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Retail Electricity Prices and Renewable Energy Generation in the United States

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Abstract

While zero-marginal-cost renewable energy has reduced wholesale electricity prices, its effect on retail electricity prices remains uncertain. A common concern is that costly investments in renewable integration, such as transmission expansion, generate system-level costs that may offset or even exceed savings from lower generation costs. This paper tests this conjecture empirically using annual sales data from the EIA 861 and electricity generation data from the EIA 923 for the majority of the United States between 2004 and 2023. To address the inherent simultaneity between prices and energy generation, I leverage spatial variation in wind and solar potential and time-varying levelized costs of wind and solar energy to construct a Bartik-style instrument to predict renewable penetration. I find that a one percentage point increase in renewable penetration at the balancing authority level reduces real utility level yearly average retail prices by 0.3%, implying a 3.5% decrease in real retail prices at the mean change in renewable penetration. Crucially, OLS estimates that do not account for endogeneity are positively biased and insignificant. Even under alternate instruments and sample restrictions, the estimated effect is tightly bounded between -0.7% and 0.7, suggesting that increased renewable penetration has had, at most, a modest impact on energy affordability. Back of the envelope calculations suggest that system costs offset roughly two-thirds of the marginal generation cost savings estimated in the literature.

1 Introduction

Over the last two decades, the share of wind and solar in both the United States' and global electricity mix has grown substantially. Early in the United States' energy transition, policies like renewable portfolio standards (RPS) were the driving force behind the adoption of environmentally beneficial but costly renewable technologies. More recently, rapidly falling costs of renewable technologies have spurred adoption independent of policy. Between 2010 and 2023, the real levelized cost of electricity per megawatthour fell from $101 to $49 for wind power and from $227 to $46 for solar power (Wiser et al. (2024); Seel et al. (2024)). At these levels, solar and wind are often cost-competitive with least cost conventional generating technologies, such as combined-cycle natural gas.[1] Despite these trends, wind and solar are often blamed for declining electricity affordability, even as recent cross-sectional studies, such as Wiser et al. (2025), find no association between increasing renewables and rising costs.

Economically, countervailing forces make the relationship between renewables and electricity prices theoretically ambiguous. First, lower cost renewables have reduced wholesale electricity costs (Bushnell and Novan (2021), Liebensteiner et al. (2025)), which should, all else equal, translate to lower retail rates. At the same time, wind and solar are associated with costly integration investments, such as transmission expansion, incurring system-level costs which may diminish or even surpass savings from reduced generation costs (Petersen et al., 2024). Texas' Competitive Renewable Energy Zones (CREZ) transmission project provides a salient example of this tension. The CREZ project reduced transmission congestion between east and west Texas and enabled the expansion of low cost wind generation in the state; but, its $7 billion price tag was ultimately paid by increasing retail rates, amounting to 3% of the average customer's bill (PoweringTexas, 2021).

Panel A of Figure 1 illustrates this tension more broadly by comparing changes in inflation-adjusted average retail prices and renewable shares of balancing authority energy mixes for utilities between 2004 and 2023. A simple fitted line depicts a weakly negative relationship. However, for any given change in renewable penetration, there is substantial variation in realized price changes, highlighting the diverse range of experiences across the United States. Panels B and C depict trends in wind generation shares and average prices at the state level. The highlighted states in these figures have maximum single-year wind shares in the top five of all states in the sample while the dashed line represents the national average inclusive of the highlighted states. Panel B shows a clear upward trend in wind generation shares with marked disparity between the selected states and the average, especially after 2011. If wind generation was responsible for increasing retail prices, we would expect prices in these states to trend upward. Conversely, if wind affected retail prices primarily through generation cost channels, we would expect prices to fall. However, the plots in Panel C do not clearly exhibit either pattern, suggesting that there may be multiple mechanisms acting simultaneously.

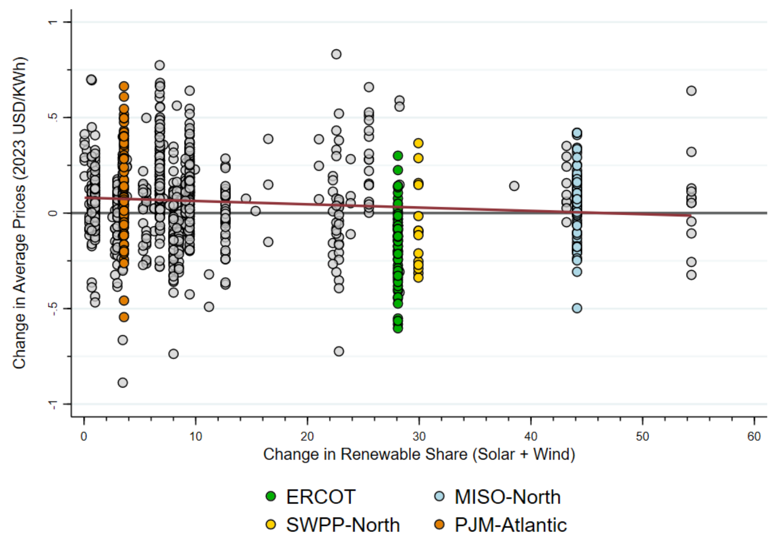
Taken together, neither theory nor data reveal a clear relationship between renewable energy generation and retail electricity prices. As a result, identifying the causal effect of renewables on prices is, fundamentally, an empirical exercise. A clear understanding of this effect is particularly important for policymakers seeking to balance the transition to renewable energy with public concerns for energy affordability.[2] Motivated by these concerns, this study employs rigorous econometric methods to estimate the causal effect of increasing wind and solar generation on real retail electricity prices in the United States.

