-328.30
Clusters	509	497	509	76	509	158
Observations	2543	2485	2543	380	2543	790

Note: Outcome is the number of annual renewable power plants installed in a municipality. The data sample used covers within 10 km from the boundary. Distance to the treatment assignment boundary is specified as the cubic polynomials. Robust standard error is clustered by municipality in brackets. Statistically significant coefficients are denoted by the following rule: * p<0.1, ** p<0.05, *** p<0.01. All random-effects estimates contain year dummies and time-invariant covariates such as solar potential, wind power potential, agricultural land, elevation, slope, and state dummies.

Last, I explore a possible causal channel using the fact that most renewable power plants are connected to the distribution grid controlled by DSOs in Germany. As Figure 1 describes, there are some DSOs owned by the Big 4 as well as hundreds of independent DSOs in Germany. If ownership unbundling by E.ON induces investment in renewable electricity generating capacity, E.ON's subsidiary's DSOs should accept more connections from renewable power plants than other DSOs after 2010. This last robustness check adds a DSO fraction variable and the interaction term to the model to test this hypothesis:

$$Y_{it}=c+\beta_1 T_i+\beta_2 \mathrm{Post}_t+\beta_3 T_i \times \mathrm{Post}_t+\beta_4 \mathrm{DSO}_i^{\mathrm{eon}}+\beta_5 T_i \times \mathrm{Post}_t \times \mathrm{DSO}_i^{\mathrm{eon}}+\beta_6 f(C_i)+\beta_7 X'_{it}+\alpha_i+\mathrm{State}_i+\mathrm{Year}_t+\varepsilon_{it.}$$

where β_5 is the parameter of interest, and $\mathrm{DSO}^{\mathrm{eon}}$ is a fraction of renewable electricity generation capacity connected to the DSO that E.ON owns as a subsidiary, and take value between one to zero. Tables 9 and 10 show that the coefficient of the interaction term implies that the effect of ownership unbundling is not positive and significant; this indicates that the ownership unbundling does not increase the new renewable power plant connections to DSOs owned by E.ON. This result does not change across any specifications or when I redefine the DSO variable as the subsidiary of subsidiary of E.ON. These robustness checks further reinforce the reliability of the estimation results in the previous section.

Table 9. Robustness checks: Interaction with DSO share variable

Panel A. Outcome: Solar power capacity

Model	DID	Tobit RE	Poisson RE	Poisson FE
T*Post	0.035	0.037	0.051	0.035
[Std.Err]	[0.08]	[0.09]	[0.06]	[0.06]
$\mathrm{DSO}^{\mathrm{eon}}$	0.02	0.084	0.117	0.095
[Std.Err]	[0.11]	[0.09]	[0.10]	[0.11]
T*Post* $\mathrm{DSO}^{\mathrm{eon}}$	-0.072	-0.13	0.051	0.073
[Std.Err]	[0.07]	[0.10]	[0.07]	[0.07]
Covariates	Yes	Yes	Yes	Yes
Adj-R^2/Log likelihood	0.145		-9661.52	-6872.58
Clusters	509		509	497
Observations	2543	2543	2543	2485

Panel B. Outcome: Wind power capacity

Model	DID	Tobit RE	Poisson RE	Poisson FE
T*Post	-0.349**	-0.206	-1.613*	-1.717**
[Std.Err]	[0.18]	[0.34]	[0.89]	[0.86]
DSO^{eon}	1.233	0.496*	0.034	-0.212
[Std.Err]	[1.94]	[0.29]	[0.93]	[0.82]
T*Post* DSO^{eon}	0.445	-0.124	1.349	1.126
[Std.Err]	[0.41]	[0.30]	[1.19]	[1.49]
Covariates	Yes	Yes	Yes	Yes
Adj-R^2/Log likelihood	0.005		-682.494	-332.68
Clusters	509		509	76
Observations	2543	2543	2543	380

Panel C. Outcome: Biomass power capacity

Model	DID	Tobit RE	Poisson RE	Poisson FE
T*Post	0.007	0.006	0.259	0.321
[Std.Err]	[0.03]	[0.02]	[0.44]	[0.47]
DSO^{eon}	0.0001	0.026	0.412	-0.828
[Std.Err]	[0.05]	[0.02]	[0.38]	[1.29]
T*Post* DSO^{eon}	-0.03	0.003	0.263	-0.04
[Std.Err]	[0.05]	[0.02]	[0.43]	[0.54]
Covariates	Yes	Yes	Yes	Yes
Adj-R^2/Log likelihood	0.056		-783.944	-327.776
Clusters	509		509	158
Observations	2543	2543	2543	790

Note: The data sample used covers within 10 km from the boundary. Distance to the treatment assignment boundary is specified as the cubic polynomials. Average marginal effect is reported for the Tobit model. Robust standard error is clustered by municipality in brackets. Statistically significant coefficients are denoted by the following rule: * p<0.1, ** p<0.05, *** p<0.01. All random-effects estimates contain year dummies and time-invariant covariates such as solar potential, wind power potential, agricultural land, elevation, slope, and state dummies.

