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Empirical Studies on Renewable Energy Policies

（再生可能エネルギーの普及政策に関する実証研究）

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Yimeng Du

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Chapter 1

Introduction

Access to energy is a necessity for the economic development of every country around the world. Despite being the major source of energy, fossil fuels are also the main contributor to the high levels of carbon dioxide emissions and the resulting increase in global temperature. Until now, considerable efforts have been directed towards minimizing dependence on fossil fuels by increasing renewable energy supply. However, for various reasons, the current renewable energy implementation in some countries falls far short of their potential. For instance, Japan has experienced a slow rate of development because of limited access to renewable energy. This is because of a lack of suitable energy policies, technological advances, and power transmission infrastructures. Japan's national target for carbon emissions reduction has been announced as 26% from those of 2013 to be achieved by the year 2030, equal to a 17% reduction over emissions in 1990.[1] The Japanese government's low target is not only insufficient, and significantly less than that of many other developed nations, such as the 40% reduction target compared to 1990 levels of the EU[2], but also likely to be missed.[3] Similarly, although China is rich in renewable energy resources, conventional energy resources have

[1]Submission of Japan's Intended Nationally Determined Contribution, MOE, 2015. <https://www.env.go.jp/en/earth/cc/2030indc.html>, accessed on December 1, 2018.

[2]2030 Energy Strategy, European Commission, 2015. <https://ec.europa.eu/energy/en/topics/energy-strategy-and-energy-union/2030-energy-strategy>, accessed on December 6, 2018.

[3]Energy Mix 2030 and Japan's Collapse in Nuclear Power Generation, Greenpeace Germany, 2015. <https://www.greenpeace.org/japan/Global/japan/pdf/20150428-briefing-energy-mix.pdf>, accessed on December 1, 2018.

continued to be the dominant source of electricity because of their availability, suitability for meeting consumers requirements, and relatively low cost. Despite China has steadily decreased its coal consumption by a few percentage points every year since 2013, coal still accounted for nearly 58% of Chinas total energy consumption in 2016.[4] As a consequence, a large quantity of electricity from wind and solar power plants is wasted, and the air pollution and carbon dioxide emissions in China continue to be severe.

Apart from the over-reliance on fossil fuels, there are two main barriers to renewable energy utilizaition can be divided into two parts: geographic barriers and social barriers. Geographic barriers include obstacles in procuring land required for installation, and difficulties in ensuring that the renewable energy resources reach the area where there is large demand. The distribution of renewable energy sources across natural barriers is the greatest limitation or barrier to the utilization of renewable energy and the promotion of its use. On the other hand, social barriers arise from the existing social system and include environmental regulations and technical regulations. For instance, strict environmental regulations prohibit geothermal development in national parks and protected forest areas. In addition, the environmental assessment associated with the installation of renewable energy, such as hydropower and wind power, has become stricter. Further, the barriers to interconnection with the existing power grid is a major factor preventing the promotion of renewable energy. To promote renewable energy, the environmental regulations need to be reviewed, and it is necessary to develop a variety of appropriate promotion policies in order to expand renewable energy installations.

There was growing interest in renewable energy as an important policy measure in developed countries after the first oil crisis in 1973. Since then, there has been major investment in research and development; however, most of these efforts did not lead to the introduction of renewable energy. The promotion of renewable energy was actually initiated in the early 1990s, after the convention for the prevention of global warming. Several policies were in-

[4]World Energy Outlook 2017: China, IEA. <https://www.iea.org/weo/china/>, accessed on December 1, 2018.

troduced to promote the utilization of renewable energy during this period. Currently, the Feed-in Tariff (FIT) and Renewable Portfolio Standard (RPS) system have become major policy instruments to promote the introduction of renewable energy in the world. After the enforcement of the Kyoto Protocol in 1997, environmental taxes and green certificate trading schemes were adopted as policy instruments to mitigate climate change. The protocol defines several flexibility mechanisms that can be used by Annex I Parties in meeting their emission limitation commitments. The Clean Development Mechanism (CDM) is one of the flexibility mechanisms designed to encourage production of emission reductions in developing countries. In addition to its environmental benefits, the idea behind the implementation of CDM projects is that they will also create economic and social benefits, such as an increase in green technology innovation and green job opportunities, in the host countries.

This research has three main objectives. First, we discuss the trade-off between nature conservation regulations and renewable energy installations. The construction of renewable power facilities is often prohibited under the construction rules in protected areas owing to the possibility of negative environmental externalities. Second, we investigate whether the regional differentiation under the FIT policy has effectively promoted the even distribution of renewable energy industries. existing studies confirm the effectiveness of FIT as a policy instrument for expanding the use of renewable energy, its potential impacts on excessive concentration of renewable power industry in resource-rich region should also be considered. Last, we examine whether the promotion of renewable energy development can play a key role in mitigating rural poverty. Given that both energy access and poverty reduction are issues needing consideration in the economically backward regions, the introduction of renewable energy industry in such communities may offer an effective solution to achieve these targets simultaneously.

The remainder of the paper is organized as follows. Chapter 2 uses the fixed effect OLS model to estimate the impacts of nature conservation regulations and renewable energy promotion policies on annual installations of wind facilities from 1998 to 2016. The findings

of this chapter demonstrate that the existence of national nature parks has hampered the development of wind power in Japan. Particularly, special protection zones in nature parks, which observe the strictest construction regulations, have the greatest impact on reducing the annual installations of wind turbines. The results also indicate that, in contrast to financial subsidy programs, the RPS did not play a significant role in increasing wind power installations in Japan. Additionally, limited transmission grids have led to a reduction in installations of wind turbines. The results of this chapter suggest that further deregulation of the construction rules under the nature parks law, stricter obligation targets regulated by government promotion policies, and improvement of the transmission system are important for the development of wind power.

Chapter 3 uses a spatial regression discontinuity design (RDD) to examine the impacts of regionally differentiated FITs on the outcome indicators of wind and solar power generation. The results show that FIT implementation plays a role in promoting renewable energy development in resource-poor regions. A small difference in the tariff rate leads to statistically significant differences among regions in the outcome indicators. The findings of this chapter suggest that regionally differentiated FITs might help mitigate the overproduction of wind electricity in regions with abundant wind resources, but low electricity demand. In addition, we find that the rapid growth in China's solar sector still depends on financial support, in the form of higher tariffs paid to renewable power generators.

Chapter 4 investigates the impacts of the renewable energy-based clean development mechanism (RE-CDM) projects on rural communities in China. The social benefits of RE-CDM projects are estimated by combining propensity score matching with the difference-in-differences approach (PSM-DID). We find that the biomass-based CDM projects significantly contribute to income improvement and employment generation in rural communities in China. Our estimation results in this chapter also reveal that CDM projects based on wind energy have the potential to increase income and the share of the labor force in the primary industry in rural areas. These results suggest different channels through which re-

newable energy sources affect income. Finally, Chapter 5 presents our concluding remarks and research implications.

Chapter 2

Trade-off between Nature Conservation and Wind Power Development

2.1 Introduction

As of 2015, 433 GW of wind energy had been installed in more than 80 countries worldwide (Global Wind Energy Council, 2016). Globally, wind power is one of the fastest-growing energy sources due to its various advantages, the most significant of which is that the energy conversion efficiency of wind power is much higher than that of other energy sources. For example, the energy efficiency of a wind turbine can reach up to 59% compared to the efficiency range of between 6% and 40% for a photovoltaic panel. Secondly, the land used to install wind turbines can also be used for agriculture purposes. For example, farmers who use sections of their cropland for wind power development can continue working the soil under the wind turbines and earn extra revenue. Thirdly, increasing efficiency through larger facilities and technological development has helped to decrease the operation cost of wind turbines. Substantial investments have made wind power one of the cheapest forms of

renewable electricity generation worldwide.

As a remote island nation, Japan appears to be ideally situated to capture wind power. In 2014, the New Energy and Industrial Technology Development Organization (NEDO) estimated that Japan has potential resources of 290 GW for onshore wind, and 1,500 GW for offshore wind. However, wind power in Japan has developed at a slow pace, and generates only a small proportion of the countrys electricity. The total installed wind capacity for 2015 generated just 0.5% of Japans electricity supply (Heger, 2016). As of 2016, the cumulative wind capacity of Japan was approximately 3,234 MW, accounting for no more than 0.7% of the global total (GWEC, 2016). Figure 2.1 illustrates the spatial distribution and installed capacity of wind turbines in each municipality. As shown, the existing on-shore wind farms in Japan have been distributed along the coastline, with nearly 56.3% of total wind capacity concentrated in the Tohoku, Hokkaido, and Kyushu areas.

[Figure 2.1]

At the same time, nature parks, including National Parks, Quasi-National Parks, and Prefectural Nature Parks, cover approximately 14.7% of Japans territory and contain many locations with ideal conditions for wind power.[1] However, very few wind power facilities have been installed within nature parks in Japan. In order to achieve the countrys wind power target, it is necessary to promote the installation of wind power facilities, where possible, in nature parks (Eurus Energy, 2004). However, a report released by the Ministry of the Environment in 2004 emphasizes environmental conservation, with a particular focus on scenery, and prohibits the installation of wind power facilities on nature park lands.[2] The report makes permission for wind turbine siting in protected areas with easing conditions and clearer operational decision-making rules an essential condition for promoting the installation of wind turbines in Japan. In addition, the wind industry perceives the technical guidelines

[1]Summary Table of Nature Park Area <https://www.env.go.jp/park/doc/data/natural/naturalpark_1.pdf>, accessed October 30, 2018 (in Japanese).

[2]Final Report of the Working Group on the Installation of Wind Power Generation Facilities in National and Quasi-National Parks <https://www.env.go.jp/info/iken/h160315a/a-3.pdf>, accessed October 30, 2018 (in Japanese).

for siting wind turbines in nature park areas, which were established in March 2012, to be very strict. Thus, in March 2013, it issued an amendment to streamline the National Park Act and technical guidelines (Mizuno, 2014).

In this chapter, we examine what factors have affected the development of the wind power industry in Japan. The aims of this paper can be summarized as follows. We first investigate whether the regulations for nature and wildlife conservation have restricted wind power installations in Japan. There are a variety of environmental externalities associated with wind power generation that should be recognized. The impact of wind turbines on wildlife, most notably on birds and bats, has been widely documented. In addition, sound and visual impact are the two main public health and community concerns associated with operating wind turbines. Furthermore, Tang et al. (2017) provide significant observational evidence that wind farms can inhibit the growth and productivity of the underlying vegetation. Secondly, we examine whether the national level renewable energy promotion policies, such as the RPS, and subsidy programs have contributed to the promotion of wind power in Japan. Finally, by focusing on the enforcement of renewable energy curtailment under the FIT, we investigate whether wind turbine installations are limited by the restrictions to grid connection.

This chapter contributes to the existing literature in several ways. Firstly, we empirically examine the tradeoff between nature conservations and the development of the wind power industry in Japan. Many existing studies have focused on the environmental externalities of wind turbines. For example, adopting the conjoint analysis approach, Alvarez-Farizo and Hanley (2002) investigated the potential environmental impacts of wind farm developments and demonstrated that environmental concerns play an important role in the construction decision process of wind turbines. Meyerhoff et al. (2010) concluded that expanding wind power generation would cause negative landscape externalities. Finally, Mizuno (2014) noted that the landscape guidelines of nature parks in Japan should consider wind technology characteristics, and need to be streamlined to increase wind development. However, few

existing studies have focused on examining how the regulations applied to such externalities affect actual investment in wind capacity, a gap that will be addressed in this chapter.

Existing studies with positive findings on the impact of the RPS, such as Menz and Vachon (2006) and Adelaja and Hailu (2010) suggest that they could contribute to promoting wind industry development. However, several researchers have provided contrasting results. Lewis and Wiser (2007) note that the RPS offer less incentive for wind localization, since they may create market uncertainty and lower overall industry profitability. Similarly, Hitaj (2013) concluded that financial incentives are more efficient than the RPS at promoting wind power development. The results of previous studies have been inconclusive with respect to whether or not the RPS actually contribute to wind power development. Furthermore, very few empirical studies have evaluated the effectiveness of Japanese government financial incentives for renewable energy promotion. Thus, in this chapter, we empirically evaluate the effectiveness of the RPS, financial subsidy programs, and renewable power curtailment in Japan.

The main result of this chapter indicates that the construction regulations in national nature parks significantly hamper wind power development in Japan. Our findings suggest that the region with the most restrictive construction rules has the greatest impact on reducing the installations of wind turbines. For instance, upgrading the conservation regulations by transforming special zones into special protection zones in national parks has caused a reduction in annual wind turbine installations of approximately 7.81 kW, which is nearly 7.57% of the municipalitys average wind capacity. Our results also indicate that government policy plays a significant role in wind power development by providing financial subsidies. In contrast, obligations defined under the RPS fail to incentivize the development of wind industries, while the enforcement of renewable energy curtailment did not significantly reduce wind turbine installations.

The remainder of this chapter is organized as follows. The next section discusses factors that affect the installation of wind turbines. In Section 3, we introduce the data for estimation

and the measures of each variable. Section 4 follows with an analysis framework, including a description of the empirical model. Section 5 presents the estimation results and discussions. Finally, the implications and conclusions are presented in Section 6.

2.2 Determinants of Wind Power Installations

Wind turbines contain several potential negative environmental externalities, including noise exposure, landscape destruction, and negative impact on biodiversity (Hotker et al., 2006; Wolsink, 2007; Leung and Yang, 2012; Nissenbaum et al., 2012; Premalatha et al., 2014). Using conjoint analysis, Alvarez-Farizo and Hanley (2002) found that the construction of an onshore wind farm could lead to significant social costs in the form of environmental externalities. Meyerhoff et al. (2010) also found that, in Germany, residents disapprove of repowering wind turbines or building new ones due to the associated negative impacts. Therefore, areas with rich natural resources and biodiversity, such as nature parks and wildlife preservation areas, may prohibit the construction of wind facilities under nature conservation laws. In Japan, the Nature Parks Law was firstly legislated in 1937, with the aim of preserving Japans scarce natural resources, with a jurisdiction over national, quasi-national, and prefectural nature parks. Regarding the conservation regulations provided for national nature parks, a zoning system divides the parkland of each national park into three grades of protection: special protection zones, special zones (sub-divided into Class I, Class II, and Class III), and ordinary zones. The establishment of facilities in special zones and ordinary zones requires approval from the Minister of the Environment, and even more stringent regulations are imposed in special protection zones. Figure 2.2 illustrates the spatial distribution and total land area of national nature parks in municipalities of Japan. Nearly 83.7% of municipalities have national parks located within their respective administrative areas. However, very few wind power facilities have been installed in such areas. Therefore, we assume that there may exist a tradeoff between nature conservation

and the promotion of renewable energy in Japan.

[Figure 2.2]

In order to promote wind capacity installation, several promotion policies have been adopted by the Japanese government, of which the RPS was considered one of the most prevalent and innovative policy instruments. Both Menz and Vachon (2006) and Adelaja and Hailu (2010) established a positive correlation between the existence of RPS policies and wind power development using an empirical method. In addition, Yin and Powers (2010) introduced a new way of measuring the stringency of the RPS. As a result, RPS policies have also been found to be positively and significantly related to renewable energy deployment. However, contrary to the positive results of RPS, Hitaj (2013) argues that the presence of state-level RPS policies has not yet improved the development of wind power in the United States. The results of Hitaj (2013) suggest that compared with the RPS, financial incentives such as sales tax credit, corporate tax credit, and production incentives play significant roles in increasing the share of wind power electrification in the electricity market. Under the RPS, electricity retailers were obliged to use a certain amount of electricity from new energy sources such as solar energy, wind power, biomass, geothermal energy, and hydropower. An electricity retailer may choose from the following three options to meet its obligation: through the generation of electricity itself, by purchasing new energy electricity from a third party, or by purchasing a new energy certificate from a third party. If the electricity retailer failed to meet the quota without proper reason, a fine not exceeding one million yen was charged. Figure 2.3 represents the trends in electricity generated by renewable energy power plants installed under the RPS during the implementation period. Since the introduction of the RPS in 2003, wind power generation has increased greatly. As of 2011, the total amount of wind power based electricity had nearly quadrupled compared with 2003. However, as shown in Figure 2.4, despite increases in wind power generation due to the adoption of the RPS, renewable energy electricity generation still accounted for no more than 1.04% of the total electricity generation. Because the renewable energy target is moderate, with no

forecast for a drastic increase in the future, the contract pricing for RPS electricity could not reach the level necessary to induce further investment (Ito, 2015). Therefore, we assume that the effect of implementation of the RPS on improvements in wind power development in Japan might be negligible.

[Figure 2.3]

[Figure 2.4]

In July 2012, Japan shifted from RPS to FIT, due to the growing expectation that renewables would replace nuclear as a power source following the Fukushima accident in 2011. The FIT scheme obligates electric utilities to buy electricity generated from renewable energy sources at a fixed price and for a long-term period guaranteed by the government.[3] However, the tariff rate and contract duration differ by different project scales and energy sources. For instance, the FIT offered 40 yen per kWh power generation of utility scale solar panels ($\geqslant$ 10 kW), and 22 yen/kWh for large scale ($\geqslant$ 20 kW) onshore wind power plants.[4]

The FIT and RPS schemes differ in so far as the FIT is subject to price regulation, while the RPS is subject to quantitative regulations. However, as the introduction of the FIT scheme has rapidly expanded the utilization of renewable power facilities, utility companies are facing issues in relation to the limited capacity of the power grid system (METI, 2014). In Japan, regions with rich renewable energy resources are concentrated in areas whose system capacities and electricity demand are comparatively small.[5] Adjusting the supply-demand balance across service areas makes it difficult for the utility companies to accept additional connection requests from renewable powers. To verify the utility companies' capacity of power grid connection for renewable energy, a Working Group on Grid Connection of Renewable Energy was established in 2014. As presented in Table 2.1, this working group

[3]The tariff price is calculated based on the cost of setting up the system in the long-term.

[4]System revision under the revised FIT scheme, <http://www.enecho.meti.go.jp/category/saving_and_new/saiene/kaitori/dl/fit_2017/setsumei_shiryou.pdf>, accessed May 21, 2018 (in Japanese).

[5]For instance, most wind resources are located in the Hokkaido and Tohoku network, where peak demand ranges between 5 GW and 15 GW. However, in the Tokyo area, which has electricity demand of nearly 60 GW, few suitable locations for wind power exist.

reported the potential curtailed amount of wind and solar powers, which are calculated under the electricity supply and demand data released by utility companies in the last fiscal year. The curtailment of renewable powers is mainly due to two reasons. First, both wind power and solar energy are intermittent energy sources, which create distinct challenges for connection into the larger power system (Chi et al., 2007). Second, the generation capacities of wind and solar are growing rapidly in many areas; thus, their impacts on the grid network are likely to increase over time. Therefore, the curtailment rate of renewable powers illustrates the capability of the electricity grids to accept connection requests.

[Table 2.1]

2.2.1 Empirical Model

This chapter uses unbalanced panel data on the annual additions in the capacity and unit of wind turbines for 1,698 municipalities in Japan from 1998 to 2016.[6] To measure the wind development related impacts of the nature conservations and renewable energy promotion policies, we employed a fixed effects ordinary least squares (OLS) model. The general form of the empirical model estimated can be written as follows:

$$y_{it} = \beta_0 + \beta_1 Nature_i + \beta_2 RPS_{ct} + \beta_3 FIT \times Curtail_{ct} + \beta_4 L.Subsidy_{it} + \beta_5 X_{it} + \theta_t + \lambda_j + \epsilon_{it},$$

where y_{it} indicates the wind facility indicators, which include: annual capacity additions of wind turbines; annual capacity additions of large-scale ($\geqslant$ 50 kW) wind turbines; annual capacity additions of small-scale ($<$ 50 kW) wind turbines; and annual plant additions of wind turbines in municipality i in year t. $Nature_i$ is the total land area of national nature parks, land area of the subdivision of national parks, namely the Special Protection Zones, Special Zones, and Ordinary Zones, and land area of wildlife protection zones in

[6] Isolated islands are excluded from the sample due to lack of data.

municipality i. RPS_{ct} is the obligation amount of renewable electricity regulated from 2003 to 2012 in region c year t.[7] $FIT \times Curtail_{ct}$ is the cross term of the FIT dummy and curtailment rates in region c year t. The FIT dummy equals to one on and after year 2012. Furthermore, $L.Subsidy_{it}$ represents the one year lagged capacity of wind turbines installed under the support of subsidy programs in municipality i in year t. County characteristics are captured by X_{it}, while θ_t is the year dummy used to capture external events that affect the development of renewable energies. Finally, λ_j is the regional dummy that accounts for the prefecture-specific fixed effects. Table 2.2 presents the summary statistics of variables used in the empirical analysis. On average, 103.2 kW wind turbines are installed annually in each municipality of Japan. Furthermore, the mean area of nature parks in municipalities in Japan is approximately 16.56 km^2.

[Table 2.2]

2.3 Data

2.3.1 Wind Facility Indicators

In this chapter, annual installation capacity and plant additions of wind turbines were used to capture the development of wind power. First, we used the annual capacity additions of wind turbines in municipalities. We also adopted the annual capacity installations of large-scale ($\geqslant$ 50 kW), and small-scale ($<$ 50 kW) wind turbines.[8] It is noteworthy that large-scale wind power plants contain the largest share of total installed wind capacity in Japan. Adopting variations in the scale of wind turbines as the explained variables allowed

[7] In this chapter, region c is defined as one of the service areas of general electricity utilities, namely the Hokkaido, Tohoku, Tokyo, Hokuriku, Chubu, Kansai, Chugoku, Shikoku, Kyushu, and Okinawa Electric Power Company in Japan.

[8] Under the classification criteria of wind turbines defined by the NEDO, scale of wind turbines is divided into four categories related to installation capacity: large-scale ($\geqslant$ 1,000 kW), medium-scale ($<$ 1000 kW,$\geqslant$ 50kW), small-scale ($<$ 50 kW, $\geqslant$ 1kW), and micro-scale ($<$ 1 kW) wind turbines. The large- and medium-scale wind turbines tend to be used to produce electricity for the electric grid, while small- or micro-scale wind turbines are often used for homes, farms, water pumping, diesel generators, batteries, and photovoltaic systems (Clean Technica, 2017).

us to distinguish whether a regulation or policy has influenced specific aspects of the wind power industry. Lastly, the annual plant additions of wind turbines during the research period were employed as the dependent variable.

[Figure 2.5]

Figure 2.5 illustrates the trends in annual installed capacity of wind turbines during the research period. As shown in this figure, during the implementation period of the RPS, between 2003 and the first half of 2012, the annually installed capacity of large-scale wind turbines increased sharply compared to the previous years. The sudden decrease in the annual installation amount of wind facilities in 2012 is due to the replacement of the RPS by FIT in that year. After 2013, the expansion of the wind power sector was improved by the adoption of FIT, but the impact thereof seems to have been temporary. Information on wind turbines in Japan was obtained from the database on installation situations of wind power generation equipment provided by the NEDO. The database includes information on the plant capacity, number of turbines, operation starting date, locations, and project providers.

2.3.2 Nature Conservation Indicators

We included the land areas of national nature parks by different categories of protection strength to illustrate the extent of nature conservation regulations under the NPL. The total land area of national nature parks and land area of the subdivisions, i.e., special protection zones, special zones, and ordinary zones, in each municipality were adopted in the empirical analysis. In the special protection zones of national nature parks, the construction of buildings and roads is strictly prohibited, while the establishment of buildings, roads, and other equipment is restricted in special zones. For instance, only facilities that do not significantly obstruct viewing from the main observation site, and at a height of 13 meter or below can be located in special zones. Japan has a total of 401 nature parks nationwide, 32 of which are defined as national nature parks. The land area of national nature parks

accounts for nearly 8.61% of the landmass of Japan.[9]

The land area of the wildlife preserve area was used to measure the impact of wildlife conservation on the construction of wind turbines. We measured this impact since wildlife conservation is one of the difficulties faced by wind industry developers. The construction of large-scale wind turbines often leads to opposition from wildlife protectors, as wildlife, particularly birds, can be injured by the operating turbines. The wildlife preserve is one of the institutions that sets the area, including the habitat, as a protected area for the protection and management of wildlife. As of 2016, there are a total of 3,765 wildlife preserve sites in Japan, with a total land coverage of nearly 35,490 km^2, although only 8.51% of the area is regulated by construction rules.[10] Therefore, the wildlife protection sites in Japan may have insufficient legal power to protect natural habitats from the construction of wind facilities inside the preserve area. In addition, the findings of several existing studies suggest that the negative impacts of wind farms on wildlife might be small. Erickson et al. (2001) revealed that the mortality rate of birds due to collisions at wind farms is negligible. Similarly, both H'otker et al. (2006) and Leung and Yang (2012) found no statistically significant evidence of negative impacts from wind turbines affecting populations of breeding birds.

GIS data on national nature parks in Japan were collected from the National Land Digital Information provided by the Ministry of Land, Infrastructure, Transport and Tourism. Information on wildlife refuges was obtained from the Natural Environment Survey Web-GIS provided by the Biodiversity Center of Japan. ArcGIS 10.1 was used to calculate the average land area of the national parks and wildlife protection zones by municipality.

2.3.3 Policy Indicators

Policy indicators were used to measure the impact of renewable energy promotion policies on wind power development. The annual obligation amount of the RPS imposes an obligation

[9]Outline of permission standards related to various acts within the National Nature Parks <https://www.env.go.jp/nature/ari_kata/shiryou/031208-4-14.pdf>, accessed May 15, 2018 (in Japanese).

