Assessing the impact of Wind Power Investment Utilizing Electricity: Based on Demand Information in China

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ABSTRACT

China has been actively developing wind power for several decades, and its installed capacity has grown rapidly, which can be largely attributed to the favorable policy support and subsidies provided to wind power investments. However, China’s resource-based strategy for wind power layout may not be fully taking into account the information on electricity demand. Therefore, the authors aim to identify the key factors driving the regional distribution of wind power in China, with a particular focus on the relationship between wind farm investments and local electricity demand. The study reveals that, compared to earlier stages of development, wind power installation growth is now more concentrated in regions with high electricity demand rather than just in resource-rich areas. Moreover, the model results demonstrate that the leading effect of demand on wind investment is more pronounced in resource-rich regions than in other areas. Demand information and mechanism analysis highlight the significant role of zoning policies in moderating the impact of demand on wind power siting and investment.

KEYWORDS

Electricity demand, FIT, Wind power investment, Wind turbines distribution

1. INTRODUCTION

1.1. Background

As global environmental concerns continue to rise, clean and renewable energy sources are receiving increased attention from countries around the world estimation (Pandey et al., 2020). However, China’s rapid economic growth has resulted in the world’s highest carbon emissions (Z. Liu et al., 2015; Lu et al., 2021). In response, China has set a goal of achieving net-zero emissions by 2060 (A. Wang et al., 2021; Y. Wang et al., 2022), and wind power is being viewed as an eco-friendly alternative to balance economic growth and environmental sustainability (Fan et al., 2019; Zheng et al., 2016). The
Chinese government has provided strong support for wind power, resulting in significant industry growth (Dai et al., 2018). As of 2021, China's installed wind power capacity has reached 300 GWh.

China’s wind power industry development is unique from many perspectives, particularly in terms of government policies and regulations. Unlike many Western countries, where wind power investments are typically operated by competitive markets and private investors, China’s wind power investments are largely driven by national plans and government subsidies. The government implemented policies that guarantee a minimum on-grid power for every wind farm and provide subsidies for each unit of electricity on the grid. These policies have created an imbalance in the distribution of wind power investments across different regions in China.

The favorable government policies implemented by China have been identified as a key driving factor for the rapid growth of wind power in the country (Yuan, 2016; M. Zhang et al., 2022). Since the approval of the Renewable law in 2005, China has implemented a range of regulations and policies aimed at promoting the development of renewable energy sources (Chen et al., 2022). Among these policies, the resource-based regional division and related feed-in-tariff (FIT) are considered to have had the broadest impact in China (T. Liu et al., 2022; Wei et al., 2019; R. X. X. Zhang et al., 2019). In addition to these policies, China’s substantial wind energy reserves have also contributed significantly to the development of wind power (Y. Wang et al., 2022; H. Zhang et al., 2020). He and Kammen (2014) estimated China’s annual potential for wind power to be between 2000-3500 TWh, while Feng et al. (2020) estimated the potential to be between 2560 and 3501 TWh. As a result of the Chinese government’s favorable policies and the country’s advanced wind energy conditions, the installed capacity for wind power in China has experienced significant growth in recent decades (Shen & Lyu, 2019). However, China has also experienced uneven development both in terms of supply-demand and geographical distribution.

Figure 1 illustrates a comparison between the top three provinces in China in terms of installed wind power capacity and the top three provinces in terms of GDP in 2021. The figure clearly indicates a mismatch between economic development and wind power growth, highlighting the potential supply-demand imbalance in China’s wind power development.

The imbalanced development of wind power in China can be attributed to various factors, including the uneven distribution of wind resources (X. Zhao et al., 2012a). Although China has vast wind energy reserves, primarily located in the north, northwest, and northeast regions, the power load centers are situated in areas different from these energy reserves. He and Kammen’s (2014) estimation of China’s potential for wind power capacity revealed significant regional variations, ranging from 1GW to 600GW at the provincial level, highlighting the imbalanced distribution of wind energy resources across the country.

Previously, China’s strategy for the wind power industry was focused on utilizing wind resources at the lowest cost to rapidly increase wind power capacity. As a result, the government supported the construction of numerous wind farms in areas with abundant wind energy reserves, leading to the development of several large wind power bases in Inner Mongolia, Xinjiang, Gansu, and Hebei, which are China’s primary wind power distribution points (Sahu, 2018; H. Zhang et al., 2020). This approach, while promoting the growth of the wind power industry, may have led to an imbalanced distribution. In contrast to the distribution of wind energy, China’s population and economy are concentrated along the eastern coast and in some parts of the central region, which also represent the power load centers of China. As a result, the efficiency of China’s wind power industry remains low due to a mismatch in distribution. For instance, in 2015, wind power generation only accounted for 2.5% of the total electricity generated in China (Z. Y. Zhao et al., 2016). Additionally, according to the Chinese National Energy Administration’s 2018 report, a total of 187 billion kWh of wind power was curtailed during 2011-2017, further highlighting the inefficiencies in the industry (Yu et al., 2021).

