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(Citation)
神戸大学経済学研究科 Discussion Paper,1828

(Issue Date)
2018

(Resource Type)
technical report

(Version)
Version of Record

(URL)
https://hdl.handle.net/20.500.14094/81010582

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**November 2018**

**Discussion Paper No.1828**

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# Does a Small Difference Make a Difference? Impact of Feed-in Tariff on Renewable Power Generation in China

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November 16, 2018

**Abstract**

This study investigates the effectiveness of regionally differentiated feed-in tariffs (FIT) for the development of renewable energy in China. By using a spatial regression discontinuity design, we estimate the impacts of regionally differentiated FITs on the outcome indicators of wind and solar power generation, such as utilization rate, installed capacity, power generation, and hours of operation. Our findings 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 in outcome indicators among regions. Our results suggest that regionally differentiated FITs might help mitigate the overproduction of wind electricity in regions with abundant wind resources but low electricity demand.

*Keywords:* Feed-in Tariff; Renewable Energy; Renewable Curtailment; Spatial Regression Discontinuity Design

JEL classification: Q42, Q48

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# 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 feed-in tariff (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 study 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 difference-in-differences (DID) model with spatial RDD.

This study 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 study 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, our study 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 study'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 paper 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.

## 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 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 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 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.

[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.

[Figure 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 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 1]

Figure 3 shows the spatial distribution of the counties selected as the study area of this research. The FIT boundary divides the study area into the south and north. Wind 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

[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.

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 Empirical strategy

## 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 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

[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.

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

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.

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

[5] More precisely, as presented in Table 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.

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 2, and those for solar power are presented in panel B. Table 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 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. Figures 4 and 5 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 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 4]

[Figure 5]

[Table 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:

$$W_{it} = \alpha + \beta south_i + \gamma X_{it} + f(geographic\ location_i) + \lambda_b + \theta_t + \epsilon_{it}, \tag{1}$$

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, $\beta$, 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

[6]Results of two-tailed t-tests are shown in column (4) of Tables 2 and 3.

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. $\lambda_b$ 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 $\theta_t$ 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:

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

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 $\theta_t$. 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. $\beta_t$ is the coefficient on the $t$th 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.

# 4 Results and discussions

## 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 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 operation hours. Panels A and B in Table 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 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 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

[7]According to the summary statistics in Table 2, the average utilization rate of wind facilities in the control group is around 5.69%.

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 operation 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 operation 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 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 5]

Table 5 limits the sample to counties located within 80 km of the FIT boundary. The specification reported in panel A of Table 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 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.

[8]According to the summary statistics in Table 2, the average operation hours of wind facilities in the control group are around 104,800 hours.

## 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 6]

Table 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 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 $South \times 2011$ in Table 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 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 6]

Figure 6 illustrates the same results as Table 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 counties located in the north of the FIT boundary.

[Table 7]

Similar to the wind power regression, Table 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

[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 in our study 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 1.

[11]According to the summary statistics in Table 2, the mean solar capacity in the control group is 24.3 MW.

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 7 suggest a statistically significant and positive effect of the solar tariff at around 146.7 MW in 2016.

# 5 Conclusions

By focusing on the wind and solar power industry in China, this study 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 has been implemented, instead of the regionally differentiated one. The findings from this study 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.

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

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# Acknowledgements

This work was supported by JSPS KAKENHI Grant Number JP16H03006. We thank helpful comments from Daisuke Ishinose and session participants at the 2018 Annual Meeting of the Society for Environmental Economics and Policy Studies. All errors are our own.

Table 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 2: Descriptive Statistics *(Full Sample)*

Table 2-1: Summary 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 |

Table 2-2: Summary 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: Descriptive Statistics
*(Sample Falling within $\leq$ 80 km of the Boundary)*

Table 3-1: Summary 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 |

Table 3-2: Summary 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 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 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 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 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 *** $p < 0.01$.