Table 10. Censored quintile regression estimates

year	2008	2010	2013	2014	2015
T*Post * DSO^{eon}	-0.665	-2.242**	-0.216	-0.956***	-0.134
[Std.Err]	[1.817]	[1.131]	[0.216]	[0.294]	[0.605]

Covariates	Yes	Yes	Yes	Yes	Yes
Observations	517	517	517	517	517

Note: Outcome is solar power generation capacity installed (start operation) per year. The data sample used covers within 10 km from the boundary. Distance to the treatment assignment boundary is specified as the cubic polynomials. Standard error is in brackets. Statistically significant coefficients are denoted by the following rule: * p<0.1, ** p<0.05, *** p<0.01. All estimates contain time-invariant covariates such as solar potential, wind power potential, agricultural land, elevation, slope, and state dummies. A logit model is used in the first stage.

7. Discussion

Table 11 summarizes the estimated causal effect on renewable electricity investment with 95 percent confidence interval (CI). Almost all point estimates imply small, economically and statistically insignificant effects. The point estimates tell us that the ownership unbundling by E.ON caused a change in solar power capacity from 0.007 to -0.018 MW per municipality-year. The upper end of CI shows that I can rule out an effect over 0.13 MW. Similarly, the upper bound of CI rules out a causal effect of more than a 0.31 MW increase of wind power capacity and a 0.05 MW increase of biomass power capacity, respectively. These estimates are very small, compared to the fact that more than 22,800 MW of solar power capacity, 15,000 MW of onshore wind power capacity, and 1,700 MW of biomass power capacity were installed in Germany during 2010–2016 (Clean Energy Wire, 2019).

Table 11. Causal effect on renewable electricity investment

Outcome	Solar		Wind		Biomass	
Model	DID	Tobit	DID	Tobit	DID	Tobit
Point estimate	0.007	-0.018	-0.308	-0.305	0.001	0.007
Upper end of 95% CI	0.14	0.13	0.1	0.31	0.05	0.04

Note: Estimates are obtained based on the results from Tables 5 and 6.

This result is consistent with Höffler and Kranz (2011), who demonstrates that legal unbundling with regulation for a network company can work as perfectly as ownership unbundling in separating the interests of the network company from the rest of the integrated group. Moreover, they show that even if legal unbundling itself cannot make TSOs act independently, behavior regulations can complement legal unbundling to focus only on its own profit, without caring about the profit of downstream firms.

From this perspective, the Renewable Energy Act amendment in 2000 is the first important federal law for renewable electricity investment by independent generation firms. It requires the TSO to interconnect and dispatch the renewable electricity with priority. Second, the Federal Network Agency in 2005 started to supervise over the electricity network company, to foster competition and ensure fair and non-discriminatory access. Third, a special regulation exists for the grid connection of biomass power plants: Section 33 of the Gas Network Access Ordinance set grid connection requirements and a procedure for connecting biogas plants in April 2008. Last and probably most important, the Energy Industry Act (Section 10) transposed the 3rd European Directive regarding the ITO model into the federal regulation regime in August 2011. This federal law effectively functioned to strengthen regulation of legally unbundled TSOs. The estimates in this paper provide evidence that these regulations on TSOs together with legal unbundling effectively made TSOs independent and removed any room for incumbents to prevent potential competitors from investing in renewable electricity generation.

8. Conclusion

This study investigated the causal effect of ownership unbundling of TSOs on renewable electricity investment in Germany. Using a GQE approach, I found that neither solar power, wind power, nor biomass power capacity significantly increased due to ownership unbundling. Several robustness checks confirmed the results. They are surprising, because the treatment was potentially confounded by divestitures of large-scale non-renewable generation power plants owned by E.ON. Both E.ON's power plant sales and transmission network unbundling are expected to increase competition in the generation market, thereby reducing conflict of interest for the vertically integrated utility. While Duso et al. (2020) estimate that divestitures by E.ON significantly decreased the wholesale price in the peak period, this paper found that these competition increasing measures did not decrease but hardly increased renewable electricity investment.