[10]Authors' own calculations.

on electricity retailers to use a certain amount of electricity from new energy. The data on the RPS obligation amount were obtained from annual reports on the obligation amount of electricity utilization. The annual amount of obligation by region, namely the service areas of utility companies, from 2003 to 2012 were adopted in the empirical analysis.

In addition to the RPS, a cross term of the FIT dummy variable and curtailment rate was included in the estimation. The cross term was used to capture the impact of enforcement of renewable power curtailment under the FIT scheme. The FIT dummy takes the value of one if the year is equal to or later than 2012, which illustrates the implementation period of the FIT. The curtailment rate was used to capture the capability of the electricity grids to accept renewable power connection requests. As shown in Table 1, curtailment rates are calculated under the electricity supply and demand data released by utility companies. The capacities of wind turbines installed under the support of subsidy programs were used to represent the strength of the financial incentives in promoting wind development. From 2009 to 2016, a total of 1,093 MW wind turbines were installed under the support of the New Energy Promotion Council (NEPC), which comprises approximately 71.2% of the total installed wind capacity during the same period. However, only 53% of prefectures received financial subsidies for constructing wind facilities from the NEPC. The subsidy rate comprises up to 50% of the cost for installation, deployment, promotion of public awareness, and related activities.

2.3.4 Municipality Characteristics

Annual average solar radiation was used as the proxy variable for solar energy development. The radiation number of prefectures from 1998 to 2016 was adopted to measure the impact of solar energy on wind power development. Information on the radiation data was collected from the database on solar radiation provided by the Japan Meteorological Agency. Solar energy in Japan has technical and policy advantages compared with the wind industry, as Japan is the worlds second largest market for solar PV growth as well as a large

installer of domestic grid connected PV systems. According to data released by the Ministry of Economy, Trade and Industry, solar energy has accounted for 97% of additional renewable capacity since Japans renewable incentive program began in 2009, while wind power has only accounted for approximately 1.1%. Thus, the development of solar energy is also considered to negatively impact installations of wind turbines.

The wind resource characteristics include the annual average wind speed and annual typhoon landing times. Most wind turbines begin generating electricity at wind speeds of approximately 3 to 4 m/s, generate maximum power at approximately 15 m/s, and shut down to prevent storm damage at 25 m/s or above.[11] Therefore, a steady and relatively strong wind speed is an essential factor for the efficiency of wind turbines, as it helps increase the operation efficiency of wind power plants and stabilize the power supply. At the same time, severe weather conditions such as typhoons and tornados often cause the shutdown and collapse of wind turbines, thus causing wind power development to stagnate or even regress (Ishihara et al., 2005). Thus, in addition to average wind speed, we deployed the incidence of typhoons by region.

Wind speed data were obtained from the NEDO's Local Wind Conditions Map. The dataset includes GIS information for annual average wind speeds of municipalities in 2000. In this chapter, we use wind speed calculated at 70 m above ground level, since on-grid wind turbines are usually installed at 80 m or higher. Regarding typhoon landing information, we collected data on the annual typhoon landing times of the main cities of 47 prefectures between 1998 and 2016 from the digital typhoon database released by the National Institute of Informatics.[12]

[11] Wind Turbine Technology, The British Wind Energy Association <https://www.nottingham.ac.uk/renewableenergyproject/documents/windturbinetechnology.pdf>, accessed October 31, 2018.

[12] The typhoon landing times were recorded by a monitoring system when typhoons landed within 150 km of the main cities of each prefecture.

2.4 Results and Discussion

2.4.1 Impact on Wind Power Installations

Fixed effect OLS models were used to estimate the main restrictions on wind power development in Japan. Our main results suggest that the strict construction regulations of national nature parks has obstructed wind power development.

[Table 2.3]

Table 2.3 presents the impact of nature conservation regulations and renewable energy promotion policies on the annual addition of wind capacity. The coefficient of national nature parks in the first column indicates that national nature parks negatively and significantly related to annual wind capacity installations. A 1 km^2 increase in the land area of national nature parks reduces the annual installation of wind turbines by 0.356 kW, implying that, if the national nature park area in a municipality is 16.56 km^2, the annual wind capacity losses in that municipality are approximately 5.90 kW, which is nearly 5.71% of the average wind capacity.[13] This result supports our assumption that a tradeoff exists between nature conservation and the promotion of wind power. In columns 2-4, the impacts of subdivisions of national nature parks are also statistically significant. The annual wind capacity decrease caused by a 1 km^2 increase in special protection zones, special zones, and ordinary zones of national nature parks ranged from 0.58 kW to 1.57 kW. Particularly, areas with the most restrictive regulations, namely special protection zones, have the highest impact on annual wind capacity reductions, suggesting that an upgrade in conservation regulations by transforming special zones into special protection zones in national parks causes a reduction in annual wind turbine installations of approximately 9.76 kW.[14] In contrast, the impact

[13] According to the summary statistics in Table 2.2, the average land area of national nature parks is 16.56 km^2, while the average installed capacity of wind turbines is 103.2 kW in a municipality.

[14] According to the summary statistics in Table 2.2, the average land area of special zones in national nature parks in Japan is approximately 9.976 km^2.

of wildlife preservation did not demonstrate a significant effect on the installation of wind turbines.

Regarding the results of policy indicators, the estimated coefficients related to the RPS are positive but not statistically significant in all models. One reason for this insignificance might be due to problems in the design of the RPS, such as uncertainty regarding the duration of the policy and insufficient penalties for non-compliance (Jordan-Korte, 2011). This result is also in line with the arguments of DeWit and Tani (2009), who suggested that the insufficiency is due to the negligible targets of Japans RPS. On the other hand, the financial subsidy programs appear to have significantly and positively impacted on wind power development.

2.4.2 Impact on Alternative Measures for Wind Power Installation

In addition to the main regression, we conducted an additional analysis by investigating the impacts on alternative measures for wind power installations.

[Table 2.4]

We first estimated the impact of nature conservation regulations and renewable energy policies on annual capacity additions of different sized wind turbines. Table 2.4 represents the results estimated using the annual installed capacity of large-scale wind turbines as the dependent variables. Column 1 shows the negative and statistically significant impact of national nature parks on large-scale wind turbines. For instance, a 1-km^2 increase in land area of national nature parks decreases wind capacity by approximately 0.356 kW per year. Furthermore, the coefficients and significances of the other main estimators, such as the subdivisions of national nature parks, wildlife preserve area, RPS, curtailment rate, and wind capacity supported by subsidy programs, are all similar to the mail results presented

in Table 2.3.[15]

[Table 2.5]

We also estimated the impact of nature conservation areas and national-level promotion policies on the capacity of small-scale wind turbines, presented in Table 2.5. As shown in columns 1-4, the coefficients of total land area of national nature parks and their three subdivisions are negatively and significantly related to annual installations of small-scale wind turbines. Specifically, the annual capacity of small-scale wind facility decreased due to a 1 km^2 increase in national nature parks with subdivisions ranging from 0.255 W to 1.256 W. We found similar results on the impact of special protection zones with the main results, indicating that this subdivision of national nature parks has the greatest impact on reducing the capacity of small-scale wind turbines. This result indicates that the increase in annual installations of small-scale wind turbines caused by the degradation of special protection zones to special zones is approximately 2.189 W.[16] On the other hand, similar to the main result, the impact of wildlife preserves did not demonstrate a significant effect on the installation of small-scale wind turbines.

However, contrary to the results estimated under the main regression, the coefficients of the RPS and subsidy are negatively and significantly correlated with annual installations of small-scale wind turbines in all models. The coefficient of the RPS in column 1 of Table 2.5 suggests that the impact of RPS causes small-scale wind turbines to decrease by nearly 17.77 W per year.[17] These results indicate that the adoption of national level renewable energy promotion policies has led to the upsizing of wind power facilities in Japan. We also find that the introduction of renewable energy curtailment under the FIT significantly increased the small-scale wind capacity, implying that, when renewable power surplus occurs, energy

[15]The results in Table 2.3 and Table 2.4 are extermely similar with each other since almost all of the wind power generation facilities installed until 2016 are the large-scale ($\geqslant$ 50 kW) wind turbines.

[16]According to the summary statistics in Table 2.2, the average land area of special protection zones in national nature parks is approximately 2.545 km^2.

[17]According to the summary statistics in Table 2.2, the average obligation amount of the RPS is 467.6 GWh in a municipality.

producers tend to invest in those off-grid small-scale energy wind turbines.

[Table 2.6]

Lastly, we examined the effect of nature conservations and renewable energy promotion policies on the unit of wind power plants. The result in the first column of Table 2.6 demonstrates that a 1,000 km^2 increase in the land area of national nature parks decreases the unit of wind turbines by 0.22 units per year. In addition, the impact of special protection zones on the annual decrease in units of wind power plants is approximately 3.09 times greater than the impact of special zones, and 2.5 times greater than ordinary zones. The coefficients of RPS are positive but insignificant in all models. This result supports our finding in the main estimation that the RPS was insufficient to promote the development of the wind power industry in Japan. On the other hand, we found a significant effect of financial incentives, suggesting that subsidy programs can help to increase the annual addition in units of wind power plants. Finally, we find that the curtailment rate demonstrates both a negative and significant impact on the annual unit additions of wind turbines. This finding suggests that the introduction of renewable power curtailment under the FIT has led to a reduction in wind turbine installations in Japan.

2.5 Conclusions

This chapter has analyzed the main restrictions on wind power installations in Japan, by focusing on the impact of nature conservation regulations and government policy on renewable power.

The findings contribute to the limited empirical literature on restriction measures for the development of renewable energies and can be summarized as follows. First, our results suggest that deregulating nature conservation restrictions is likely to improve the ability of wind power to contribute to green electricity generation in Japan. Specifically, the existence

of national nature parks leads to an annual reduction in wind power installations by approximately 5.9 kW. This chapter also analyzes how the strength of regulations affects the location choice of wind power facilities. By estimating the impact of subdivisions of national nature parks on wind turbine installations, we find that more severe nature conservation regulations can lead to increased losses in wind capacity additions. The wind capacity reduction impact of special protection zones, which are regions regulated by the most restrictive construction rules, is 2.66 times larger than the impact of special zones, and 2.43 times that of ordinary zones. On the other hand, construction restrictions under the wildlife preserve regulations did not demonstrate a significant hampering effect on wind power development. This result implies that the legal power under the wildlife preserve regulations is insufficient to protect wildlife habitats from the construction of wind turbines.

Furthermore, the results of this chapter confirm that the obligation amount under the RPS has not sufficiently encouraged the development of on-grid wind power in Japan. More rigorous requirements should have been adopted during the implementation period. We also found that the financial incentives provided by local governments to reduce the installation and operation costs of wind turbines significantly encourage the expansion of wind power generation in Japan. The result on renewable power promotion impacts of subsidies is in line with the findings of Hitaj (2013), who indicated that government policies play a significant role in wind power development by providing financial support. Moreover, when investigating the impacts of renewable energy curtailment enforced by the grid owners, we found that a restriction on grid connection decreases the installation of wind turbines, since the curtailment reduces the earnings from wind power generation and the uncertainty can greatly hinder the business prospects of wind power producers (Mizuno, 2014).

The results of this chapter suggest that nature conservation regulations comprise the main restrictions on wind power development. A better understanding of the role of the nature park act in the process of wind power installations is important to achieve renewable energy promotion while examining the tradeoff between nature conservation and power plant

construction. It is easier for wind farms to be located in areas with easing conditions and clearer construction rules. Thus, in this chapter, we suggest that guidelines for siting wind turbines in nature park areas need to be streamlined in order to increase wind development in some of the nature park areas with good wind resources.

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Table 2.1: Amount of Curtailed Wind and Solar Energy in Japan (2012 – 2016)

	Annual Curtaiment Amount (10 MWh) (Curtailment Ratio (%))				
	2012	2013	2014	2015	2016
Hokkaido	1,072	4,943	19,738	33,927	31,135
	(0.6%)	(2.9%)	(8.3%)	(13.7%)	(13.1%)
Tohoku	42,556	52,102	77,100	81,648	71,108
	(3.6%)	(4.6%)	(6.2%)	(7.1%)	(6.1%)
Tokyo	-	-	-	-	-
	-	-	-	-	-
Hokuriku	5,400	4,400	6,348	14,683	17,605
	(4.2%)	(3.3%)	(3.6%)	(7.7%)	(7.3%)
Chubu	-	-	-	-	-
	-	-	-	-	-
Kansai	-	-	-	-	-
	-	-	-	-	-
Chugoku	7,755	11,236	58,132	60,606	55,965
	(0.9%)	(1.3%)	(6.3%)	(6.0%)	(5.4%)
Shikoku	8,900	16,400	28,054	26,326	31,117
	(2.5%)	(4.5%)	(6.7%)	(5.7%)	(6.2%)
Kyushu	28,771	46,446	48,100	50,644	85,978
	(2.7%)	(4.2%)	(4.1%)	(4.3%)	(6.8%)
Okinawa	0	0	3,872	3,049	2,693
	(0)	(0)	(4.1%)	(3.2%)	(2.7%)

Note: Tokyo, Chubu and Kansai Electricity Company did not regulated the maximum acceptable capacity of renewable powers until 2016.
Source: Working Group on Grid Connection of Renewable Energy

Table 2.2: Summary Statistics

	Unit	Obs	Mean	Std. dev.	Min	Max
Wind facility indicators						
Wind capacity	kW	32,259	103.2	1644	0.000	78000
Wind capacity_large	kW	32,259	103.1	1644	0.000	78000
Wind capacity_small	W	32,259	33.73	1557	0.000	190000
Plant additions	unit	32,259	0.068	1.019	0.000	57.00
Nature conservation indicators						
National nature parks	km^2	32,259	16.56	71.54	0.000	1152
Special protection zones	km^2	32,259	2.545	16.10	0.000	294.1
Special zones	km^2	32,259	9.976	44.69	0.000	852.4
Ordinary zones	km^2	32,259	4.752	27.66	0.000	638.0
Wildlife preserve area	km^2	32,259	5.934	24.86	0.000	852.4
Policy indicators						
RPS	GWh	32,259	467.6	738.6	0.000	3530
FIT $\times$ Curtailment	%	32,259	0.856	2.279	0.000	13.70
L.Subsidy	kW	30,561	35.76	1030	0.000	78000
County characteristics						
Solar radiation	MJ/m^2	32,259	7.037	2.403	0.000	13.70
Typhoon	times	32,259	1.012	1.075	0.000	7.000
Wind speed	m/s	32,259	5.385	0.925	3.200	8.900
Electricity grid access	km	32,259	1.235	2.435	0.000	49.39
Electricity price	yen/kWh	32,259	17.30	1.602	14.24	23.54
Population density	people/ha	32,259	10.48	23.73	0.016	218.8
Taxable income	billion yen	32,241	107.2	304.6	0.346	7328
Land area	km^2	32,259	217.6	248.9	3.470	2178

Table 2.3: Regression Results (Explained variable: wind capacity(kW))

	(1)	(2)	(3)	(4)
National nature parks	-0.356***			
	(0.109)			
Special protection zones		-1.566**		
		(0.661)		
Special zones			-0.588***	
			(0.193)	
Ordinary zones				-0.645***
				(0.222)
Wildlife preserve area	0.323	0.481	0.432	0.295
	(0.597)	(0.649)	(0.610)	(0.610)
RPS	0.023	0.022	0.022	0.023
	(0.018)	(0.018)	(0.018)	(0.018)
FIT × Curtailment	-4.219	-3.870	-4.564	-3.494
	(5.192)	(5.187)	(5.189)	(5.149)
L.subsidy	0.664***	0.664***	0.664***	0.664***
	(0.097)	(0.097)	(0.097)	(0.097)
Solar radiation	11.09*	11.15*	11.19*	11.07*
	(5.819)	(5.818)	(5.819)	(5.820)
Typhoon	2.060	1.935	2.031	1.956
	(9.617)	(9.617)	(9.615)	(9.614)
Wind speed	95.00***	95.30***	95.09***	94.73***
	(20.77)	(20.79)	(20.77)	(20.78)
Electricity grid access	2.886	2.908	2.960	2.763
	(5.201)	(5.185)	(5.202)	(5.214)
Electricity price	-2.009	-1.561	-1.583	-1.357
	(9.639)	(9.621)	(9.631)	(9.612)
Population density	0.052	0.106	0.069	0.008
	(0.246)	(0.260)	(0.248)	(0.242)
Income	0.023	0.023	0.023	0.027
	(0.020)	(0.021)	(0.020)	(0.020)
Land area	0.258***	0.250***	0.258***	0.238***
	(0.078)	(0.077)	(0.078)	(0.074)
Constant	-666.0***	-677.6***	-676.9***	-676.8***
	(213.5)	(214.0)	(214.0)	(214.0)
Year dummy	yes	yes	yes	yes
Regional dummy	yes	yes	yes	yes
Adj.R^2	0.176	0.176	0.176	0.176
Observations	30543	30543	30543	30543

Table 2.4: Regression Results (Explained variable: wind capacity_large (kW))

	(1)	(2)	(3)	(4)
National nature parks	-0.356***			
	(0.109)			
Special protection zones		-1.566**		
		(0.661)		
Special zones			-0.588***	
			(0.193)	
Ordinary zones				-0.645***
				(0.222)
Wildlife preserve area	0.323	0.481	0.432	0.295
	(0.597)	(0.649)	(0.610)	(0.610)
RPS	0.023	0.022	0.022	0.023
	(0.018)	(0.018)	(0.018)	(0.018)
FIT × Curtailment	-4.219	-3.870	-4.564	-3.494
	(5.192)	(5.187)	(5.189)	(5.149)
L.subsidy	0.664***	0.664***	0.664***	0.664***
	(0.097)	(0.097)	(0.097)	(0.097)
Solar radiation	11.09*	11.15*	11.19*	11.07*
	(5.819)	(5.818)	(5.819)	(5.820)
Typhoon	2.060	1.935	2.031	1.956
	(9.617)	(9.617)	(9.615)	(9.614)
Wind speed	95.00***	95.30***	95.09***	94.73***
	(20.77)	(20.79)	(20.77)	(20.78)
Electricity grid access	2.886	2.908	2.960	2.763
	(5.201)	(5.185)	(5.202)	(5.214)
Electricity price	-2.009	-1.561	-1.583	-1.357
	(9.639)	(9.621)	(9.631)	(9.612)
Population density	0.052	0.106	0.069	0.008
	(0.246)	(0.260)	(0.248)	(0.242)
Income	0.023	0.023	0.023	0.027
	(0.020)	(0.021)	(0.020)	(0.020)
Land area	0.258***	0.250***	0.258***	0.238***
	(0.078)	(0.077)	(0.078)	(0.074)
Constant	-666.0***	-677.6***	-676.9***	-676.8***
	(213.5)	(214.0)	(214.0)	(214.0)
Year dummy	yes	yes	yes	yes
Regional dummy	yes	yes	yes	yes
Adj.R^2	0.176	0.176	0.176	0.176
Observations	30543	30543	30543	30543

Table 2.5: Regression Results (Explained variable: wind capacity_small (kW))

	(1)	(2)	(3)	(4)
National nature parks	-0.255***			
	(0.0961)			
Special protection zones		-1.256**		
		(0.569)		
Special zones			-0.396**	
			(0.168)	
Ordinary zones				-0.734***
				(0.255)
Wildlife preserve area	0.984	1.122	1.051	1.010
	(0.696)	(0.780)	(0.704)	(0.718)
RPS	-0.038*	-0.038*	-0.038*	-0.038*
	(0.020)	(0.020)	(0.020)	(0.020)
FIT × Curtailment	6.514**	6.739**	6.308**	7.071**
	(2.859)	(2.878)	(2.849)	(2.912)
L.subsidy	-0.003*	-0.003*	-0.003*	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
Solar radiation	3.999	4.040	4.074	3.948
	(5.263)	(5.259)	(5.260)	(5.252)
Typhoon	-23.02**	-23.11**	-23.05**	-23.08**
	(11.19)	(11.20)	(11.19)	(11.20)
Wind speed	15.16	15.42	15.21	14.97
	(10.65)	(10.71)	(10.66)	(10.65)
Electricity grid access	4.010	4.038	4.056	3.918
	(3.075)	(3.069)	(3.078)	(3.080)
Electricity price	-7.809	-7.519	-7.488	-7.406
	(7.026)	(7.032)	(7.012)	(7.006)
Populatio density	-0.644	-0.600	-0.632	-0.694
	(0.552)	(0.553)	(0.552)	(0.555)
Taxable income	0.233	0.232	0.233	0.235
	(0.173)	(0.173)	(0.173)	(0.173)
Land area	0.100*	0.097*	0.098*	0.092*
	(0.057)	(0.057)	(0.057)	(0.054)
Constant	-73.86	-82.11	-81.73	-80.86
	(139.3)	(139.5)	(139.5)	(139.4)
Year dummy	yes	yes	yes	yes
Regional dummy	yes	yes	yes	yes
Adj.R^2	0.006	0.006	0.006	0.006
Observations	30543	30543	30543	30543

Table 2.6: Regression Results (Explained variable: plant additions (unit))

	(1)	(2)	(3)	(4)
National nature parks	-0.00022***			
	(0.00007)			
Special protection zones		-0.00105***		
		(0.00039)		
Special zones			-0.00034***	
			(0.00011)	
Ordinary zones				-0.00042***
				(0.00014)
Wildlife preserve area	0.00015	0.00026	0.00021	0.00014
	(0.00031)	(0.00035)	(0.00032)	(0.00032)
RPS	0.00002*	0.00002	0.00002	0.00002*
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
FIT × Curtailment	-0.00730**	-0.00710**	-0.00747**	-0.00684**
	(0.00299)	(0.00297)	(0.00300)	(0.00294)
L.subsidy	0.00031***	0.000308***	0.000308***	0.000308***
	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Solar radiation	0.00586	0.00589	0.00592	0.00584
	(0.00422)	(0.00422)	(0.00422)	(0.00422)
Typhoon	0.00306	0.00299	0.00304	0.00300
	(0.00620)	(0.00619)	(0.00619)	(0.00619)
Wind speed	0.0686***	0.0688***	0.0687***	0.0684***
	(0.0150)	(0.0150)	(0.0150)	(0.0150)
Electricity grid access	0.00079	0.00081	0.00083	0.00071
	(0.00298)	(0.00297)	(0.00298)	(0.00300)
Electricity price	0.00051	0.00077	0.00079	0.00091
	(0.00515)	(0.00514)	(0.00514)	(0.00513)
Population density	-0.00002	0.00002	-0.00001	-0.00005
	(0.00016)	(0.00017)	(0.00016)	(0.00016)
Taxable income	0.00003	0.00003	0.00003	0.00003*
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Land area	0.00015***	0.00015***	0.00015***	0.00014***
	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Constant	-0.442***	-0.449***	-0.448***	-0.448***
	(0.122)	(0.123)	(0.123)	(0.123)
Year dummy	yes	yes	yes	yes
Regional dummy	yes	yes	yes	yes
Observations	30543	30543	30543	30543
Adj.R^2	0.104	0.104	0.104	0.104

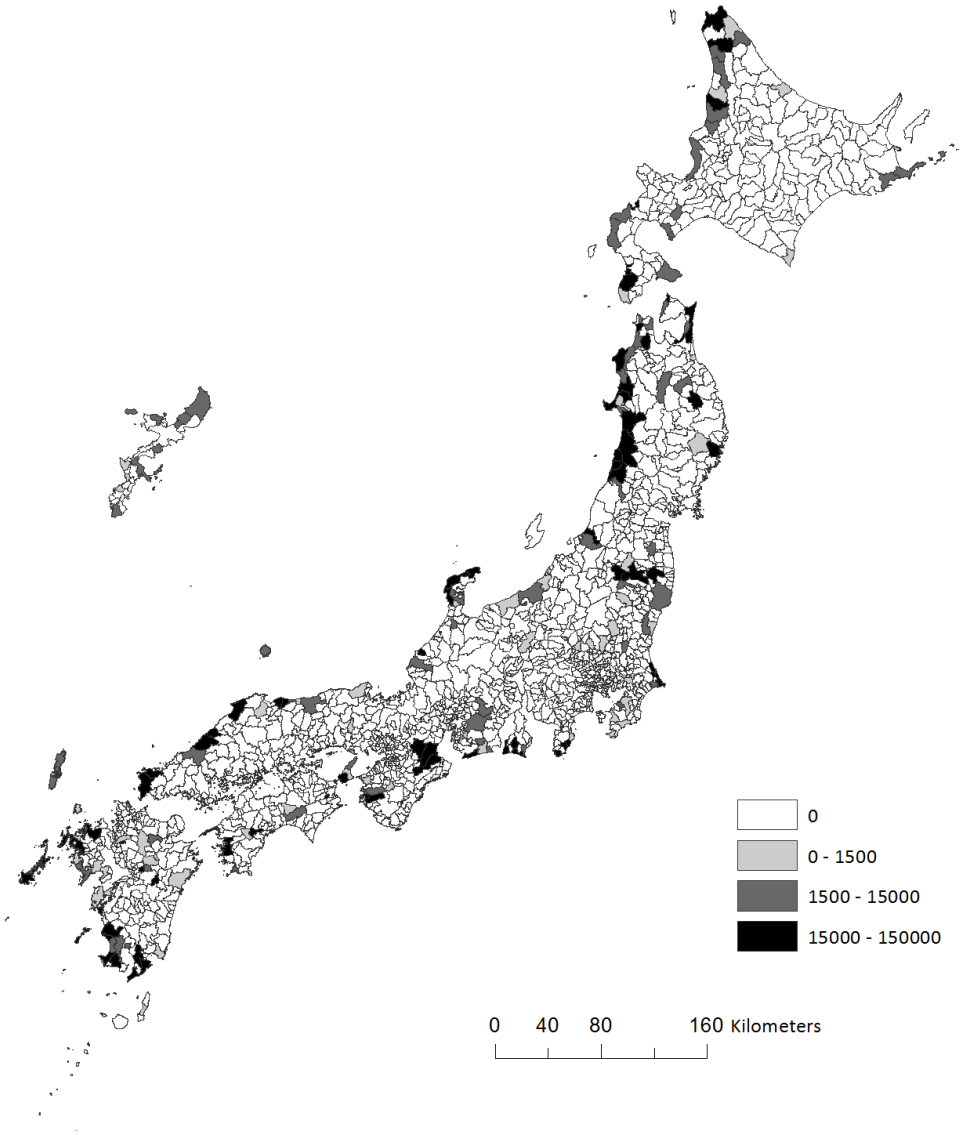

Figure 2.1: Cumulative installed capacity of wind turbines (kW) of municipalities in 2016.