[1] Over the same time period, yearly average LCOE for combined-cycle natural gas fluctuated between $96 and $56 (Lazard, 2024)

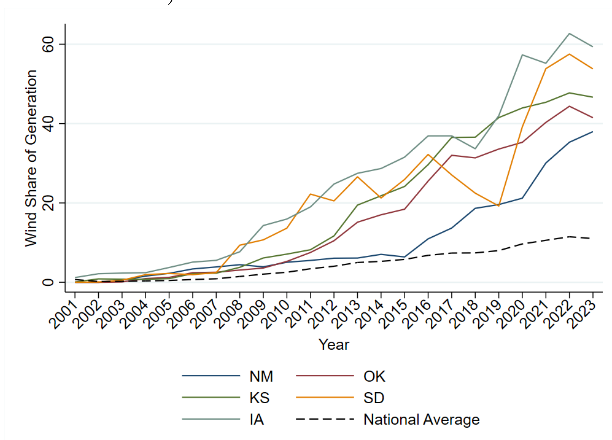
[2] A 2025 Gallup found that 35% of Americans worried "a great deal" and another 36% worried "a fair amount" about energy

Figure 1: State and Balancing Authority Level Trends in Renewable Generation and Real Retail Prices

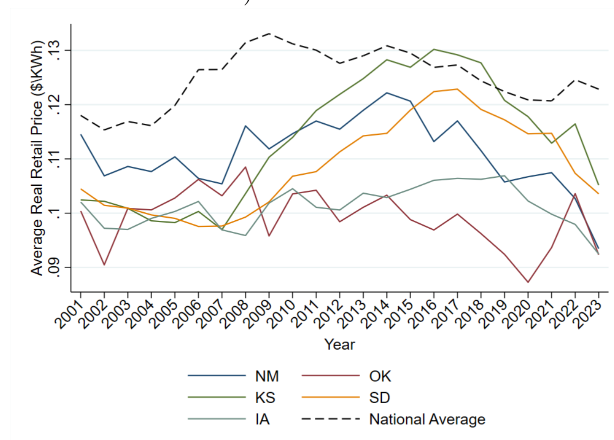
A) Difference in Retail Prices and Renewable Share (2004-2023)



B) Wind Generation Trends



C) Price Trends



Panel A: This graph shows the difference in renewable share of generation from 2004 to 2023 with the corresponding difference in real average yearly retail prices. Markers denote utility by balancing authority by state level observations. Average prices calculated across residential, commercial, and industrial customers. BA level variation on the horizontal axis informs columnar pattern in the figure, demonstrated by highlighted BAs. The maroon line provides a simple linear fit of the variables.
Panel B: This figure plots the growth in state-level wind generation over time for select states compared to the national average (selection inclusive). Selected states are the top five producers of wind as measured by maximum, single-year, wind energy share of generation.
Panel C: Figure plots trends in the real average yearly retail price for selected states compared to the national average (selection inclusive). Retail prices are the load-weighted average of all utilities operating in the state that year, given in dollars per kilowatthour, normalized to 2023 dollars.

This analysis draws on annual sales data from the EIA-861 and generation data from the EIA-923, covering 47 states and Washington, D.C., from 2004 to 2023. Retail prices are reported at the utility level by state and year to align with real variation in consumer bills. Renewable generation, represented as shares of the total generation mix, is calculated at the balancing authority level which is a useful analogue for an electrical grid. Fixed effects in the specification absorb time-invariant utility by state differences as well as time-varying regional effects, ensuring estimates are identified from within-utility changes in retail electricity prices. Crucially, this paper addresses inherent simultaneity between prices and renewable shares by constructing a Bartik-style instrument that leverages spatial variation in wind and solar potential as well as time-varying levelized costs of wind and solar energy.[3] I find that a one percentage point increase in renewable generation share reduces real average retail prices by 0.3%, implying a 3.47% decrease in real retail prices at the mean change in renewable share across the sample. Critically, this study demonstrates standard OLS estimates that do not account for endogeneity are positively biased and insignificant. Employing alternative instrument structures, allowing for separate effects across time, and splitting the sample by customer and market type reveals consistently tight bounds on the marginal effect, typically between -0.7% and 0.7%. This suggests that, at most, increased renewable penetration has had a limited impact on electricity affordability.

Following a stylized model of prices, I provide back of the envelope calculations of the implied marginal system costs of wind energy, calculated as the difference between the overall retail price effect and reductions in marginal generation costs. Net retail price effects are calculated using estimates in this paper while marginal generation cost effects of \$2.27 per gigwatthour (GWh) are adopted from Weber and Woerman (2024). For consistency with that paper, primary calculations are restricted to the Electric Reliability Council of Texas (ERCOT) for a GWh increase in wind power sustained over the course of a year. I find that a 1 GWh increase in wind power corresponds to a \$1.68 increase in the real cost of electricity per megawatthour (MWh) on average – 70% of the generation cost savings estimated in Weber and Woerman (2024). Across the sample, this translates to \$8.55 dollars per MWh, implying current renewable system costs of roughly 1 cent per kWh.

