Scale Dynamics of Renewable Energy Projects: Implications for Local Energy Cost

Zhijie Zhang*

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*University of Wisconsin–Madison. Email: zhijie@wisc.edu.

Abstract

This study investigates the impact of renewable energy installations on state-level electricity prices in the United States, emphasizing the critical role of generator scale. Existing literature predominantly focuses on aggregate impacts of renewable energy or the operational efficiency of specific technologies, often overlooking how the scale of renewable energy projects interacts with regional electricity market conditions to produce heterogeneous effects. This study bridges these gaps by employing a multilayered econometric framework—combining OLS, quantile regression, and fixed-effects panel regression—to analyze the differential impacts of small- and large-scale renewable energy installations. The findings provide novel insights into designing flexible, scale-sensitive policies for diverse market conditions.

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1 Introduction

The global energy transition has profoundly transformed electricity markets, spurred by the rapid deployment of renewable energy technologies. Wind and solar power have emerged as cornerstone technologies in decarbonized energy systems, offering scalable and cost-effective solutions to pressing global climate challenges. By 2022, renewable energy constituted approximately 29% of global electricity generation, a share projected to surpass 60% by 2050.[1] This transformation, while essential, has introduced new complexities into electricity markets. Retail electricity prices, shaped by factors such as generation costs, grid integration challenges, and policy incentives, remain a critical concern for both policymakers and consumers. Among these determinants, the scale of renewable energy installations has emerged as a significant yet underexplored factor influencing price dynamics.

Existing literature extensively examines the cost-reduction potential of renewable energy, particularly for large-scale installations that capitalize on economies of scale. For instance, utility-scale wind and solar projects have been shown to significantly reduce wholesale electricity prices due to their near-zero marginal costs.(Sorknaes et al. 2018) Conversely, small-scale installations are often lauded for enhancing energy equity and accessibility in underserved regions.[2] However, these benefits are accompanied by notable trade-offs: small-scale facilities often face higher unit costs and logistical complexities, particularly in high-priced markets, while large-scale facilities may exacerbate grid imbalances if not complemented by robust integration strategies. Despite these insights, critical gaps persist in understanding the nuanced impacts of renewable energy scale on retail electricity prices, particularly across heterogeneous market conditions. Existing studies frequently overlook distributional effects across market segments and fail to adequately account for the role of policy-driven capacity thresholds, such as 10 MW and 100 MW, which are central to U.S. energy policy and market design.

Capacity thresholds such as 10 MW and 100 MW serve as critical benchmarks for distinguishing small- and large-scale renewable energy projects. These thresholds influence regulatory frameworks, incentive eligibility, and grid management strategies, shaping the integration of renewable energy into the national electricity system. For instance, Maryland's Renewable Portfolio Standards (RPS) classify projects between 1 MW and 10 MW as small-scale systems, offering targeted incentives to promote their development.[3] Similarly, California's Los Angeles Feed-in Tariff (FiT) Demonstration Program caps project eligibility at 10 MW, streamlining permitting processes and incentivizing smaller installations.[4] In contrast, the 100

[1] International Energy Agency (IEA). "World Energy Outlook 2023." Accessed December 2024. Available at: https://www.iea.org/reports/world-energy-outlook-2023

[2] California Public Utilities Commission (CPUC). "California Solar Initiative Annual Program Assessment." 2016. Available at: https://www.cpuc.ca.gov/solar/

[3] See Maryland Renewable Portfolio Standards: https://energy.maryland.gov/Pages/info/renewable. Accessed December 2024.

[4] Los Angeles Department of Water and Power, "Feed-in Tariff Program." Available at: https://www.ladwp.com/fit. Accessed December 2024.

MW threshold delineates the transition to large-scale centralized infrastructure, necessitating comprehensive regulatory oversight and advanced grid integration measures. For example, Texas's Competitive Renewable Energy Zone (CREZ) program, which facilitated the deployment of utility-scale wind projects, underscores the effectiveness of high-capacity transmission networks in supporting large-scale renewable installations.[5]

These thresholds highlight the intricate balance between decentralized energy equity and centralized economic efficiency, offering a structured framework for aligning regulatory and market interventions. However, their specific impacts on retail electricity prices, particularly in diverse market contexts, remain insufficiently studied.