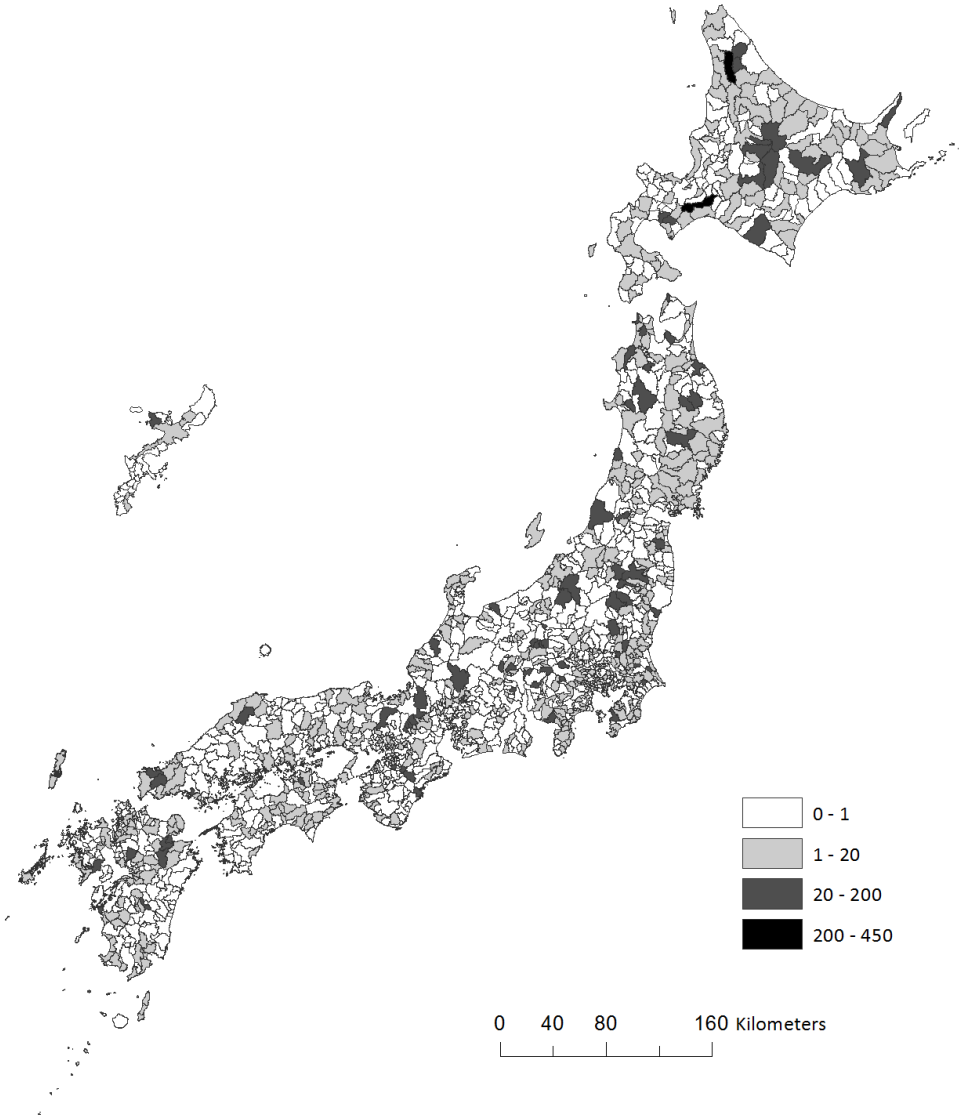

Figure 2.2: Total land area of national nature parks (km^2) in municipalities.

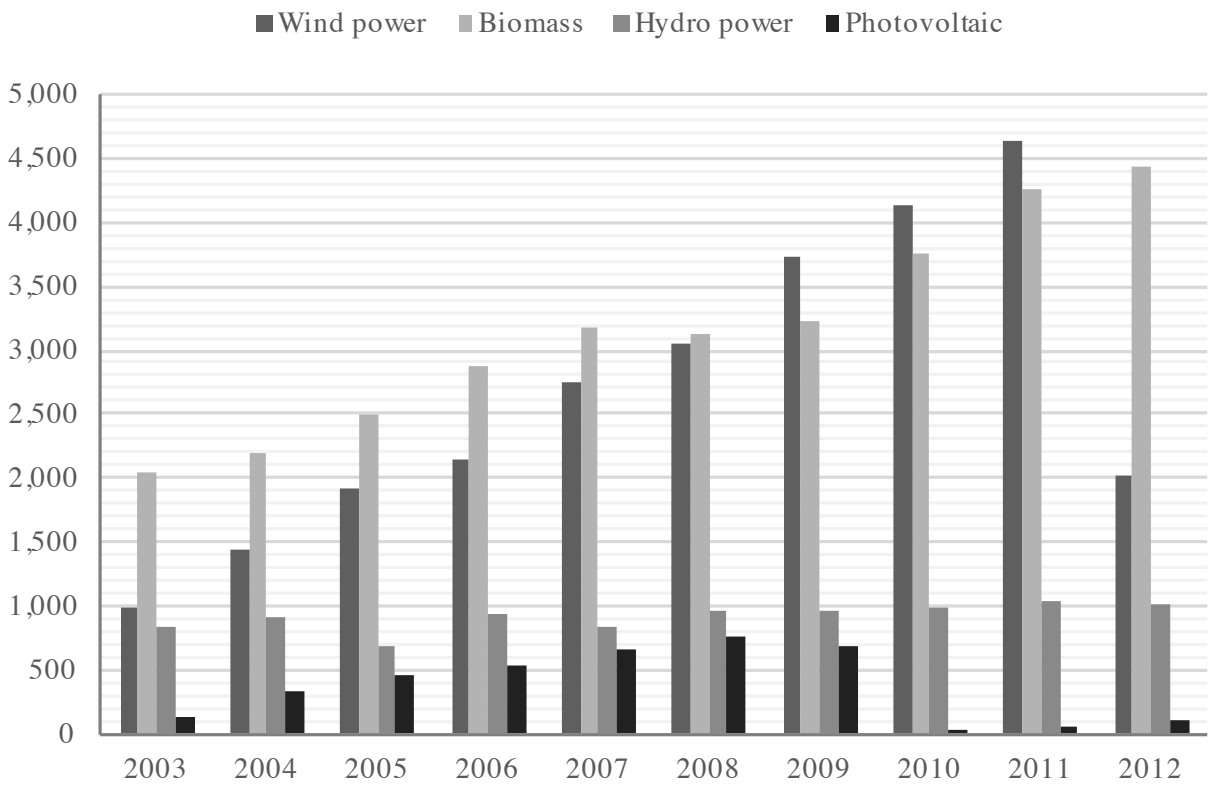

Figure 2.3: Trends in annual power generation of renewable energy facilities accredited by the RPS in Japan (GWh). Source: Enforcement Status Report of RPS

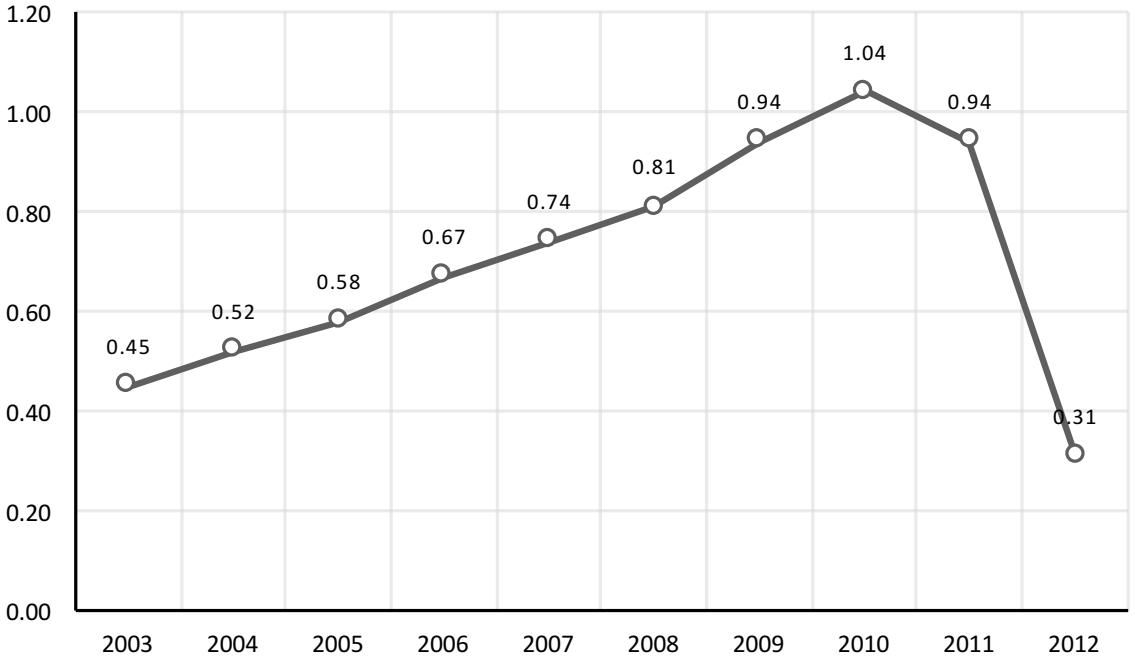

Figure 2.4: Trends in share of annual electricity generation from renewable energy facilities accredited by the RPS in total electricity generation of Japan (%). Source: Handbook of Energy and Economic Statistics in Japan

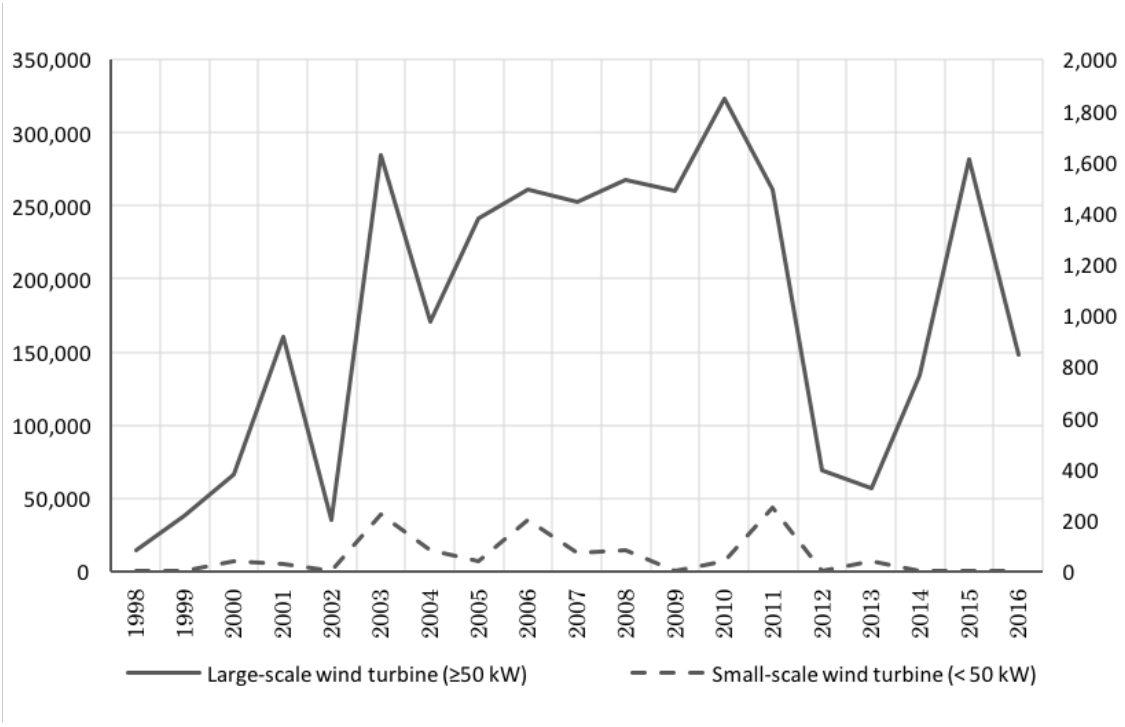

Figure 2.5: Trends in annual installed capacity of wind turbines by scales (kW).

Chapter 3

The Impact of Feed-in Tariff on Renewable Energy Deployment

3.1 Introduction

Wind and solar power generation in China have achieved tremendous growth. In 2016, the cumulative wind and solar capacity reached approximately 150 GW and 77 GW, respectively, which was the largest worldwide (China National Renewable Energy Center, 2017). However, since 2010, renewable energy industries in China have faced the issue of oversupply, leading to the curtailment of renewable power. The country's renewable curtailment is the worst in the world, with a total of 56,200 GWh of renewables curtailed in 2016 – the national average curtailment rate was as high as 17% and 10% for wind and solar energies, respectively (China Electricity Council, 2018). The high curtailment rate is partly due to the dramatic regional disparity of China's renewable energy development. Because of the uneven distribution of renewable energy resources, over 70% of China's large-scale wind and solar farms have been built in resource-rich regions where electricity demand and export capacity are low. Oversupply is particularly significant in Inner Mongolia, with 75 GW of available capacity versus only 20 GW of peak demand in 2016 (Bloomberg New Energy Finance, 2017). The

imbalance between resource abundance and low electricity demand has led to overcapacity and high rates of curtailment.

To resolve the overcapacity issue, the regionally differentiated FIT scheme for on-grid wind power was issued in 2009. Similarly, the policy for on-grid solar energy was announced in 2013. Several studies explore the weakness of the FIT policy with a national uniform tariff rate and claim that regional differentiation of tariffs can optimize the investment of renewable energy power plants. For instance, Obermüller (2017) points out that a uniform FIT policy would incentivize unfavorable wind capacity allocations. By investigating the discrepancy between economically optimal wind locations under a uniform wind tariff and system optimal wind locations in Germany, Obermüller (2017) finds that the uniform FIT attains the highest regional revenues in locations with rich wind resources but independent of electricity demand. Using an empirical optimization model, Schmidt et al. (2013) compare investment behavior under fixed and premium FITs for the case of Austria. As a result, they find that the premium FIT scheme promotes the location diversification of wind turbines.

The main objective of this chapter is to estimate whether the implementation of regional differentiation of tariffs has a positive impact on mitigating uneven distribution and overproduction of renewable energy in China. Assuming that counties located just south of the FIT boundary do not differ systematically from those located north of the boundary on relevant covariates, we estimate the effect of the difference in wind and solar tariffs across the boundary using the spatial regression discontinuity design (RDD). In addition, to investigate the effects of regionally differentiated FITs on subsequent dynamics, we adopt an approach that combines the multiple-period DID model with spatial RDD.

This chapter makes the following contributions to the literature on the economics of renewable energy policy. First, we examine the impact of regional tariff policy on reduction in the overcapacity of renewable energy projects through a quasi-experimental design. Existing empirical studies show inconclusive results regarding the FIT's impact on the location choice of renewable energy projects among regions in China. Xia and Song (2017b) empirically

investigate the driving factors of the regional disparity of China's wind power development. Their findings show that the FITs are most effective in wind resource-rich regions and have little impact on other regions. The results indicate that one driving force of the uneven development of wind power in China is the regional differentiation of on-grid wind tariffs. On the contrary, Zhao et al. (2016) empirically analyze the impacts of regionally differentiated FITs on the increase in installed wind capacity and conclude that the FIT is more effective in areas with poor wind resources. Second, while previous studies use installed capacity and power generation as indicators to capture wind power development, this chapter uses alternative measures of indicators. For instance, Menz and Vachon (2006) estimate the effects of the state renewable energy policy on wind power capacity and generation in the United States. In addition to these indicators, we use the utilization rate and operation hour of wind turbines in our analysis. These alternative measures allow us to capture the degree of effective utilization of the installed wind turbines. Third, while previous studies on the impact of FIT mainly focus on wind power development, we investigates the impact of regional differentiation of tariffs on the solar energy industry as well. Our findings on solar energy deployment are in line with the finding of Wang et al. (2016) that the FIT policy significantly mitigates the overcapacity of China's solar power industry.

This chapter's results suggest that regionally differentiated FITs have promoted the development of both the wind and solar energy industries in China. Specifically, our findings show that wind facilities' utilization rate has improved in regions with relatively poor wind resources through adoption of higher tariff rates. To explore this impact of the FIT, we use the actual amount of power generation and installed power capacity to calculate the utilization rate, which is used as a major production indicator of wind facilities. In addition, we find that the implementation of regional tariffs relieved the uneven distribution of renewable power facilities by attracting more projects to resource-poor regions. Interestingly, our findings show that the FIT provided for on-grid solar projects only had a significant impact in the year the tariff rates were revised. This result indicates an acute impact of the regional tariff

gap, which incentivizes renewable energy developers to locate the projects in resource-poor regions. Therefore, we conclude that the rapid growth in China's solar sector still depends on financial support in the form of higher tariffs paid to renewable power generators.

The remainder of this chapter is organized as follows: Section 2 introduces the policy of regionally differentiated FIT to promote the wind and solar industries in China. Section 3 describes the data. Section 4 follows with an analysis framework, including a description of the spatial RDD approach and regression discontinuity (RD) polynomial. Estimation results and discussions are provided in Section 5. Finally, Section 6 presents our conclusions and discusses the research implications.

3.2 Regionally Differentiated FIT in China

To mitigate the uneven distribution of renewable energy industries, the tariff rate is differentiated regionally under the FIT regime in China. The regionally differentiated FIT policy for on-shore wind power was first introduced by the National Development and Reform Commission (NDRC) in August 2009. As illustrated in Figure 3.1, the FIT policy divided the regions of China into four zones, each with a different tariff rate according to onshore wind resources and construction conditions. Regions with the richest wind resources in the north and west were given the lowest tariff of 0.51 yuan/kWh, reflecting lower production costs resulting from resource endowments. Regions with modest wind resources have tariffs of 0.54 yuan/kWh or 0.58 yuan/kWh. Regions with comparatively poor wind resources and construction conditions in the central area and coastline of China were given the highest tariff of 0.61 yuan/kWh.

[Figure 3.1]

Compared with the rapid growth of the wind power sector, the growth of solar power industries in China lagged until the cost of the technology declined sharply since 2009. In response to the introduction of a national, *uniform*, on-grid, solar FIT policy in 2011,

installation of solar power plants in China reached a record high of 2.5 GW, accounting for 9.12% of the world total that year (Zhang and He, 2013).[1] Because the uniform tariff rate leads to concentration of solar energy projects in mainly the western regions with rich solar resources in China, the NDRC issued a new FIT scheme in 2013 that applied different tariff rates based on the cost of electricity generation. Figure 3.2 illustrates the division of China into three resource zones under the regionally differentiated FIT policy. The tariff rates applied for each resource zone range from 0.90 to 1.00 yuan/kWh.

[Figure 3.2]

As production and construction costs of solar power continue to fall, the NDRC announced that it will cut the FIT offered to solar power to reflect the new market conditions in 2016 (NDRC, 2015). The tariff rates have reduced by as much as 11%, that is, by 0.02 to 0.1 yuan/kWh for on-grid solar farms. In addition, solar energy developers announced in December 2016 that the solar tariff will be cut further by as much as 19% in 2017. Therefore, some argue that this series of tariff cut announcements led to a rush in solar power installation ahead of the start of tariff cuts in June 2016 and January 2017 (Daiwa Capital Markets, 2015). Table 3.1 represents changes in tariff rates for on-grid wind and solar projects. It shows that the national uniform tariff rate for solar power was applied in 2011. The tariff has been regionally differentiated since 2013, creating a gap of 0.1 yuan/kWh at the largest. Subsequently, the tariff gap between the highest and lowest areas increased to 0.18 yuan/kWh in 2016.

[Table 3.1]

Figure 3.3 shows the spatial distribution of the counties selected as the study area of this chapter. The FIT boundary divides the study area into the south and north. Wind

[1] According to the uniform solar FIT, projects approved prior to July 1, 2011, that have completed construction and achieved commercial operation prior to December 31, 2011, are entitled to a tariff of 1.15 yuan/kWh; projects approved after July 1, 2011, or approved prior to that date but not completed before the end of 2011 are entitled to a tariff of 1 yuan/kWh.

power developers in counties north of the boundary receive the lowest tariff rate in China. In contrast, those in the southern counties receive the highest tariff rate for wind power in the country. The difference in the on-grid wind tariff rates between counties south and north of the FIT boundary is 0.1 yuan/kWh. We choose this part of the country as the study area because the regions with highest and lowest wind tariff rates share the same border only in this area. Similarly, the tariff rate provided for electricity generated by on-grid solar panels in the south is 0.05 yuan/kWh higher than that in the north.[2] Under the RDD, border cities near the FIT boundary provide good comparison because the observable differences in renewable resources, land use, and population characteristics tend to be small near the boundary line. Likewise, since the RD design's validity requires all relevant factors besides treatment to vary smoothly at the cutoff, we can focus exclusively on the counties located in these border cities.[3]

[Figure 3.3]

3.3 Empirical Strategy

3.3.1 Data

Our data consist of a panel of 64 counties located in Inner Mongolia, Shanxi Province, and Shaanxi Province. These are unbalanced yearly panel data from 2009 to 2012 for wind power regression and from 2011 to 2016 for solar energy regression.

Installed power capacity and wind power generation are typically used by previous studies to measure wind power development. In addition to these two indicators, we adopt the utilization rate and operation hour to capture the effectiveness of wind power facilities. The

[2]Due to the announcement about tariff rate cuts, the difference in solar tariff rate between the southern and northern counties increased to 0.08 yuan/kWh in 2016.

[3]The counties in our sample are located in border cities of the FIT boundary, including Yulin, Xinzhou, Shuozhou, Datong, Ordos, Huhhot, and Ulanqab. Yulin is a prefecture-level city located in Shaanxi Province. Xinzhou, Shuozhou, and Datong are cities in Shanxi Province. These cities border Ordos, Huhhot, and Ulanqab in Inner Mongolia to the north.

utilization rate is calculated by the percentage of time a turbine can be used during the 8,760 hours of the year (Welch and Venkateswaran, 2009).[4] On the other hand, due to data availability, only installed capacity is used as the indicator of solar power development. Production indicators of renewable power plants are obtained from the Compilation of Power Industry Statistics collected by the China Electricity Council. This dataset contains information on the production status of electric power plants of over 6,000 kW, which represent over 85% of total capacity in China.

As a treatment indicator for the regionally differentiated tariffs, we adopted a dummy variable that equals one if the county in the study area is located in the south of the FIT boundary and zero otherwise. During the study period, the tariff applied for wind power developers in counties south of the FIT boundary is 0.61 yuan/kWh generated electricity, while that for developers in northern counties is 0.51 yuan/kWh. In the case of solar energy, the tariff provided for on-grid solar energy facilities located in southern counties under the regionally differentiated FIT is 0.95 yuan/kWh, while that for facilities in counties north of the FIT boundary is 0.90 yuan/kWh.[5] Thus, the south dummy captures the higher tariff rate applied in counties south of the boundary under the FIT regime.

To control for counties' demographic and geographic characteristics, we use data on population density and agricultural land area of each county from the Statistical Yearbook of Shanxi Province, Shaanxi Province, and the Inner Mongolia Autonomous Region. Information used to capture the endowment of renewable energy resources, such as annual average wind speed measured at 70 meters height above the ground level and annual average solar radiation, are obtained from the China Meteorological Data Service Center. ArcGIS 10.1 is used to calculate the mean area slope and weighted elevation of each county. The elevation data, namely digital elevation models, are produced by the NASA Shuttle Radar Topography Mission database.

[4]Utilization rate = power generation / capacity $\times$ 24 $\times$ 365.

[5]More precisely, as presented in Table 3.1, the tariff rate for solar energy projects in southern counties under the regionally differentiated FIT is cut to 0.88 yuan/kWh, and that for solar projects in northern counties is 0.80 yuan/kWh in 2016.

To capture the impact of conventional energy on the deployment of renewable energy, we use the installed capacity of thermal power plants provided by the Compilation of Power Industry Statistics. The database contains thermal power plants whose capacity is larger than 300 MW. By including information on thermal power plants, we can consider the substitution between renewable and traditional energy sources. Although efforts have been made to diversify the primary sources for power generation, China will continue to rely on coal for power generation in the near future (Ma, 2011). At present, power grid companies are obligated to pay a part of the tariff to renewable energy developers, that is, 0.4 yuan/kWh, while the average thermal power price ranges from 0.2 to 0.3 yuan/kWh in China. This makes the price of renewable power higher than that of coal-fired power. Thus, renewable electricity appears less attractive to power companies (Xia and Song, 2017a). In addition, subsidies for fossil fuels in China are far larger than those for renewable energy, which may discourage renewable energy production and investment (Ouyang and Lin, 2014).