This evidence suggests that the electricity generation market in Germany is competitive even without ownership unbundling. In other words, legal unbundling with tougher regulations as implemented in Amprion's and TransnetBW's areas can perform as effective in creating a level playing field as ownership unbundling implemented by E.ON. Although some people believe ownership unbundling is necessary to accelerate renewable electricity investment, this study supports the opposite view, in line with the analysis of industrial organization theory by Höffler and Kranz (2011) in that legal unbundling with regulation works well for transmission network companies to remove sabotage incentives. With various regulations on vertically integrated utility and TSOs in the federal legislation, it is possible for independent renewable electricity developers to enter the generation market and invest in renewable electricity.

This study has an encouraging implication for energy policymakers in other countries, because politically difficult ownership unbundling of the privately owned incumbent's power network asset is not necessarily required to achieve renewable electricity investment; rather, the government can encourage renewable electricity investment with national-level regulations for a vertically integrated utility with relatively cheap costs.

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References

Barrett, E., 2016. A case of: who will tell the emperor he has no clothes?—market liberalization, regulatory capture and the need for further improved electricity market unbundling through a fourth energy package. J. World Energy Law Bus. 9, 1–16. https://doi.org/10.1093/jwelb/jwv039

Bauwens, T., Gotchev, B., Holstenkamp, L., 2016. What drives the development of community energy in Europe? the case of wind power cooperatives. Energy Res. Soc. Sci. 13, 136–147. https://doi.org/10.1016/j.erss.2015.12.016

Brunekreeft, G., 2015. Network unbundling and flawed coordination: Experience from the electricity sector. Util. Policy 34, 11–18. https://doi.org/10.1016/j.jup.2015.03.003

Brunekreeft, G., 2008. Ownership Unbundling in Electricity Markets – A Social Cost Benefit Analysis of the German TSOs. Work. Pap.

Brunekreeft, G., Buchmann, M., Meyer, R., 2016. The Rise of Third Parties and the Fall of Incumbents Driven by Large-Scale Integration of Renewable Energies: The Case of Germany. Energy J. 37. https://doi.org/10.5547/01956574.37.SI2.gbru

Brunekreeft, G., Goto, M., Meyer, R., Maruyama, M., Hattori, T., 2014. Unbundling of electricity transmission system operators in Germany: An experience report, Bremen Energy Working Papers.

Chawla, M., Pollitt, M.G., 2013. Global Trends in Electricity Transmission System Operation: Where Does the Future Lie? Electr. J. 26, 65–71. https://doi.org/10.1016/J.TEJ.2013.05.004

Chernozhukov, V., Fernández-Val, I., Han, S., Kowalski, A., 2019. Censored quantile instrumental-variable estimation with Stata. Stata J. 19, 768–781. https://doi.org/10.1177/1536867X19893615

Chernozhukov, V., Fernández-Val, I., Kowalski, A.E., 2015. Quantile regression with censoring and endogeneity. J. Econom. 186, 201–221. https://doi.org/10.1016/j.jeconom.2014.06.017

Chernozhukov, V., Hong, H., 2002. Three-step censored quantile regression and extramarital affairs. J. Am. Stat. Assoc. 97, 872–882. https://doi.org/10.1198/016214502388618663

Conley, T.G., 1999. GMM estimation with cross sectional dependence. J. Econom. 92, 1–45. https://doi.org/10.1016/S0304-4076(98)00084-0

Dell, M., 2010. The Persistent Effects of Peru's Mining Mita. Econometrica 78, 1863–1903. https://doi.org/10.3982/ecta8121

Dharshing, S., 2017. Household dynamics of technology adoption: A spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany. Energy Res. Soc. Sci. 23, 113–124. https://doi.org/10.1016/J.ERSS.2016.10.012

Duso, T., Szücs, F., Böckers, V., 2020. Abuse of dominance and antitrust enforcement in the German electricity market. Energy Econ. 92, 104936. https://doi.org/10.1016/j.eneco.2020.104936

Economides, N., 1998. The incentive for non-price discrimination by an input monopolist. Int. J. Ind. Organ. 16, 271–284. https://doi.org/10.1016/S0167-7187(98)00005-8

Eikeland, P.O., 2011. The Third Internal Energy Market Package: New Power Relations among Member States, EU Institutions and Non-state Actors? JCMS J. Common Mark. Stud. 49, 243–263. https://doi.org/10.1111/j.1468-5965.2010.02140.x

Fiorio, C. V., Florio, M., 2013. Electricity prices and public ownership: Evidence from the EU15 over thirty years. Energy Econ. 39, 222–232. https://doi.org/10.1016/j.eneco.2013.05.005

Fleiß, E., Hatzl, S., Seebauer, S., Posch, A., 2017. Money, not morale: The impact of desires and beliefs on private investment in photovoltaic citizen participation initiatives. J. Clean. Prod. 141, 920–927. https://doi.org/10.1016/j.jclepro.2016.09.123