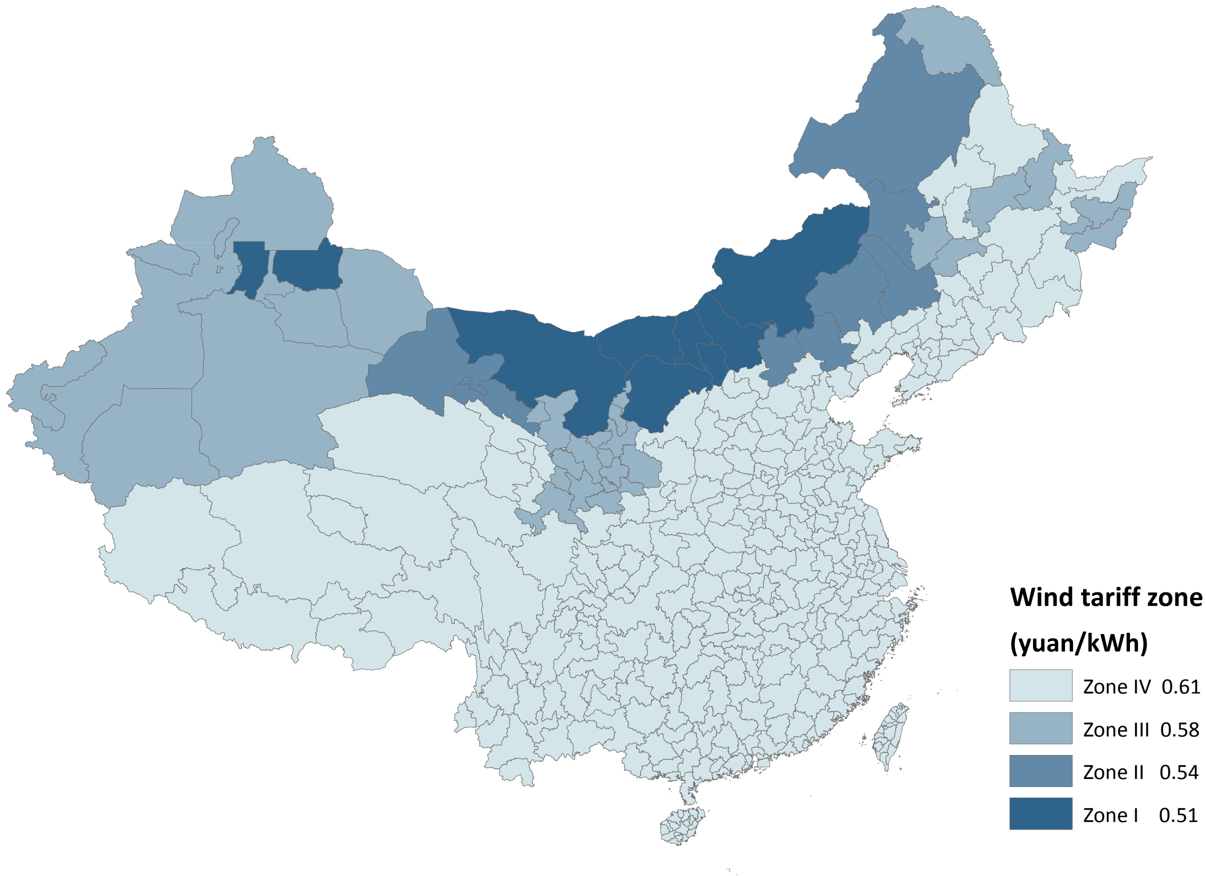


Figure 1: Distribution of wind resource zones and regionally differentiated on-grid wind tariffs in China.