Despite extensive research on renewable energy's price impacts, most studies lack a systematic comparison of small- versus large-scale generation effects on retail electricity prices. Moreover, the role of policy frameworks and market design in moderating these impacts remains insuffi- ciently explored. For example, Bushnell and Novan (2021) emphasized that while large-scale renewables reduce average electricity prices, their intermittency challenges traditional baseload generation, underscoring the need for adaptive market mechanisms. This study addresses these gaps by analyzing the differential effects of small- and large-scale renewable facilities on retail prices, offering insights for market reform and policy design.

To address this gap, this study systematically examines the impact of small-scale (<10 MW) and large-scale (>100 MW) renewable energy installations on retail electricity prices across heterogeneous markets. Leveraging a hierarchical econometric framework that integrates Ordinary Least Squares (OLS) regression, quantile regression, and fixed-effects panel regression, the analysis captures average effects, distributional heterogeneity, and temporal dynamics. This comprehensive approach enables a nuanced understanding of how renewable energy scale influences market outcomes, offering actionable insights for designing scale-sensitive policy interventions.

The dataset spans 2015 to 2022, incorporating data from the U.S. Energy Information Administration (EIA), Bureau of Economic Analysis (BEA), and National Centers for Environmental Information (NCEI). Key variables include inflation-adjusted retail electricity prices, renewable energy proportions by scale, heating and cooling degree days, and state-level economic indicators such as real GDP. By integrating these data and methods, this study not only advances the understanding of renewable energy's economic impacts but also provides a robust foundation for policy frameworks aimed at achieving cost-effective and equitable energy transitions.

[5] Public Utility Commission of Texas, "CREZ Transmission Program Information." Available at: https://www.puc.texas.gov/. Accessed December 2024.

2 Literature Review

Renewable energy integration has been extensively studied for its impacts on electricity market prices, particularly focusing on the comparative dynamics of small- and large-scale generation facilities. Existing literature highlights notable differences in how these facilities influence wholesale and retail electricity markets, emphasizing regional and structural contexts.

Impacts of Renewable Energy on Electricity Prices

The integration of renewable energy generally exerts downward pressure on wholesale electricity prices due to its near-zero marginal costs. For instance, Sorknaes et al. (2018) analyzed the Danish Nord Pool Spot market using a holistic energy system model, demonstrating that a 15% increase in wind and solar generation reduced system prices by up to 10%. Similarly, Prokhorov and Dreisbach (2022) showed that in the German-Luxembourg coupled market, rising renewable penetration increased the frequency of negative clearing prices, highlighting potential market volatility.

In retail markets, however, the dynamics are more complex. Oosthuizen et al. (2021), using panel data from 34 OECD countries, found that while renewables reduce wholesale prices, retail prices are marginally affected by regulatory policies and grid costs. Xu et al. (2020) further noted that the increasing involvement of renewable enterprises in medium- and long-term market transactions introduces new pricing challenges.

Small-Scale vs. Large-Scale Generation Facilities

Small-scale renewable energy installations, such as rooftop photovoltaics, often have localized impacts. Li et al. (2020) analyzed the Chinese distributed photovoltaic market and found that rooftop solar installations alleviated grid pressure during peak hours, reducing local electricity prices by 5%. Conversely, large-scale facilities like utility-scale wind farms reshape broader market dynamics. Steffen (2020) demonstrated that between 2010 and 2018, large-scale renewables in Germany reduced wholesale prices by 12%, driven by their near-zero marginal costs and intensified competition.

Notably, small-scale facilities contribute to distributed energy systems and demand smoothing, while large-scale facilities create system-wide impacts, including structural shifts in wholesale markets. Sorknaes et al. (2018) compared these effects in Denmark, concluding that while small-scale installations stabilize local prices, large-scale facilities significantly lower nationwide electricity costs. Additionally, Parlane and Ryan (2019) emphasized the importance of optimizing procurement contracts for renewable electricity in centralized and decentralized settings, highlighting the cost-efficiency challenges of large-scale integration.

3 Data Description

3.1 Data Sources

This study integrates data from multiple sources spanning 2015 to 2022 to analyze the impact of generator scale on state-level electricity prices across the United States. Primary data on electricity pricing and generation capacity are sourced from the U.S. Energy Information Administration (EIA), including Forms EIA-861 and EIA-860. Economic indicators, such as GDP and population, are retrieved from the U.S. Bureau of Economic Analysis (BEA) and U.S. Census Bureau, respectively. Climatic data, including heating and cooling degree days, are provided by the National Centers for Environmental Information (NCEI).