Chinese government policies for wind power investment have exacerbated misallocation in the industry. In the early stages of wind power development, China adopted a resource-based development
strategy to accelerate the expansion of wind power capacity (Qi et al., 2019). In 2009, the government divided the national area into four resource zones and implemented a differential fixed feed-in-tariff policy across zones. The FITs were designed as a subsidy mechanism and were set based on regional wind resource characteristics, as well as the specific needs of local economic growth (Wei et al., 2019). This subsidy mechanism provided wind power companies with financial incentives based on the cost of wind power generation in different zones. In other words, lower FITs were given in zones with abundant wind resources, while higher FITs were given in zones with scarce wind resources. The policy aimed to enhance wind power competitiveness and achieve a nationwide balance in wind power industry development through differentiated subsidy prices.

However, the issue of misallocation in wind power distribution has not been adequately addressed, and the problem has only worsened over time, as evidenced by the situation in 2017. On the positive side, the wind power industry in China has expanded rapidly, with installed capacity ranking first globally (S. Zhang et al., 2020). As a result, more and more researchers and scholars have begun to focus on the distribution of the wind power industry.

1.2. Literature Reviews

The factors impacting the wind power industry’s distribution have been widely discussed, and lots of studies have focused on the use of resources, including wind energy resources and land use. Studies on wind energy utilization focused on wind farms sitting mainly from the perspective of wind energy distribution and related technical conditions. For example, Santos-Alamillos et al. (2014) evaluated the potential contribution of wind resources to provide stable electricity generation, and their study employed principal component analysis to analyze the spatial balance of regional wind energy for assessing the optimal location of wind farms in terms of reducing wind energy fluctuations. Amjad et al. (2021) identified the optimal geographical clustering of wind farm distribution using spatial multi-criteria analysis, cluster analysis, and hierarchical analysis. Xing and Wang (2021) also provided a practical framework for wind farm siting based on the ecological system constraint and mapped a suitable wind farm siting in China.

Further studies of wind power deal with the occupied land of the wind power industry. Land acquisition was considered one of the biggest challenges in constructing the wind farm successfully (Arent et al., 2014). Mai et al. (2021) emphasize the importance of land use considerations in wind power siting, and they find that social and physical land use factors are significant determinants of wind power capacity, with the assessment finding a 37% reduction in onshore wind power capacity in 2050 under constrained conditions. Obane et al. (2020) identified the categories and areas of land in Japan that could be used for renewable energy development, including wind power, and assessed their power generation potential. Saraswat et al. (2021) conducted a study on wind power siting using GIS and MCDM methods from three perspectives: technology, economy, and social environment, to optimize the use of resources.

Besides the studies of wind power focusing on the resources, scholars have studied the role of the market in wind power development; however, the conclusions of Chinese scholars and foreign scholars are not consistent. Scholars believed that the economic factor was an important factor in attracting wind power investment because a better economy and higher income are more able to afford a higher price for wind power and, therefore in these places higher demand for wind power (Dorrell & Lee, 2020). Biresselioglu et al. (2016) also mentioned this point in their study on wind power construction influencing factors in 26 OECD countries. Mueller and Brooks (2020) stated in their research on the justice of wind power investment in the United States that income positively impacts wind power investment. However, early studies on the development of China’s wind power industry found no significant correlation between investment in Chinese wind power and local or regional demand. Xia and Song (Xia & Song, 2017) analyzed data on installed wind power in China from 2004 to 2011 and found that neither local nor off-site demand had a significant effect on the siting of wind farms. The over-concentration of wind power installations and the unbalanced development
between load demand and an installed capacity of wind power is also responsible for a large amount of wind power abandonment in China around 2017 (Xia et al., 2020).

In addition, most studies on wind power investment and distribution in China are still in their early stages. However, in recent years, limited data has hindered further research on this topic. Therefore, this study seeks to contribute to the existing literature by analyzing the influencing factors, with a focus on the demand factor, for wind power investment using more recent and available data.

1.3. Contribution

Previous wind power installation data suggests that investment in China’s wind power industry is geographically imbalanced. Studying wind power investments in China can provide insights into the factors that are driving the negative outcomes associated with government-led investments, as well as the effectiveness of markets and policies in promoting the sustainable growth of wind power industries. This paper’s contribution to literature is threefold:

Firstly, in terms of research perspective, there have been relatively few studies in China on the investment factors of wind farms. Some related research has focused more on resource distribution, with little discussion on the role of demand. However, based on the characteristics of wind power being produced and consumed simultaneously, it can be inferred that the demand side of the wind power market is very important for alleviating imbalances. Ignoring the role of demand will lead to market imbalances. Therefore, this paper focuses on analyzing the impact of current demand on wind power investment.

Secondly, regarding research data, the data used in this study is more recent than in previous studies. The authors collected data from wind power generation companies and grid companies. This makes it possible to analyze the factors affecting wind power investment in China more accurately and with the most up-to-date information.

Finally, the research results found that the role of demand is weaker in areas with higher loads, and unreasonable policy divisions further weaken the role of demand. Based on this, the authors propose some policy suggestions, such as emphasizing the role of demand in areas with concentrated loads to promote a balance in wind power investment and creating a reasonable price mechanism to increase the attractiveness of investment demand. By understanding the current state of wind power investments in China, policymakers and industry stakeholders can develop more effective strategies for promoting sustainable energy production and reducing carbon emissions.