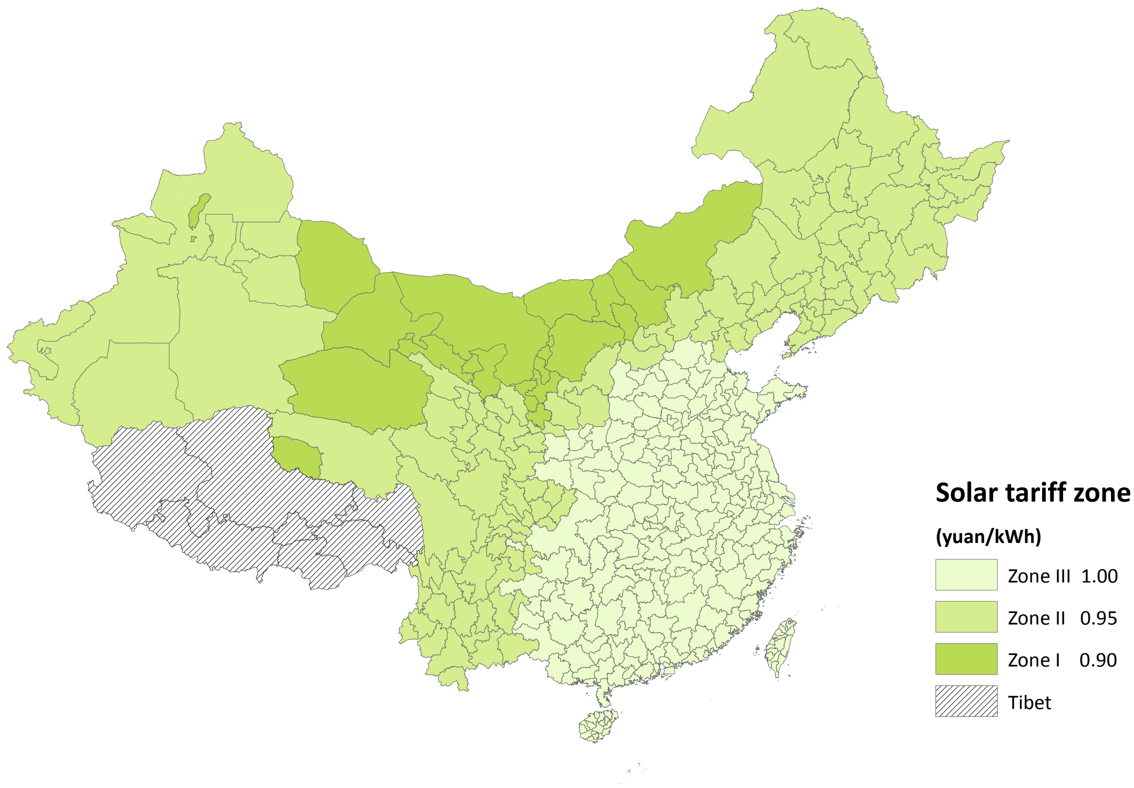


Figure 2: Distribution of solar resource zones and regionally differentiated on-grid solar tariffs in China.