This work provides causal estimates of the relationship between renewable energy generation and retail electricity prices. In doing so, it extends the existing literature by explicitly considering renewable energy generation rather than policy induced effects (Greenstone et al. (2024), Reguant (2019), Fabra and Reguant (2014)) and retail instead of wholesale prices (Bushnell and Novan (2021), Liebensteiner et al. (2025), Cacciarelli et al. (2025)). Additionally, the approach in this study advances similar efforts causally linking renewables and prices (see Argosino and Knittel (2025), Würzburg et al. (2013), and Oosthuizen et al. (2021)) by robustly addressing endogeneity biases. The present paper also relates to the literature on the pass through of wholesale prices to customers (e.g., Mirza and Bergland (2012), Perez et al. (2022), and Duso and Szücs (2017)). Additionally, it meaningfully diverges from existing efforts by analyzing a broader time frame, which includes the post-2015 period, when solar technologies became cost-competitive with traditional fossil fuel generators.

While frequently discussed, empirical estimates of the role of system costs in the price effects of renewable generation are scarce (e.g, Petersen et al. (2024), Ciarreta et al. (2014)). The present work provides new evidence for the system costs of both wind and solar generation in the American context and calculates the implied marginal system costs for wind. Finally, this paper connects to the body of work studying the role of market structures in determining electricity prices. By examining system costs, which typically arise

affordability (Brenan, 2025).

[3]Specifically, the possibility areas with higher retail rates are likely to be more attractive to wind and solar developers and, consequently, have increased renewable generation (Colombo, 2026).

from uncertainty or investment decisions, it relates to earlier works that have emphasized generation costs (Cicala, 2022) and policy induced cost shocks (Fabra and Imelda, 2023).

The rest of the paper is structured as follows: in Section 2, I discuss important institutional details that inform the empirical strategy and identification. In Section 3 I discuss the construction of my data and in Section 4 I connect this to my empirical approach. Section 5 presents results and various robustness checks. Section 6 estimates marginal system costs through a conceptual decomposition and explores heterogeneity in these costs by distance from generation. Finally, Section 7 concludes.

2 Background

This section summarizes a set of design-relevant facts about electricity markets and renewable energy generation i n the United States. These stylized facts inform the empirical strategy by clarifying (i) how retail prices are set, (ii) where renewable supply shocks enter, and (iii) the most probable sources of confounding. Additional institutional detail and documentation are provided in Appendix XXX

Stylized Fact 1. *Retail electricity prices are determined at the utility by state level, following a yearly "rate-case" structure*

Electric utilities handle distribution of electricity to end-use consumers and are the billing-entity for retail customers. In each state, Public Utility Commissions (PUCs) regulate electric utilities through a board of governor-appointed commissioners.[4] PUCs primarily regulate investor owned utilities while municipal and cooperative utilities generally receive limited or full exemption.

A key function of PUCs is to set bespoke retail prices for utilities through a "rate-case" proceeding. In this process, the utility submits key organizational information to the regulator regarding proposed investments, estimated demand, and operating costs for review. Based on this information, the PUC establishes a revenue requirement for that utility which covers costs plus a reasonable rate of return on investment and is spread across its customers.[5] The duration of these proceedings vary by case, but are generally reviewed annually.

Based on the rate-case framework, I propose the following conceptual model of retail prices:

$$\rho_{us,t} = \lambda_{us,t-1} + \sigma_{us,t-1} \tag{1}$$

Where ρ is the retail price for utility u in state s for year t while λ and σ are its generation and system costs in the preceding year. The first purpose of this structure is to identify the level of variation in the dependent variable. It also informs the use of lags to relate independent variables with the price. Finally, I use this model to calculate implied system costs in Section 6 below.

Stylized Fact 2. *Balancing authorities act as local grids where electricity supply is functionally interconnected*

Balancing authorities are entities that oversee the generation and transmission of electricity within their footprint. They are primarily responsible for ensuring real time equilibrium between electricity supply and demand in order to maintain grid reliability and integrity. BAs also provide oversight on system development, regional and interregional planning efforts, and within-BA transmission investments FERC CITE. In

[4]While appointment is the norm, a non-trivial proportion of states elect their PUC members (EPA, 2010)

[5]This discussion focuses on the regulated utilities case as it is the dominant price structure in the United States. For utilities that set their own prices in restructured markets with retail choice, I assert that similar factors determine their costs and that the stickiness of electricity prices maintains rough alignment with the rate-case process.

restructured electricity markets (e.g. NYISO), the ISO or RTO that operates the market typically serves as the balancing authority too.

Generally, utilities operate within one balancing authority that determines the mix of electricity the utility supplies.[6] Within a BA there are few barriers to electricity transmission allowing, for example, wind electricity from one area in the BA to be used throughout it. Conversely, trade between balancing authorities is more limited. Operational differences mean that even adjacent utilities and generators are unlikely to trade if delineated by BA.[7] Based on this structure, I argue that for any given utility the mix of electricity it supplies is effectively determined at the balancing authority level. It follows that the effects of increased renewable generation should be identified off a shock at the same level.