2. DATA AND METHOD

2.1. Data

This study adopts a county-level analysis with 2252 observations included in the cross-sectional data from 2019. County information was sourced from public statistics in the yearbook, while land values were obtained from the website of the Chinese land market, which provides comprehensive information on land trading across China. The land value included in the model represents the average land price from 2010 to 2019 for each county. The wind speed is an average annual data of 2010 to 2019 at a height of 50m, as provided by NASA. The original wind speed data is in raster format at 200m cells. The policy indicators consist of four dummy variables indicating whether a county is located in a specific policy area. As the data on wind turbines is not publicly available in China, the authors collected cross-sectional data on county-level wind farms from government websites, grid companies, and wind power generation corporations.

During the data cleaning process, certain samples were either removed or reorganized. Notably, Tibet was excluded from the study due to insufficient data. Furthermore, some municipal districts were classified as county-level, but their individual data was not available. To account for this, these districts were amalgamated within the same city, as they were generally smaller than the typical counties. As a result, these districts were merged to form a single sample.
2.2. Variables

The dependent variables of this study are the number of wind turbines in each county, which are considered as the local investment in wind power. The explanatory variables are three perspectives based on wind power investment, including 1) capital and resources, 2) demand for electricity, and 3) government strategy, which are considered as the impact factors for the wind power investment in a county. And the main variables of interest in this study are local electricity demand and the government’s wind power investment strategy.

1) Local Demand

A successful market is characterized by a balance between supply and demand. However, the Chinese government’s focus on rapid wind power installations has resulted in policies and subsidies that prioritize the supply side over the demand side. This tendency has led to an imbalanced distribution of wind power supply and demand, exacerbated by the concentration of wind farm construction in the “Three North” regions, while high-demand areas are mostly located in the eastern coastal regions (X. Zhao et al., 2012b). To address this imbalance, it is necessary to consider market forces, particularly as the wind power industry matures. However, because the Chinese government does not officially publish precise electricity demand data at the county level, this study uses two indicators, namely county-level GDP and the share of GDP from the secondary sectors, to represent this variable, which was obtained from the State Statistical Bureau.

2) Capital and Resources

Wind power resources are a critical element to consider whether or not a site has the potential to construct a wind farm (Blanco, 2009; Toke et al., 2008). China has plenty of wind energy reserves, most of which are concentrated in the north, northeast, and northwest of the country (Xia & Song, 2017a). He and Kammen (2014) concluded in their research that the potential wind capacity in China could achieve 1300 GW to 2300 GW, which generates wind power of 2000TWh to 3500TWh each year. Therefore, this study adopts wind speed as a capital indicator for wind power investment.

Besides the wind energy resources, the value and availability of the land occupied by the wind farm are other critical indicators that investors must consider (Obane et al., 2020a). The land cost directly impacts the fixed cost, the largest part of the wind power investment cost. Also, the valuable land could have other competing uses, not only in the wind power installation but even for environmental purposes such as forest reserves. In China, the majority of land used for wind power exploitation needs to be transferred land classification to the construction land. Therefore, this study adopts the price of the construction land to be the indicator of the capital of land use for wind power exploitation. Therefore, these two indicators of capital and resources are considered the main control variables.

3) Government strategy

To accelerate the installation of wind power, the Chinese government divided the national regions into four parts based on their wind energy reserves. They implemented a stack of policies and incentives to attract investment and encourage the national development of wind power generation within each of these regions (Shen & Lyu, 2019). Feed-in tariffs (FITs) are among the most effective policies for promoting wind power competitiveness (Y. He et al., 2015; Zhu et al., 2022). FITs are supposed to be regionally differentiated to mitigate the uneven distribution of wind energy resources (Du & Takeuchi, 2020a). Specifically, wind projects in the same area receive the same FIT mechanism when they first access the local grid. These resource-based regional policies and FIT mechanisms produced the desired result in the early stages of wind power development, helping China become
the world’s leading wind power capacity rank (Chen et al., 2022). While this favorable policy can significantly promote wind energy capacity, it may misallocate investments. In this study, the policy divisions are included as an indicator of the supporting policy’s impact on wind energy investment.

4) Other control variables

Several control variables are considered in this study, including the local population and county area. Additionally, some samples in the dataset are composed of multiple municipal districts, and these samples have different features than other counties. To address this, a dummy variable indicating whether the sample is a composed one derived from several county-level districts is introduced in the model.

Table 1 shows the descriptive statistics of variables.

2.3. Methodology

For modeling the positive integer count data, several econometric methods are considered, including the Poisson regression, zero-inflated Poisson (ZIP) regression, and zero-Inflated Negative Binomial (ZINB) regression. Previous studies reveal that the wind turbine distribution follows the Poisson distribution such as Dunnett et al. (2020) and Mueller & Brooks (2020b), and therefore various models suitable for count data including Poisson regression are tested to construct the model.