The summary statistics for wind power regression are presented in panel A of Table 3.2, and those for solar power are presented in panel B. Table 3.2 shows that there are an average of 20 MW wind turbines per county in the south of the FIT boundary, and 89 MW in the north. Thus, counties in the north seem to have more power capacity. However, as the comparison does not consider that observations further from the boundary are different in many respects from those that are closer, we cannot draw any credible causal inferences from them (MacDonald et al., 2016).

[Table 3.2]

The two-tailed t-tests show that there are statistically significant differences in the mean values of demographic and geographic characteristics between counties south and north of the boundary. A visual inspection of the data is more informative. Figure 3.4, Figure 3.5, and Figure 3.6 plot county characteristics other than renewable energy development at the county level based on distance to the FIT boundary. Using the ArcGIS 10.1, we calculate the Euclidean distance from each county's government office to the FIT boundary.

Counties located south (north) of the boundary are assigned a positive (negative) distance value. We find that there exist significant discrete changes in county characteristics such as agricultural land area, annual average wind speed, solar radiation, and elevation at the FIT boundary. Therefore, these county demographic and geographic characteristics are included as covariates in our estimation model. Besides, whereas some counties north of the boundary have relatively high wind speed and solar radiation, this pattern dissipates for counties that are close to the FIT boundary. Thus, we test our estimate's robustness by limiting the sample within 80 km from the boundary as well. Table 3.3 represents summary statistics for the sample within 80 km of the FIT boundary. The t-test results denote that the differences in geographic characteristics such as agricultural land area, elevation, and slope are statistically insignificant between the treatment and control groups when we restrict the sample to those close to the boundary.[6]

[Figure 3.4]

[Figure 3.5]

[Figure 3.6]

[Table 3.3]

3.3.2 Model

Our empirical analysis aims to measure the impact of the regionally differentiated FITs on the development of renewable energies in China. The spatial RDD approach exploits the discontinuous changes in tariff rates that drive variations in wind power development between the south and north of the FIT boundary. The general form of the spatial RDD model is as follows:

$$W_{it} = \alpha + \beta south_i + \gamma X_{it} + f(geographic\ location_i) + \lambda_b + \theta_t + \epsilon_{it}, \tag{3.1}$$

[6]Results of two-tailed t-tests are shown in column (4) of Tables 3.2 and 3.3.

where W_{it} refers to the production indicators of wind power generation facilities in county i and year t. The wind power indicators include utilization rate, installed capacity, power generation, and operation hour of power plants. $south_i$ is a dummy variable for counties south of the resource zone boundary. Our coefficient of interest, β, measures the discontinuous changes in W_{it} just south of the policy boundary. The time-varying county characteristics are captured by X_{it}, which include the demographic and geographic characteristics such as population density, agricultural land area, annual average wind speed, annual average solar radiation, installed capacity of thermal power plants, and mean area weighted slope for county i in year t. $f(geographic\ location_i)$ denotes the regression discontinuity polynomial, which controls for smooth functions of the geographic location. Recent studies suggest that the local linear polynomial should be run with kernel weights that assign more weights on observations near the cutoff (Imbens and Kalyanaraman, 2012; Calonico et al., 2014). Therefore, our main results are estimated with a local linear regression with triangular kernel weights. We also estimate regressions with quadratic and quartic polynomials for checking the robustness of the main results. λ_b represents the boundary segment fixed effects that denote which of the five equal-length segments of the boundary is the closest to the county's government offices. Finally, the year dummy θ_t is used to capture external events that commonly affect the development of the wind and solar industries, such as changes in policies and regulations at the national level.

In addition, to investigate the effects of regionally differentiated FITs on the subsequent dynamics of solar power development, we adopt an approach that combines the multi-period DID model with the spatial RDD:

$$S_{it} = \alpha + \beta_0 south_i + \sum_{t=-2}^{3} \beta_t south_i \times \theta_t + \gamma X_{it} + f(geographic\ location_i) + \lambda_b + \theta_t + \epsilon_{it}, \quad (3.2)$$

where S_{it} denotes the indicator of solar power development. Compared with the wind power regressions, only the cumulative installed capacity of on-grid solar power generation facilities

in county i in year t has been adopted due to data availability. $south_i \times \theta_t$ are interaction terms between the treatment indicator $south_i$ and year dummy θ_t. The excluded time category is 2012 ($t = -1$) such that the effects are measured relative to the year prior to the implementation of the solar FIT policy in 2013. β_t is the coefficient on the tth lead or lag of the policy implementation year. These coefficients of $south_i \times \theta_t$ capture the effects of a discontinuous change in the solar tariff rate between the southern and northern counties on the installation of solar power generation facilities in each year during the research period.

3.4 Results and Discussions

3.4.1 Impact on Wind Power Industries

We estimate the effects of regionally differentiated tariffs on renewable energy development using the spatial RDD model. Table 3.4 reports the regression results regarding the FIT's impact on the production indicators of wind power facilities, including the annual utilization rate, installed capacity, power generation, and operating hours. Panels A and B in Table 3.4 report the specification that includes a single-dimensional RD approach. Particularly, the linear polynomial in distance from the county government to the FIT boundary with kernel weights in panel A allows us to assign more weights on observations near the boundary. We also report alternative specifications that use multiple dimensional discontinuities in the longitude-latitude space in panels C and D of the table. It provides useful checks on the regression results estimated by the model with the single-dimensional RD polynomial. All regressions include controls for boundary segment fixed effects and year fixed effects. Controls for demographic and geographic conditions as well as conventional energy sources are adopted in all regressions as well.

[Table 3.4]

Our estimates imply that regional differentiation of tariffs has positively affected the

development of the wind power industry in China. According to the results in column (1) in panel A of Table 3.4, a 0.1 yuan difference in the tariff rate will result in approximately an 8.66% increase in annual utilization rates of wind facilities. This implies that the adoption of regionally differentiated FIT increases the utilization rate by 1.53 times of the total utilization rate per year.[7] In column (2), the coefficient of *South* is positive and statistically significant. The result suggests that the regionally differentiated tariff encourages the installation of wind power plants of nearly 82.93 MW in regions with higher tariff rates. This implies that the regional FIT has attracted more plants to resource-poor regions. In addition, according to the results in columns (3) and (4), implementation of the regionally differentiated tariffs is related positively to the annual total power generation and operating hours of wind facilities. The annual increase in power generation of wind turbines caused by the difference in tariff rate is approximately 163.4 GWh. Moreover, due to the FIT, the annual operating hours have increased to 157,900 hours, which is about 1.51 times the annual average.[8] These results indicate that the implementation of regional FITs might help mitigate the overproduction of wind electricity in regions with rich wind resources but lower electricity demand. Panels B, C, and D in Table 3.4 examine the robustness of the main results through two alternative specifications of the RD polynomial. The effects of regionally differentiated FIT on wind deployment are statistically significant across all specifications.

[Table 3.5]

Table 3.5 limits the sample to counties located within 80 km of the FIT boundary. The specification reported in panel A of Table 3.5 suggests a statistically significant and positive effect of the tariff at around 12.65%, as compared with the mean utilization rate of 2.41% throughout the north counties located within 80 km of the FIT boundary, which again is statistically significant in panels B, C, and D. We find that the regression results are broadly

[7] According to the summary statistics in Table 3.2, the average utilization rate of wind facilities in the control group is around 5.69%.

[8] According to the summary statistics in Table 3.2, the average operating hours of wind facilities in the control group are around 104,800 hours.

robust to the choice of average distances to the boundary, that is, for counties located within 80 km from the boundary, counties located within 50 km from the boundary (see Table A1 in Appendix), or all counties. Our estimation results are consistent with the findings of Zhao et al. (2016), showing that the FIT policy had a strong impact on the promotion of wind power in areas with fewer wind resources, namely the southern counties, than in areas with rich wind resources in China.

3.4.2 Impact on Solar Power Industries

This section investigates the effect of the regionally differentiated FIT on the development of solar energy, with a focus on location choices of the solar industries. The installed power capacity of solar power is adopted as the dependent variable in the regression model. The sample period of the solar power-related regression can be divided into two sub-periods: pre-FIT period from 2011 to 2012 and post-FIT period from 2013 to 2016. The approach of spatial RDD combined with the multiple time-period DID model allows us to estimate the evolution of the coefficients of *South* over time.

[Table 3.6]

Table 3.6 illustrates the regression results on the impact of the regional differentiation of tariffs on the installed capacity of solar energy facilities. Similar to the wind power regression, specifications that include a single-dimensional location polynomial are reported in columns (1) and (2) of Table 3.6. Particularly, the location polynomial used in column (1) is a linear polynomial in the distance to the FIT boundary with kernel weights. In addition, specifications that use multiple dimensional location polynomials are reported in columns (3) and (4). As represented by the coefficients of *South*×2011 in Table 3.6, solar capacity additions caused by the implementation of the FIT is insignificant in the pre-treatment period. The result indicates that the observed FIT effect is not driven by the fact that counties just south and north of the FIT boundary are affected differently based on geographic and

demographic conditions. On the other hand, we find that the estimated coefficients are negative and significant in 2013, the year in which regionally differentiated FIT had been adopted. This result may be because the announcement about the implementation of the on-grid solar FIT was made in the last quarter of the year and investments from developers were suspended until then. After that, the FIT's impact was insignificant until 2016, which is when the tariff cut of on-grid solar power was announced. This result indicates that the difference in tariff rate between resource regions when the on-grid solar FIT was first adopted in 2013 was not enough to incentivize developers to locate the power plants in resource-poor regions.[9] When the tariff rate cuts for solar power were announced in 2016, the difference in tariff rates between resource-poor and rich regions became larger. A large gap in tariffs helps to incentivize solar energy developers to invest in regions with relatively poor resources and location conditions.[10] The coefficient of $South \times 2016$ in column (1) of Table 3.6 suggests that the solar installed capacity increased to 99.6 MW due to the 0.08-yuan/kWh difference in solar tariff. This result shows that the annual capacity addition of solar facilities caused by the FIT in 2016 is approximately 1.88 times the average solar power installed capacity in each county.[11] Our results suggest that the regionally differentiated FIT was not effective until new tariffs with higher differences in tariff rates among regions were announced.

[Figure 3.7]

Figure 3.7 illustrates the same results as Table 3.6 but in a more intuitive way. The interaction coefficient was positive and statistically significant in 2016. This result suggests that, only in the year when the new tariff rates of on-grid solar power were announced, the installed capacity of solar power plants increased in the southern counties compared with

[9] In our case, the difference in on-grid solar tariff rates between the southern and northern counties was 0.05 yuan/kWh before the tariff cut had been announced in 2016.

[10] Because the tariff cut occurred in early 2016, the difference in solar tariff rates between the treatment and control groups increased from 0.05 yuan/kWh to 0.08 yuan/kWh. In other words, after the tariff cut, tariff provided for per kWh electricity generated by on-grid solar projects located in the southern counties is 0.08 yuan higher than that for solar projects located in the north. More details can be found in Table 3.1.

[11] According to the summary statistics in Table 3.2, the mean solar capacity in the control group is 24.3 MW.

counties located in the north of the FIT boundary.

[Table 3.7]

Similar to the wind power regression, Table 3.7 limits the sample to counties located within 80 km of the FIT boundary. In addition, the regression results estimated by the sample limited to the counties located within 50 km of the FIT boundary are reported in Table A2 in Appendix. We find that the regression results are robust to the choice of average distances to the boundary. The coefficients of $South \times 2016$ in the first column of Table 3.7 suggest a statistically significant and positive effect of the solar tariff at around 146.7 MW in 2016.

3.5 Conclusions

By focusing on the wind and solar power industry in China, this chapter estimates whether the implementation of regionally differentiated FIT mitigated the uneven development of renewable energy. The spatial RDD approach allows us to examine the impact of differentiated FIT across the resource zone boundary through a quasi-experimental design. In addition, the multiple time-period model helps us to consider how the estimated impact changes over time.

According to the estimation results, the adoption of regional differentiation of tariffs effectively enhanced location diversification of renewable projects, at least for a limited distance around the FIT boundary. In the case of wind power industry, we find that a higher tariff rate leads to an increase in the utilization rate of wind turbines in counties located in resource-poor regions by approximately 8.66%, as compared with the mean wind facility utilization rate of 5.69% throughout the northern counties. In addition, when considering the FIT's effect on the installation of wind power plants, we find that the annual wind capacity additions caused by FIT adoption are about 82.9 MW. The effect of regionally differentiated FIT is also found in the case of solar energy. The annual increase in cumulative installed

capacity of solar power plants through adoption of the FIT is estimated at about 99.6 MW in 2016, the year when the significant cut in solar tariff was proposed. Before that, the FIT for on-grid solar power did not have a significant effect on promoting the location diversification of the solar power industry.

Our results suggest that the regional differentiation of tariffs has mitigated the uneven regional distribution of both the wind and solar industries in China. This finding is in line with those in the existing literature, which indicate that cost-based tariffs can incentivize renewable energy developers to diversify the locations of wind turbines (Schmidt et al., 2013; Zhao et al., 2016). In addition, we also find that the regionally differentiated FIT mitigates overproduction in wind-rich yet remote regions, by improving the utilization rate of wind turbines in resource-poor regions. Lastly, our results indicate that the tariffs provided for on-grid solar projects significantly encouraged installations of solar panels in the year that new tariff rates with a higher regional gap were enforced. This result indicates that even a small increase in the tariff rate can provide a strong incentive for the development of solar power.

The endowment of renewable energy is regionally diverse. Therefore, the renewable curtailment issue arising from geographical concentration of the renewable project and the limited transmission grid is a challenge for many countries in the world. For instance, Kyushu Electric Power Co. in Japan restricted third-party solar power supplies four times during October 2018. With rich endowment of solar radiation, there has been massive investment in solar power in Kyushu area, particularly after the FIT policy's introduction in 2012. The capacity of solar power in Kyushu area is 8.07GW, which accounts for more than 80% of the electricity demand when demand is low.[12] Moreover, in the case of Germany, wind power projects are concentrated in the northern area with abundant wind resources, while most solar projects are located in the southern areas rich in solar radiation (Obermüller, 2017). In these countries, the unified nationwide tariff policy for on-grid renewable electricity

[12] *The Nikkei* newspaper, 13 October 2018.

has been implemented, instead of the regionally differentiated one. The findings from this chapter provide a policy implication for countries throughout the world facing the challenge of overproduction of renewable energy, which is caused by the increasing capacity installation and shortage of the transmission grid.

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Table 3.1: Tariff Rates for On-grid Wind and Solar Projects in China (yuan/kWh)

Wind			
	2009	2013	2016
Zone I	0.51	0.49	0.47
Zone II	0.54	0.52	0.50
Zone III	0.58	0.56	0.54
Zone IV	0.61	0.61	0.60
Solar			
	2011	2013	2016
Zone I	1.15/1.00	0.90	0.80
Zone II	1.15/1.00	0.95	0.88
Zone III	1.15/1.00	1.00	0.98

Source: The National Development and Reform Commission.

Table 3.2: Descriptive Statistics (Full Sample)

Panel A: Descriptive Statistics (Wind)

		Control groups (south=0)			Treatment groups (south=1)		
	Unit	Obs	Mean	Std.dev.	Obs	Mean	Std.dev.
Wind facility production indicators							
Utilization rate	%	112	5.690	8.946	172	3.574	7.912
Wind capacity	MW	112	89.25	185.4	172	20.17	50.44
Power generation	GWh	112	149.5	345.1	172	33.76	98.02
Operation hour	1,000 hour	112	104.8	287.1	172	47.97	155.6
County characteristics							
Population density	1,000 person/km^2	112	0.192 **	0.315	171	0.668	2.527
Secondary industry output	billion yuan	112	9.760***	11.71	172	5.255	9.506
Agricultural land area	10^5 ha	112	0.371*	0.241	171	0.336	0.187
Wind speed	m/s	112	5.862***	1.027	172	5.456	0.773
Weighted average elevation	100 m	112	13.53***	1.719	172	12.75	2.047
Slope	degree	112	4.098***	2.728	168	8.438	3.456
Thermal capacity	GW	112	0.763***	1.379	172	0.398	0.934

Panel B: Descriptive Statistics (Solar)

		Control groups (south=0)			Treatment groups (south=1)		
	Unit	Obs	Mean	Std.dev.	Obs	Mean	Std.dev.
Solar facility production indicators							
Solar capacity	MW	168	24.30	55.41	258	27.16	90.51
County characteristics							
Secondary industry output	billion yuan	168	12.58***	14.80	258	7.010	12.18
Weighted average elevation	100 m	168	13.53***	1.716	258	12.75	2.045
Slope	degree	168	4.098***	2.724	258	8.242	3.642
Solar radiation	100 kWh/m^2	168	16.26***	0.258	258	15.30	0.448

Note: Mean value of variables differ with statistical significance in a two-tailed t-test between the treatment and control groups, and they are denoted by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 3.3: Descriptive Statistics (Sample Falling within $\leq$ 80 km of the Boundary)

Panel A: Descriptive Statistics (Wind)

		Control groups (south=0)			Treatment groups (south=1)		
	Unit	Obs	Mean	Std.dev.	Obs	Mean	Std.dev.
Wind facility production indicators							
Utilization rate	%	64	2.410	5.956	108	4.593	8.860
Wind capacity	MW	64	23.46	63.42	108	26.62	59.16
Power generation	GWh	64	28.10	83.14	108	46.66	118.4
Operation hour	1,000 hour	64	23.30	81.49	108	63.28	185.8
County characteristics							
Population density	1,000 person/km^2	64	0.207*	0.306	107	0.979	3.159
Secondary industry output	billion yuan	64	12.15**	13.40	108	7.533	11.37
Agricultural land area	10^5 ha	64	0.301	0.184	107	0.345	0.188
Wind speed	m/s	64	5.646	0.748	108	5.665	0.757
Elevation	100 m	64	13.41	1.489	108	13.08	1.846
Slope	degree	64	3.890***	2.571	104	6.701	2.901
Thermal capacity	GW	64	0.928*	1.503	108	0.621	1.115

Panel B: Descriptive Statistics (Solar)

		Control groups (south=0)			Treatment groups (south=1)		
	Unit	Obs	Mean	Std.dev.	Obs	Mean	Std.dev.
Solar facility production indicators							
Solar capacity	MW	96	14.17	30.77	162	41.72	110.93
County characteristics							
Secondary industry output	billion yuan	96	15.72**	16.90	162	10.12	14.46
Elevation	100 m	96	1341	148.5	162	1308	184.4
Slope	degree	96	3.890***	2.564	162	6.453	3.112
Radiation	100 kWh/m^2	96	16.12***	0.179	162	15.52	0.296

Note: Mean value of variables differ with statistical significance in a two-tailed t test between the treatment and control groups, and they are denoted by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 3.4: Effect of FIT on Wind Power Development (Full Sample)

	Utilization rate	Wind capacity	Power generation	Operation hour
	(1)	(2)	(3)	(4)
Panel A: Linear Polynomial in Distance with Kernel Weights				
South	8.656***	82.93***	163.4***	157.9***
	(1.825)	(17.58)	(31.63)	(36.58)
Adj.R^2	0.407	0.492	0.466	0.349
Panel B: Quadratic Polynomial in Distance				
South	8.240***	69.41***	135.9***	152.0***
	(1.748)	(20.13)	(35.87)	(37.64)
Adj.R^2	0.455	0.522	0.493	0.371
Panel C: Linear Polynomial in Longitude and Latitude				
south	6.633***	10.84	32.02	95.46**
	(1.730)	(21.15)	(39.14)	(39.28)
Adj.R^2	0.482	0.511	0.473	0.362
Panel D: Quadratic Polynomial in Longitude and Latitude				
South	8.437***	53.79**	110.7***	149.6***
	(1.800)	(22.02)	(39.46)	(40.66)
Adj.R^2	0.499	0.585	0.535	0.384
Geographic location polynomial	yes	yes	yes	yes
Control	yes	yes	yes	yes
Segment fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	279	279	279	279

Note: Robust standard errors, adjusted for clustering by county, are in parentheses. If z denotes the geometric distance to the tariff zone boundary, the linear polynomial in distance is $z + z \times south$ and the quadratic polynomial in distance is $z + z^2$. If x denotes the longitude and y denotes the latitude of each county, the linear polynomial in longitude and latitude is $x + y$ and the quadratic polynomial in longitude and latitude is $x + y + x^2 + y^2 + xy$. Coefficients that are significantly different from zero are denoted by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 3.5: Effect of FIT on Wind Power Development (Sample Falling within $\leq$ 80 km of the Boundary)

	Utilization rate	Wind capacity	Power generation	Operation hour
	(1)	(2)	(3)	(4)
Panel A: Linear Polynomial in Distance with Kernel Weights				
South	12.65***	82.05***	153.9***	174.1***
	(2.440)	(19.60)	(34.03)	(52.65)
Adj.R^2	0.395	0.337	0.318	0.282
Panel B: Quadratic Polynomial in Distance				
South	12.73***	80.64***	153.1***	176.7***
	(2.463)	(19.62)	(33.82)	(53.00)
Adj.R^2	0.400	0.349	0.327	0.283
Panel C: Linear Polynomial in Longitude and Latitude				
south	12.45***	74.70***	149.1***	175.7***
	(2.543)	(21.93)	(43.51)	(63.16)
Adj.R^2	0.378	0.349	0.320	0.277
Panel D: Quadratic Polynomial in Longitude and Latitude				
South	10.10***	64.05***	132.6***	157.7**
	(2.567)	(21.80)	(41.42)	(61.58)
Adj.R^2	0.419	0.363	0.332	0.277
Geographic location polynomial	yes	yes	yes	yes
Control	yes	yes	yes	yes
Segment fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	167	167	167	167

Note: Robust standard errors, adjusted for clustering by county, are in parentheses. If z denotes geometric distance to the tariff zone boundary, the linear polynomial in distance is $z + z \times south$ and the quadratic polynomial in distance is $z + z^2$. If x denotes the longitude and y denotes the latitude of each county, the linear polynomial in longitude and latitude is $x + y$ and the quadratic polynomial in longitude and latitude is $x + y + x^2 + y^2 + xy$. Coefficients that are significantly different from zero are denoted by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 3.6: Effect of FIT on Solar Power Development (Full Sample)

	Explanatory variable: solar capacity (MW)			
	Single-dimensional RDD		Multi-dimensional RDD	
	Linear	Quadratic	Linear	Quadratic
	(1)	(2)	(3)	(4)
South	45.67***	35.69***	59.24***	67.82***
	(14.75)	(12.78)	(16.10)	(19.79)
South×2011	0.278	1.605	1.688	1.580
	(1.253)	(2.276)	(2.269)	(2.290)
South×2013	-7.284*	-9.950**	-10.12**	-9.897**
	(4.071)	(4.282)	(4.289)	(4.313)
South×2014	-11.01	-18.38	-18.67	-18.29
	(13.30)	(14.11)	(14.12)	(14.19)
South×2015	1.865	-8.648	-9.151	-8.494
	(15.47)	(16.48)	(16.51)	(16.56)
South×2016	99.62***	68.75**	68.16**	68.92**
	(37.14)	(33.43)	(33.33)	(33.50)
Cons.	-16.90	-401.9	1778	-16451
	(349.1)	(274.9)	(1250)	(25012)
Geographic location polynomial	yes	yes	yes	yes
Control	yes	yes	yes	yes
Segment fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	426	426	426	426
Adj.R^2	0.234	0.185	0.200	0.207

Note: Robust standard errors, adjusted for clustering by county, are in parentheses. If z denotes geometric distance to the tariff zone boundary, the linear polynomial in distance is $z + z \times south$ and the quadratic polynomial in distance is $z + z^2$. If x denotes the longitude and y denotes the latitude of each county, the linear polynomial in longitude and latitude is $x + y$ and the quadratic polynomial in longitude and latitude is $x + y + x^2 + y^2 + xy$. Coefficients that are significantly different from zero are denoted by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 3.7: Effect of FIT on Solar Power Development (Sample Falling within $\leq$ 80 km of the Boundary)

	Explanatory variable: solar capacity (MW)			
	Single-dimensional RDD		Multi-dimensional RDD	
	Linear	Quadratic	Linear	Quadratic
	(1)	(2)	(3)	(4)
South	31.89	32.46	30.30	19.15
	(22.46)	(20.33)	(22.90)	(24.51)
South×2011	-0.693	-0.460	-0.434	-0.401
	(1.662)	(1.870)	(1.699)	(1.520)
South×2013	-2.093	-1.447	-1.639	-1.882
	(4.759)	(4.440)	(4.347)	(4.274)
South×2014	2.086	1.796	1.524	1.180
	(14.93)	(15.86)	(15.85)	(15.66)
South×2015	20.65	20.01	19.47	18.78
	(17.12)	(17.78)	(17.79)	(17.38)
South×2016	146.7***	143.3***	142.7***	141.9***
	(45.84)	(46.59)	(46.55)	(46.25)
Cons.	-468.6	-651.5	-7.192	-19659
	(562.5)	(498.6)	(1557)	(50567)
Geographic location polynomial	yes	yes	yes	yes
Control	yes	yes	yes	yes
Segment fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	258	258	258	258
Adj.R^2	0.292	0.282	0.278	0.281