3.2 Variable Definitions

Key variables used in this study are summarized in Table 3.1, categorized into dependent variables, independent variables, and control variables. The generator scales, distinguished by capacities below 10 MW and above 100 MW, are defined based on operational classifications in the EIA-860 database. These thresholds capture distinct market dynamics and facilitate the investigation of their varying influences on electricity prices.

Table 3.1. Summary of Variables

Variable Name	Definition	Unit	Source
Electricity Price_2015_base	Inflation-adjusted average retail electricity price	USD/kWh	EIA-861
Real GDP in state-level	Inflation-adjusted gross domestic product	Million USD	BEA
Total Population in state-level	Total number of residents per state	Count	Census Bureau
HDD	Annual Heating Degree Days	Degree-days	NCEI
CDD	Annual Cooling Degree Days	Degree-days	NCEI
Renewable Energy Proportion (%)	Share of electricity from renewable sources	%	EIA-860
Small-Scale Generators (%)	Proportion of capacity from generators less than 10 MW	%	EIA-860
Large-Scale Generators (%)	Proportion of capacity from generators greater than 100 MW	%	EIA-860

3.3 Descriptive Statistics

Descriptive statistics for the key variables are presented in Table 3.2. The dependent variable, `Electricity Price_2015_base`, exhibits substantial inter-state variability, with a mean of $0.104 per kWh and a standard deviation of $0.025. The wide range of generator scales and renewable energy proportions highlights the diversity in state-level energy market structures, which this study seeks to analyze in detail.

Table 3.2. Descriptive Statistics of Key Variables

Variable	Mean	Std. Dev.	Min	Max
`Electricity Price_2015_base` (USD/kWh)	0.104	0.025	0.071	0.202
`Small-Scale Generators (%)`	62.4	10.5	40.2	81.6
`Large-Scale Generators (%)`	29.7	12.3	10.1	55.4
`Log Real GDP`	13.17	0.76	10.37	14.96
`HDD`	4,250	1,250	400	8,500
`CDD`	1,350	870	100	4,800

3.4 Data Processing

To ensure robustness and validity of regression analysis, a series of preprocessing steps were applied, including transformations, multicollinearity diagnostics, and normality checks.

Logarithmic Transformation Logarithmic transformations were applied to `Electricity Price_2015_base`, `Real GDP`, and `Total Population` to reduce skewness and heteroscedasticity, aligning the data with the assumptions of regression analysis. These transformations also allow regression coefficients to be interpreted in terms of percentage changes, enhancing economic interpretability.

Normality Check The Shapiro-Wilk test was conducted to evaluate the normality of `Electricity Price_2015_base` before and after the logarithmic transformation. As shown in Table 3.3, the log transformation significantly improved the W statistic, indicating reduced skewness and better suitability for regression analysis.

Table 3.3. Shapiro-Wilk Test for Normality of `Electricity Price_2015_base`

Variable	W Statistic	p-value
Original Data	0.940	2.1×10^{-10}
Log-Transformed	0.981	3.5×10^{-4}

Multicollinearity Diagnosis Variance inflation factors (VIFs) were calculated to detect multicollinearity among the independent variables. Table 3.4 shows that `Log Real GDP` and `Log Total Population` exhibit extremely high VIF values (26.80 and 27.67, respectively), reflecting their strong correlation ($r = 0.98$). Given this redundancy, `Log Real GDP` was retained while `Log Total Population` was excluded.

The choice to retain GDP is based on its theoretical significance in explaining electricity pricing. GDP serves as a comprehensive indicator of economic activity, encompassing both population-driven demand and productivity effects. This aligns with prior research, which highlights GDP's central role in energy economics as a proxy for overall demand patterns Ang and Choi (2013). By contrast, population effects are indirectly captured within GDP, making it a less direct explanatory variable for electricity prices.