It is important to note that there is substantial variation in the geographic footprint of balancing authorities. In the case of very large BAs, physical properties of electricity transmission are effective boundaries to trade within the BA. This is primarily a concern in the three largest balancing authorities by footprint: the Midcontinent Independent Service Operator (MISO), the Southwest Power Pool (SWPP), and the Pennsylvania-New Jersey-Maryland (PJM) RTO which each operate across several states. In the spirit of the stylized fact above, these BAs are split into sub-regions that align with known energy-model and intra-organizational divisions.[8]

Stylized Fact 3. *In the last two decades, wind and solar have become primary sources of renewable electricity generation in the United States*

The United States has a diverse endowment of renewable energy sources, headlined by wind, solar and hydroelectric power. While hydro was the dominant renewable of the past century and it remains a critical contributor to modern energy landscape, this paper focuses on wind and solar generation that both overtook hydro in terms of total capacity and new constructions since the turn of the century. Rapidly falling costs driven by technological advancements played a key role in this regime change. By 2015, wind and solar were, on average, the least-cost sources of electricity, beating out hydro and all other traditional fuels.[9]

Wind and solar power are also resource dependent and non-dispatchable which presents unique economic challenges such as intermittency and transmission congestion. As a result, they require costly supporting infrastructure (i.e., system costs). Combined with their widespread adoption, it is these costs of wind and solar that fuel concerns of renewables driving higher electricity prices around the country. Thus the supremacy of wind and solar extends from the firm's choice to the public's concerns. Taken together, these points inform the construction and thrust of the key variable of interest.

Stylized Fact 4. *Retail prices and renewable generation respond to the same state-level forces, such as fuel costs or policy regimes*

In addition to governing the prices utilities charge for electricity, states often have other policies that affect prices and renewable generation. For example, renewable portfolio standards (RPS) mandate the inclusion of renewable energy in the electricity mix provided to customers. Utilities meet the the standard by either increasing renewable generation or by purchasing renewable energy credits (RECs). In both cases,

[6] There are a few cases where a *utility company* operates in more than one BA (e.g., Xcel Energy). However, data observations in these cases are for subsidiary *utilities* which do map to a unique BA.

[7] Trade barriers are further amplified when adjacent BAs are in separate interconnections (i.e., East, West, ERCOT)

[8] MISO is divided into North, South, and Central subregions; SWPP is separated into North and South; and PJM is split into Atlantic and Central regions. For a complete discussion of these divisions, refer to Appendix X.

[9] Many related papers such as Greenstone et al. (2024) and Reguant (2019) end their analyses before this inflection point. While this is useful for policy-focused papers, it omits market-based renewable decisions from estimates of the net effect of renewables on prices.

the utility's costs will increase and, in the first case, renewable generation may too. Other policies, such as net-metering, may have similar affects though the specific mechanisms may differ.

Non-policy factors, like fuel costs, are also possible sources of confounding. Natural gas powered generators are the dominant traditional fuel alternative to renewable energy. In states with high natural gas prices, perhaps from poor pipeline infrastructure, the cost of generating electricity with natural gas will be high. This will increase the operating costs of utilities and, all else being equal, the price of their electricity determined by a rate-case. At the same time, these costs incentivize the expansion of renewable energy sources. In both cases, the potential for confounding remains even when treatment varies at a higher level. Therefore, causal analysis requires explicitly controlling for dynamic state-level forces.

Stylized Fact 5. *The structure of a state's electricity market structures affects how costs are priced into retail rates*

In the United States, state electricity markets fall into two categories: *traditional* natural monopolies or *restructured* markets defined by deregulated energy generation. Under traditional markets, utilities control generation and distribution, both of which are regulated by the state. While restructured markets vary by state, the key features are deregulated generation and a secondary market, termed the wholesale electricity market, that links generators with distributing utilities.

While differences in market do not necessarily affect the operation and regulation of utilities, it can alter how they are affected by other cost shocks. Importantly, the existing literature finds that generation costs (i.e., fuel prices) (Cicala, 2022) and policy-induced costs (Fabra and Imelda, 2023) differ between market types. To address this issue, I interact the state-level confounders above with a dynamic measure of market structure to capture differential effects.

3 Data

Data used in this paper are primarily taken from the United States Energy Information Administration (EIA). The EIA provides administrative data for the United States' energy industry at several levels of aggregation. For this paper, I use plant-, utility-, and balancing authority-level data. These data are collected both from internal forms and external sources, as part of either raw data or summary publications. Supporting data are borrowed from several publicly available government or institutional sources as described below.