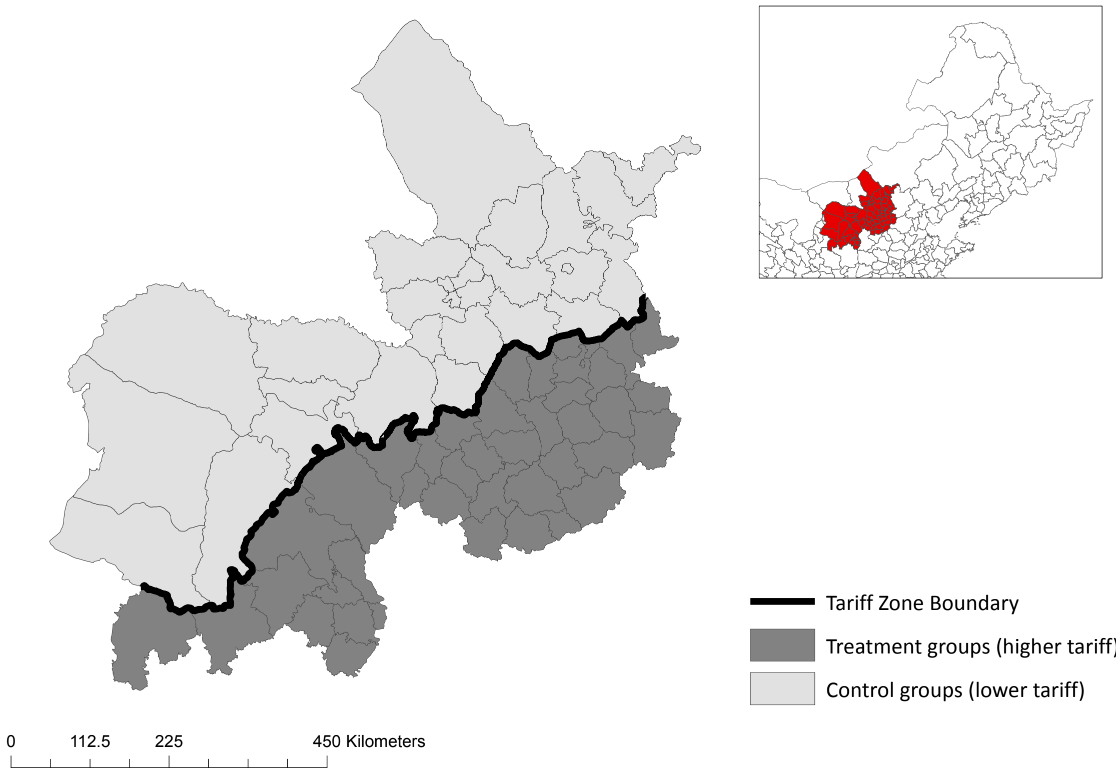


Figure 3: Distribution of the feed-in tariff (FIT) boundary and counties in the study area. Counties located in the south of the FIT boundary contributed to the treatment group and are colored in dark grey *(south=1)*.