Table 3.4. Variance Inflation Factor (VIF) Analysis for Key Variables

Variable	**VIF**
Log Real GDP	26.80
Log Total Population	27.67
HDD	5.35
CDD	4.46
Small-Scale Generators (%)	1.91
Large-Scale Generators (%)	1.91
Renewable Energy Proportion (%)	1.53

4 Methodology

Focusing on the scale of renewable energy generators, this study employs a hierarchical econometric framework that progressively integrates analytical depth to uncover their distinct impacts on electricity prices (Figure 4.1). The approach begins with an Ordinary Least Squares (OLS) regression, which serves as a foundational tool to estimate the average effects of renewable energy penetration. While OLS is widely acknowledged for its interpretive simplicity and robustness in identifying mean trends, its inherent limitations—most notably, the inability to address distributional heterogeneity—necessitate the incorporation of more advanced methodologies.

To address this gap, the analysis transitions to quantile regression, a method that enables the estimation of impacts across different points in the price distribution. This technique is particularly salient in the context of electricity markets, where pricing mechanisms often display high levels of volatility and skewness (Koenker and Bassett 1978; Yu and Moyeed 2001). By examining the effects of renewable energy installations across low-, median-, and high-priced markets, quantile regression offers critical insights into how policy interventions might differentially affect diverse market segments.

Finally, the fixed effects panel regression introduces a dynamic dimension, capturing within-state variations over time while controlling for unobserved, time-invariant characteristics. This model addresses the structural heterogeneity inherent in state-level electricity markets, where factors such as regulatory environments, market concentration, and infrastructure investments vary significantly (Baltagi 2005). By focusing on temporal dynamics, the fixed effects model complements the static perspectives offered by OLS and quantile regression, thereby enabling a comprehensive understanding of renewable energy's influence.

Taken together, the integration of these three models provides a robust framework for analyzing the impacts of renewable energy installations. This progression—from national-level average effects to distributional heterogeneity and temporal-spatial dynamics—not only ensures methodological rigor but also aligns with better practices in empirical energy economics.

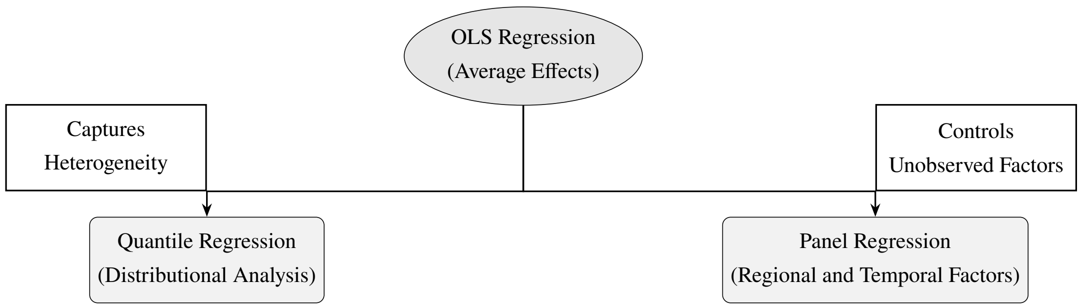

Figure 4.1. Flowchart illustrating the three regression models used in the analysis.

4.1 Ordinary Least Squares (OLS) Regression

The ordinary least squares (OLS) regression serves as the baseline model, offering insights into the average effects of renewable energy installations on electricity prices. Although OLS effectively captures these average effects, its inability to account for distributional heterogeneity necessitates further analysis using quantile regression.

The OLS specification is as follows:

$$\begin{aligned}\log(P_{it}) = \beta_0 + \beta_1 RE_{it}^{\text{small}} + \beta_2 RE_{it}^{\text{large}} + \beta_3 RE_{it}^{\text{total}} \\ + \beta_4 STP_{it} + \beta_5 WP_{it} + \beta_6 \log(\text{GDP}_{it}) \\ + \beta_7 \text{HDD}_{it} + \beta_8 \text{CDD}_{it} + \varepsilon_{it}.\end{aligned} \tag{4.1}$$

Here, $\log(P_{it})$ represents the log-transformed electricity price for state i in year t, facilitating percentage-based interpretation. All models share common variables: RE_{it}^{small}, RE_{it}^{large}, and RE_{it}^{total} measure renewable energy proportions by facility scale. Energy shares include STP_{it} (solar thermal plus photovoltaic) and WP_{it} (wind power). HDD_{it} and CDD_{it} represent heating and cooling degree days, while $\log(\text{GDP}_{it})$ measures economic conditions.

4.2 Quantile Regression

Quantile regression extends the analysis by estimating the effects of explanatory variables across different quantiles of the electricity price distribution. This method complements OLS by capturing how renewable energy installations impact electricity prices across different market segments.