3.1 Primary Data

Retail price data are constructed using the EIA-861 *Annual Electric Power Industry Report*, a mandatory, yearly census of utilities operating in the contiguous 48 states and Washington, D.C.. This form reports total revenue in 1000's USD and total sales in megawatthours at the utility by state by year level, with disaggregation by consumer types which includes residential, commercial, industrial, transportation, and a residual "miscellaneous" category. For this paper, analysis is restricted to residential, commercial, and industrial consumers; these are the primary designations shared by all utilities and comprise the vast majority of reported energy consumption. Average yearly retail prices charged by utility u in a particular year t and state s are calculated as follows:

$$\text{Retail Price}_{us,t} = \frac{\text{Revenue}_{us,t}}{\text{Sales}_{us,t}} \tag{1}$$

Equation (1) provides retail prices in nominal dollars per kilowatthour (kWh). Prices are then real-adjusted to a 2023 basis using the GDP deflator. The values calculated in (1) yields a sales-weighted average retail price of electricity.[10] Additionally, sales values aggregated across customers measures the total load serviced by the utility. For heterogeneity analysis, customer-specific average prices can be calculated using the same formula restricted a chosen customer type, C.

The share of total electricity (in MWh) generated from intermittent renewable sources within a balancing authority is the key regressor in my specification. This measure is constructed using plant-level generation data from the EIA-923, which reports generation by fuel type f.[11] Each reporting plant p is associated with a utility which is then mapped to balancing authority b. Total generation for the balancing authority in year t is given by:

$$\text{Generation}_{b,t}^{total} = \sum_{p(f)} \text{Total Generation}_{p(f),t} \quad \forall p \in b \tag{2}$$

Similarly, renewable generation for the balancing authority is given by:

$$\text{Generation}_{b,t}^{ren} = \sum_{p(f)} \text{Total Generation}_{p(f),t} \quad \forall p \in b \text{ s.t. } f \in \{wind, solar\} \tag{3}$$

Combining equations (2) and (3), the share of renewable electricity generation in the balancing authority is:

$$\text{Renewable Share}_{b,t} = \frac{\text{Generation}_{b,t}^{ren}}{\text{Generation}_{b,t}^{total}} \tag{4}$$

Table 1: Renewable Share Summary Statistics

Panel A: Levels

	Mean	Min	Max	SD
Total (Wind & Solar)	4.77	0	57.69	8.31
Wind Generation	3.58	0	49.04	7.30
Solar Generation	1.19	0	22.59	3.31

Panel B: Differences(2023 - 2004)

	Mean	Min	Max	SD
Total (Wind & Solar)	11.52	0	54.37	12.77
Wind Generation	6.87	0	45.71	11.26
Solar Generation	4.65	0	21.88	5.81

Note: Shares are represented as percentages of total.

Table 1 presents summary statistics for renewable shares in the sample of balancing authorities. Panel A shows statistics for levels. Across all renewable types, mean penetration is relatively low but with substantial variation. At two standard deviations, most balancing authorities fall at or below 20% renewable penetration. As expected, most generation appears to be from wind technology. Panel B presents differences in renewable

[10]For a brief explanation of this equivalence, refer to Appendix XXX.

[11]In addition to wind and solar, reported fuels also include the following categories: coal, distillate petroleum, geothermal, conventional and pumped hydroelectric, biogenic solid waste and landfill gas, natural gas, nuclear, petroleum coke, residual petroleum, waste coal, waste oil, and wood and wood waste with three "other" categories including one for gas and one for renewables.

shares across the sample period 2004 to 2023. Values in this panel are calculated as $Share_{2023} - Share_{2004}$ and are restricted to BAs that are present throughout the sample. The mean difference in renewable generation was 11.52 percentage points and a standard deviation of 12.77 percentage points.

Utility level demand for electricity, load, is taken from the EIA-861 as the sum of total energy sales in a given year across all customer types. The EIA-861 is also combined with the EIA-923 to dummy for market restructuring using the share of energy generation produced by independent power producers (IPPs) following Borenstein and Bushnell (2015) and their proposed threshold of 40%. State by year level natural gas prices for electric power consumers are reported in the EIA-923 for most years, with pre-2007 values taken from the EIA-423. Finally, I control for RPS stringency following Hollingsworth and Rudik (2019) using state level policy data from the Lawrence Berkeley National Laboratory (LBNL) (Barbose, 2025). These data estimate the demand for RPS eligible generation or renewable energy certificates induced by the policy after accounting for differential firm obligations, credit multipliers, and alternative policy calendars.