Goetzke, F., Rave, T., 2016. Exploring heterogeneous growth of wind energy across Germany. Util. Policy 41, 193–205. https://doi.org/10.1016/J.JUP.2016.02.010

Gugler, K., Liebensteiner, M., Schmitt, S., 2017. Vertical disintegration in the European electricity sector: Empirical evidence on lost synergies. Int. J. Ind. Organ. 52, 450–478. https://doi.org/10.1016/J.IJINDORG.2017.04.002

Gugler, K., Rammerstorfer, M., Schmitt, S., 2013. Ownership unbundling and investment in electricity markets — A cross country study. Energy Econ. 40, 702–713. https://doi.org/10.1016/j.eneco.2013.08.022

Haas, R., Panzer, C., Resch, G., Ragwitz, M., Reece, G., Held, A., 2011. A historical review of promotion strategies for electricity from renewable energy sources in EU countries. Renew. Sustain. Energy Rev. 15, 1003–1034. https://doi.org/10.1016/J.RSER.2010.11.015

Heim, S., Krieger, B., Liebensteiner, M., 2018. Unbundling, regulation and pricing: Evidence from electricity distribution. ZEW Discuss. Pap. No. 18-050.

Herrera Anchustegui, I., 2018. Transmission Networks in Electricity Competition: Third-Party Access and

Unbundling – A Transatlantic Perspective, in: Ruiz Peris, J.I. (Ed.), Competencia En Mercados Con Recursos Esenciales Compartidos: Telecomunicaciones y Energía. University of Valencia.

Hitaj, C., 2013. Wind power development in the United States. J. Environ. Econ. Manage. 65, 394–410. https://doi.org/10.1016/j.jeem.2012.10.003

Hitaj, C., Löschel, A., 2019. The impact of a feed-in tariff on wind power development in Germany. Resour. Energy Econ. 57, 18–35. https://doi.org/10.1016/j.reseneeco.2018.12.001

Höffler, F., Kranz, S., 2011. Legal unbundling can be a golden mean between vertical integration and ownership separation. Int. J. Ind. Organ. 29, 576–588. https://doi.org/10.1016/J.IJINDORG.2011.01.001

Hu, J., Harmsen, R., Crijns-Graus, W., Worrell, E., 2018a. Barriers to investment in utility-scale variable renewable electricity (VRE) generation projects. Renew. Energy. https://doi.org/10.1016/j.renene.2018.01.092

Hu, J., Harmsen, R., Crijns-Graus, W., Worrell, E., van den Broek, M., 2018b. Identifying barriers to large-scale integration of variable renewable electricity into the electricity market: A literature review of market design. Renew. Sustain. Energy Rev. https://doi.org/10.1016/j.rser.2017.06.028

Jacobsson, S., Bergek, A., 2004. Transforming the energy sector: the evolution of technological systems in renewable energy technology. Ind. Corp. Chang. 13, 815–849. https://doi.org/10.1093/icc/dth032

Joskow, P.L., 1997. Restructuring, Competition and Regulatory Reform in the U.S. Electricity Sector. J. Econ. Perspect. 11, 119–138. https://doi.org/10.1257/jep.11.3.119

Keele, L., Lorch, S., Passarella, M., Small, D., Titiunik, R., 2017. An overview of geographically discontinuous treatment assignments with an application to children’s health insurance. Adv. Econom. https://doi.org/10.1108/S0731-905320170000038007

Keele, L., Titiunik, R., 2016. Natural Experiments Based on Geography. Polit. Sci. Res. Methods 4, 65–95. https://doi.org/10.1017/psrm.2015.4

Keele, L., Titiunik, R., 2015. Geographic Boundaries as Regression Discontinuities. Polit. Anal. 23, 127–155. https://doi.org/10.1093/pan/mpu014

Krohn, S., Morthorst, P.-E., Awerbuch, S., 2009. The Economics of Wind Energy. Belgium: European Wind Energy Association.