Note: Robust standard errors, adjusted for clustering by county, are in parentheses. If z denotes geometric distance to the tariff zone boundary, the linear polynomial in distance is $z + z \times south$ and the quadratic polynomial in distance is $z + z^2$. If x denotes the longitude and y denotes the latitude of each county, the linear polynomial in longitude and latitude is $x + y$ and the quadratic polynomial in longitude and latitude is $x + y + x^2 + y^2 + xy$. Coefficients that are significantly different from zero are denoted by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

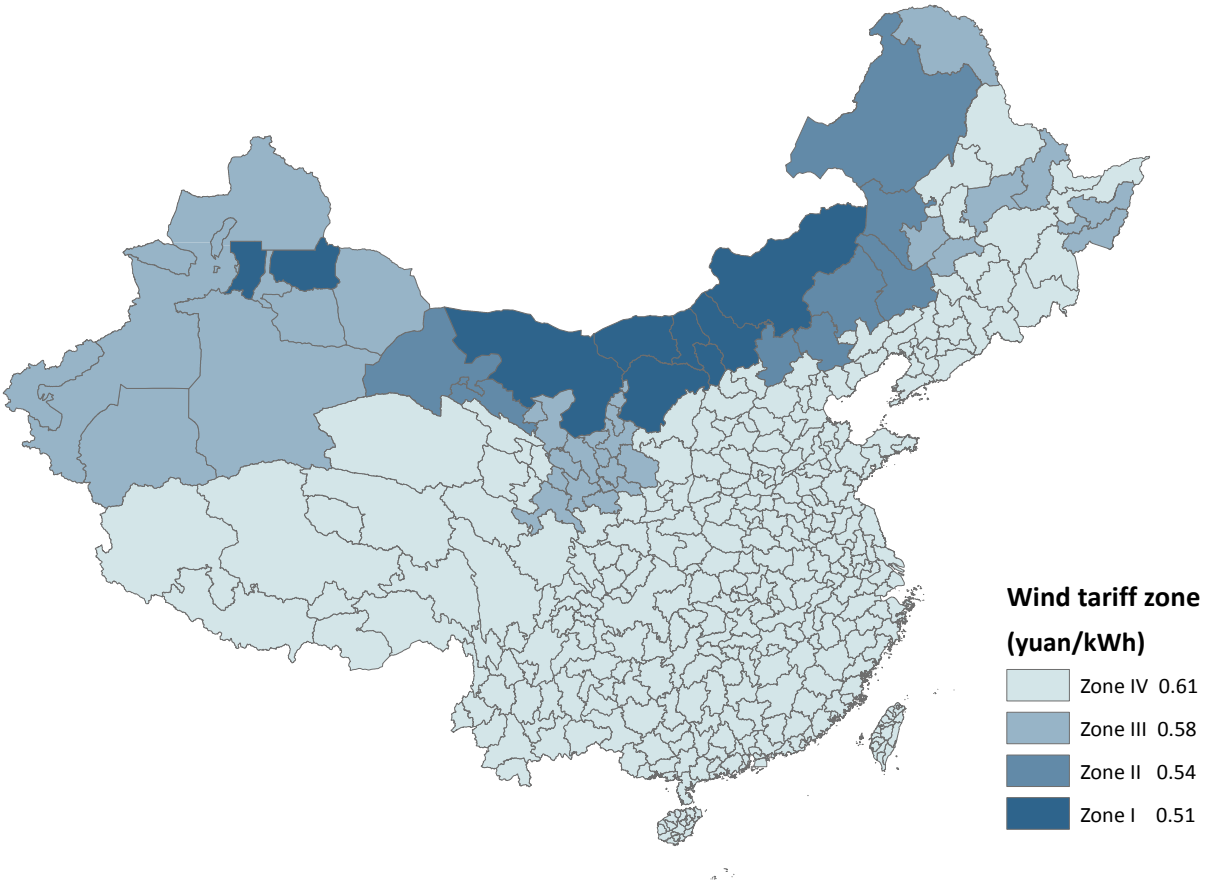

Figure 3.1: Distribution of wind resource zones and regionally differentiated on-grid wind tariffs in China.

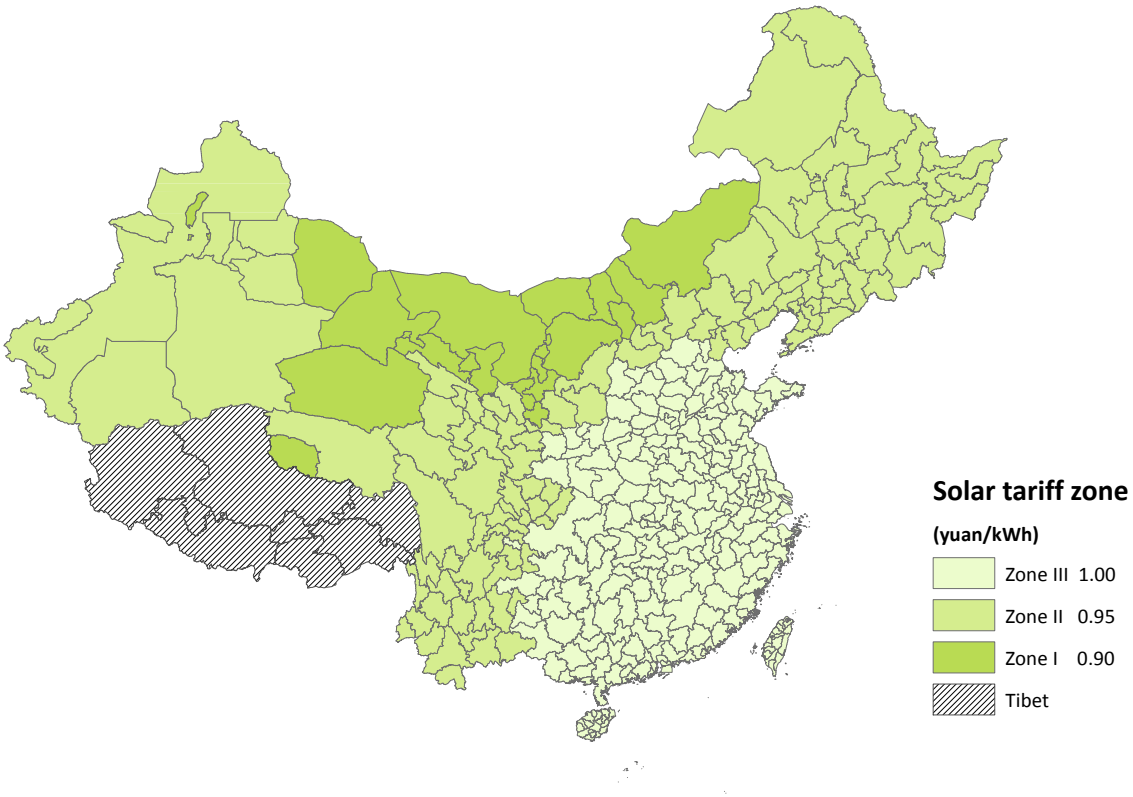

Figure 3.2: Distribution of solar resource zones and regionally differentiated on-grid solar tariffs in China.

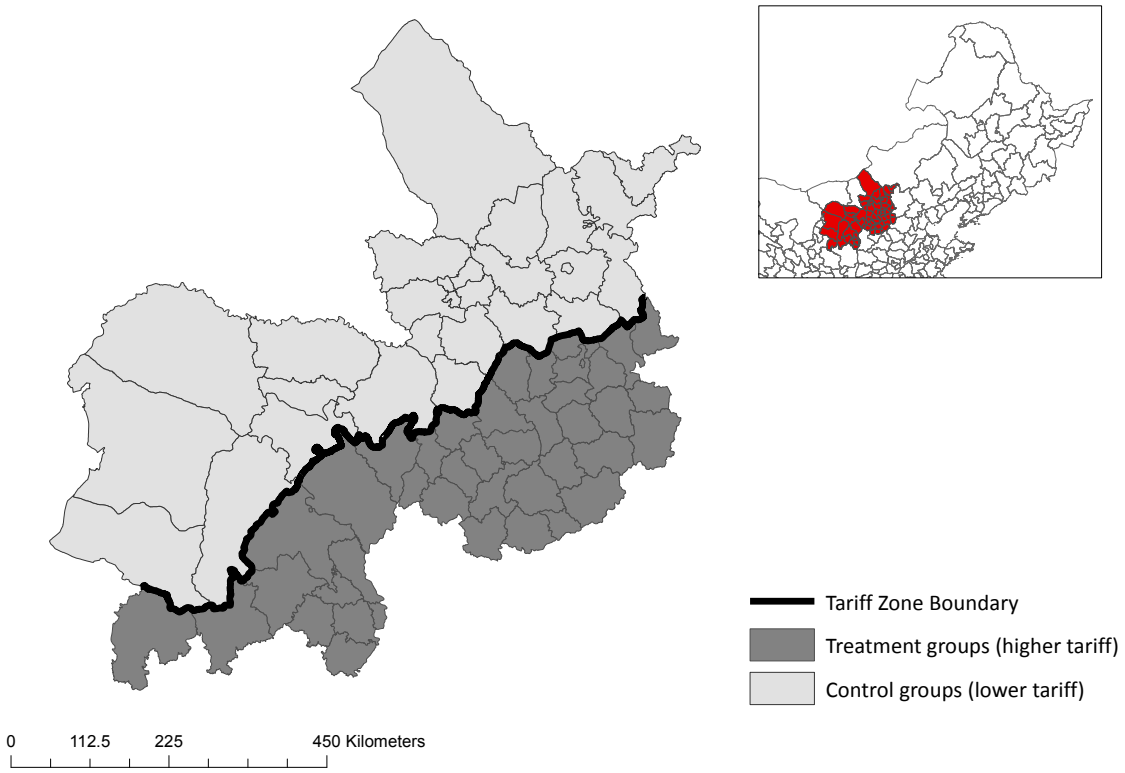

Figure 3.3: Distribution of the feed-in tariff (FIT) boundary and counties in the study area. Counties located in the south of the FIT boundary contributed to the treatment group and are colored in dark grey *(south=1)*.

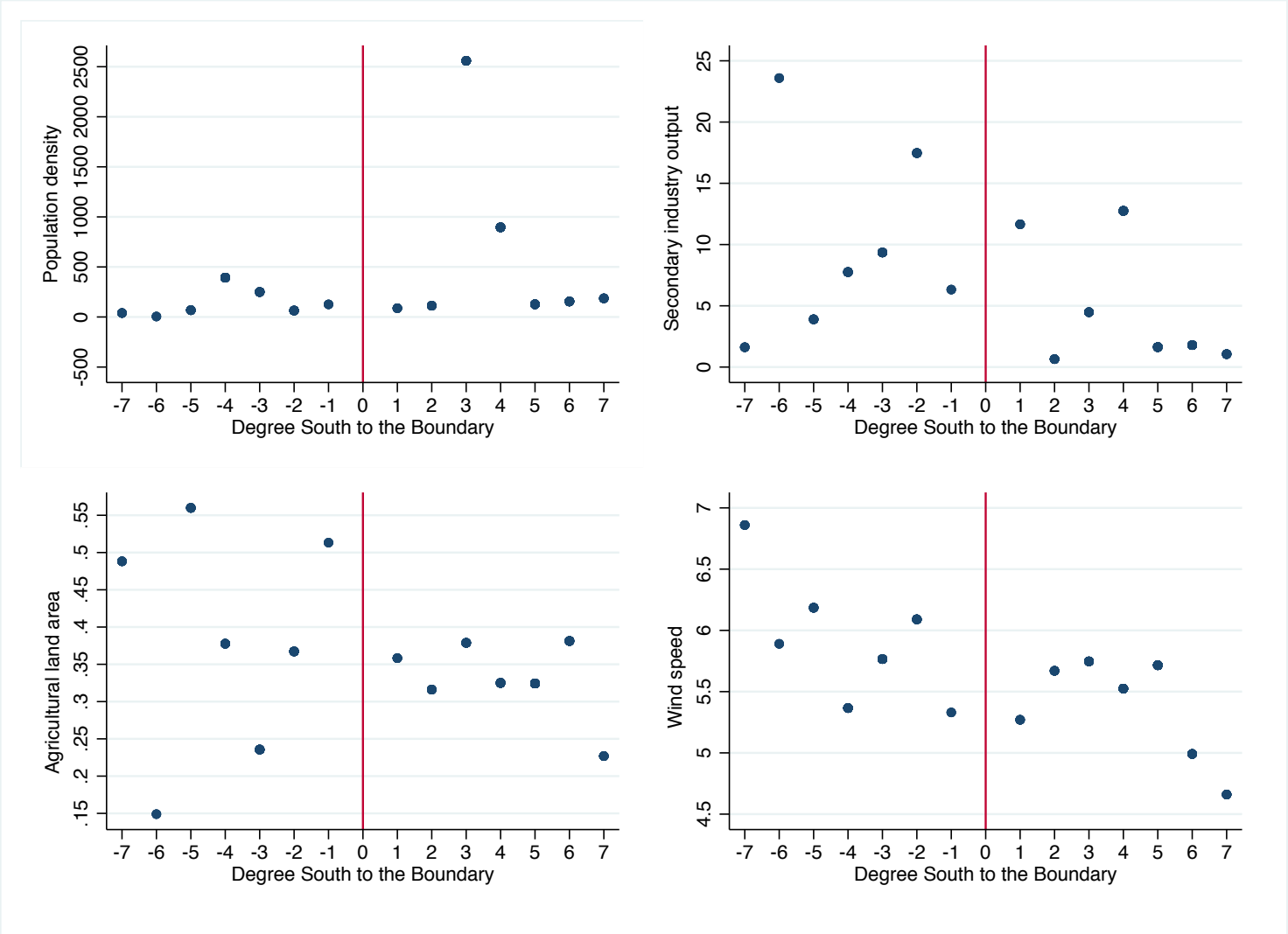

Figure 3.4: Local polynomial smoothing of characteristics by county relative to the distance from the feed-in tariff boundary (wind).

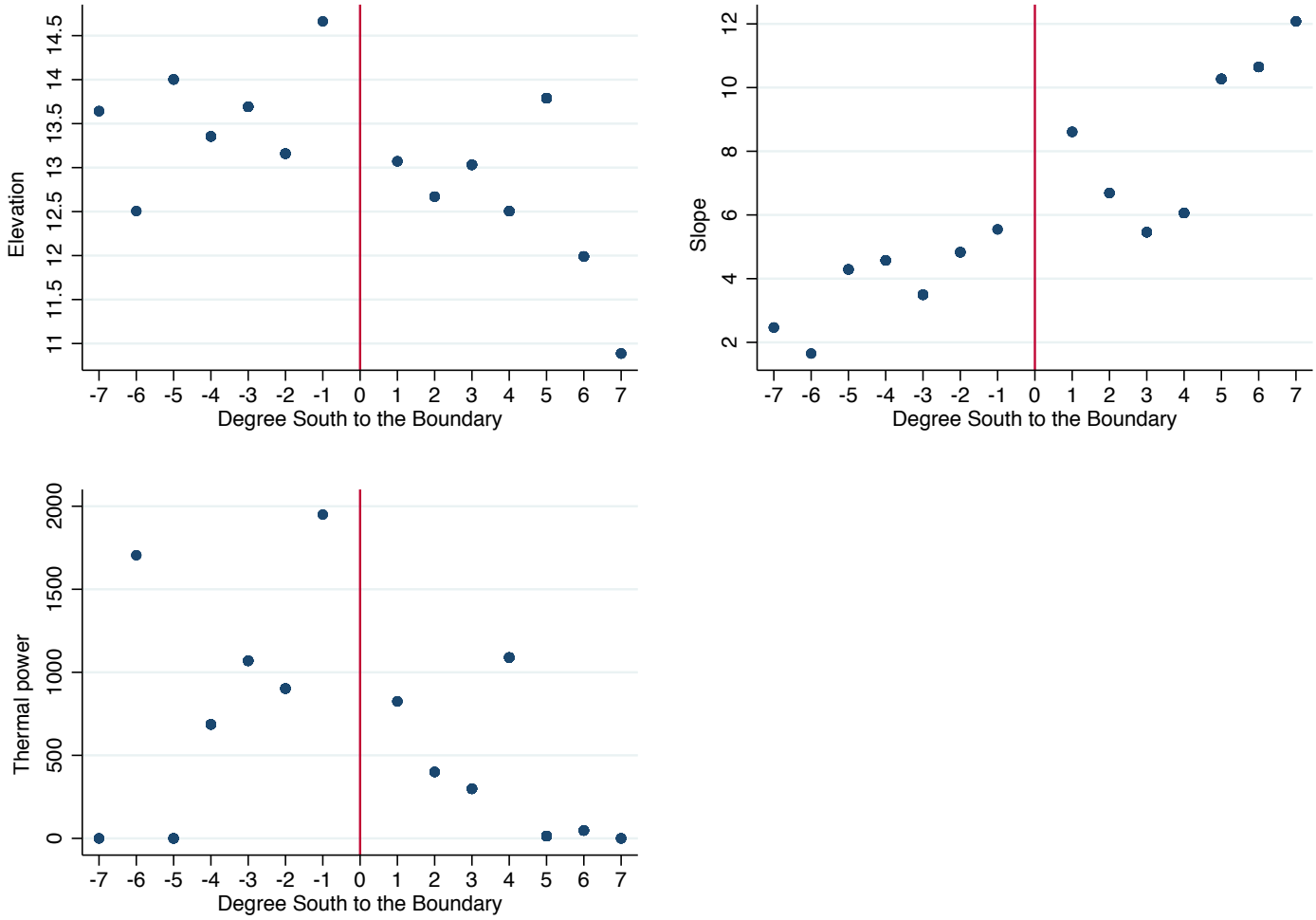

Figure 3.5: Local polynomial smoothing of characteristics by county relative to the distance from the feed-in tariff boundary (wind) -*Continued*.

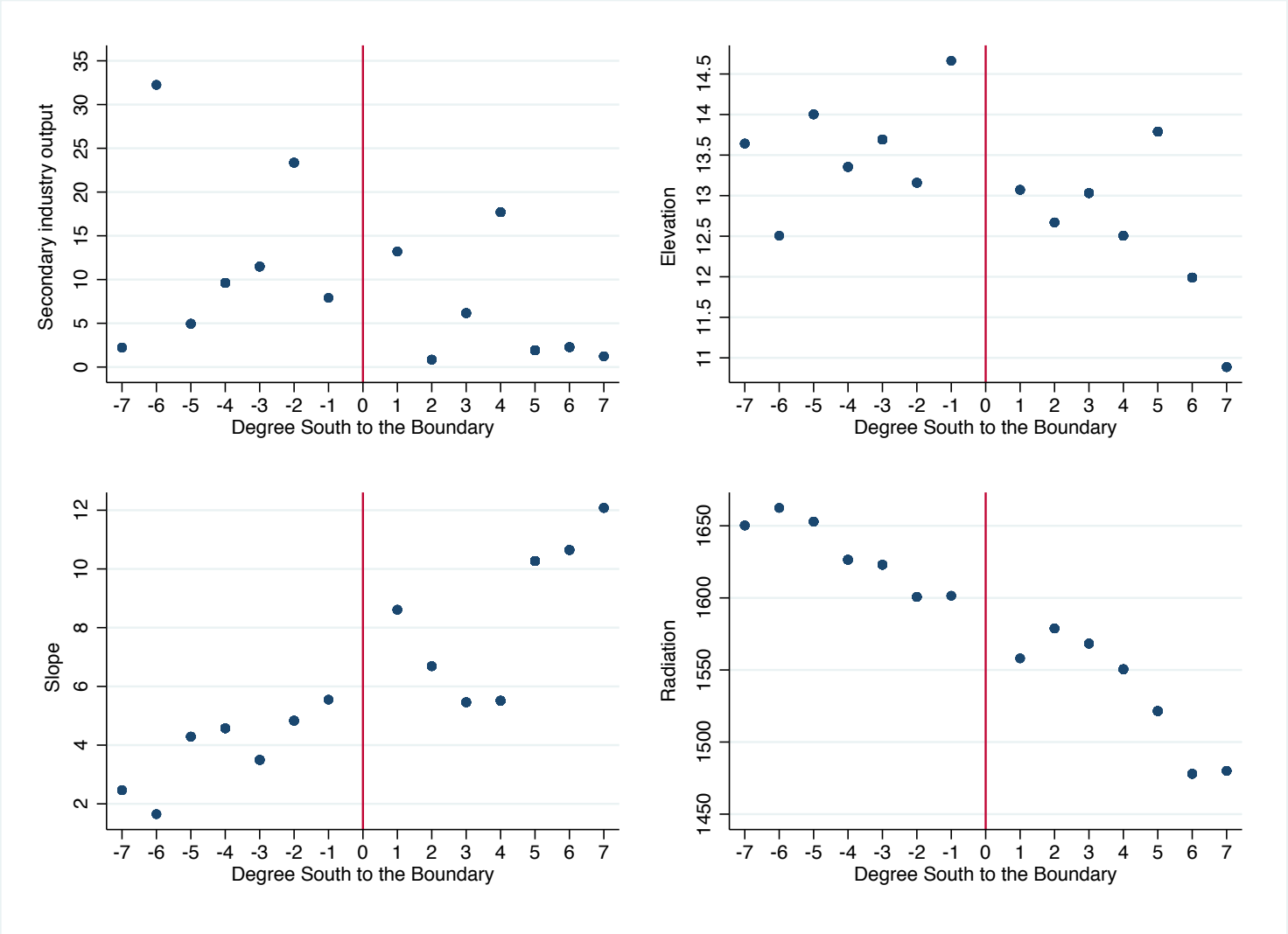

Figure 3.6: Local polynomial smoothing of characteristics by county relative to the distance from the feed-in tariff boundary (solar).

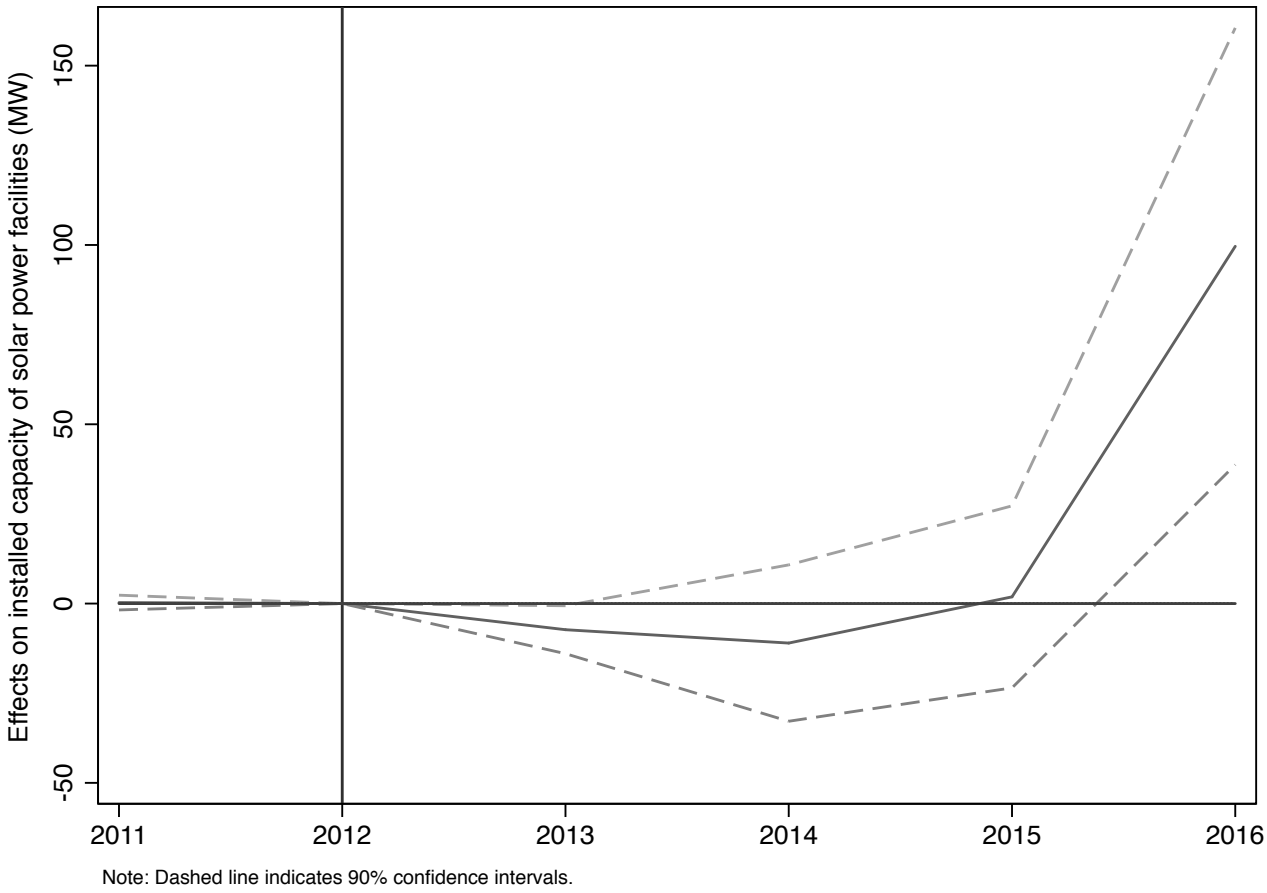

Figure 3.7: Annual effect of on-grid solar feed-in tariffs from the regression discontinuity design and multi difference-in-differences model.