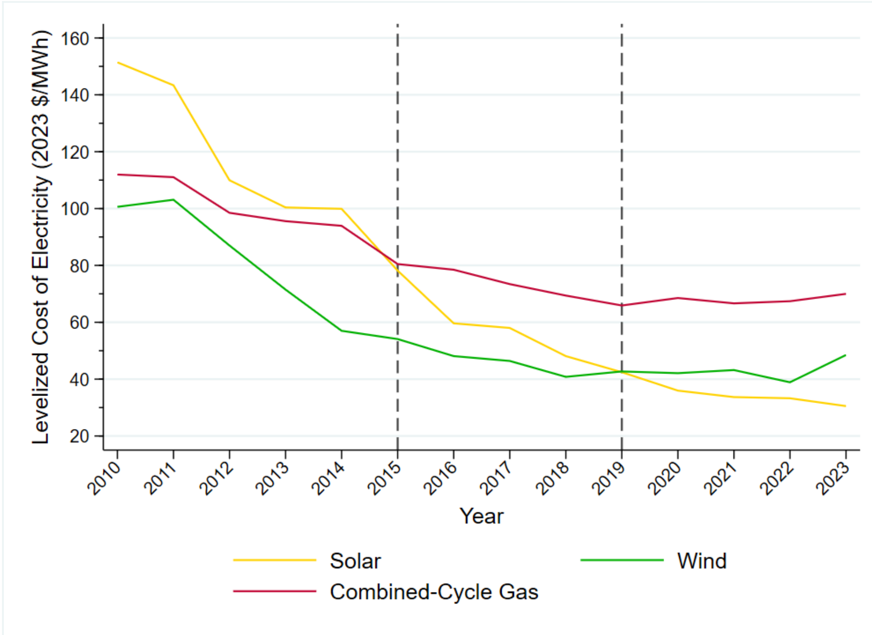
3.2 Instrumental Variables Data

Additional data for the instrumental variables specification (below in Section 4.2) are taken from the Lawrence Berkeley National Laboratory (LBNL) and the National Renewable Energy Lab (NREL). Wind- and solar-specific estimates of the levelized costs of energy (LCOE) by year are taken from Wiser et al. (2024) and Seel et al. (2024). Wind LCOEs are given as the generation-weighted real levelized-costs (2023 basis) per MWh for a sample of on-shore wind projects that began commercial operation in a given year across the U.S., these data are available from 1998 to 2023. Solar LCOEs are derived similarly and include available tax-credits in their estimates. Given the early scarcity of solar projects, these data are only available 2007 to 2023. To match the coverage of wind data, solar LCOEs are imputed back to 2001 by multiplying LCOE in 2007 by the relative efficiency of crystalline silicon photovoltaic cells in the target year to the same statistic in 2007. This imputation relies on two observations. First, that the primary cost of solar power pre-2007 came from the cost of PV cells and second, that crystalline silicon cells comprised the majority of PV cells at that time.

For the IV strategy, capacity factors must be determined at the balancing authority level, however, no such measure is readily available. Instead, to create this measure, state level wind and solar capacity factors are borrowed from Bento et al. (2018) who derived them from NREL estimates. These are not observed data but rather engineering estimates of the solar and wind energy potential in each state. For wind, suitably windy areas are defined as those having at least 30% gross capacity factor at 80 meters elevation; available land is further reduced by existing infrastructure and inhabitation. The maximum capacity that could be built on that land is calculated along with estimated generation given standard meteorological assumptions. Dividing estimated generation by the theoretical maximum generation provides the implied capacity factor. Solar capacity factors are the state-average capacity factor of 10km grid-cells under typical meteorological assumptions, south-facing fixed tilt panels, and 1 kW system size.

To aggregate to the balancing authority level, every utility by state pair operating in the BA is identified in the EIA-861. Then, using reported service territories for each utility, each county served by the utility is mapped to the balancing authority. The BA level capacity factor is then calculated as the weighted average of individual state capacity factors where weights are the number of counties from state s divided by the total number of counties served by the balancing authority. Ultimately, this gives me an instrument with time-series variation in the cost of renewable energy and cross-sectional variation in balancing authority potential.

Figure 2: Levelized Costs of Electricity Over Time



Notes: This figure plots the levelized costs of electricity from solar photovoltaic, on-shore wind, and combined-cycle natural gas generators. Prices are given in dollars per megawatthour, real-adjusted to 2023. Plots begin in 2010 where solar and gas data are observable. Dashed lines mark key inflection points in relative prices. Data sources: (Seel et al., 2024); wind (Wiser et al., 2024); gas, nominal values from (Lazard, 2024), real-adjusted by author.

4 Empirical Strategy

In this section, I describe my methodology for identifying the effects of intermittent renewable energy generation on retail electricity prices. There are two key identification challenges. First, the complex nature of electrical markets makes it difficult to align the levels of identifying variation with the outcome of interest. Second, renewable energy generation and retail electricity prices are jointly determined and thus subject to endogeneity, such as when high retail prices induce renewable investment.

The strategy presented here overcomes these obstacles by (i) employing a two-way fixed effects model based on the rate-case process described in Section 2 that identifies effects from within utility variation conditional on key price determinants and (ii) constructing conditionally exogenous instrumental variables using time-varying costs of renewable energy and spatial variation in renewable resource suitability.

4.1 OLS Estimation Framework

The core estimation framework in this paper is a two-way fixed effects model based on the utility rate-case process described in Section 2. Within a state, this utility-specific process explicitly determines the retail prices the utility can legally charge consumers in that state for electrical services. While not universally used, rate-cases are the dominant mechanism for setting retail electricity prices in the United States. In cases where market forces determine prices, I assert that the rate-case model parallels price-setting decisions by forward-planning firms.

$$y_{usb,t} = \beta_1 \mathcal{R}_{b,t-1} + \beta_2 X_{s,t-1} + \beta_3 X_{us,t-1} + \gamma_{us} + \gamma_{r,t} + \varepsilon_{usb,t} \tag{5}$$

In Equation 5, retail prices y are determined at the utility (u) by state (s) by balancing authority (b) level in year t. My coefficient of interest is β_1, which represents the percent increase in retail prices for a one percentage point increase in BA renewable share, $\mathcal{R}$. Shares are used in place of nominal generation to reflect that it is the mix of energy and not necessarily the volume that affects system operation. The model employs utility by state (γ_{us}) and census region by year ($\gamma_{r,t}$) fixed effects.[12] The former absorbs static variation such as geographic challenges or general PUC structure and relations with the utility while the latter controls for broader regional trends which may include alternative fuel prices, policy atmospheres, or resource constraints. Importantly, the relation between utilities and balancing authorities ensures that γ_{us} also absorbs static BA-level variation while census region (r) designations do not perfectly align with balancing authorities. As a result, the remaining variation for identification is utility by year level.