The Poisson regression is an analysis technique for modeling the count data. It assumes that the explained variable follows the Poisson distribution, and it could be constructed as a linear model with unknown parameters (Mouatassim & Ezzahid, 2012). The Poisson regression could be explained as follow:

$$ \Pr(Y = k) = \frac{e^{-\lambda} \lambda^k}{k!} \quad \text{where } i = 0, 1, 2 $$  \hspace{1cm} (1)

Table 1. Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>TN</td>
<td>2252</td>
<td>49.35</td>
<td>178.46</td>
<td>0.00</td>
<td>3484.00</td>
</tr>
<tr>
<td>TNyn</td>
<td>2252</td>
<td>0.33</td>
<td>0.47</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Wind</td>
<td>2252</td>
<td>4.64</td>
<td>1.05</td>
<td>1.70</td>
<td>7.97</td>
</tr>
<tr>
<td>Area</td>
<td>2252</td>
<td>0.38</td>
<td>0.87</td>
<td>0.01</td>
<td>20.23</td>
</tr>
<tr>
<td>SXQ</td>
<td>2252</td>
<td>0.11</td>
<td>0.31</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>EMP</td>
<td>2252</td>
<td>0.29</td>
<td>0.20</td>
<td>0.01</td>
<td>5.01</td>
</tr>
<tr>
<td>DIST</td>
<td>2252</td>
<td>0.02</td>
<td>0.04</td>
<td>0.00</td>
<td>1.44</td>
</tr>
<tr>
<td>TIF</td>
<td>2252</td>
<td>0.60</td>
<td>0.02</td>
<td>0.51</td>
<td>0.61</td>
</tr>
<tr>
<td>GDP</td>
<td>2252</td>
<td>408.34</td>
<td>1175.34</td>
<td>3.61</td>
<td>26927.00</td>
</tr>
<tr>
<td>POP</td>
<td>2252</td>
<td>92.01</td>
<td>360.59</td>
<td>0.00</td>
<td>6814.82</td>
</tr>
<tr>
<td>Sec. GDP</td>
<td>2252</td>
<td>167.84</td>
<td>444.18</td>
<td>0.36</td>
<td>10496.14</td>
</tr>
<tr>
<td>LP</td>
<td>2252</td>
<td>980.33</td>
<td>2915.42</td>
<td>0.05</td>
<td>35984.91</td>
</tr>
</tbody>
</table>
Where subscript $i$ is the observation numbers; $k_i$ is the observed number of times an event occurs; $\lambda_i$ is the occurrence rate at per unit time; $Pr_i$ is the predicted probability that something happens at a certain number.

There is an important premise of Poisson distribution that its mean and variance should be equal. However, in practical scenarios, the zero value count may be too high that cannot be satisfied the Poisson distribution. Therefore the zero-inflating Poisson (ZIP) model was constructed. The zero-inflated model was introduced by Lambert (Lambert, 1992) to solve the problem of excess zero samples in Poisson models. He assumes that the outcome of the zero-inflation model originates from two processes, one of which is the zero inflating process ($y_i = 0$), and the other is the non-zero counting model, which is the general Poisson model ($y_i > 0$). The equation of the modified zero-inflated regression model is shown as follows.

$$
(Y_i = k_i) = \left\{ \begin{array}{ll}
\theta + (1 - \theta) Pr(k_i = 0) & \text{if } y_i = 0 \\
(1 - \theta) Pr(k_i = y_i) & \text{if } y_i > 0
\end{array} \right.
$$

(2)

Where $\theta$ is the probability that only zero outcomes are produced in the process, whilst the other possibility $(1 - \theta)$ results in a Poisson distribution (Jang et al., 2010; Jansakul & Hinde, 2002). Other parameters in Eq. (2) is consistent with Eq.(1). The mean of $y_i$ in ZIP model is $E(y_i) = (1 - \theta) \lambda_i$; The variance is $Var(y_i) = (1 - \theta)(\lambda_i + \theta \lambda_i^2)$.

In case of count data is overdispersion, the Zero-inflated negative binomial (ZINB) regression is considered. Same with the ZIP regression, the ZINB model also estimates two sets of parameters: one for a binary process that generates excess zeros, and another for the negative binomial process that generates the counts. The distribution of the ZINB could be shown as follows (Greene, 1994):

$$
Pr(Y_i = y_i) = \left\{ \begin{array}{ll}
\pi + (1 - \pi) G(K_i = 0) & \text{if } y_i = 0 \\
(1 - \pi) G(K_i = y_i) & \text{if } y_i > 0
\end{array} \right.
$$

(3)

Where $G(K_i)$ is the negative binomial distribution given by

$$
G(K_i) = Pr(Y = k_i) = \left( \frac{r}{r + \lambda} \right)^r \frac{\Gamma(r + k_i)}{k_i! \Gamma(r)} \left( \frac{\lambda}{r + \lambda} \right)^k_i
$$

(4)

$r$ is a positive constant; $\lambda_i$ is the occurrence rate at per unit time; $k_i$ is the observed number of times an event occurs.