The quantile regression model is specified as follows:

$$\begin{aligned}\log(P_{it}) = \beta_0(\tau) + \beta_1(\tau) RE_{it}^{\text{small}} + \beta_2(\tau) RE_{it}^{\text{large}} + \beta_3(\tau) RE_{it}^{\text{total}} \\ + \beta_4(\tau)\text{HDD}_{it} + \beta_5(\tau)\text{CDD}_{it} \\ + \beta_6(\tau)\log(\text{GDP}_{it}) + \varepsilon_{it}(\tau).\end{aligned} \tag{4.2}$$

Here, $\tau \in (0, 1)$ represents the quantile of interest (e.g., 0.25, 0.50, 0.75). This model reveals how market segments respond differently to renewable energy installations. For example: - Low-price regions may benefit from small-scale installations to enhance affordability. - High-price regions rely more on large-scale facilities to stabilize markets.

Quantile regression has been widely applied in energy economics to address price volatility and extreme values (Koenker and Bassett 1978; Yu and Moyeed 2001).

4.3 Fixed Effects Panel Regression

While OLS and quantile regression capture static relationships, they do not account for temporal and spatial dynamics. To address this, a fixed effects panel regression model is applied, enabling the analysis of within-state variations over time.

The fixed effects model is specified as follows:

$$\begin{aligned}\log(P_{it}) = \alpha_i &+ \beta_1 RE_{it}^{\text{small}} + \beta_2 RE_{it}^{\text{large}} + \beta_3 RE_{it}^{\text{total}} \\ &+ \beta_4 \text{HDD}_{it} + \beta_5 \text{CDD}_{it} + \beta_6 \log(\text{GDP}_{it}) \\ &+ \varepsilon_{it}.\end{aligned} \tag{4.3}$$

Here, α_i represents state-specific fixed effects, capturing unobservable, time-invariant characteristics. The dependent variable $\log(P_{it})$ allows for percentage-based interpretation of coefficients, while the explanatory variables include renewable energy proportions, climate-driven energy demand, and economic conditions. Fixed effects models are extensively used in energy economics to analyze temporal and spatial heterogeneity (Baltagi 2005).

By focusing on within-state variations over time, the fixed effects model enhances the robustness of the analysis and provides a more accurate understanding of how renewable energy installations impact electricity prices across regions.

5 Results

This section presents findings from three regression approaches: OLS, quantile regression, and fixed-effects panel regression. Each method offers unique insights into the relationship between renewable energy installations and electricity prices.

The OLS model provides an overarching view of average effects, quantile regression captures distributional heterogeneity across different price levels, and the panel regression accounts for unobserved, time-invariant regional characteristics. Together, these methods paint a comprehensive picture of how small- and large-scale renewable energy installations influence electricity prices across diverse market conditions.

The results are structured to first explore average effects using the OLS model, followed by distributional analysis via quantile regression, and finally, a fixed-effects panel regression to address unobserved regional and temporal factors.This section answers key questions through three models, starting with an analysis of average effects via OLS regression.

5.1 How do small-scale and large-scale installations affect electricity prices on average?

The OLS regression provides an overarching view of average effects, revealing contrasting impacts of small- and large-scale renewable energy installations on electricity prices. These findings establish a baseline for understanding how project scale influences pricing dynamics.

The OLS results, based on the specification in Equation 4.1 and detailed in Table 5.1, provide an overarching view of average effects, revealing significant positive impacts of small-scale installations (<10 MW) on electricity prices ($\beta_1 = 0.0026, p < 0.0001$). This translates to an approximate 0.26% increase in electricity prices for each percentage point rise in small-scale installations. This effect is likely driven by the higher unit costs associated with small-scale projects and their concentration in rural or remote areas, where transportation and maintenance expenses are substantial. Conversely, large-scale installations (>100 MW) exhibit a statistically significant price-reducing effect, with each percentage point increase in large-scale installations corresponding to an average price decrease of approximately 0.43% ($\beta_2 = -0.0043, p < 0.0001$). This result underscores the nationwide significance of economies of scale in reducing production costs and alleviating price pressures.