Lauf, T., Ek, K., Gawel, E., Lehmann, P., Söderholm, P., 2019. The regional heterogeneity of wind power deployment: an empirical investigation of land-use policies in Germany and Sweden. J. Environ. Plan. Manag. 1–28. https://doi.org/10.1080/09640568.2019.1613221

Lee, D.S., Lemieux, T., 2010. Regression Discontinuity designs in economics. J. Econ. Lit. 48, 281–355. https://doi.org/10.1257/jel.48.2.281

McCrary, J., 2007. Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test. National Bureau of Economic Research, Cambridge, MA. https://doi.org/10.3386/t0334

Meyer, R., 2012a. Vertical Economies and the Costs of Separating Electricity Supply—A Review of Theoretical and Empirical Literature. Energy J. https://doi.org/10.2307/23268109

Meyer, R., 2012b. Economies of scope in electricity supply and the costs of vertical separation for different unbundling scenarios. J. Regul. Econ. 42, 95–114. https://doi.org/10.1007/s11149-011-9166-z

Nagayama, H., 2009. Electric power sector reform liberalization models and electric power prices in developing countries: An empirical analysis using international panel data. Energy Econ. 31, 463–472. https://doi.org/10.1016/J.ENECO.2008.12.004

Nagayama, H., 2007. Effects of regulatory reforms in the electricity supply industry on electricity prices in developing countries. Energy Policy 35, 3440–3462. https://doi.org/10.1016/J.ENPOL.2006.12.018

Neuhoff, K., 2005. Large-Scale Deployment of Renewables for Electricity Generation. Oxford Rev. Econ. Policy 21, 88–110. https://doi.org/10.1093/oxrep/gri005

Newbery, D., Pollitt, M.G., Ritz, R.A., Strielkowski, W., 2018. Market design for a high-renewables European electricity system. Renew. Sustain. Energy Rev. 91, 695–707. https://doi.org/10.1016/J.RSER.2018.04.025

Neyman, J., Scott, E.L., 1948. Consistent Estimates Based on Partially Consistent Observations. Econometrica 16, 1. https://doi.org/10.2307/1914288

Nikogosian, V., Veith, T., 2012. The impact of ownership on price-setting in retail-energy markets-The German case. Energy Policy 41, 161–172. https://doi.org/10.1016/j.enpol.2011.10.028

Ohlhorst, D., 2015. Germany’s energy transition policy between national targets and decentralized responsibilities. J. Integr. Environ. Sci. 12, 303–322. https://doi.org/10.1080/1943815X.2015.1125373

Owen, A.D., 2006. Renewable energy: Externality costs as market barriers. Energy Policy 34, 632–642. https://doi.org/10.1016/J.ENPOL.2005.11.017

Pishgar-Komleh, S.H., Keyhani, A., Sefeedpari, P., 2015. Wind speed and power density analysis based on Weibull and Rayleigh distributions (a case study: Firouzkooh county of Iran). Renew. Sustain. Energy Rev. https://doi.org/10.1016/j.rser.2014.10.028

Pollitt, M., 2008. The arguments for and against ownership unbundling of energy transmission networks. Energy Policy 36, 704–713. https://doi.org/10.1016/j.enpol.2007.10.011

Powell, J.L., 1986. Censored regression quantiles. J. Econom. 32, 143–155. https://doi.org/10.1016/0304-4076(86)90016-3

Schaffer, A.J., Brun, S., 2015. Beyond the sun—Socioeconomic drivers of the adoption of small-scale photovoltaic installations in Germany. Energy Res. Soc. Sci. 10, 220–227. https://doi.org/10.1016/j.erss.2015.06.010

Sovacool, B.K., 2009. Rejecting renewables: The socio-technical impediments to renewable electricity in the United States. Energy Policy 37, 4500–4513. https://doi.org/10.1016/J.ENPOL.2009.05.073

Sovacool, B.K., Schmid, P., Stirling, A., Walter, G., MacKerron, G., 2020. Differences in carbon emissions reduction between countries pursuing renewable electricity versus nuclear power. Nat. Energy 1–8. https://doi.org/10.1038/s41560-020-00696-3

Sugimoto, K., 2019. Does transmission unbundling increase wind power generation in the United States? Energy Policy 125, 307–316. https://doi.org/10.1016/J.ENPOL.2018.10.032

Tobin, J., 1958. Estimation of Relationships for Limited Dependent Variables, Econometrica.

Toke, D., Breukers, S., Wolsink, M., 2008. Wind power deployment outcomes: How can we account for the differences? Renew. Sustain. Energy Rev. https://doi.org/10.1016/j.rser.2006.10.021

Van Koten, S., Ortmann, A., 2008. The unbundling regime for electricity utilities in the EU: A case of legislative and regulatory capture? Energy Econ. 30, 3128–3140. https://doi.org/10.1016/J.ENECO.2008.07.002

Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data, 2nd edition. The MIT press.