Chapter 4

The Role of Renewable Energy Projects in Rural Poverty Reduction

4.1 Introduction

More than 5.7% of Chinese population live below the poverty line in 2015, mainly in remote rural areas with limited energy access and job opportunities (Asian Development Bank, 2017).[1] As one of the policy packages to alleviate poverty in the rural area, the Chinese government has adopted programs that promote renewable energy in remote areas, including the Solar Energy for Poverty Alleviation Programme (SEPAP)[2] and the 13th Five-year Plan (FYP) for Rural Bioenergy Development.[3] Implementation of the SEPAP, which commenced in 2014, demonstrates the government's aim to alleviate rural poverty through deploying distributed solar photovoltaic (PV) systems in poor areas. Another critical targets of the

[1]The official national rural poverty line of China is 2,300 yuan per year at constant 2011 purchasing power parity. 1 Chinese Yuan ≈ 0.15 U.S. Dollar in 2011.

[2]The National Energy Administration and Poverty Alleviation Office of the State Council decided to implement a poverty alleviation program through the installation of solar PV panels in poor households to increase their incomes. The SEPAP is scheduled to run for six years, starting from 2014. Information on the SEPAP is available at <http://www.nea.gov.cn/2014-10/17/c_133723326.htm>, last accessed on July 17, 2017.

[3]Released by the National Development and Reform Commission (NDRC) on 25 January 2017. More information is available at <http://www.gov.cn/xinwen/2017-02/16/content_5168559.htm#1>, last accessed on January 16, 2018.

13th FYP for Rural Bioenergy Development is to increase the income of rural residents and improve the living conditions of rural households by promoting the utilization of agricultural waste. Moreover, the Announcement on Accelerating Construction of Energy Projects in Impoverished Areas for Promoting Poverty Alleviation, published by the National Energy Administration (NEA) in 2017, emphasizes the contribution of renewable energy to poverty reduction.[4]

Can renewable energy really play a key role in reducing the rural poverty? To explore the question, we investigate the previous Chinese experiences with clean development mechanism (CDM) projects and examine their impacts on poverty reduction. The CDM, which is a part of the flexible mechanisms defined in the Kyoto Protocol, has led to numerous possibilities to absorb foreign investment and enhance sustainable development (SD) in developing countries. According to the definition by the United Nations Framework Convention on Climate Change (UNFCCC), the SD benefits of CDM projects can be divided into three categories: social benefits, economic benefits, and environmental benefits. Examples of these benefits include social benefits such as poverty alleviation, employment generation and enhanced education services; economic benefits such as new industrial activities, productivity growth, and technology innovation; and environmental benefits such as improvement of air, water, and land quality.[5]

Many existing studies have examined the extent to which the CDM can achieve its SD goals. Studies with positive findings suggest that the CDM contributes to SD in host countries in different ways. In particular, small-scale rural renewable energy projects, seem to offer the best prospects for poverty alleviation under the CDM (Brunt and Knechtel, 2005; Newell et al., 2011). However, when considering SD benefits, Olsen and Fenhann (2008) conclude that on the basis of a text analysis of 744 project design documents (PDDs), the

[4]Information on the announcement is available at <http://zfxxgk.nea.gov.cn/auto82/201711/t201711083046.htm>, last accessed on January 16, 2018.

[5]The SD tool provided by the UNFCCC enables the project owners to show the value of their CDM projects behind the certified emission reductions by describing the SD benefits of projects. Available at: http://cdmcobenefits.unfccc.int/Pages/SD-Tool.aspx.

project type is more significant than the differences between small- and large-scale projects. Wood (2011) confirms that the CDM projects that involve energy efficient or renewable energy-based cook stoves create substantial benefits for the poor, mainly by significantly improving the air quality within their houses and reducing household expenditure on fuel. Wang et al. (2013) evaluate the employment impacts through an input-output approach. Their results show that solar projects have the greatest potential for indirect job creation, whereas hydro projects induce job losses. By contrast, Mori-Clement (2019) examines impacts of CDM projects on SD in Brazilian municipalities, revealing that only hydro projects have contributed to long-term poverty reduction. Weitzel et al. (2015) maintain that larger CDM projects and more advanced technologies are more likely to involve technology transfer. The impact of CDM projects on technology transfer has been also studied by many researchers (Seres et al., 2009; Wang, 2010; Zhang and Yan, 2015; Tang and Popp, 2016; Huenteler et al., 2018; and Hayashi et al., 2018). Particularly, Tang and Popp (2016) observe that a project developer's experience and the joint learning within partnerships lead to the largest cost reductions and capacity factor improvement in CDM projects in China.

However, some researchers have suggested neutral or even negative SD impacts. For example, Zhang and Wang (2011) employ an econometric approach to estimate the CDM effect on reducing local air pollution in China and conclude that the CDM does not have a statistically significant effect in lowering SO_2 emissions. On the other hand, by examining a sample of working CDM projects in South Africa, Pillay (2015) concludes that the contribution of CDM to sustainable development is heavily skewed toward greenhouse gas reduction, with little priority given to health, education, and employment generation. Results from other studies have also suggested that the CDM projects do not contribute to poverty reduction and employment generation. Sirohi (2007) indicates that the socio-economic development potential of CDM projects in India is ambiguous and suggests that for CDM to emerge as a "win-win" poverty alleviation strategy, its projects should be implemented at the rural community level. Sutter and Parreno (2007), after assessing 16 officially registered

CDM projects, conclude that less than 1% of the CDM projects are likely to contribute significantly to SD in the host country. Subbarao and Lloyd (2011) examine 500 registered small-scale CDM projects in the fields of employment, migration, access to electricity, health, the use of local resources, local environment and stakeholder perception. They reveal that CDM projects have generated a modest impact on employment generation for the local community. Crowe (2013) examines 114 CDM projects for pro-poor benefits and the results indicate that nearly 74% of projects are categorized as delivering no pro-poor benefits at the local community level. Dirix et al. (2016) review empirical studies on the pro-poor benefits of the CDM to host country communities, concluding that the CDM has failed to deliver poverty alleviation. By assessing the ex-post quantitative effect that CDM projects have had on SD in Peru, Pécastaing et al. (2018) suggest that CDM investments had a slight effect on household consumption expenditure and had no effect on employment or in poverty alleviation.

In summary, previous studies have shown inconclusive results on whether CDM activities truly contribute to the SD in host countries. In this chapter, we aim to evaluate the social benefits of the CDM on rural communities of the host country. We particularly focus on income growth, the creation of job opportunities, and changes in the industrial structure as indicators of social benefits. Based on the PDD evaluations submitted in the context of the CDM, the UNFCCC has concluded that the most prominent benefits claimed by project developers are the stimulation of the local economy through employment creation and poverty alleviation (Dirix et al., 2016). Moreover, the eradication of poverty is also regarded as an indispensable requirement for SD (United Nations, 2012).

The contributions of this chapter can be summarized as follows: Currently, there are two primary approaches to study the SD benefits of CDM: (1) input-output methods or computable general equilibrium model (Wang et al., 2013; Timilsina and Shrestha, 2006); and (2) analytical methods, which generally rely on extensive surveys or PDDs of the projects (Olsen and Fenhann, 2008; Subbarao and Lloyd, 2011; and Crowe, 2013). Although Pécastaing et

al. (2018) and Mori-Clement (2019) have used difference-in-differences (DID) methodology to study SD benefits of CDM projects in Peru and Brazil, respectively, their studies are limited in terms of the type and number of projects involved, and length of study period investigated. To fill this research gap, we used a fixed effects DID model in conjunction with the propensity score matching (PSM), to investigate the social benefits of RE-CDM projects in rural communities of China. China has been the largest host country for CDM projects and offers the best environment to study the impact of various types of renewable energy-based projects.

We also contribute to the literature by performing a rigorous robustness check of estimation results. In our context, selection bias matters if the siting of CDM projects is based on the expected growth in the hosting counties. To confirm whether this is the case, we implement a balancing test on differences in the baseline characteristics between treatment and control before and after matching. We also estimate the main models with interactions between baseline characteristics and year dummy as a robustness check to account for growth trends. Furthermore, we check the robustness of our estimation results, obtained through the PSM-DID approach by adopting the Mahalanobis distance matching (MDM) method. In addition, we investigate the impact of conventional thermal power projects on income and employment to compare with our main results.

Another contribution of this chapter is that our findings provide policy implications on the possibility of simultaneously achieving the goal of climate change mitigation and poverty alleviation. It is imperative that countries achieve their targets of poverty reduction under the Sustainable Development Goals (SDGs),[6] while meeting their commitments to greenhouse gas emission reductions under the Paris Agreement.[7] Thus, our study relates to the literature on poverty reduction and the environmental protection. By using satellite-based estimates

[6]On 1 January 2016, the United Nations SDGs officially came into force. The first of the seventeen proposed SDGs is "End poverty in all its forms everywhere." More information on the SDGs is available at: <http://www.un.org/sustainabledevelopment/>, last accessed on January 17, 2018.

[7]The Paris Agreement on climate change came into force in 2016 to limit the rise in global temperatures. More information on the agreement is available at: <http://unfccc.int/paris_agreement/items/9485.php>, last accessed on January 17, 2018.

of forest cover, Sims (2010) finds that protected areas increased average consumption and lowered poverty rates in Thailand. On the other hand, Sims and Alix-Garcia (2017) estimate the impacts of protected areas and payment for ecosystem services and confirm that the former had neutral impacts on livelihoods, while the latter led to small poverty alleviation. Meek et al. (2017) estimate the environmental and socio-economic impacts of biogas adoption by households in Nepal. Their results suggest that biogas adoption reduces forest cover loss as well as the amount of fuelwood collected and purchased.[8] We complement these studies by focusing on the renewable energy projects that require substantial investment and labor force thereby leading to significant impact on rural development.

The main result of this chapter is that the RE-CDM contributes significantly to rural development in China. Our findings suggest that biomass-based CDM projects can bring about income growth and job creation in rural communities in China. For example, implementing the biomass-based CDM projects increases the annual income of rural residents by 5.75%. Moreover, we find that wind energy projects can help to increase incomes and the share of workers in the primary sector in rural communities. These findings imply that investment in climate change mitigation can play a simultaneous role in poverty alleviation.

This chapter is organized as follows. Section 2 provides the current status of income inequality and the promotion of the renewable energy in China. Section 3 describes the data for estimation and the measures of social benefits. Section 4 follows with an analysis framework, including a description of the empirical model and matching techniques. Estimation results and discussions are provided in Section 5. Finally, Section 6 presents our conclusions and discusses the policy implication of this chapter.

[8]Köhlin et al. (2015) review studies investigating the co-benefits of forest conservation and household energy interventions in developing countries.

4.2 Background

4.2.1 Income inequality in China

China's economic reforms since 1978 have not only led to rapid economic growth but also to severe income inequality. Figure 4.1 shows the income trends of rural and urban residents in China from 1985 to 2015.[9] The rural population of China comprised 618 million in 2014, accounting for about 45.2% of the total populations (NBSC, 2014). At the end of 2015, the net income of urban residents was nearly 3.5 times as much as that of rural residents. In the mid-1980s, the Gini coefficient, a measure of income inequality, has soared to 0.47 from 0.25 (China Digital Times, 2013). Xie and Zhou (2014) argue that China's current income inequality is significantly driven by the rural-urban divide and the regional variation in economic well-being. The differences in economic structure play a critical role in creating the overall income inequality between rural and urban residents.

[Figure 4.1]

Simultaneously, the income structure of the rural population has transformed over the past two decades. As of 2015, the wage income[10] has increased to around 43% of the total income of rural residents, while the proportion of rural residential income from the primary sector has decreased to about 29%.[11] This change reflects the fact that the source of income of rural residents has shifted from the primary to the secondary and tertiary sectors. Rural areas tend to have a relatively smaller range of job opportunities, lower wages, and thus higher unemployment. These difficulties induced a large number of rural laborers to

[9]Individuals are categorized as either "rural" or "urban" residents by the *Hukou* system, a household registration system that serves as an internal passport regime in China. Residents are required to stay and work within their designated geographic areas. Individuals living in rural areas depend on agriculture to make a living and are commonly known as rural residents. On the contrary, urban residents usually dependent on nonagricultural sources of income. Migration rules in China were gradually relaxed in the 1990s. As a result, the number of rural migrants to cities almost reached 145 million by 2009, quadrupled from that of 1990 (Meng, 2012). Unfortunately, it is unclear how much of these inter-county migrations are accurately captured in labor force numbers reported in the provincial statistical yearbooks.

[10]The income earned by an individual working as an employee.

[11]Authors' calculations based on the *China Statistical Yearbook* in 1996 and 2016.

migrate from their registered places of residence and migrate to urban cities in search of job opportunities. The total stock of rural migrant labor, estimated to be around 286 million as of 2017, constitutes more than one-third of the entire working population of China (NBSC, 2018). The sizable rural-to-urban migration not only increases the burden on urban cities but also creates many social problems in rural areas, such as mental health and education of the left-behind children, aging of the rural population, and decline in agricultural productivity (China Labour Bulletin, 2016). To alleviate these issues of rural China, policymakers focus on improving the employment environment by providing high quality job opportunities to the rural community.

4.2.2 Rural poverty and renewable energy

Recently, the Chinese government promoted investment in renewable energy in rural areas. With the formulation of several national promotion policies for renewable energy, such as the SEPAP and the 13th FYP for Rural Bioenergy Development, new energy industries are ready to exploit the vast development space in rural areas. The development of the renewable energy industry is expected to attract both domestic and foreign investment, as well as the working-age population, into rural areas. Also, access to cleaner and affordable energy options can improve the livelihood of rural households by raising their living conditions and transforming the production structure of local firms. Moreover, renewable energy industries can focus on retraining the low-skill and low-income workers. For instance, by the end of December 2014, a total of 16,542 rural residents in Qingxiu County[12] had received vocational training related to renewable energy, and 15,308 of them had obtained national vocational qualifications through an examination system.[13]

By 2020, China's renewable energy industries are expected to provide employment opportunities for nearly a million people, including research and development, design, production,

[12]Qingxiu county belongs to Nanning city, Guangxi Zhuang Autonomous Region.

[13]The Office of Rural Energy, Guangxi Province. <http://www.gxncny.cn/gxnycms/pxjn/3175.jhtml>, last accessed on February 15, 2018.

construction, operation, service, transportation, management, education, training, consulting, and other related jobs (Worldwatch Institute, 2011).

Meanwhile, with the aggravation of the energy crisis and the increasing importance of environmental problems, climate policies have been high on the agenda of the Chinese government for about a decade. The necessity and urgency of promoting the renewable energy sector in China have been providing entry points for the RE-CDM. Moreover, the adoption of RE-CDM projects could bring additional foreign investment to the host community, ultimately driving the development of local renewable energy industries. China has become the world's largest host country for CDM projects. Between 2005 and 2012, a total of 2,983 CDM projects were formally registered in China. Among the registered CDM projects, renewable energy projects make up the largest share, at about 82.7%. Of these, 40.6% comprise wind power projects while other projects, including bioenergy and solar energy, make up about 5.2% and 1.6%, respectively.[14]

Rural counties[15] manage to attract a large part of investment related to RE-CDM deployment because they tend to be sparsely populated, amply endowed with renewable sources of energy, and spacious enough for land-intensive developments like wind farms. As of 2012, a total of 461 rural counties had adopted RE-CDM activities in China, which installed capacity accounts for about 86.8% of the total installed capacity of the RE-CDM. Figure 4.2 depicts the locational distribution of RE-CDM projects by the cumulative installed capacity at the prefecture level. RE-CDM projects are not evenly distributed among regions, but mainly concentrated in regions endowed with sizable renewable energy resources, i.e., the northern, northeastern, and northwestern regions.

[Figure 4.2]

[14] Authors calculations based on UNFCCC's Database for Project Activities and Programme of Activities.

[15] County-level administrative areas in China include the county and county-level city and municipal districts, where the county is usually considered as the backward region in each prefecture. Considering that the objective of this chapter is to evaluate the impact of the CDM on rural development, we only adopt those CDM projects located in the county, also known as the rural area in our analysis.

4.3 Data

4.3.1 Measures of the social benefits

There are three dimensions that compose SD in the local community. The first is the social dimension, which includes welfare indicators such as household income, employment, and spending on health and education. The second is the economic dimension, which is often related to consumption and investment in productive capital. The last is the environmental dimension, including environmental quality, pollution emissions, and material consumption (IRENA, 2016). Although various existing studies have empirically analyzed the economic and environmental benefits of the CDM (Seres et al., 2009; Wang, 2010; Tang and Popp, 2016; Zhang and Wang, 2011; and Castro, 2012), as per the authors knowledge, the existing research on the causal effects of projects on local income and labor demand based on econometric approach is still limited. In order to estimate the social impacts of increased renewable energy deployment under the CDM, this chapter employs three indicators: income generation, job creation, and the transformation of industrial structure.

First, we adopt the per capita net income of rural households to measure the impact of the RE-CDM activities on rural income. By adopting RE-CDM activities, rural communities can diversify, stabilize, or increase the income of their residents in several ways. For instance, RE-CDM projects can alleviate poverty by helping unskilled laborers in rural areas, such as farmers, unemployed persons, and women with low education level, to serve as assembly line workers, equipment installers, and maintenance or sales staff. Another channel might be lease and compensation payment to farmers and residents by developers of renewable energy projects.

Second, the share of employed persons in the total population is used as an indicator of job creation in a rural county. The working populace of rural communities increases with more job opportunities for rural residents. Development and promotion of the renewable energy industry is an important way to increase the employment among residents. In 2013,

the renewable energy sector provided about 6.5 million direct and indirect jobs worldwide. Fuel supply from bioenergy feedstock, installations, and equipment manufacturing will generate most jobs in the renewable energy value chain (IRENA, 2014). Some argue that the decentralized nature of renewable energy deployment will raise the overall number of jobs. However, others believe that the relatively higher monetary costs of deploying renewables will reduce purchasing power and, consequently, employment. These arguments underscore the need for more detailed analyses and rigorous strategies to estimate the potential social benefits, especially employment creation from renewable energy deployment.

Lastly, we employ the share of rural laborers in the primary sector to capture the impact of RE-CDM on industrial transformation. Renewable energy industries can create valuable job opportunities for people in regions with low employment rates. It provides both direct jobs, such as operating and maintaining equipment, and indirect jobs along the supply chain, such as fuel supply, manufacturing, construction, and other related specialized services. For example, if the presence of renewable energy installations can revive construction activities related to renewable energy power plants, the primary income sources of farm households could switch from agricultural activities to the construction industry.

4.3.2 Data sources

To examine the effect of the RE-CDM on rural development, we obtained information on the construction period and location of RE-CDM projects, rural residential income, share of employed persons in rural area, and other characteristics of each county.[16] The panel data used for analysis cover a total of 1,955 rural counties across China and comprise three types of variables, namely, social benefits, county characteristics, and characteristics of RE-CDM projects. The sample period for this chapter is between 2002 and 2011, whereas the period 2002−2004 serves as preceding years because the first CDM project is registered in 2005.[17]

[16] A county is an administrative unit ranking below a prefecture and above a township.

[17] The first CDM project in China was the Huitengxile wind farm project, which was successfully registered in 2005. <https://cdm.unfccc.int/Projects/DB/TUEV-SUED1113481234.64/view>, last accessed on

After matching was applied, 82% of the counties had complete panel data from 2002 to 2010, and 48% of the counties had complete panel data from 2002 to 2011.[18] We restricted our data till 2011 because we focused on the short-term effects of RE-CDM projects and avoided evaluation of the long-term effects on outcome indicators that might be influenced by many factors. For example, outcome variables can be affected by technological development, growth in human capital, and change in industrial structure in the long run. To investigate the long-term impacts of CDM, these factors must be taken into consideration.

Table 4.1 contains descriptive statistics on the variables used in our analysis. Counties that adopted RE-CDM projects between 2005 and 2011 are included in the treatment group in this chapter. On the other hand, counties with no RE-CDM activities during the research period are included in the control group. The average rural household income is about 4,455 yuan in the treatment group and approximately 4,938 yuan in the control group. The average share of employed persons in a county is around 53.19% in the treatment group and about 53.36% in the control group. The average share of laborers in the primary sector is about 35.09% in the treatment group; the corresponding number in the control group is 33.65%. A two-tailed t-test shows statistically significant differences in the mean value of social benefits and county characteristics. This suggests the need to adopt matching techniques in order to avoid selection bias.

[Table 4.1]

Data related to social benefits are collected from the statistical yearbook of each province. Per capita net income of rural households, the share of employed persons in the total population, and the share of rural laborers in the primary sector are used as indicators of social benefits. Data in the provincial statistical yearbooks are generally based on two sources: (1) rural household survey data collected by the State Statistical Bureau (SSB) and (2)

December 21, 2017.

[18]The provincial statistical yearbooks do not include data on some counties for some years. The reason for this might be a change in county boundaries or a lack of data collection by the province. For example, the Hebei and Jilin provinces do not indicate the 2011 rural income of many counties. In such cases, the missing data occurs in particular provinces.

Ministry of Agriculture (MOA) data based on annual reports of village leaders aggregated at the township and county levels (Park and Wang, 2001). Particularly, the latter dataset has been criticized for the possibility of misreporting and biases. Meng (2013) compares the MOA data with the National Poverty Monitoring Survey, which is another data source for poor counties, and finds no systematic over-reporting in the MOA data.

The county characteristic variables, including the gross output of the primary sector, the area of agricultural land, total government revenue, the share of students in compulsory education, production of oil crop, and the total capacity of agricultural machinery, are based on the China Rural Statistical Yearbook. Wind potential is based on National Development and Reform Commission (NDRC, 2016), where higher wind power potential regions are those regions with on-grid tariffs for wind power less than or equal to 0.54 yuan per kWh including tax. According to The Notice on Tariff Price of On-shore Wind Power, on-grid tariffs for wind power generators are 0.47–0.60 yuan per kWh, with the lower tariffs applying in regions with higher wind power potential. Both geographical and social characteristics are considered because these factors may affect the existing energy infrastructure and influence the promotion of renewable energy industries.

CDM data are obtained from the UNFCCC's Database for Project Activities and Programme of Activities, which includes basic information on every registered project. Hydroelectric projects are excluded from the sample because of their potential to generate social benefits and social problems for rural communities at the same time.[19] The geographic location of each project is collected from the CDM location map provided by the NDRC. ArcGIS 10.1 is used to generate the location data of RE-CDM projects.

[19]The construction of reservoirs can improve water supply, increase farmland irrigation, produce electricity, and produce other social and economic benefits. However, it also has its disadvantages. For example, the resettlement of residents will lead to changes in the economic structure.

4.4 Empirical analysis

4.4.1 Model

To measure the social benefits of RE-CDM in rural communities, we employ a DID estimator combined with a mix of fixed effects by running an Least Squares Dummy Variable model. The DID estimator compares the change in social benefits connected to RE-CDM projects in counties that adopted the project to the change in social benefits in counties that did not. The fixed effects estimation allows us to control for time-invariant and time-varying unobservable county characteristics that may be correlated with a county's RE-CDM project adoption decision.

This chapter uses unbalanced panel data on the social benefit indicators for 1,955 rural counties in China from 2002 to 2011. The general form of the model adopted can be written as follows:

$$y_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 X_{it} + \delta_i + \gamma_t + \varepsilon_{it},$$

where y_{it} indicates the social benefits variables, which includes: (a) rural residential income; (b) the share of employed persons in total population; and (c) the share of rural laborers in the primary sector in the county i in year t.

D_{it} is the treatment indicator that takes on the value one in and after the year the CDM renewable energy power plants have been constructed in county i, and zero otherwise. In addition, we interact the treatment indicator with different types of renewable energy sources, namely, biomass, wind, and solar energy, to capture their differences in social benefits.[20] X_{it} is a vector of time-varying county characteristics: primary industry output, agricultural land area, government revenue, the share of students in compulsory education, oil crop production, and total capacity of agricultural machinery. δ_i is the vector of the county dummy variable, which is used to control for unobserved county characteristics that shape the level of development across counties. Year dummy γ_t is included to control for trends

[20]Most of the biomass-based CDM projects use agricultural residue as burning fuels for power generation.

that shape rural development over time such as changes in policies and regulations at the national level. ε_{it} is the error term.

4.4.2 Matching techniques

There is a concern that the DID estimator may suffer from two sources of bias. The first may arise if the levels and trends in social benefit indicators in treatment and control counties differ before the CDM project adoption. Another bias could arise if the CDM project sites are not randomly assigned but determined by various geographical, political, and socio-economic factors. Therefore, in this chapter, we adopt two matching approaches to mitigate potential bias by pairing treatment counties with counties that have similar observed attributes from the control pool.

We adopt the PSM approach developed by Rosenbaum and Rubin (1983). The objective of the PSM is to construct a control group by finding controls that have observed x similar to those of the treatment group. To match treatment and control units on the basis of x is equivalent to matching them using a propensity score $p(x)$, which gives the probability of receiving treatment given the pretreatment value of x, that is, $p(x) = Pr(D = 1|x)$. The matching method assumes that within in a set of subjects, all with the same propensity score, the observed outcome distribution will be the same between the treatment and control groups. To check the robustness of the PSM, we also use the simple MDM, which was first discussed by Cochran and Rubin (1973). For the MDM, the variance-covariance matrix of x is estimated by the pooled with-in group sample covariance matrix S. The distance between covariate x_1 and x_2 is $M(x_1,x_2) = (x_1\text{-}x_2)^T \mathrm{S}^{-1}(x_1\text{-}x_2)$.