2.4. Model Specification

Based on the above analysis, we construct the following model for empirical analysis:

$$
TN_i = \alpha + \beta_1 GDP_i + \beta_2 Zones_i + \sim X_i + \eta_i + \varepsilon_i
$$

(5)
Where, $TN_i$ is the number of the county-level wind turbines; $GDP_i$ refers to the county GDP, which represents the electricity demand of the region. $Zones_i$ is an indicator variables of each policy area, including zone 1, zone 2, zone 3 and zone 4, to measure the policy impact between zones in the model and zone 4 are used as the baseline. $X_i$ is the vector of the control variables. $\eta_i$ is the unobserved fixed effect at the provincial level, and $\varepsilon_i$ is the error term.

3. RESULTS

3.1. Baseline Model Results

Data in this study include 2252 county-level samples, with 753 of them being non-zero samples meaning that there is more than one wind farm in these counties. As we mentioned in the methodology section, the zero-inflation problems need to be dealt with in the empirical analysis. A criteria introduced by Vuong (1989) are normally used to compare whether the ZIP model is more fitting for the counts’ data.

Table 2 shows the results of the baseline model, including the Poisson regression, the Vuong test, the ZIP regression, and the zero-Inflated Negative Binomial regression (ZINB). It can be seen from the results that the statistics of the Vuong test is 15.14 and the corresponding P-value is 0, indicating a statistically significant selection of ZIP over the Poisson model. Then, considering the degree of sample dispersion, ZINB regression was considered, and the result of the alpha value was significantly not zero indicating that there is a high degree of zero-inflation in the data. Consequently, ZINB model was considered the best fit for this empirical study.

The model coefficients are estimated through the maximum likelihood estimation method. Analysis of the Zero-Inflated Negative Binomial (ZINB) model reveals a statistically significant positive relationship between the coefficient of GDP, used as a proxy for demand, and the distribution of wind power investment at the 0.1% significance level. This finding suggests a significant correlation between the present distribution of wind power investment and the local demand for power. Furthermore, a comparison with Xia and Song’s (2017) study on China’s wind power industry from 2004 to 2011 indicates a change in the effect of power demand from insignificance to statistically significant positivity. This change implies that the distribution of wind power reflects the promotional effect of local power demand on wind power investment after years of China’s wind power industry development.

Regarding the main control variables, it is apparent that the wind speed variable’s coefficient is positively and significantly associated with wind turbine deployment at the 0.1% level, providing evidence that wind resource is a significant factor influencing the number of wind turbines installed. This outcome is consistent with the findings of Mueller and Brooks (2020). Thus, counties that experience higher wind speeds are more likely to install additional wind turbines. This conclusion underscores the critical role of wind energy reserves, particularly wind speed, in determining the optimal location for wind turbine deployment and investment.

Meanwhile, previous research has demonstrated the positive impact of land availability on wind power investment (Obane et al., 2020b). However, this study’s results indicate that the proxy variable for land resources, i.e., land price, is significantly and negatively associated with the number of wind turbines installed. Specifically, higher land prices result in reduced land availability and increased investment costs, resulting in lower chances of wind power investment. In practice, investors tend to favor areas with ample wind resources and lower land prices to construct more wind power facilities, aligning with investors’ expectations of achieving high investment returns. Moreover, the coefficients of the dummy variables for both zone 2 and zone 3 are statistically significant, indicating the significant role played by resource-based zoning policy in wind power investment.
3.2. Robustness Check

This study provides evidence of the robustness of our results through three distinct approaches: first, by examining the endogeneity of the findings, second, by replacing the primary variables, and third, by replacing the model.

Table 2. Baseline regression results

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poi</td>
<td>TN</td>
<td>TN</td>
<td>TN</td>
</tr>
<tr>
<td>ZIP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ZINB</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind</td>
<td>0.967***</td>
<td>0.707***</td>
<td>0.459***</td>
</tr>
<tr>
<td></td>
<td>(10.218)</td>
<td>(8.632)</td>
<td>(7.661)</td>
</tr>
<tr>
<td>LP</td>
<td>0.259***</td>
<td>-0.148***</td>
<td>-0.101**</td>
</tr>
<tr>
<td></td>
<td>(6.305)</td>
<td>(-3.613)</td>
<td>(-2.945)</td>
</tr>
<tr>
<td>lnGDP</td>
<td>0.415***</td>
<td>0.404***</td>
<td>0.271***</td>
</tr>
<tr>
<td></td>
<td>(3.662)</td>
<td>(4.800)</td>
<td>(3.859)</td>
</tr>
<tr>
<td>lnPOP</td>
<td>-0.398***</td>
<td>-0.204**</td>
<td>-0.388***</td>
</tr>
<tr>
<td></td>
<td>(-4.873)</td>
<td>(-2.804)</td>
<td>(-5.525)</td>
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<td>-0.055</td>
<td>-0.049</td>
<td>-0.069</td>
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<td>(-0.907)</td>
<td>(-1.159)</td>
<td>(-0.954)</td>
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<td>SXQ</td>
<td>2.847***</td>
<td>1.572*</td>
<td>3.547***</td>
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<td></td>
<td>(3.564)</td>
<td>(2.246)</td>
<td>(5.231)</td>
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<tr>
<td>EMP</td>
<td>-0.226</td>
<td>-0.278</td>
<td>-0.267*</td>
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<td>(-0.580)</td>
<td>(-0.930)</td>
<td>(-2.354)</td>
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<tr>
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<td>1.265</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(-0.425)</td>
<td>(1.665)</td>
</tr>
<tr>
<td>Zone1</td>
<td>1.671**</td>
<td>1.457***</td>
<td>0.799*</td>
</tr>
<tr>
<td></td>
<td>(3.268)</td>
<td>(4.289)</td>
<td>(2.138)</td>
</tr>
<tr>
<td>Zone2</td>
<td>1.615***</td>
<td>1.362***</td>
<td>0.936**</td>
</tr>
<tr>
<td></td>
<td>(4.175)</td>
<td>(4.792)</td>
<td>(3.070)</td>
</tr>
<tr>
<td>Zone3</td>
<td>0.343</td>
<td>0.003</td>
<td>-0.242</td>
</tr>
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Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
3.2.1. Endogeneity Check