Web References

BMWi, 2018. Development of renewables-based electricity generation in Germany (URL: https://www.bmwi.de/Redaktion/EN/Infografiken/development-of-renewables-based-electricity-generation-in-germany.html, accessed at 23/08/2020)

BMWi, 2020. Renewable Energy Sources Act (EEG 2017). (URL:https://www.bmwi.de/Redaktion/EN/Downloads/renewable-energy-sources-act-2017.pdf?__blob=publicationFile&v=3, accessed at 23/08/2020)

Clean Energy Wire, 2019. 20 years on: German renewables pioneers face end of guaranteed payment. (URL:https://www.cleanenergywire.org/factsheets/20-years-german-renewables-pioneers-face-end-guaranteed-payment, accessed at 12/11/2020)

Council of European Energy Regulators, 2016. Status Review on the Implementation of Transmission System Operators' Unbundling Provisions of the 3rd Energy Package, CEER Status Review, Ref: C15-LTF-43-04 (URL: https://www.ceer.eu/documents/104400/-/-/8f18879a-411e-2fd8-c367-1fa66e3739ed, accessed at 23/08/2020)

Deutsche Welle 2008a. EON Gives In to EU Pressure, Sells Power Network. (URL: https://www.dw.com/en/eon-gives-in-to-eu-pressure-sells-power-network/a-3157517, accessed at 23/08/2020)

Deutsche Welle 2008b. EU Agrees to Germany's Electricity Unbundling Proposal. (URL: https://www.dw.com/en/eu-agrees-to-germanys-electricity-unbundling-proposal/a-3365672 accessed at 23/08/2020)

European Commission, 2007. DG COMPETITION REPORT ON ENERGY SECTOR INQUIRY (SEC(2006)1724, 10 January 2007) (URL: https://ec.europa.eu/competition/sectors/energy/2005_inquiry/index_en.html, accessed at

23/08/2020)
European Commission, 2008. Summary of Commission Decision of 26 November 2008 relating to a proceeding under Article 82 of the EC Treaty and Article 54 of the EEA Agreement (Cases COMP/39.388 — German Electricity Wholesale Market and COMP/39.389 — German Electricity Balancing Market) (notified under document number C(2008) 7367 final) (URL: https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:C:2009:036:0008:0008:EN:PDF, accessed at 23/08/2020)
European Commission, 2010. Commission Staff Working Paper Interpretative Note on Directive 2009/72/EC concerning common rules for the internal market in electricity and directive 2009/73/ ec concerning common rules for the internal market in natural gas the unbundling regime(URL: https://ec.europa.eu/energy/sites/ener/files/documents/2010_01_21_the_unbundling_regime.pdf, accessed at 23/08/2020)
European Commission, 2014. COMMISSION STAFF WORKING DOCUMENT Report on the ITO Model Accompanying the document COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS Progress towards completing the Internal Energy Market (URL: https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=SWD:2014:0312:FIN:EN:PDF, accessed at 23/08/2020)
European Commission, 2020. Solar radiation data, Climate Monitoring Satellite Application Facility. (URL: https://ec.europa.eu/jrc/en/PVGIS/downloads/CMSAF, accessed at 23/08/2020)
Krohn, S., Morthorst, P.-E., Awerbuch, S., 2009. The Economics of Wind Energy. Belgium: European Wind Energy Association. (URL: http://www.ewea.org/fileadmin/files/library/publications/reports/Economics_of_Wind_Energy.pdf, accessed at 01/12/2020)
RAP (2015): Report on the German power system. Version 1.2 Study commissioned by Agora Energiewende.(URL: https://www.agora-energiewende.de/fileadmin2/Projekte/2014/CP-Deutschland/CP_Germany_update_1015_web.pdf, accessed at 01/12/2020)

Data References

[Dataset] Federal Statistical Office, 2020. Regional database. Code: 12411-01-01-5 (population), 33111 (agricultural land), 71231-01-02-5 (property tax rate), 73111-01-01-5 (income). (URL: https://www.regionalstatistik.de/genesis/online, accessed at 23/08/2020)
[Dataset] GADM, 2018. Download GADM data (version 3.6). (URL: https://gadm.org/download_country_v3.html, accessed at 02/12/2020)

[Dataset] German Meteorological Service, 2020. weibull_cdat_geo_80m_BRD_200m.asc.zip and weibull_kdat_geo_80m_BRD_200m.asc.zip. (URL:https://opendata.dwd.de/climate_environment/CDC/grids_germany/multi_annual/wind_parameters/resol_200x200/, accessed at 23/11/2020)

[Dataset] Netztransparenz.de, 2019. EEG-Anlagenstammdaten. Netztransparenz Anlagenstammdaten 2017 50Hertz Transmission GmbH, Netztransparenz Anlagenstammdaten 2017 Amprion GmbH_V03, Netztransparenz Anlagenstammdaten 2017 TenneT TSO GmbH, Netztransparenz Anlagenstammdaten 2017 TransnetBW GmbH. (URL: https://www.netztransparenz.de/EEG/Anlagenstammdaten, accessed at 15/03/2019)