First, to estimate the propensity score, we use covariates in the baseline year to identify the probability of a county adopting a RE-CDM project, which include gross regional product of the primary sector, agricultural land area, amount of oil crop production, a dummy variable for regions that have relatively higher wind power potential, net income of rural residents, and the share of employed person in total population. These covariates are chosen

on the basis that the CDM projects are scrutinized regarding project additionality before registration. We suppose that project additionality relates to various county characteristics, particularly on the potential for economic growth and natural resource endowments that can be used as inputs for renewable energy generation. We use 2004 as the baseline year, which is one year before the year that the first RE-CDM projects in China were registered.

Second, we use the estimated propensity score to match treatment and control groups in the baseline year. A one-to-one matching approach without replacement was adopted while using the nearest-neighbor PSM and MDM algorithm. In other words, we choose only one county from the counties without RE-CDM activities as a match for a treatment county regarding their closest propensity score and Mahalanobis distance. An untreated county cannot be used more than once as a match. The total number of county decrease from 1,955 to 426 after the PSM and to 448 after the MDM because the observations out of the common support have been dropped from the sample.

Finally, to ensure that the matching procedure successfully balances the two groups, we compare the treatment and control groups after matching. Table 4.2 present the balancing test results for the PSM in Panel A and that of the MDM in Panel B. The results indicate that the differences between the treatment and control groups become statistically insignificant after matching. For instance, in Panel A of Table 4.2, we find that the difference of primary industry output between the treatment and control groups is nearly 14.2%. The difference between these two groups drops to 7.60% when the sample is matched.

[Table 4.2]

The balancing test results are also shown in Figure 4.3, which depicts the differences in the distribution of the propensity scores by treatment and control groups. The figure shows that selected observations of the control groups have similar kernel density of propensity score with observations in the treatment groups. It suggests that differences in the distribution of the two groups have been significantly reduced after the PSM is applied.

[Figure 4.3]

4.5 Results and discussion

4.5.1 Impact on rural residential income

The estimation results of the RE-CDM's effect on rural residential income are reported in Table 4.3. Columns (1)–(4) show the results estimated by the PSM-DID approach and columns (5)–(8) represents the results estimated by the MDM-DID approach. We find that a positive relationship exists between RE-CDM activities and rural residential income. The coefficients of the treatment indicator *re_cdm* are positive and statistically significant at the 1% level in all models as shown in the first row of Table 4.3. The estimated effects correspond to an increase of approximately 311 yuan in annual income, which is about 6.3% of the average rural income of residents.[21] To check whether the results are not driven by the expected growth trends, we estimate models with the interactions between two baseline characteristics, namely, the primary industry output and oil crop production, and year dummy in columns (3)–(4) and (7)–(8). The significance of RE-CDM remains robust in these specifications.

[Table 4.3]

Table 4.3 also reports the impact of the RE-CDM by different energy sources. The *biomass* and *wind* dummy variables are also positive and statistically significant in all regressions. This result indicates that both biomass and wind power-based CDM projects stimulated income growth substantially for rural residents. Specifically, the adoption of biomass-CDM projects generated 284 yuan, about a 5.75% increase in annual income for the rural residents. The coefficient of *wind* in column (2) in Table 4.3 suggests that the adoption of wind power-based CDM projects raises the annual income of rural residents by

[21] According to the summary statistics in Table 4.1, the annual average net income of rural residences for control group in the sample is 4,938 yuan.

approximately 223 yuan or approximately a 4.52% increase in annual income. On the other hand, we do not find a significant impact of solar energy-based CDM projects on income generation.

Our results regarding the impact of the RE-CDM on income improvement illustrates that biomass and wind energy-based CDM projects are significant in stimulating income generation. Gan and Smith (2007) estimate the co-benefits associated with the utilization of logging residues for bioenergy production in East Texas, USA. The input–output modeling revealed that the most noticeable socio-benefits of bioenergy production were income and job creation. Based on a survey conducted for users and non-users in three villages of China, Van Groenendaal and Gehua (2010) conclude that the main benefit in relation to household income incurred from a bio-digester is reduction of expenditure on fuels and fertilizer. Similarly, Garfí et al. (2012) evaluate household biogas digesters technical, environmental, and socio-economic impacts in rural communities of the Peruvian Andes, concluding that the family's annual income is increased by 35.5% due to fertilizer savings and potato sales. As for the income generation impact of wind power, it is said that rural communities involved in wind power generation activities benefit from payments farmers receive to host turbines on their property (Farm Bureau, 2017). In the case of an on-grid wind power project located in Longchuan county in Guangdong province, the land rent provided for local residents is 4,500 yuan per ha.[22]

To confirm that the identifying assumption of common pre-trends is satisfied, we estimate models with interaction between treatment dummy and year dummy. Treatment dummy takes value one if the county is in the treatment group and zero otherwise. The results are reported in Table A1 in Appendix. Coefficients of interactions between treatment group dummy and year dummy before CDM period, namely the *Treatment* × *2002* and *Treatment* × *2003*, are not statistically significant. On the other hand, interactions of the treatment dummy with post-CDM period are statistically significant in many cases. These results

[22] Available at <http://www.longchuan.gov.cn/sy/tzgg/4406064.html>, last accessed on 23 January 2018.

suggest that the outcome variable have statistically significant differences between control and treatment only after the RE-CDM projects were adopted. As an additional robustness check, we also include a regression specification using the full sample without applying matching techniques for comparison. The estimation results are reported in Table A2 in Appendix. We find that they are similar to our main results although the sizes of estimated coefficients in the full sample analysis are higher than those in matched sample analysis.

4.5.2 Impact on employment generation

In Table 4.4, we assess the impact of the RE-CDM projects on employment generation using the PSM- and MDM-DID method. The coefficients of *RE-CDM* in all models in Table 4.4 indicate that the existence of renewable energy CDM projects raises the working population share by roughly 1.13%. This finding confirms the employment generation benefit of the renewable energy projects adopted under the CDM.

[Table 4.4]

In addition, the results illustrate that the employment generation impact of RE-CDM activities in rural areas differ by different renewable energy sources. The coefficients of *Biomass* are positive and significant at the 5% level as shown in the second row in Table 4.4. This result suggests that the adoption of biomass-CDM projects increase the share of working population in a rural county by approximately 1.48% points compared with the average rural labor share (53.4%) for control group. In line with the arguments of Thornley et al. (2008) and Openshaw (2010), our results illustrate that biomass energy-based projects show remarkable contributions to employment generation in rural communities. Thornley et al. (2008) quantify the expected employment impacts of individual bioenergy development and suggested that the larger bioenergy power plants had a larger employment impact, which confirms our results on the employment creation impact of biomass projects. Openshaw (2010) find that in Malawi, Africa, the equivalent to 93,500 and 133,000 full-time workers

were employed in the biomass supply chain in 1996 and 2008, respectively. In contrast, about 3,400 and 4,600 people were employed in the supply chain of other conventional fuels, such as coal and petroleum, in those years. Chen et al. (2017) mention that the employment rate can be increased during and after the construction of the biogas CDM project, and also afterwards as operation and maintenance workers are needed to keep the facilities functioning.

On the other hand, we did not find a statistically significant impact on employment rate in the rural communities for wind and solar energy projects. Compared with biomass energy, electricity generation by these energy sources require less labor input and, therefore results to an insignificant increase in labor demand. The insignificance of wind energy projects on employment generation also suggests that the increase of rural income by wind power projects are caused by channels other than employment generation. The coefficient of solar power-based CDM projects is negative and statistically significant. It suggests that solar power-based CDM projects have negative impact on employment generation.

4.5.3 Impact on employment in the primary sector

In Table 4.5, we report the estimated impact of the RE-CDM adoption on the share of employment in the primary sector in rural communities. The coefficients of *Wind* shown in columns (2) and (4) in Table 4.5 indicate that the implementation of wind power projects under the CDM is associated with an increased share of rural laborers in primary industry by 1.42% points compared to the average value for control group in the sample 33.7%. We confirm the robustness of above results by the MDM-DID approach in columns (6) and (8) in Table 4.5. One of the attractiveness of wind power for farmers is to allow developers to install large wind turbines on their land. Large wind turbines typically use less than half an acre of land, including access roads; thus, farmers are able to earn extra income and continue their agricultural production. As a result, there is a potential of wind power-based CDM projects for attracting more laborers in the primary sector. If this shift is promoted by an incentive payment from wind developers to local farmers and land holders, then the shift

of the labor force will persist for a considerable period during operations of wind power. Further research is required to investigate whether CDM projects contribute to long-run industrial transformation.

[Table 4.5]

In contrast, we find that solar power-based CDM projects decrease the share of rural laborers in the primary sector in rural communities. In the second column in Table 4.5, the coefficient of *Solar* is negative and statistically significant; that is, due to the adoption of solar energy-based CDM projects, the share of rural laborers in the primary sector decrease by 4.97% points. The finding implies that the presence of solar power projects may reduce the share of labor force in primary sector which is consistent with the argument that there is a tradeoff between solar power installation and agricultural practice. For example, Hernandez et al. (2015) investigated the impact of solar energy development on land use change in California and found that 28% of utility scale solar power plants are located in croplands and pastures. Nonhebel (2005) also found that the land required for solar energy is about 25% of the area required for food production in the rich situation yields. Moreover, Sacchelli et al. (2016) estimated potential crop production losses in case of solar panels installation on arable lands.

4.5.4 Impact by different project scales

Table 4.6 reports the estimated impact of the RE-CDM adoption on income generation and employment creation by different project scales. Project scales are captured by three dummy variables (*1 project*, *2 projects*, and $\geq$ *3 projects*) that take on the value one according to the number of RE-CDM projects that the county has in the year. While the coefficient of *1 project* is positive and statistically significant, those of *2 projects* and $\geq$ *3 projects* are not statistically significant. These results indicate that impact of RE-CDM projects on net income of rural residents is not observed in counties with multiple numbers of projects.

[Table 4.6]

On the other hand, results for *Rural labor%* and *Rural labor_primary%* indicate that project scales might matter to the size of the effect on these outcomes, although statistical significance is marginal for *2 project* and $\geq$ *3 project* in *Rural labor%*. Comparing the coefficients of *1 project* and $\geq$ *3 project* in column (3) of Table 4.6, we find that adopting more than three RE-CDM projects has a 2.6 times greater impact on increase of the working population share in the rural county than adopting one projects. Besides, the coefficients of $\geq$ *3 project* in columns (5) and (6) of Table 4.6 are all positive and significantly correlated with the share of working population in primary sector. The result shows that adopting more than three RE-CDM projects increase the share of labor force in primary sector by 2.14% points.

In summary, we find that having a larger number of projects in a county leads to a higher impact on employment generation and the share of laborer in primary sector. On the other hand, we find such effect is not significant for rural income. Although we cannot speculate the mechanism behind this, a possible interpretation is that larger number of projects increase inflow of labor force but does not affect income of local residents.

4.5.5 Impact of thermal power projects

To compare the social benefits of RE-CDM projects with traditional energy sources, we also investigate the income generation and job creation impact of the addition of thermal power plants. Information on the annual addition of thermal power plants over 10,000 kW are obtained from the Compilation of Power Industry Statistics collected by the China Electricity Council. The sample period for the thermal power-related regression is from 2005 to 2010. Study area is the same with our main regression, which includes a total of 1,955 rural counties in China.

Similar with the main regression, we adopt both the PSM-DID and MDM-DID approach to reduce possible selection bias caused by the location decisions of thermal power plants and

trends of economic growth. The baseline year is set at 2005 in this regression and we drop all the counties that have newly added thermal power plants in that year. Covariates used for matching the sample are: gross output of the primary sector, agricultural land area, amount of oil crop production, net income of rural residents, and the share of employed person to total population. The balancing test results show that no statistical difference emerges after matching the treatment and control groups.

The treatment indicator of additional thermal power plants is the *Thermal* dummy variable. Similar with the *RE-CDM* dummy in the main regression, it takes on the value one in and after the year a new thermal power plants have been constructed in the rural county, and zero otherwise. As shown in Table A3 in the Appendix, the coefficients of *Thermal* are negatively and significantly correlated with the rural residential income. This result indicates that the addition of thermal power plants reduce the net income of rural residents by approximately 2,585 yuan.

The negative impact of thermal power plants on rural net income is generally consistent with previous findings on the relationship between resource abundance and economic performance in Chinese provinces. Zhang et al. (2008) investigated the relationship and found that provinces with abundant resources perform worse than their resource-poor counterparts in terms of per capita consumption growth. The negative effect of coal dependence was also found by Dai et al. (2018) that exploit a drop of global coal price as an exogenous shock to identify the effect on entrepreneurial activities. On the other hand, Xu and Nakajima (2016) estimated positive impact of coal mine regulations on regional economic growth in China.

4.6 Conclusions

Focusing on the social benefits brought by renewable energy projects, we examined whether the RE-CDM improved Chinese rural communities in terms of rural residential income, job opportunities, and transforming the industrial structure. In addition, in order

to understand which energy source provides higher social benefits, our study investigated the impact generated by various renewable energy sources.

Our results indicate that the RE-CDM projects can contribute to income and employment of the host counties. The increase in annual income of rural residents is 5.75% by adopting biomass- and 4.52% by adopting wind power-based RE-CDM projects. Moreover, we find that not all renewable energy technologies contribute to the social benefits in the same manner. Biomass-based CDM projects had the greatest potential in increasing the employment opportunities in rural areas. This result indicates that bioenergy projects provide more job opportunities for unskilled laborers than other types of energy sources. In contrast, wind power-based CDM projects promote rural development by attracting the labor force into the primary sector.

Climate change represents a direct and immediate threat to poverty alleviation (World Bank, 2015). In this chapter, we assess whether activities for climate change mitigation can alleviate the poverty of rural communities in China. We conclude that the adoption of renewable energy projects under the CDM can offer an effective method to both reduce poverty and address the global externality. By promoting the development of renewable energy, particularly biomass and wind power in local communities, it might be possible to reduce poverty in ways that support low-carbon growth. Providing clean electricity and access to modern energy services may also contribute to other types of social benefits by improving health, welfare, access to education and jobs, and driving economic growth while reducing pollution (Climate Advisers, 2014).

Although our study confirms the role of RE-CDM in assisting host countries to advance rural development, further investigation is necessary to understand the links between climate change mitigation and poverty reduction strategies. For example, it is important to compare the social benefits of domestic renewable energy projects and RE-CDM projects in order to evaluate the effectiveness of different investment channels. Another limitation of our study is that the long-run effect of the RE-CDM has not been considered. Future research should

be designed to capture the dynamics of the relationship between the RE-CDM and rural development in the long-run.

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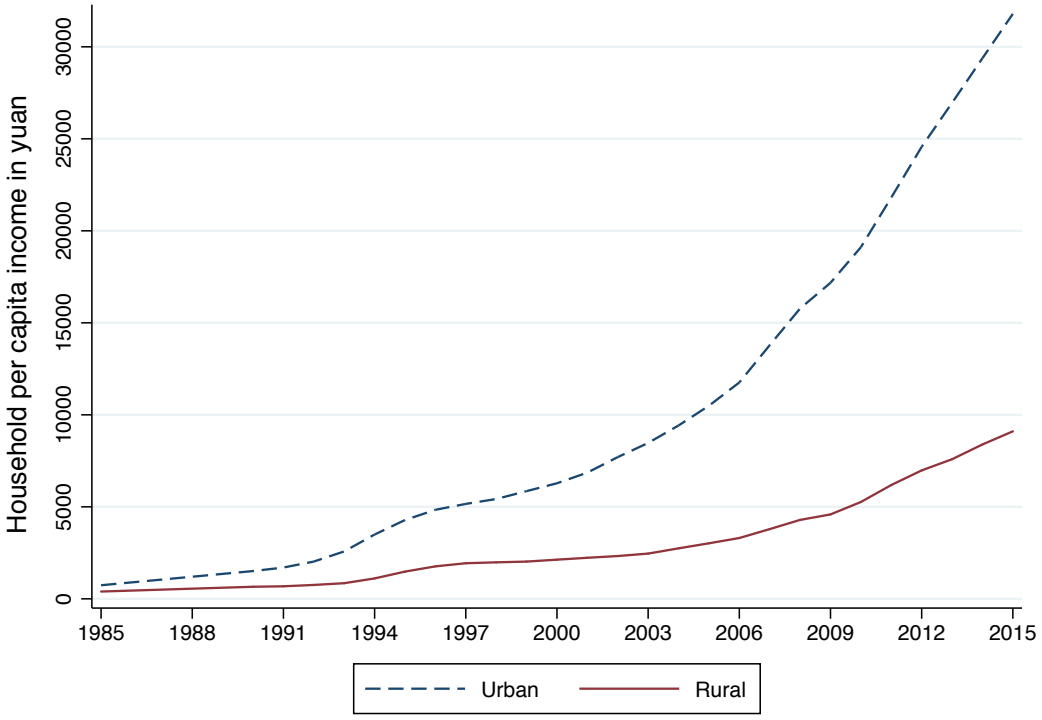

Source: China Statistical Yearbook.

Figure 4.1: Per capita income of urban and rural households in China

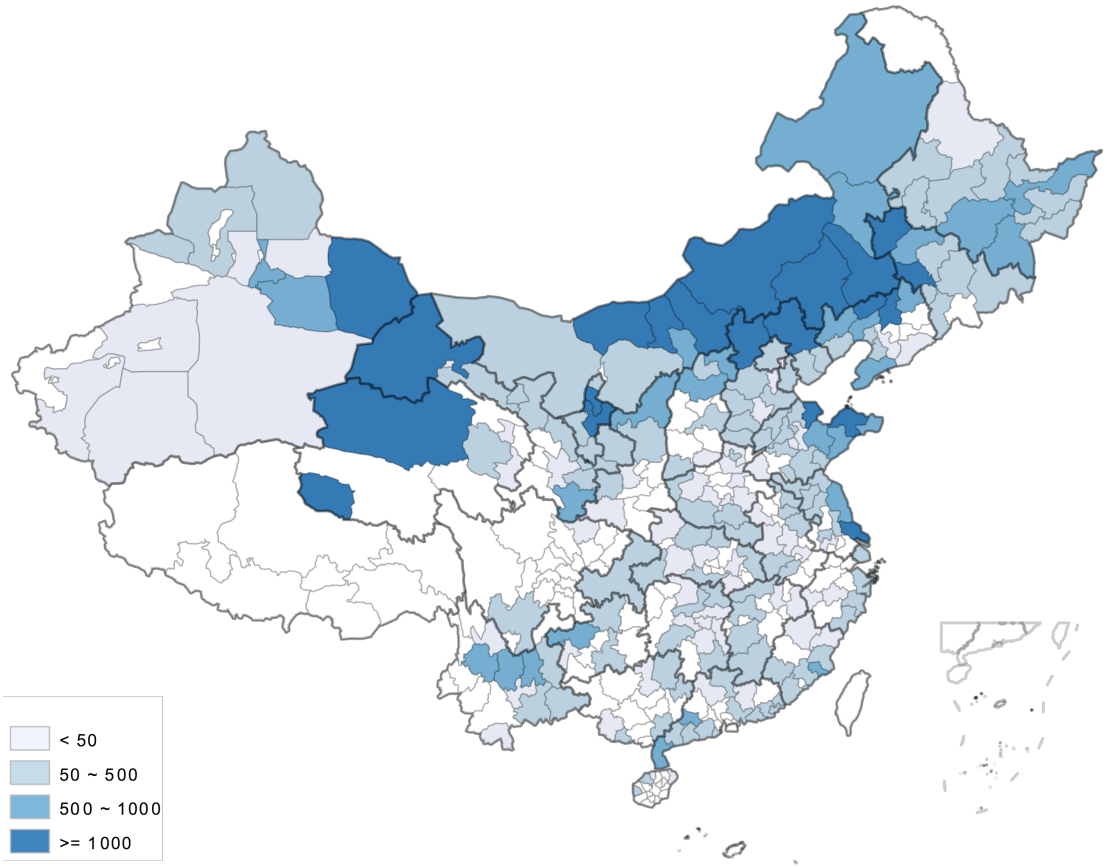

Figure 4.2: Locational distributions of RE-CDM projects by the cumulative installed capacity (MW) of power plants in 2012

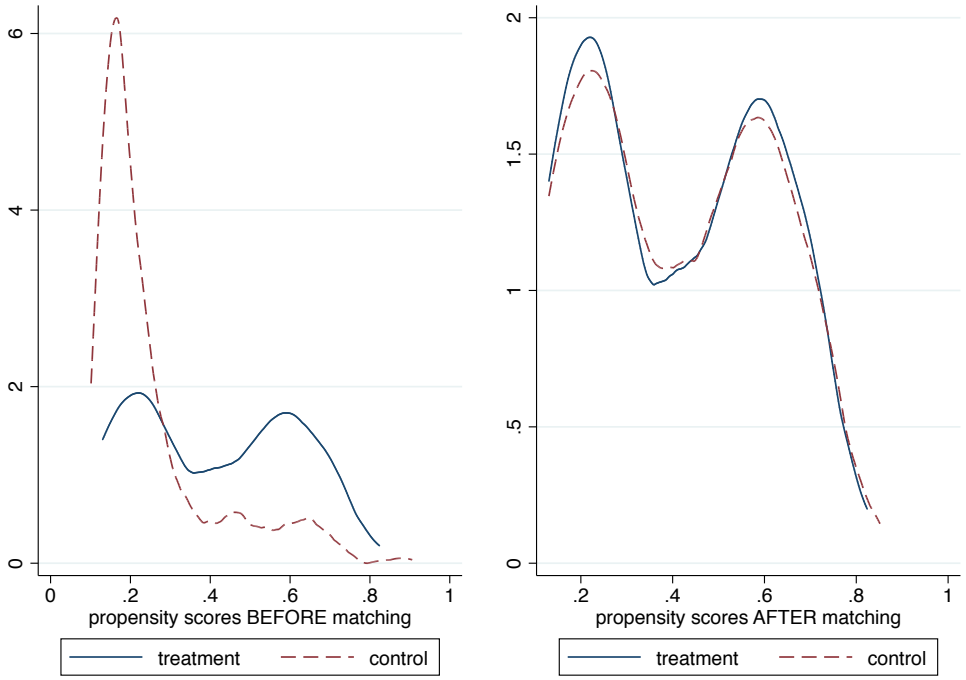

Figure 4.3: Distribution of propensity scores by treatment and control groups: before and after the nearest-neighbor PSM

Table 4.1: Descriptive statistics

		(1) Control groups			(2) Treatment groups		
	Unit	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.
Treatment Indicators							
RE-CDM	dummy	12,697	0.000	0.000	4,078	0.214	0.410
Biomass	dummy	12,697	0.000	0.000	4,078	0.041	0.199
Wind	dummy	12,697	0.000	0.000	4,078	0.172	0.377
Solar	dummy	12,697	0.000	0.000	4,078	0.014	0.115
Multi-projects	dummy	12,697	0.000	0.000	4,078	0.013	0.114
1 project	dummy	12,697	0.000	0.000	4,078	0.103	0.303
2 projects	dummy	12,697	0.000	0.000	4,078	0.024	0.154
$\geq$ 3 projects	dummy	12,697	0.000	0.000	4,078	0.016	0.124
Social Benefit Variables							
Income_rural	1,000 yuan	10,279	4.938***	7.932	3,683	4.455	2.710
Rural labor%	%	12,350	0.534	0.122	4,025	0.532	0.090
Rural labor_primary%	%	12,350	0.337***	0.118	4,025	0.351	0.120
County Characteristics							
Primary industry output	billion yuan	12,351	1.144***	1.074	4,024	1.546	1.392
Agricultural land area	1,000 km^2	10,371	0.376***	0.386	3,228	0.622	0.504
Government revenue	billion yuan	12,351	0.329	0.804	4,023	0.346	0.550
Student%	%	12,350	0.146***	0.038	4,023	0.141	0.049
Oil crop production	million ton	12,081	0.013***	0.021	3,922	0.019	0.033
Machinery power	1,000 kW	12,351	0.241***	0.330	4,024	0.323	0.449
Wind potential	dummy	12,697	0.153***	0.360	4,078	0.282	0.450

Note: 1) *** indicates that the means differ with statistical significance in a two-tailed t-test at the 1% level between the treatment and control groups; 2) *Multi-projects* is a dummy variable that indicates if a county has more than two types of RE-CDM projects in the same year.