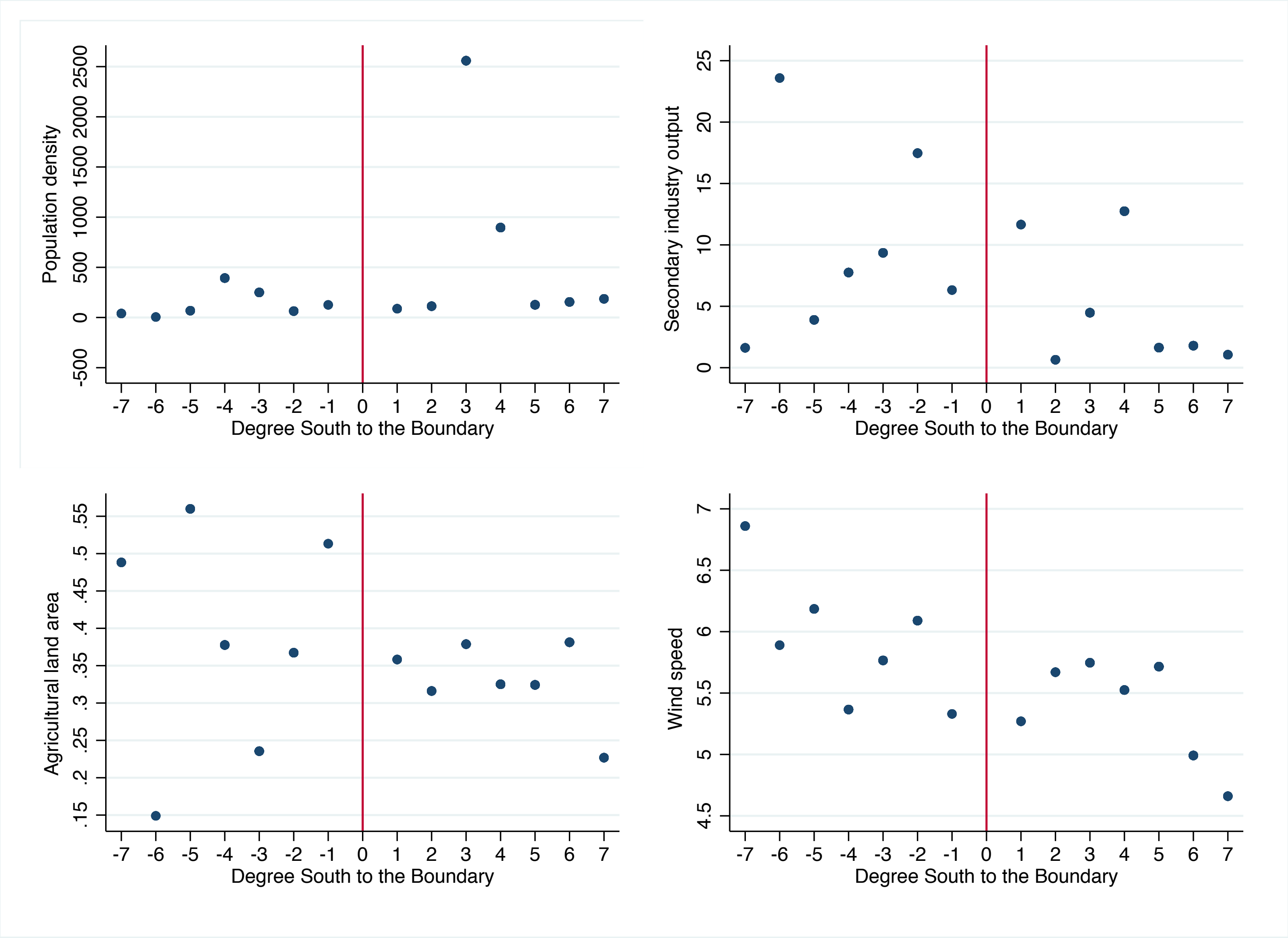


Figure 4(a): Local polynomial smoothing of characteristics by county relative to the distance from the feed-in tariff boundary (wind).

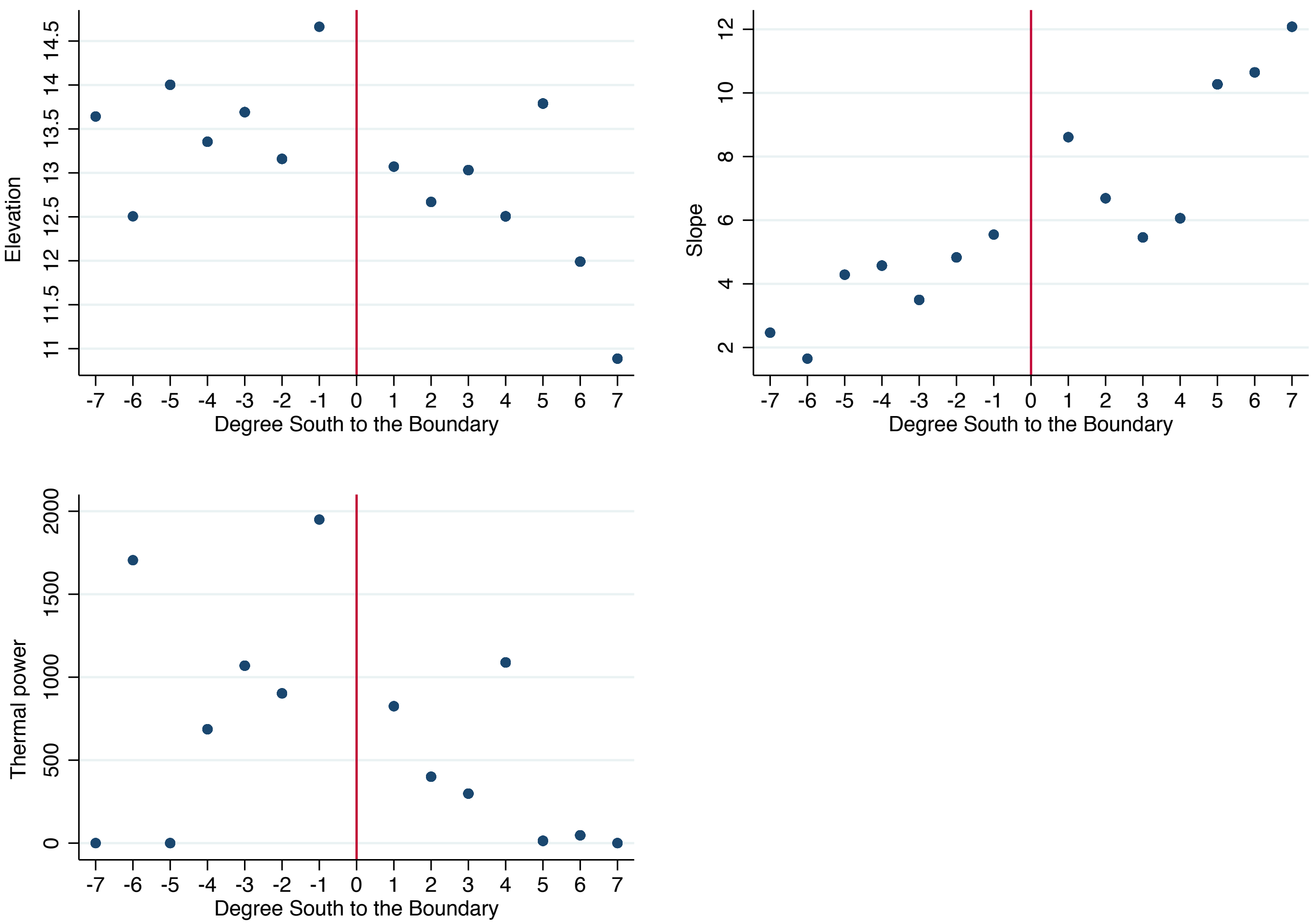


Figure 4(b): Local polynomial smoothing of characteristics by county relative to the distance from the feed-in tariff boundary (wind) - *Continued*