[Dataset] OpenDEMData.info, 2020. SRTM Digital Terrain Model of Germany. (URL: https://www.opendem.info/download_srtm.html, , accessed at 23/08/2020)

Appendix

Table A. Local linear DID regression estimates including Rhineland-Palatinate (Table 4')

Panel A. Outcome: Solar power capacity

Distance within	30km	20km	10km
T*Post	0.063**	0.044	0.026
[Std.Err]	[0.03]	[0.04]	[0.06]
Covariates	Yes	Yes	Yes
Adj-R-squared	0.134	0.126	0.139
Clusters	1588	1075	534
Observations	7933	5371	2668

Panel B. Outcome: Wind power capacity

Distance within	30km	20km	10km
T*Post	-0.058	-0.038	-0.256
[Std.Err]	[0.08]	[0.09]	[0.19]
Covariates	Yes	Yes	Yes
Adj-R-squared	0.003	0.004	0.004
Clusters	1588	1075	534
Observations	7933	5371	2668

Panel C. Outcome: Biomass power capacity

Distance within	30km	20km	10km

T*Post	0.025	0.012	0.002
[Std.Err]	[0.02]	[0.02]	[0.02]
Covariates	Yes	Yes	Yes
Adj-R-squared	0.029	0.04	0.054
Clusters	1588	1075	534
Observations	7933	5371	2668

Note: Outcome is renewable electricity generation capacity installed (start operation) per year. The data sample includes municipalities from 30 km, 20 km, to 10 km from the border including Rhineland-Palatinate. Robust standard error clustered by the municipality in bracket. Statistically significant coefficients are denoted as the following rule: * p<0.1, ** p<0.05, *** p<0.01.

Table B. Tobit random effect model estimates including Rhineland-Palatinate (Table 5')

Panel A. Outcome: Solar power capacity

Outcome	Solar					
Cubic Polynomial	Distance to Boundary			Longitude and Latitude		
Distance within	30km	20km	10km	30km	20km	10km
T*Post	0.039	0.030	0.010	0.039	0.030	0.011
[Std.Err]	[0.03]	[0.05]	[0.07]	[0.03]	[0.05]	[0.07]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7933	5371	2668	7933	5371	2668

Panel B. Outcome: Wind power capacity

Outcome	Wind					
Cubic Polynomial	Distance to Boundary			Longitude and Latitude		
Distance within	30km	20km	10km	30km	20km	10km
T*Post	-	-0.049	-0.296	-	-0.053	-0.297
[Std.Err]	-	[0.14]	[0.30]	-	[0.14]	[0.30]
Covariates		Yes	Yes		Yes	Yes
Observations		5371	2668		5371	2668

Panel C. Outcome: Biomass power capacity

Outcome	Biomass	
Cubic Polynomial	Distance to Boundary	Longitude and Latitude

Distance within	30km	20km	10km	30km	20km	10km
T*Post	0.012	0.004	0.006	0.012	0.005	0.006
[Std.Err]	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.02]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7933	5371	2668	7933	5371	2668

Note: Outcome is renewable electricity generation capacity installed (start operation) per year. The data sample includes municipalities from 30 km, 20 km, to 10 km from the border including Rhineland-Palatinate. Note that the maximum likelihood estimator for wind power capacity does not converge using sample within 30 km from the boundary so the result is not shown. Column 1-3 use cubic polynomial of distance to the treatment assignment boundary and column 4-6 use that of longitude and latitude. Average marginal effect is reported. Statistically significant coefficients are denoted as the following rule: * p<0.1, ** p<0.05, *** p<0.01. All estimates contain year dummies and time invariant covariates such as solar potential, wind power potential, agricultural land, elevation, slope, and state dummies.

Table C. Tobit random effect model estimates using quadratic and quartic of polynomial to the boundary (Table 5'')

	Solar		Wind		Biomass	
Distance to Boundary	Quadratic	Quartic	Quadratic	Quartic	Quadratic	Quartic
T*Post	-0.0185	-0.0184	-0.3047	-0.3106	0.0062	0.0067
[Std.Err]	[0.07]	[0.07]	[0.31]	[0.31]	[0.02]	[0.02]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2543	2543	2543	2543	2543	2543

Note: Outcome is renewable electricity generation capacity installed (start operation) per year. Odd-numbered columns report quadratic polynomial of distance to the treatment assignment boundary and even-numbered columns report the quartic polynomial. The data sample includes municipalities 10 km from the border. Average marginal effect is reported. Statistically significant coefficients are denoted as the following rule: * p<0.1, ** p<0.05, *** p<0.01. All estimates contain year dummies and time invariant covariates such as solar potential, wind power potential, agricultural land, elevation, slope, and state dummies.