Xia and Song (2017) indicated in their study that local demand did not affect wind power investment. However, it has been 10 years since then, and this study shows the opposite result that the demand indicator significantly impacts the number of wind turbines. However, considering that the results of the study may be biased due to endogeneity caused by reverse causation, the study adopted instrumental variable method to test the endogeneity.

The chosen instrumental variables are the distance to the provincial capital and the government expenditure. The variable of distance has been included in the baseline model and shows no significant relationship with the wind investment. Besides, as wind power subsidies come from the state budget, county governments’ expenditure has no impact on the wind power investments directly, but it does have a direct impact on the local economy. Therefore the choice of instrumental variables satisfies the exogeneity. Also, a series of tests were conducted to determine whether the selected instrumental variables were appropriate. First, the Anderson LM statistic was used to test for instrumental variable validity. The result showed an LM statistic of 325.2 with a corresponding p-value of 0, indicating a significant rejection of the null hypothesis that the instrumental variable is invalid. Second, the Cragg-Donald Wald test was used to test for weak instrumental variable problems. The F-value was 281.263, which is greater than the critical value at the 10% level of the Stock-Yogo weak ID test, indicating that there is no weak instrumental variable problem. Finally, the over-identification test was conducted to examine the validity of instrumental variable selection. The Sargan statistic value was 0.064 with a corresponding p-value of 0.7996, indicating that the selected instrumental variable is exogenous.

To address zero inflation concerns, we employed the approach utilized by Tan and Lin (2019), which involves utilizing a selection model to mitigate the issue of excessive zero samples before implementing Poisson regression with instrumental variables. The results obtained from the instrumental variable Poisson regression show that the impact of the GDP indicator on the number of wind turbines remains significant, indicating the robustness of demand’s impact on wind power investment. These findings are presented in Table 3.

3.2.2. Robustness Check of Replacing the Main Variables

The benchmark regression uses local GDP as a proxy variable for demand. To test the robustness of our findings, we conducted an additional regression using the output of the secondary industry as a proxy variable for power demand. The secondary industry primarily refers to the manufacturing industry, which is highly energy-intensive. Our test results demonstrate that industrial output, as a proxy variable for demand, continues to exert a significant impact on wind power investment. Consequently, our primary regression’s robustness is supported. The results of this analysis are presented in Table 4.

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*Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
3.3. Heterogeneity Analysis

The zoning of the Chinese wind power strategy is based on wind resources, and 4 zones issue different policies for wind power investment. The zone 1, zone 2, and zone 3 are all areas with intensive resources of wind energy. From the perspective of wind energy utilization and investment cost, it is more suitable to invest in and construct wind farms in these areas. Zone 4 has relatively few wind energy reserves, but zone 4 includes most of the economically developed areas in China, so the demand for power load is significant in this region. From the policy perspective, FITs are the most powerful and impactful policies targeting the wind power growth in these zones which also have a differential based on the resource reserve level (Du & Takeuchi, 2020b; Xia & Song, 2017b). In order to reveal whether there is a gap in the impact of demand in resources-intensive zones and load-intensive zone, a regional heterogeneity analysis is carried out.

In this section, we grouped zone 1 to zone 3, comprising 333 samples, as a single entity for analysis purposes, while zone 4 was considered a distinct group. As presented in Table 5, our results reveal that the impact of local demand on wind power investment in the first three resource-intensive regions is significant at a 0.1% level. These regions are the earliest developers of wind power in China and thus signify that demand-oriented development models have emerged in the country’s wind energy-intensive areas. Regarding zone 4, our results demonstrate that local GDP also significantly influences the number of wind turbines at a 1% level. However, the coefficients of GDP are lower than those observed in resource zones, implying that local demand in zone 4 does attract wind power investment, but this effect is less pronounced than in resource zones. We propose two possible explanations for this observation. Firstly, as an area lacking abundant wind energy reserves, wind power investment in zone 4 is mostly restricted by the availability of wind resources. In other words, wind farms cannot be established in areas with inadequate wind energy, regardless of the demand. Secondly, zone 4 encompasses some of China’s most economically developed regions, resulting in high costs associated with constructing wind farms in these areas. Even if the region has significant power demand indicating a massive market, most investors cannot meet the investment requirements, particularly in counties with high GDP. Consequently, our findings suggest that the impact of local demand on wind power investment in zone 4 is relatively weaker compared to that observed in resource zones.