Table 4.2: Balancing test results

Panel A: Nearest-neighbor propensity score matching (PSM)

	Unmatched/	Mean				t-test	
Outcome: income_rural	Matched	Treatment	Control	%bias	%bias reduction	t-value	p-value
Primary industry output	U	1.287	1.087	14.2		1.84	0.065
	M	1.287	1.180	7.60	46.1	0.69	0.491
Agricultural land area	U	0.672	0.467	46.4		6.46	0.000
	M	0.672	0.606	15.0	67.8	1.72	0.087
Oil crop production	U	0.025	0.019	20.0		2.87	0.004
	M	0.025	0.025	2.30	88.3	0.23	0.816
Wind potential	U	0.313	0.146	40.2		5.71	0.000
	M	0.313	0.378	-15.7	61.0	-1.56	0.119
Income_rural	U	3.098	2.949	11.9		1.57	0.118
	M	3.098	2.927	13.7	-15.0	1.60	0.110
Rural labor%	U	0.527	0.551	-15.4		-1.83	0.067
	M	0.527	0.523	3.0	80.4	0.70	0.482

Panel B: Mahalanobis distance matching (MDM)

	Unmatched/	Mean				t-test	
Outcome: income_rural	Matched	Treatment	Control	%bias	%bias reduction	t-value	p-value
Primary industry output	U	1.287	1.087	14.2		1.84	0.065
	M	1.287	1.146	10.0	29.2	1.53	0.126
Agricultural land area	U	0.672	0.467	46.4		6.46	0.000
	M	0.672	0.638	7.80	83.1	0.86	0.392
Oil crop production	U	0.025	0.019	20.0		2.87	0.004
	M	0.025	0.023	8.5	57.4	0.90	0.370
Wind potential	U	0.313	0.146	40.2		5.71	0.000
	M	0.313	0.313	0.0	100.0	0.00	1.000
Income_rural	U	3.098	2.949	11.9		1.57	0.118
	M	3.098	3.039	4.8	60.1	0.59	0.557
Rural labor%	U	0.527	0.551	-15.4		-1.83	0.067
	M	0.527	0.532	-2.7	82.2	-0.66	0.510

Table 4.3: Effect of RE-CDM on rural residential income

	Explained variable: Income_rural							
	PSM-DID				MDM-DID			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RE-CDM	0.311***		0.343***		0.237***		0.255***	
	(0.060)		(0.060)		(0.060)		(0.060)	
Biomass		0.284***		0.218**		0.188**		0.162**
		(0.082)		(0.085)		(0.076)		(0.074)
Wind		0.223***		0.272***		0.161***		0.192***
		(0.060)		(0.059)		(0.059)		(0.059)
Solar		-0.458		-0.565		-0.426		-0.628*
		(0.337)		(0.349)		(0.325)		(0.334)
Multi-projects		-0.0303		0.102		-0.00250		0.105
		(0.298)		(0.310)		(0.285)		(0.293)
Primary industry output	0.109	0.109	0.0677	0.0709	0.314***	0.315**	0.321	0.331
	(0.070)	(0.071)	(0.047)	(0.050)	(0.121)	(0.122)	(0.200)	(0.206)
Agricultural land area	-1.006***	-0.998***	-1.157***	-1.164***	-1.005***	-0.999***	-1.022***	-1.010***
	(0.233)	(0.246)	(0.260)	(0.273)	(0.218)	(0.227)	(0.259)	(0.268)
Government revenue	1.252***	1.255***	1.162***	1.168***	1.271***	1.271***	1.281***	1.285***
	(0.131)	(0.132)	(0.132)	(0.134)	(0.115)	(0.116)	(0.113)	(0.115)
Student%	-3.903***	-3.989***	-3.429***	-3.572***	-2.782***	-2.824***	-2.802***	-2.859***
	(0.801)	(0.828)	(0.792)	(0.825)	(0.820)	(0.840)	(0.813)	(0.837)
Oil crop production	2.630***	2.873***	2.973**	3.133**	2.129**	2.324**	1.346	1.440
	(1.002)	(1.020)	(1.478)	(1.527)	(1.008)	(1.030)	(1.779)	(1.823)
Machinery power	0.167**	0.163*	0.101*	0.105*	0.081	0.080	0.097*	0.100*
	(0.085)	(0.085)	(0.057)	(0.060)	(0.060)	(0.060)	(0.051)	(0.053)
Constant	5.342***	5.350***	5.380***	5.395***	3.770***	3.770***	3.773***	3.766***
	(0.276)	(0.279)	(0.244)	(0.250)	(0.175)	(0.178)	(0.232)	(0.239)
Baseline characteristics × Year dummy	No	No	Yes	Yes	No	No	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3384	3384	3384	3384	3566	3566	3566	3566
Adj. R^2	0.928	0.928	0.931	0.930	0.929	0.929	0.930	0.930

Note: Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4.4: Effect of RE-CDM on employment generation

	Explained variable: Rural labor%							
	PSM-DID				MDM-DID			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RE-CDM	1.128***		1.185***		1.222***		1.187***	
	(0.395)		(0.397)		(0.389)		(0.392)	
Biomass		1.484**		1.438**		1.472**		1.465**
		(0.659)		(0.641)		(0.651)		(0.638)
Wind		0.637		0.762*		0.796*		0.798*
		(0.454)		(0.460)		(0.450)		(0.453)
Solar		-4.016**		-4.504**		-3.685**		-3.823**
		(1.723)		(1.755)		(1.709)		(1.725)
Multi-projects		2.190		2.421*		2.070		2.113
		(1.349)		(1.325)		(1.337)		(1.327)
Primary industry output	0.212*	0.208*	0.267*	0.275*	0.634**	0.625**	1.004*	1.039*
	(0.115)	(0.113)	(0.160)	(0.167)	(0.265)	(0.263)	(0.586)	(0.606)
Agricultural land area	-1.350	-1.258	-1.129	-1.029	-1.100	-1.070	-0.525	-0.438
	(1.186)	(1.236)	(1.145)	(1.187)	(1.084)	(1.126)	(1.088)	(1.122)
Government revenue	-0.043	-0.032	0.011	0.049	0.210	0.222	0.272	0.312
	(0.311)	(0.313)	(0.341)	(0.345)	(0.338)	(0.340)	(0.353)	(0.357)
Student%	-0.013	-0.016	-0.008	-0.012	0.022	0.020	0.031	0.029
	(0.059)	(0.059)	(0.059)	(0.059)	(0.062)	(0.062)	(0.062)	(0.062)
Oil crop production	19.68**	21.11***	22.35***	23.35***	13.16*	14.43*	11.53	12.23
	(7.643)	(7.744)	(8.125)	(8.239)	(7.405)	(7.508)	(8.282)	(8.447)
Machinery power	-0.481*	-0.516*	-0.0192	-0.0354	-0.455	-0.481	0.004	-0.0145
	(0.279)	(0.294)	(0.234)	(0.240)	(0.285)	(0.297)	(0.207)	(0.213)
Constant	58.24***	58.26***	57.61***	57.63***	48.98***	49.00***	48.31***	48.28***
	(1.393)	(1.404)	(1.391)	(1.400)	(1.131)	(1.138)	(1.266)	(1.281)
Baseline characteristics × Year dummy	No	No	Yes	Yes	No	No	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3397	3397	3397	3397	3579	3579	3579	3579
Adj. R^2	0.705	0.705	0.707	0.707	0.715	0.714	0.717	0.716

Note: Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4.5: Effect of RE-CDM on employment in the primary sector

	Explained variable: Rural labor_primary%							
	PSM-DID				MDM-DID			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RE-CDM	0.548		0.579		0.809**		0.815**	
	(0.385)		(0.401)		(0.381)		(0.404)	
Biomass		-0.428		-0.447		-0.289		-0.259
		(0.438)		(0.438)		(0.425)		(0.416)
Wind		1.418***		1.500***		1.705***		1.714***
		(0.467)		(0.484)		(0.460)		(0.484)
Solar		-4.974**		-5.130**		-4.850**		-4.365**
		(1.979)		(2.057)		(1.963)		(2.040)
Multi-projects		-2.015		-2.020		-2.043		-2.276
		(1.438)		(1.506)		(1.411)		(1.505)
Primary industry output	-0.103	-0.102	-0.031	-0.023	-0.323	-0.311	-0.325	-0.286
	(0.103)	(0.102)	(0.080)	(0.06)	(0.210)	(0.205)	(0.343)	(0.326)
Agricultural land area	3.244***	3.230***	3.346***	3.328***	3.379***	3.326***	3.311***	3.273***
	(1.034)	(1.034)	(1.000)	(1.010)	(1.013)	(1.010)	(0.974)	(0.987)
Government revenue	-1.418**	-1.468**	-1.389**	-1.415**	-1.261*	-1.316**	-1.382**	-1.415**
	(0.572)	(0.573)	(0.624)	(0.624)	(0.648)	(0.649)	(0.699)	(0.700)
Student%	0.229***	0.231***	0.231***	0.231***	0.168**	0.168**	0.174***	0.174***
	(0.066)	(0.065)	(0.066)	(0.066)	(0.065)	(0.065)	(0.066)	(0.066)
Oil crop production	19.51**	19.09**	15.52	15.17	17.16**	16.51**	11.02	10.20
	(8.342)	(8.210)	(12.66)	(12.62)	(7.559)	(7.372)	(11.35)	(11.31)
Machinery power	-1.115***	-1.059***	-0.682**	-0.600**	-0.721**	-0.661**	-0.464**	-0.384**
	(0.407)	(0.388)	(0.288)	(0.263)	(0.295)	(0.283)	(0.199)	(0.192)
Constant	16.04***	16.02***	15.58***	15.55***	22.35***	22.40***	22.71***	22.72***
	(1.587)	(1.584)	(1.711)	(1.715)	(1.345)	(1.350)	(1.845)	(1.855)
Baseline characteristics × Year dummy	No	No	Yes	Yes	No	No	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3398	3398	3398	3398	3580	3580	3580	3580
Adj. R^2	0.607	0.608	0.607	0.607	0.603	0.604	0.603	0.604

Note: Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4.6: Number of RE-CDM projects

	Income_rural		Rural labor%		Rural labor_primary%	
	(1)	(2)	(3)	(4)	(5)	(6)
1 project	0.247***	0.187***	0.909**	1.031**	0.577	0.815*
	(0.0566)	(0.0542)	(0.442)	(0.438)	(0.430)	(0.424)
2 projects	0.229*	0.136	1.170*	1.256*	0.894	1.238**
	(0.119)	(0.120)	(0.693)	(0.694)	(0.628)	(0.624)
$\geq$ 3 projects	0.155	0.0696	2.404*	2.558*	2.138**	2.548**
	(0.160)	(0.158)	(1.347)	(1.341)	(1.052)	(1.043)
Primary industry output	0.111	0.318***	0.220*	0.656**	-0.101	-0.311
	(0.0714)	(0.123)	(0.119)	(0.271)	(0.102)	(0.206)
Agricultural land area	-1.015***	-1.006***	-1.532	-1.265	3.067***	3.195***
	(0.245)	(0.226)	(1.223)	(1.114)	(1.003)	(0.979)
Government revenue	1.256***	1.274***	-0.0553	0.192	-1.438**	-1.283**
	(0.117)	(0.132)	(0.310)	(0.336)	(0.573)	(0.648)
Student%	-4.047***	-2.853***	-0.0181	0.0170	0.228***	0.164**
	(0.832)	(0.843)	(0.0589)	(0.0616)	(0.0654)	(0.0654)
Oil crop production	2.774***	2.256**	19.63**	13.03*	19.12**	16.71**
	(1.023)	(1.024)	(7.673)	(7.440)	(8.338)	(7.549)
Machinery power	0.168*	0.0813	-0.472*	-0.450	-1.108***	-0.715**
	(0.0859)	(0.0599)	(0.275)	(0.284)	(0.405)	(0.295)
Constant	5.361***	3.774***	58.39***	49.10***	16.15***	22.48***
	(0.281)	(0.179)	(1.394)	(1.133)	(1.593)	(1.351)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	3384	3566	3397	3579	3398	3580
adj. R^2	0.928	0.929	0.705	0.715	0.607	0.603

Note: Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Chapter 5

Concluding Remarks

This paper analyzed the effectiveness of renewable energy policy in Japan and China. We focus on the main barriers to the development of the wind power industry, and whether the severe regulations promoting nature conservations have restricted the wind power installations in Japan. On the other hand, we investigated the effectiveness of regionally differentiated FIT for the development of renewable energy in China. In addition, we examined whether investment in climate change mitigation can also contribute to poverty alleviation in developing countries.

As a result, we found that more severe environmental regulations can decrease the construction of renewable facilities. Despite the fact that fossil fuels do much greater damage to wildlife and nature environment, a great deal of attention has been paid in recent years to the potential negative environmental externalities that renewables can inflict; further, environmental regulations are often used to oppose renewable energy projects. Some of the renewable energy systems have been repeatedly shut down for causing habitat damage. For instance, the USD 2.2 billion Solar Farm in the Mojave Desert, the largest solar facility in the US, was almost completely abandoned because of the death of an endangered desert tortoise.[1] The results of Krewitt et al. (2005) show that Germanys target of expanding the

[1]The Impact of Environmental Regulations on the Energy Market, 2017. <https://lawstreetmedia.com/issues/energy-and-environment/environmental-regulations-energy-market/>, accessed on December 4, 2018.

share of renewable energy sources of primary energy consumption to 50% in 2050 can be realized without getting in conflict with nature conservation requirements. To ensure long term societal acceptance and further expansion of renewable energy technologies, we suggest that more adequate environmental assessments should be given in the process of revising construction guidelines on protected areas.

On the other hand, the FIT policy, the most widely implemented incentive policy, for renewable technologies has accounted for a greater share of renewable energy promotion than any other policy support scheme (Fouquet and Johansson, 2008; Mendonca et al., 2009). The estimation results of the second chapter of this research show that the adoption of differentiated tariffs across regions under the FIT has effectively enhanced location diversification of renewable projects in China. However, as mentioned above, in the case of Chinas solar energy industry, insufficient tariff rates under the FIT have lead to the uneven development of power industries. In addition, Lange (2011) concluded that very aggressive tariffs may attract a wider range of investors by making less efficient projects financially viable. Therefore, we suggest a dynamic design that requires tariff rate to adjust as the amount of production capacity increases; further, the regional differentiation of tariff rates based on the cost of electricity generation should be widely adopted too.

Furthermore, by focusing on the social benefits of renewable energy projects under the CDM, this study concluded that the expansion of renewable energy industries has promoted rural development in China. In line with the conclusion of Thiam (2011), our results demonstrated the fact that a renewable energy promotion policy could be an important component of the poverty reduction plan. In consideration of the stressful climate change mitigation requirements nowadays, we suggest that the governments provide political and financial support for the greater use of renewable energy sources, especially in remote areas, by setting adequate targets and offering suitable subsidies.

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Appendix

Table A1: Effect of FIT on Wind Power Development (Sample Falls within $\leq$ 50 km of Boundary)

	Utilization rate	Wind capacity	Power generation	Operation hour
	(1)	(2)	(3)	(4)
Panel A: Linear Polynomial in Distance with Kernel Weights				
south	10.29***	50.15**	84.10**	82.41*
	(3.623)	(21.93)	(32.77)	(47.85)
Adj.R^2	0.379	0.299	0.271	0.256
Panel B. Quadratic Polynomial in Distance				
South	9.020**	41.68*	68.92**	68.23
	(3.193)	(23.85)	(32.85)	(48.00)
Adj.R^2	0.383	0.293	0.268	0.252
Panel C. Linear Polynomial in Longitude and Latitude				
South	9.306**	35.33	76.55*	95.24
	(3.763)	(23.19)	(41.57)	(58.80)
Adj.R^2	0.387	0.296	0.264	0.256
Panel D. Quadratic Polynomial in Longitude and Latitude				
South	9.863***	39.08**	66.79*	80.81
	(3.463)	(19.61)	(35.20)	(54.71)
Adj.R^2	0.510	0.379	0.325	0.253
Geographic location polynomial	yes	yes	yes	yes
Controls	yes	yes	yes	yes
Segment fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	112	112	112	112

Note: Robust standard errors, adjusted for clustering by county, are in parentheses. If z denotes geometric distance from the county's government office to the tariff zone boundary, x denotes the longitude, and y denotes the latitude of the county, the linear polynomial in distance is $z + z \times south$, the quadratic polynomial in distance is $z + z^2$, the linear polynomial in longitude and latitude is $x + y$, and the quadratic polynomial in longitude and latitude is $x + y + x^2 + y^2 + xy$. Coefficients that are significantly different from zero are denoted by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A2: Effect of FIT on Solar Power Development (Sample Falling within $\leq$ 50 km of the Boundary)

	Explanatory variable: solar capacity (MW)			
	Single-dimensional RDD		Multi-dimensional RDD	
	Linear	Quadratic	Linear	Quadratic
	(1)	(2)	(3)	(4)
south	38.19*	17.50	23.32	20.12
	(21.42)	(18.86)	(27.22)	(23.98)
South×2011	-1.797	-1.668	-1.745	-1.685
	(1.738)	(1.669)	(1.781)	(1.804)
South×2013	-3.378	-3.127	-3.077	-3.116
	(6.133)	(5.858)	(5.882)	(5.940)
South×2014	2.280	1.688	1.782	1.709
	(14.28)	(14.03)	(14.10)	(14.22)
South×2015	21.87	20.67	20.88	20.72
	(17.38)	(17.00)	(17.10)	(17.27)
South×2016	146.4***	145.1**	145.4**	145.2**
	(52.65)	(53.55)	(53.85)	(54.28)
Cons.	-782.1	-897.2	-1709	-22978
	(556.8)	(577.3)	(1901)	(44733)
Geographic location polynomial	yes	yes	yes	yes
Control	yes	yes	yes	yes
Segment fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	174	174	174	174
Adj.R^2	0.339	0.332	0.328	0.320

Note: Robust standard errors, adjusted for clustering by county, are in parentheses. If z denotes geometric distance from the county's government office to the tariff zone boundary, x denotes the longitude, and y denotes the latitude of the county, the linear polynomial in distance is $z + z \times south$, the quadratic polynomial in distance is $z + z^2$, the linear polynomial in longitude and latitude is $x + y$, and the quadratic polynomial in longitude and latitude is $x + y + x^2 + y^2 + xy$. Coefficients that are significantly different from zero are denoted by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$

Table A3: Interaction between treatment and each year

	Income_rural		Rural labor%		Rural labor_primary%	
	PSM-DID	MDM-DID	PSM-DID	MDM-DID	PSM-DID	MDM-DID
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × 2002	-0.033	0.001	0.304	0.275	-1.871	-2.505*
	(0.081)	(0.075)	(0.510)	(0.483)	(1.446)	(1.451)
Treatment × 2003	0.025	0.074	0.212	0.131	-1.781	-2.333
	(0.077)	(0.072)	(0.503)	(0.483)	(1.452)	(1.454)
Treatment × 2005	0.099	0.119**	0.043	0.098	-1.858	-2.384*
	(0.062)	(0.060)	(0.478)	(0.464)	(1.433)	(1.440)
Treatment × 2006	0.151**	0.138**	0.565	1.002**	-1.167	-1.514
	(0.068)	(0.063)	(0.550)	(0.487)	(1.498)	(1.500)
Treatment × 2007	0.213***	0.152**	1.054*	1.331**	-1.059	-1.206
	(0.065)	(0.062)	(0.567)	(0.557)	(1.446)	(1.456)
Treatment × 2008	0.271***	0.152**	1.125**	1.274**	-0.594	-0.780
	(0.071)	(0.067)	(0.554)	(0.512)	(1.459)	(1.464)
Treatment × 2009	0.298***	0.172**	0.800	1.204**	-1.414	-1.267
	(0.087)	(0.085)	(0.547)	(0.539)	(1.504)	(1.506)
Treatment × 2010	0.385***	0.208*	0.905	1.158	-1.713	-1.216
	(0.116)	(0.118)	(0.832)	(0.825)	(1.562)	(1.558)
Treatment × 2011	3.034***	2.700***	5.826***	4.977***	-4.042**	-4.258***
	(0.265)	(0.295)	(1.952)	(1.922)	(1.626)	(1.603)
Primary industry output	0.0799	0.257**	0.161*	0.542**	-0.0474	-0.231
	(0.054)	(0.102)	(0.093)	(0.236)	(0.0795)	(0.178)
Agricultural land area	-0.371**	-0.479**	-0.130	-0.208	2.424**	2.466**
	(0.173)	(0.197)	(1.167)	(1.085)	(1.039)	(0.981)
Government revenue	1.211***	1.246***	-0.114	0.174	-1.335**	-1.172*
	(0.109)	(0.126)	(0.306)	(0.335)	(0.567)	(0.645)
Student%	-2.591***	-1.676**	0.005	0.028	0.202***	0.135**
	(0.709)	(0.765)	(0.060)	(0.063)	(0.067)	(0.067)
Oil crop production	3.051***	2.675***	21.18***	14.69**	19.24**	17.10**
	(0.905)	(0.947)	(7.704)	(7.492)	(8.395)	(7.687)
Machinery power	0.128*	0.060	-0.556*	-0.510*	-1.072***	-0.706**
	(0.068)	(0.048)	(0.299)	(0.292)	(0.395)	(0.297)
Constant	4.831***	3.502***	57.24***	48.96***	17.21***	22.18***
	(0.219)	(0.178)	(1.459)	(1.167)	(1.935)	(1.126)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	3384	3566	3398	3580	3398	3580
adj. R^2	0.935	0.934	0.692	0.701	0.607	0.604

Note: The general form of the multi-period DID model can be written as: $y_{it} = \alpha + \sum_{t=-2}^{7} \beta_t Treatment_i \times \gamma_t + \lambda X_{it} + \delta_i + \gamma_t + \epsilon_{it}$. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$

Table A4: Full sample without matching

	Income_rural		Rural labor%		Rural labor_primary%	
	(1)	(2)	(3)	(4)	(5)	(6)
RE-CDM	0.475**		1.270***		0.801***	
	(0.196)		(0.353)		(0.299)	
Biomass		1.412***		1.060*		0.183
		(0.305)		(0.577)		(0.474)
Wind		0.270		1.140***		1.660***
		(0.225)		(0.415)		(0.348)
Solar		0.005		-3.920*		-2.830**
		(0.718)		(2.180)		(1.410)
Multi-projects		-0.258		2.510		-2.850**
		(0.670)		(1.750)		(1.110)
Primary industry output	-0.292	-0.300	0.230	0.232	-0.469*	-0.467*
	(0.218)	(0.221)	(0.192)	(0.193)	(0.243)	(0.241)
Agricultural land area	4.822***	4.857***	-3.340***	-3.340***	1.710**	1.850**
	(0.625)	(0.625)	(1.160)	(1.180)	(0.822)	(0.839)
Government revenue	11.34***	11.34***	-0.140	-1.350	-0.496***	-0.495***
	(1.059)	(1.059)	(0.148)	(0.147)	(0.139)	(0.139)
Student%	2.205	2.163	-0.083	-0.084	-0.006	-0.007
	(2.230)	(2.235)	(0.058)	(0.058)	(0.035)	(0.035)
Oil crop production	12.28**	12.93**	16.60	16.80	-1.040	-0.813
	(6.077)	(6.102)	(13.80)	(13.90)	(6.740)	(6.660)
Machinery power	-1.864***	-1.890***	-0.057	-0.053	-1.540***	-1.510***
	(0.686)	(0.698)	(0.260)	(0.261)	(0.463)	(0.005)
Constant	0.940	0.950	52.60***	52.60***	0.252***	0.252***
	(0.592)	(0.594)	(0.012)	(1.220)	(0.934)	(0.932)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	11105	11105	12938	12938	12938	12938
Adj. R^2	0.529	0.529	0.316	0.316	0.540	0.540

Note: Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A5: Effect of additional thermal power

	Income_rural				Rural labor%				Rural labor_primary%			
	PSM-DID		MDM-DID		PSM-DID		MDM-DID		PSM-DID		MDM-DID	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Thermal power	-2.585***	-1.524**	-1.050**	-0.212	-0.305	-0.524	-0.150	-0.407	0.143	0.222	0.393	0.478
	(0.745)	(0.653)	(0.443)	(0.301)	(0.331)	(0.339)	(0.348)	(0.359)	(0.392)	(0.389)	(0.371)	(0.374)
Primary industry output	-2.186***	-3.721***	-1.213**	-1.935**	0.654**	0.912***	0.631**	0.834**	-0.062	0.350	-0.606**	-0.372
	(0.651)	(0.847)	(0.610)	(0.854)	(0.324)	(0.337)	(0.321)	(0.354)	(0.268)	(0.281)	(0.244)	(0.261)
Agricultural land area	6.947***	5.680***	4.231***	3.359***	-2.852**	-2.617*	-1.543	-1.399	-3.418**	-3.547**	-1.297	-1.413
	(1.192)	(1.158)	(0.801)	(0.737)	(1.436)	(1.438)	(1.445)	(1.448)	(1.507)	(1.489)	(1.365)	(1.363)
Government revenue	15.236***	16.693***	11.112***	11.558***	-0.249	-0.560***	-0.156	-0.273	-0.248*	-0.193	-0.056	-0.013
	(2.933)	(3.142)	(2.666)	(2.999)	(0.168)	(0.176)	(0.141)	(0.182)	(0.140)	(0.123)	(0.173)	(0.158)
Student%	0.054	0.080	0.148***	0.149***	-0.180***	-0.171***	-0.118*	-0.109	-0.078	-0.088	-0.166	-0.161
	(0.052)	(0.050)	(0.046)	(0.046)	(0.061)	(0.060)	(0.068)	(0.068)	(0.059)	(0.059)	(0.109)	(0.108)
Oil crop production	18.791	14.470	11.561	8.810	4.125	14.991	1.910	8.314	-4.140	21.460*	4.480	20.250**
	(11.630)	(12.235)	(10.719)	(10.833)	(11.974)	(12.720)	(10.462)	(10.974)	(11.367)	(12.384)	(9.349)	(10.227)
Machinery power	-1.001	-1.110	-1.162	-1.101	-0.029	0.068	0.041	0.140	-0.334	-0.053	-0.139	0.041
	(0.699)	(0.695)	(0.840)	(0.834)	(0.120)	(0.183)	(0.131)	(0.165)	(0.204)	(0.197)	(0.086)	(0.146)
Constant	4.073**	7.869***	-0.568	1.413	61.227***	59.875***	51.178***	50.142***	22.676***	21.423***	26.499***	26.012***
	(1.622)	(1.884)	(0.848)	(1.001)	(1.521)	(1.609)	(1.152)	(1.205)	(1.345)	(1.366)	(1.769)	(1.819)
Baseline characteristics × year dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3148	3148	3436	3436	3148	3148	3436	3436	3149	3149	3437	3437
adj. R^2	0.493	0.531	0.509	0.525	0.750	0.752	0.724	0.725	0.896	0.897	0.879	0.880

Note: Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.