Climate variables, such as heating degree days (HDD) and cooling degree days (CDD), demonstrate significant and expected impacts on electricity prices. HDD, with a coefficient of $\beta_7 = 5.46 \times 10^{-5}$ ($p < 0.0001$), suggests that increased heating demand in colder regions contributes to higher electricity prices. Similarly, CDD, with a coefficient of $\beta_8 = 0.0001$ ($p < 0.0001$), reflects the upward price pressure caused by increased cooling demand in hotter regions.

In contrast, the results for state-level transmission and distribution prices (STP, WP), real GDP ($\log(\text{GDP}_{it})$), and the proportion of renewable energy (RE_{it}^{total}) are not statistically significant (e.g., $\beta_3 = 0.0013, p = 0.351$ for RE_{it}^{total}). These findings likely reflect the limitations of the OLS model in addressing distributional heterogeneity and unobserved regional and temporal factors. As discussed in subsequent sections, these limitations are addressed using quantile regression to explore heterogeneous effects across the price distribution and fixed-effects panel regression to account for unobserved, time-invariant characteristics.

Table 5.1. OLS Regression Results: Impacts of Renewable Energy Installations on Electricity Prices

Variable	Coefficient	Std. Error	t-Statistic	p-Value
Intercept	34.2407	11.172	3.065	0.002
Small Scale	0.0026	0.001	4.767	0.000
Large Scale	−0.0043	0.001	−4.308	0.000
Renewable Proportion	0.0013	0.001	0.934	0.351
HDD	5.46×10^{-5}	1.24×10^{-5}	4.419	0.000
CDD	0.0001	2.66×10^{-5}	4.504	0.000
Log(Real GDP)	0.0092	0.014	0.644	0.520

5.2 Do these effects differ across lower-priced, median-priced, and higher-priced markets?

Quantile regression extends the analysis by capturing how renewable energy installations impact electricity prices across various market segments, revealing heterogeneous effects beyond those identified by OLS (Equation 4.2). Unlike OLS, this method uncovers responses at different points of the price distribution, offering a more nuanced understanding of price dynamics under varying market conditions (Table 5.2).

In lower-priced markets (25th percentile), small-scale installations (RE_{it}^{small}) exert significant upward pressure on electricity prices ($\beta_1(0.25) = 0.0009, p = 0.004$). This likely reflects the pronounced unit costs of small-scale projects in competitive markets, where cost increases are more easily passed on to consumers. Conversely, large-scale installations (RE_{it}^{large}) significantly reduce prices ($\beta_2(0.25) = -0.0019, p = 0.001$), showcasing economies of scale more prominently in these segments.

In median-priced markets (50th percentile), the upward impact of small-scale installations intensifies ($\beta_1(0.50) = 0.0018, p < 0.0001$), suggesting greater cost pass-through sensitivity in these markets. Meanwhile, the price-reducing effect of large-scale installations persists but diminishes slightly ($\beta_2(0.50) = -0.0021, p = 0.005$), possibly due to marginally weaker cost-adjustment mechanisms.

In higher-priced markets (75th percentile), the upward pressure from small-scale installations peaks ($\beta_1(0.75) = 0.0040, p < 0.0001$), reflecting their limited efficiency in meeting the demands for energy stability and quality in these markets. However, the effect of large-scale installations becomes statistically insignificant ($\beta_2(0.75) = -0.0022, p = 0.168$), suggesting that factors such as infrastructure constraints or market monopolies may overshadow economies of scale.

The total proportion of renewable energy (RE_{it}^{total}) also exhibits varying impacts across markets. In lower-priced markets, renewable energy adoption is associated with reduced prices ($\beta_3(0.25) = -0.0017, p = 0.039$), possibly due to lower production costs or competitive pricing.

However, this effect is not significant in median- and high-priced markets ($p = 0.228$ and 0.337, respectively), where external factors such as policy support and market dynamics play a more dominant role.

These results demonstrate the nuanced role of renewable energy installations in electricity price dynamics and highlight the importance of analyzing price distributions to capture the diversity of impacts across different market conditions.