State by year level controls that may correlate with prices and renewable generation are given by the vector, $X_{s,t-1}$, including supply-side factors such as natural gas prices, RPS stringency, and quantity of net metering contracts. $X_{us,t-1}$ controls for utility by state varying factors, specifically the utility's load.[13] Additionally, observations are weighted by their load of serviced electricity. This weighting scales the regression such that each observation is, essentially, a MWh of electricity. Weighting by load is preferable to weighting by customers to account for industrial and commercial sales which may be large in volume but linked to few unique customer accounts.

The key distinguishing feature of this model are the lags imposed on the independent variables. The core of the rate-case process is the use of known information to set future prices. Regulators review previous cost and operation data then decide prices for a future period. While there is not a uniform duration of this process, lagging the model by a year replicates the underlying process.[14] Lags in the model also capture the short-term stickiness of retail electricity prices that results from regulation and service contracting.

4.2 Instrumental Variables Approach

While the OLS specification is informative, simultaneity between retail prices and energy generation may bias its estimates. If, for example, higher retail prices spur renewable investment, leading to higher renewable penetration in the energy mix, then OLS estimates will be positively biased. Lags in Equation 5 may reduce this bias but are unlikely to remove it, even when the lagged period is increased, because energy markets rely on strategic planning and expected future prices inform current operations and investments. Therefore, to rigorously address endogeneity, I employ an instrumental variables (IV) strategy.

I construct Bartik-style instruments for renewable generation by leveraging spatial variation in resource suitability and national trends in renewable energy costs independently for wind and solar. In this setting, resource suitability defines the share and national cost trends provide the exogenous shift. Mechanically, resource suitability is determined by fixed geographic characteristics within a balancing authority, while national renewable cost trends vary over time and affect all balancing authorities uniformly. Intuitively, the instruments predict that decreases in the cost of electricity from wind or solar should induce greater investment in that technology where it is better suited. For example, declining costs of wind energy should lead to relatively more wind development in Kansas, while declines in solar costs should result in relatively more solar investment in Arizona.

Each balancing authority's capacity factors, as defined in Section 3, are used to measure resource suitabil-

[12] Alternative specifications include census-division by year FE as well as non-interacted state and year FE.
[13] Additional controls are included in some specification to test the robustness of this parsimonious set.
[14] Robustness checks in Section 5 vary the lag period and return quantitatively similar results.

ity over its footprint. Specifically, capacity factors, $\mathcal{C}_b$, are engineering estimates of the potential generation from a given technology, $g \in \{\text{wind}, \text{solar}\}$, attainable under model estimates of maximum usage and efficiency. A higher $\mathcal{C}_b^g$ indicates greater potential for energy generation from g, or greater suitability for the technology.

Technology-specific levelized costs of electricity (LCOE), $\mathcal{L}^g$, are used to capture trends in the cost of renewables. LCOEs are industry-standard estimates for the cost of generating one unit of electricity through a specific technology, conditional on a set of assumptions including costs of capital, subsidies or taxes, and operating costs. Because assumptions may be subjective, there are concerns about the accuracy of LCOEs as a measure for realized costs. However, their usefulness in the instrument depends on their predictive power, which is based on their practical use in investment decisions - not on their accuracy. Another concern is that some LCOE assumptions (e.g., subsidies) may affect electricity prices through channels other than renewable generation; therefore, robustness checks using only capital expenditures (CAPEX) are conducted in Section 5(TBD). For each technology, the instrument is defined as the ratio of the capacity factor to LCOE ,as described in Equation 6:

$$Z_{b,t}^g = \frac{\mathcal{C}_b^g}{\mathcal{L}_t^g} \tag{6}$$

In this formulation, $Z_{b,t}^g$ measures how many megawatthours of electricity a dollar of investment in g buys. Intuitively, it is the “bang for your buck” of renewable energy and scales predictably such that BAs with higher $Z_{b,t}^g$ are those where technology g is efficient and inexpensive to install. Figure 3 depicts aggregate variation in both instruments over time.