3.4. Mechanism Analysis

Through the process of heterogeneity analysis, it has been determined that the coefficient of demand in the load area (zone 4) is comparatively smaller than that of the resource area (zone 1 to 3). As such, the current study endeavors to investigate whether regional policy has played a role in the observed
decrease in demand. In order to accomplish this objective, the intersection of zone 4 (dummy variable) and demand, as well as the intersection of Feed-in Tariff (FIT) and demand, have been included in the initial model to assess the impact of regional policies on demand.

The results are presented in Table 6. It shows that the coefficient of the intersection term between GDP and zone 4 in the second column is significantly negative. This finding suggests that the moderating effect of the fourth region on local demand is also negative. One possible explanation for this negative moderating effect is the scarcity of land resources in economically developed areas, which hinders the construction of wind farms nearby. As a result, wind powers facilities are more likely to be invested in off-load areas.

Also, as mentioned, the feed-in tariffs (FITs) are the most effective policies issued in these zones (Xia & Song, 2017b; X. Zhao et al., 2016). Therefore, to explore the impact of the FITs system on the demand traction effect on wind power investment, the regional FIT and the intersection term between feed-in tariff and GDP are added to the basic model. FIT is naturally a price mechanism, but in this study, we cannot obtain the real FIT values for each zones and the real FITs are changing; therefore, the original FITs are used to be the proxy of the real FITs. The results are shown in the fourth column of Table 6, and it can be seen that the intersection term of FITs and local GDP is significantly negative. The negative effect proves that higher FIT has a negative moderating effect on the impact of investment on the demand. In other words, FIT subsidies substantially reduce the impact of local load demand on wind power investment.

It is important to note that FIT in zone 4 is consistently higher than the other three wind resource zones. The government’s intention is also to balance the cost of wind power investment between the zones and, therefore, attract more investment in the less-wind-energy area. However, the negative effect indicates that the past subsidies still exacerbate the mismatch between the demand and supply of the wind power industry. The possible reason we propose is that the government’s ambitions of accelerating the layout of the wind power industry offered high subsidies within the first three zones, making that even if zone 4 has higher subsidies than the first three ones, it still cannot cover the rents brought by the resources in zone 1 to zone 3, and therefore leads to a certain rent-seeking behavior of enterprises. However, in recent years, with the gradual withdrawal of subsidies, the wind power investment market returned to rationality, making zone 4, with large power demand, have a higher competitiveness, which now the wind power industry in zone 4 began to grow sharply.
4. DISCUSSION

The results in this study, along with the previous studies, demonstrate the importance of wind energy reserves in wind power investment. The availability of land also significantly influences the amount of local wind power investment. As we mentioned, China’s wind resources are mainly concentrated in the north and northeast, and some western regions where are away from the power load intensive areas mostly due to their adequate wind resources, a large amount of unused land as well as the favorable policies. Therefore, in the early stage of China’s wind power development, investment will inevitably gravitate to these regions. The study by Xia & Song (2017) demonstrated these results, and they also try to find out the effect of local demand on the wind power investment which did not give any significant evidence in their study.

In this study, local demand has emerged as a significant influencing factor in wind power investment in well-developed wind resource-intensive regions. However, the impact of local demand on wind power investment is not significant in Zone 4. There are two main reasons for this. Firstly, most regions in Zone 4 already have sufficient demand to consume wind power, which means that demand is not a significant factor in attracting investment. Secondly, compared to the resource-intensive zones, development of wind power in Zone 4 lags behind, resulting in a not well-formed layout. Additionally, the power grid infrastructure in Zone 4 is more flexible and mature, making transportation more efficient. As a result, local demand is not as significant in areas with high power loads compared to low power load areas.

Previous studies indicated that during the early stage of wind power development in China from 2006 to 2011, wind power installations were mostly concentrated in resource-intensive areas, and their growth was more significant in these regions (Xia & Song, 2017). However, the results of this study in 2019 demonstrate a different trend in wind power industry allocation. The variable of zones is still statistically significant, indicating that existing wind farms are more likely to be located in zone 1 and zone 2. Nonetheless, zone 4 has experienced a significant increase in wind power investment in

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Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
recent years. To compare the trend of wind power investment between resource-intensive and load-intensive areas, Fig. 2 displays the investment indicator (logarithm of wind turbines) for the years 2011, 2015, and 2019 between zone 1-3 and zone 4. Fig. 2 shows the evident that the number of turbines in zone 4 experienced a sharp increase between 2015 and 2019. Fig. 3 presents the regional differences between the four zones over three years and features a local demand indicator. It’s worth noting that the investment and demand indicators are presented in logarithmic form in both Fig. 2 and Fig. 3 to facilitate comparison. The first three zones encompass only a small portion of Chinese cities and are not comparable to the fourth zone in terms of population, electricity demand, and economic growth. Although the statistics show that the total number of wind turbines in zone 4 has surpassed those in the first three zones combined, there is still significant potential for economic development in zone 4.