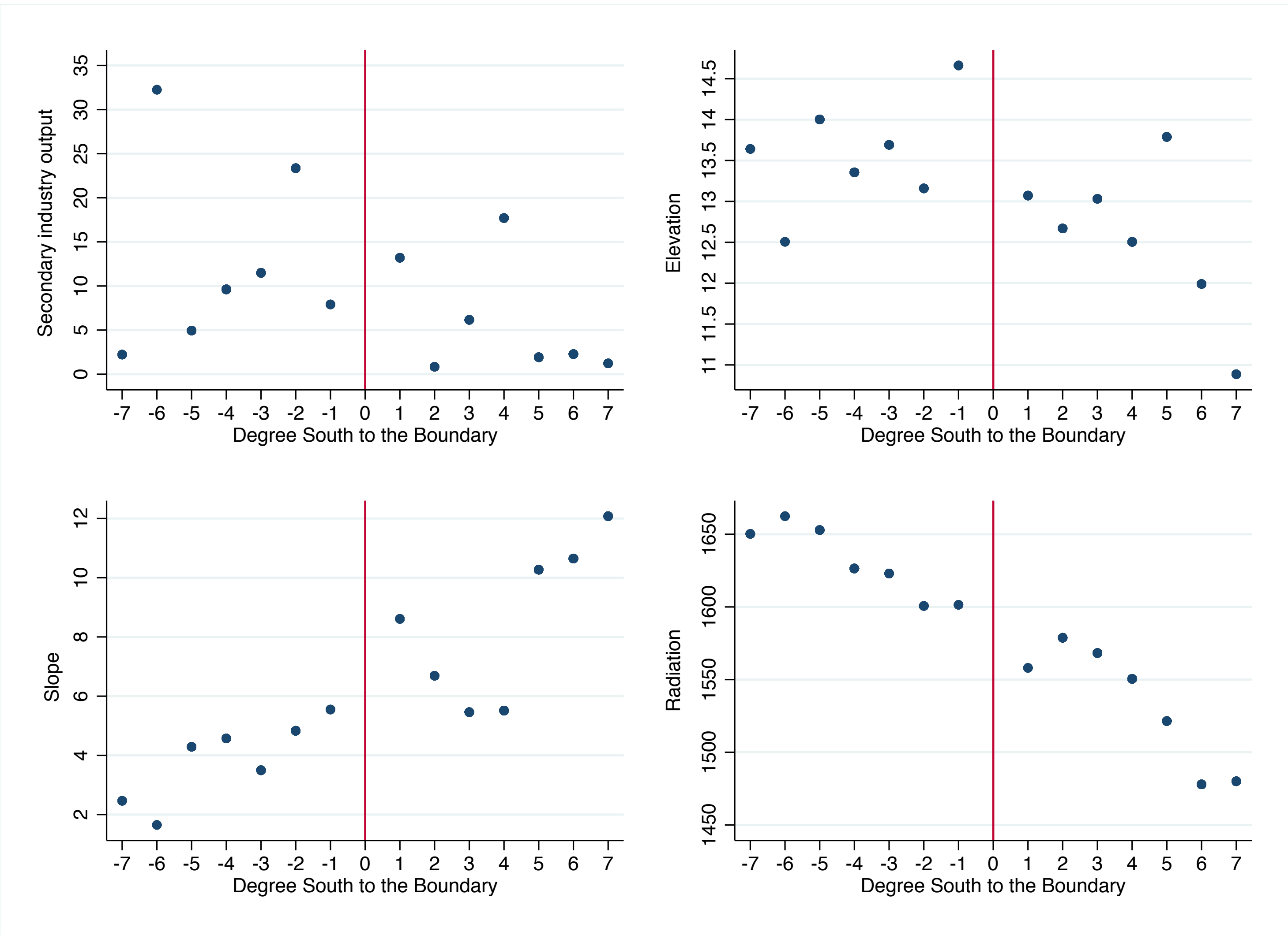


Figure 5: Local polynomial smoothing of characteristics by county relative to the distance from the feed-in tariff boundary (solar).