Table D. Robustness checks when data sample is 2008-2010 with longitude and latitude (Table 6')

	Solar	Wind	Biomass
Model	Tobit	Tobit	Tobit
T*Post	-0.295**	-0.098	0.024
[Std.Err]	[0.14]	[0.11]	[0.04]

Covariates	Yes	Yes	Yes
Observations	1018	1018	1018

Note: Outcome is renewable electricity generation capacity installed (start operation) per year. The data sample used are within 10 km from the border. Cubic polynomial of longitude and latitude are used. Robust standard error clustered by the municipality in bracket for the local linear DID. Statistically significant coefficients are denoted as the following rule: * p<0.1, ** p<0.05, *** p<0.01. All Tobit random effect estimates contain year dummies and time invariant covariates such as solar potential, wind power potential, agricultural land, elevation, slope, and state dummies.

Table E. Censored quintile regression estimates with longitude and latitude (Table 7')

year	2010	2013	2014	2015
T	-0.131	-0.001	0.008	-0.004
[Std.Err]	[0.240]	[0.040]	[0.020]	[0.011]
Covariates	Yes	Yes	Yes	Yes
Observations	517	517	517	517

Note: Outcome is solar power generation capacity installed (start operation) per year. The data sample used are within 10 km from the border. Cubic polynomial of longitude and latitude are used. Standard error is in bracket. Statistically significant coefficients are denoted as the following rule: * p<0.1, ** p<0.05, *** p<0.01. All estimates contain time invariant covariates such as solar potential, elevation, slope, and state dummies. Logit model is used in the first stage.

Table F. Poisson regression estimates with longitude and latitude (Table 8')

	Solar	Wind	Biomass
model	RE	RE	RE
T*Post	0.066	-1.237	0.328
[Std.Err]	[0.05]	[0.93]	[0.43]
Covariates	Yes	Yes	Yes
Log likelihood	-9649.94	-675.687	-772.89
Clusters	509	509	509
Observations	2543	2543	2543

Note: Outcome is the number of annual renewable electricity generation capacity installed in a municipality. The data sample used are within 10 km from the border. Cubic polynomial of longitude and latitude are used. Robust standard error clustered by the municipality in bracket. Statistically significant coefficients are denoted as the following rule: * p<0.1, ** p<0.05, *** p<0.01. All random effect estimates contain year dummies and time invariant covariates such as solar potential, wind power potential, agricultural land, elevation, slope, and state dummies.

Table G. Robustness checks: interaction with DSO and longitude and latitude (Table9')

	Solar		Wind		Biomass	
Model	Tobit RE	Poisson RE	Tobit RE	Poisson RE	Tobit RE	Poisson RE
T*Post	0.029	0.05	-0.087	-1.674*	0.005	0.293
[Std.Err]	[0.09]	[0.06]	[0.36]	[0.87]	[0.02]	[0.44]
DSO^{eon}	0.049	0.109	0.880***	0.017	0.034*	0.396
[Std.Err]	[0.09]	[0.10]	[0.33]	[0.98]	[0.02]	[0.43]
T*Post* DSO^{eon}	-0.11	0.054	-0.302	1.516	0.008	0.146
[Std.Err]	[0.10]	[0.07]	[0.33]	[1.25]	[0.02]	[0.41]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood		-9639.43		-661.95		-770.718
Clusters		509		509		509
Observations	2543	2543	2543	2543	2543	2543

Note: The data sample used are within 10 km from the border. Cubic polynomial of longitude and latitude are used. Average marginal effect is reported for the Tobit model. Robust standard error clustered by the municipality in bracket. Statistically significant coefficients are denoted as the following rule: * p<0.1, ** p<0.05, *** p<0.01. All Tobit random effect estimates contain year dummies and time invariant covariates such as solar potential, wind power potential, agricultural land, elevation, slope, and state dummies.

Table H. Censored quintile regression estimates with longitude and latitude (Table10')

year	2010	2013	2014	2015
T* DSO^{eon}	1.032	-0.163	-0.325	-0.110
[Std.Err]	[1.782]	[0.305]	[0.249]	[0.078]
Covariates	Yes	Yes	Yes	Yes
Observations	517	517	517	517

Note: Outcome is solar power generation capacity installed (start operation) per year. The data sample used are within 10 km from the border. Cubic polynomial of longitude and latitude are used. Standard error is in bracket. Statistically significant coefficients are denoted as the following rule: * p<0.1, ** p<0.05, *** p<0.01. All estimates contain time invariant covariates such as solar potential, elevation, slope, and state dummies. Logit model is used in the first stage.