In addition, the results of the mechanism analysis show that the regional increasing feed-in tariff subsidy has a negative impact on the traction effect of demand in wind power investment. Since 2009, the Chinese government has implemented various feed-in tariff subsidy systems in different zones. The feed-in tariff subsidies keep the same within zones, whilst it varies from zone to zone with an increasing trend from the zone 1 to the zone 4. In essence, the FIT was adopted to reduce the investment cost and risk of enterprises in order to achieve the goal of rapid layout of wind power. China’s FIT system has indeed promoted the development of wind power extremely speedily. However, from a national perspective, around 2015 the major wind power installations were separated from the heavy load regions, which contributed to the high curtailment rate in China before 2017. A study claims that there may be a trade-off between the rapid installation development and wind power curtailment (Xia, 2017), and the high curtailment rates may be the price of rapid development growth.

Therefore, the first reason that wind power investment has tended to the zone 4 in recent years is due to the saturation of wind power installation in wind resource areas, leading to a large amount of curtailed wind power generation between 2015 and 2017. In order to meet the government’s target for wind power curtailment rate, the construction and investment of wind power in the wind resource areas have slowed down. Secondly, the Chinese government adjusted the previously fixed feed-in tariff subsidy after 2015, reducing the subsidy for wind power projects in wind resource areas, while the adjustment for non-resource areas was relatively small. This also promoted the transfer of investment to non-resource areas and the development of wind power in the zone 4.

5. CONCLUSION

Over the past few decades, China has undergone a period of rapid growth in the wind power industry, making it the largest wind power market in the world in terms of installed capacity. However, this growth has been accompanied by a number of challenges, particularly an imbalance in regional development that has resulted in a spatial mismatch between wind power investment and actual power demand.

Previous studies have largely focused on the impact of wind resources (i.e. Alamillos et al. (Santos-Alamillos et al., 2014) and Saraswat et al. (Saraswat et al., 2021)); and land resources (i.e., Arent et al. (Arent et al., 2014) and Mai et al. (Mai et al., 2021)) on wind power investments, with less emphasis on the role of demand. Wind power is an energy commodity that must be consumed immediately after production, making its market highly dependent on demand. Moreover, the challenge of storing power products increases the difficulty of transportation, further reinforcing the dependence on wind power on demand. Thus, the influence of demand on wind power should be significant and cannot be ignored. However, in reality, wind farms are not suitable for densely populated cities due to their high wind resource requirements and large land coverage. As a result, the role of demand in wind power investment has received less attention in past discussions compared to other factors, making it an area that merits further exploration.

This study provides valuable insights into the impact of local electricity demand on wind power investment in China. The findings suggest that local demand plays a crucial role in attracting wind
Figure 2. Wind turbines (logarithmic form) of resource area and power-load area

Figure 3. Wind turbines (logarithmic form) for each zone
power investment, particularly in resource-intensive zones. This is a significant shift from previous studies, which did not observe such a significant impact on local demand. The study also highlights the importance of long-term planning and layout for wind power investment, particularly in resource-rich zones. In these areas, a more established investment pattern has been presented, which not only makes full use of wind energy but also considers the role of local demand.

In addition, the study also explores the moderating effect of China’s FIT policy on the impact of local demand on wind power investment through a mechanism analysis. The findings indicate that the FIT system in China has a significantly negative effect on the role of local demand in wind power investment, suggesting that the differential FITs between zones do not fully compensate for the high-cost difference caused by wind energy reserves. This increases the likelihood that wind power investment is distributed in resource areas rather than demand areas due to excessive subsidies. However, since data on wind farms around the time of the policy change is currently unavailable, the study cannot provide a complete assessment of the FIT policy. It should be noted that the FIT system has played a significant role in the development of the wind power industry in China, and its impact will be further explored and evaluated in future studies.

Overall, the study provides important information for policymakers and investors who are interested in the wind power industry in China. Drawing from the research findings, this study proposes the following policy implications:

Firstly, the role of demand has become evident in resource-rich zones where wind power has been developed earlier. However, in areas with fewer resources where the load itself is concentrated, the role of demand is not significant. The unpredictable nature of wind power makes it better suited for real-time local consumption, rather than being planned for the load like thermal power. Therefore, it is essential to pay more attention to the role of demand in wind power layout in zone 4, which is a load concentration area.

Secondly, the differential subsidies between regions have significantly impacted wind power investments, resulting in less investment in load-intensive (resource-poor) zones than in others. Although the original FIT design has considered the resource differential and gives a higher FIT to the load-intensive zone, it has not yielded the desired results. While the FIT system for wind has been abolished, subsidies for other renewable electricity are still in place. Hence, the government must pay attention to the role of subsidies in guiding investment more rationally and construct a premium layout for power distribution.

Lastly, zones with a higher FIT show less investment, and the demand effect has decreased. It can be concluded that the previous price mechanism is not suitable for reasonable development. Currently, many renewable energy sources are facing the subsidy withdrawal process. With a well-designed price mechanism, it is expected that the distorted investment can be corrected during the subsidy withdrawal process.

ACKNOWLEDGEMENTS

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REFERENCES


**ENDNOTE**

1 Data released by the Chinese National Energy Administration and National Bureau of Statistics.

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