Table 5.2. Quantile Regression Results: Distributional Impacts of Renewable Energy Installations

Variable	**25th Percentile**	**Std. Error**	**Median**	**Std. Error**	**75th Percentile**	**Std. Error**
Intercept	2.5911^{***}	0.126	2.8665^{***}	0.168	2.7431^{***}	0.318
Small Scale	0.0009^{**}	0.0003	0.0018^{***}	0.0004	0.0040^{***}	0.0008
Large Scale	-0.0019^{**}	0.0006	-0.0021^{**}	0.0007	-0.0022	0.0016
Renewable Proportion	-0.0017^{*}	0.0008	-0.0012	0.0010	-0.0017	0.0018
HDD	$2.41 \times 10^{-5**}$	7.22×10^{-6}	$2.67 \times 10^{-5**}$	9.11×10^{-6}	$7.81 \times 10^{-5***}$	1.60×10^{-5}
CDD	$3.12 \times 10^{-5*}$	1.38×10^{-5}	$4.32 \times 10^{-5*}$	1.96×10^{-5}	$8.75 \times 10^{-5**}$	4.09×10^{-5}
Log(Real GDP)	0.0375^{***}	0.0077	0.0145	0.0106	0.0053	0.0219

5.3 How do unobserved regional and temporal factors shape the observed relationships?

The fixed effects panel regression provides a nuanced perspective by leveraging within-region temporal variations to address unobserved, time-invariant factors. This model complements the OLS and quantile regression by isolating the influence of regional characteristics and temporal dynamics.

The fixed effects panel regression, as specified in Equation 4.3, leverages within-region temporal variations to provide a novel perspective on the heterogeneous impacts of renewable energy installations on electricity prices (see Table 5.3). Results highlight the significant role of large-scale installations (>100 MW) in reducing electricity prices ($\beta_2 = -0.0018, p = 0.0091$), where a 1% increase in large-scale installations corresponds to an average price reduction of 0.18%. In contrast, small-scale installations (<10 MW) exhibit a statistically insignificant effect ($\beta_1 = -0.0001, p = 0.6050$), likely reflecting their higher unit costs and decentralized management, which limit their capacity to achieve cost reductions at scale.

Real GDP ($\log(\text{GDP}_{it})$) significantly reduces electricity prices ($\beta_6 = -0.2826, p < 0.0001$), reflecting structural changes in the energy sector driven by economic growth, such as improved efficiency and increased renewable energy investments.

The proportion of renewable energy (RE_{it}^{total}) shows a strong negative impact on electricity prices ($\beta_3 = -0.0059, p < 0.0001$), with a 1% increase in renewable energy share reducing prices by an average of 0.59%. This finding aligns with prior studies that emphasize the role of renewable energy in reducing dependency on fossil fuels and mitigating price volatility. Across all models, climate variables (HDD and CDD) consistently highlight the role of temperature-driven energy demands in electricity pricing. In the OLS model, both HDD and CDD significantly increase prices, reflecting higher heating and cooling demands. Quantile regression refines this understanding by showing that their effects are most pronounced in high-priced markets, where extreme climate conditions exacerbate pricing pressure. However, the fixed-effects panel model finds these variables statistically insignificant (HDD: $\beta_4 = -6.91 \times 10^{-6}, p = 0.3161$; CDD: $\beta_5 = 4.52 \times 10^{-6}, p = 0.8329$). This likely reflects the absorption of regional climate heterogeneity within fixed effects, indicating that long-term regional and temporal dynamics dilute these short-term climate impacts.

Table 5.3. Panel Regression Results: Addressing Regional and Temporal Factors

Variable	**Fixed Effects Coeff.**	**Std. Error**	**Random Effects Coeff.**	**Std. Error**
Intercept	6.9928^{***}	0.5667	5.0731^{***}	0.3514
Small Scale	−0.0001	0.0003	−0.0002	0.0003
Large Scale	-0.0018^{**}	0.0007	-0.0019^{**}	0.0007
Renewable Proportion	-0.0059^{***}	0.0013	-0.0063^{***}	0.0013
HDD	-6.91×10^{-6}	6.88×10^{-6}	-1.12×10^{-5}	6.49×10^{-6}
CDD	4.52×10^{-6}	2.14×10^{-5}	-2.81×10^{-6}	1.93×10^{-5}
Log(Real GDP)	-0.2826^{***}	0.0468	-0.1244^{***}	0.0286

The Hausman test (p-value < 0.0001) confirms the fixed-effects model as more appropriate, effectively capturing unobserved regional and temporal characteristics.

Overall, the results underscore the critical role of large-scale renewable energy installations in reducing electricity prices and enhancing market stability, while small-scale installations primarily impact affordability in localized contexts. By integrating diverse analytical approaches, this study provides a holistic understanding of renewable energy's influence on electricity markets.