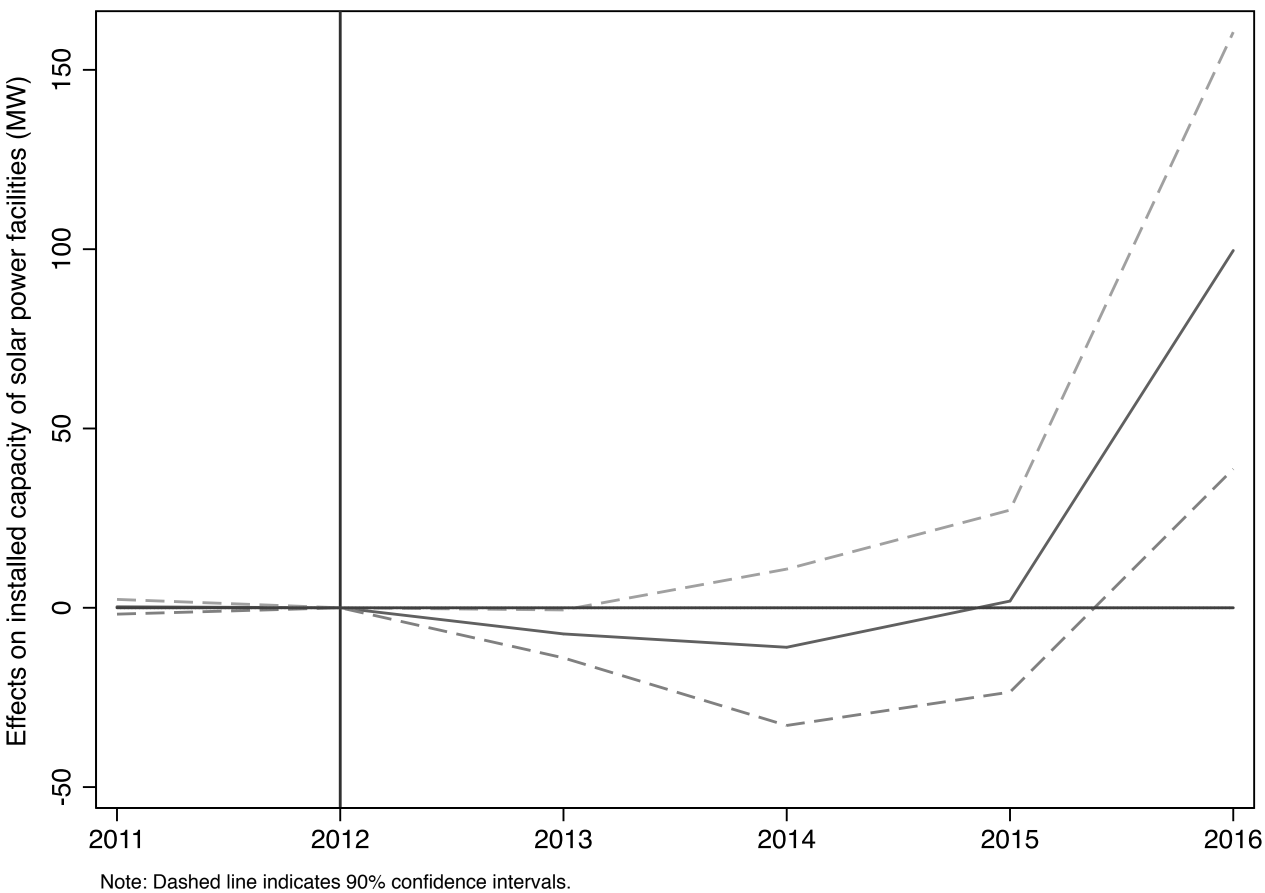


Figure 6: Annual effect of on-grid solar feed-in tariffs from the regression discontinuity design and multi difference-in-differences model.

# Appendix

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

| | Utilization rate (1) | Wind capacity (2) | Power generation (3) | Operation hour (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 *** $p < 0.01$