These findings highlight the importance of incentivizing large-scale renewable energy projects to achieve cost reductions while addressing the challenges of small-scale installations to enhance affordability in underserved regions. Policymakers should consider balancing the promotion of economies of scale with support mechanisms for smaller installations to ensure equitable energy access across diverse markets.

6 Discussion

The findings contribute significant policy-relevant insights, enabling policymakers to address market heterogeneity through the design of scale-sensitive interventions. The following recommendations reflect both the study's quantitative results and global best practices, providing a comprehensive pathway toward cost-effective, equitable, and sustainable energy transitions:

6.1 Large-Scale Facilities: Driving Cost Efficiency in Low-Priced Markets

This study underscores the necessity of prioritizing large-scale facilities (>100 MW) as a fundamental policy instrument to achieve electricity price reductions and enhance market stability. Research shows that a 1% increase in the deployment of large-scale facilities can lower electricity prices in low-priced markets by an average of 0.19% (Bushnell, Novan, and Wolfram 2018). A further 10% increase is estimated to reduce average electricity prices by approximately $0.02/kWh, yielding substantial economic benefits (Electric Reliability Council of Texas 2018). For instance, the "Competitive Renewable Energy Zone (CREZ)" program in Texas exemplifies how targeted investments—$6.8 billion allocated for 3,600 miles of transmission capacity—significantly improved wind energy transmission efficiency and allowed wind energy to meet 54% of peak demand in 2017 (Cohan et al. 2019). However, policymakers must address the risks of over-centralization by investing in grid balancing mechanisms and ensuring long-term market competitiveness.

6.2 Small-Scale Facilities: Enhancing Energy Equity in High-Priced Markets

Small-scale facilities (<10 MW) are indispensable for advancing energy equity and improving accessibility, particularly in underserved regions. However, their high unit costs frequently result in upward pressure on electricity prices, with a 1% increase leading to an average price rise of 0.26%, and as high as 0.40% in high-priced markets (Initiative 2016). To alleviate this, targeted subsidies and tax incentives are essential to offset installation and maintenance costs. The California Solar Initiative (CSI) serves as a compelling example: from 2007 to 2016, CSI supported over 650,000 rooftop photovoltaic installations, cumulatively exceeding 3,000 MW in capacity, while significantly reducing energy costs for underserved communities (Initiative 2016). Replicating such programs in high-priced markets would balance energy equity with economic sustainability.

6.3 Flexible, Region-Specific Policy Design

Market heterogeneity necessitates regionally tailored policies. For low-priced markets with robust infrastructure, prioritizing large-scale facilities can maximize cost efficiency and optimize grid performance. Conversely, high-priced markets demand targeted measures to mitigate the economic burdens associated with small-scale facilities. Denmark's differentiated incentives for wind energy and the European Union's tiered policy framework underscore the effectiveness of flexible, region-specific approaches in promoting sustainability across diverse market conditions (Bushnell, Novan, and Wolfram 2018).

6.4 Integrating Dynamic Policy Tools

Dynamic policy tools, including carbon pricing and adaptive subsidies, represent essential mechanisms to navigate the complexities of evolving energy markets. Carbon pricing internalizes fossil fuel externalities, enhancing renewable energy competitiveness and facilitating the transition from high-carbon facilities (Electric Reliability Council of Texas 2018). Adaptive subsidies complement these efforts by reducing the upfront costs of small-scale facilities in high-priced markets while optimizing large-scale deployments in low-priced regions. For example, the European Union's emissions trading system (EU ETS) illustrates how market-based instruments can amplify renewable energy integration while maintaining economic efficiency (Initiative 2016). Future policy frameworks could leverage advanced technologies, such as artificial intelligence and data analytics, to dynamically adjust subsidy allocation and carbon pricing levels, further enhancing policy efficiency and market responsiveness. These tools collectively provide a pathway to ensure cost-effective, equitable, and sustainable energy transitions while addressing fiscal sustainability and industry resistance.

Conclusion

Addressing the complexities of renewable energy deployment requires multi-faceted, scale-sensitive interventions. By integrating large-scale and small-scale facilities, tailoring region-specific policies, and adopting dynamic tools, policymakers can ensure a balanced transition toward affordable and sustainable energy systems. This comprehensive approach not only tackles immediate market challenges but also establishes a robust foundation for achieving long-term environmental and economic goals.

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