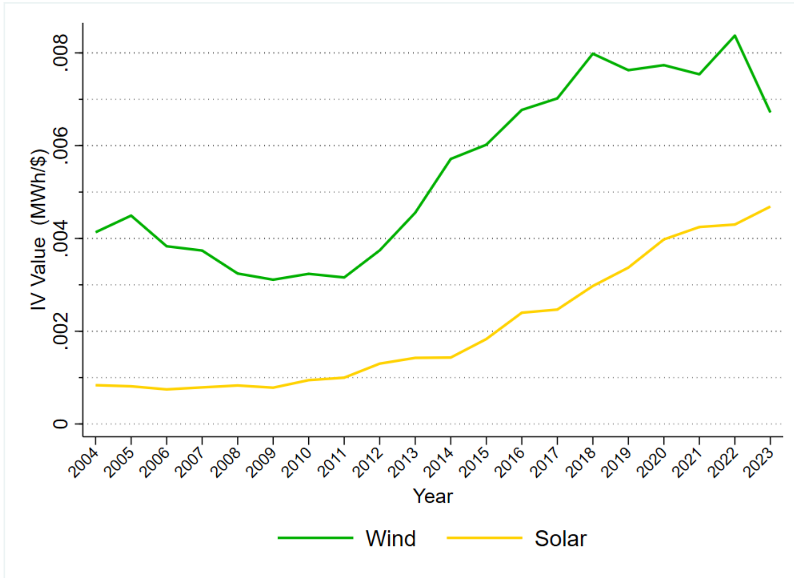
These instruments are designed to affect renewable penetration through cost-driven siting incentives, but there is usually considerable time between siting a generator and commercial operation. For on-shore wind projects, it takes roughly three years from siting to operation while solar projects may take three to six years (I-SPARK, 2025a,b). Using the lower bound of these timelines, I lag the instruments three years from generation (four years from prices). Robustness to alternative lags is assessed in Section 5. The first and second stage models are given below:

$$\mathcal{R}_{b,t} = \beta_1 Z_{b,t-3}^{wind} + \beta_2 Z_{b,t-3}^{solar} + \beta_3 X_{s,t-1} + \beta_4 X_{us,t-1} + \gamma_{us} + \gamma_{r,t} + \varepsilon_{usb,t} \tag{7}$$

$$y_{usb,t} = \beta_1 \widehat{\mathcal{R}}_{b,t-1} + \beta_2 X_{s,t-1} + \beta_3 X_{us,t-1} + \gamma_{us} + \gamma_{r,t} + \varepsilon_{usb,t} \tag{8}$$

The construction and timing of the instruments presents an intuitive case for first stage power. The exclusion restriction requires that the instruments (MWh per dollar) affect prices only through renewable generation share, conditional on controls and fixed effects. Region-by-year fixed effects capture any broad time-varying factors, while utility-by-state fixed effects capture time invariant factors across space. The remaining exogenous variation – wind in Kansas becomes relatively more productive per dollar when wind LCOE falls and solar in Arizona becomes relatively more productive per dollar when solar LCOE falls – will only affect prices through variation in adoption of wind and solar.

Figure 3: Instrument Trends



5 Results

Table 2 reports estimates of β_1 from Equation 8, which I interpret as the effect of increasing renewable share on real average retail prices. Column 1 presents the base specification using OLS, simple controls, and state and year fixed effects as is common in the literature. Column 4 is structurally identical but employs the IV strategy. In both cases, reported estimates are positive but statistically indistinguishable from zero, as well as from each other, under wild-bootstrap confidence intervals. The estimated sign and lack of precision are consistent with discussions of endogeneity bias in Section 4 as well as the existence of surviving confounding variation such as dynamic regional demand factors.

Column 2 introduces more restrictive utility by state and census region by year fixed effects which isolate within utility variation for causal identification. The OLS estimate is not statistically different from zero but flips sign from Column 1. The IV counterpart in Column 5 is the preferred specification of this paper. It finds a statistically significant 0.3% decrease in real average retail prices for every one percentage point increase in renewable share. The cluster robust first stage F-statistic evidences sufficient power to rule out weak-instrument bias in the estimate. Signs on other controls align with existing priors. Relative to Column 2, there are two notable points. First, the point estimate in (5) lies outside the 95% confidence interval of (2) indicating significant difference between their estimates. Secondly, comparing estimates indicates the OLS estimate is positively biased, consistent with expectations presented in Section 4.

In columns 3 and 6, the preferred specification is expanded on by adding a suite of additional state by year controls that might plausibly correlate renewables with prices. Party control of the governorship, upper, and lower legislative chambers are included to improve control over dynamic policy settings, especially as they relate to PUCs. Additional demand-side controls include natural disaster declarations; unemployment rate; income; retail choice; and heating- and cooling-degree days. In both the OLS and IV case, estimates with expanded controls are statistically indistinguishable from the more parsimonious preferred specification and maintain the expected bias.

Table 2: Main Results: Renewable Share and Average Retail Prices

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Renewable Share_{t-1}	0.0011	-0.0011	-0.0008	0.0004	-0.0030**	-0.0027**
	(0.0013)	(0.0009)	(0.0008)	(0.0015)	(0.0011)	(0.0011)
KP-F				72.57	62.66	65.29
95% CI	[-0.0017,0.0040]	[-0.0027,0.0011]	[-0.0024,0.0011]	[-0.0045,0.0031]	[-0.0053,-0.0003]	[-0.0048,-0.0001]
State FE	X			X		
Year FE	X			X		
Utility × State FE		X	X		X	X
Region × Year FE		X	X		X	X
Expanded Controls			X			X
Obs.	50956	50917	50867	45215	45177	45129

P-values and confidence intervals derived by wild-bootstrap. Standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 3 introduces alternative instrument timings and structures to the main specification. Columns 1 and 2 address concerns that estimates may be sensitive to instrument timing resulting from the long and fluid process of renewable investments. In Column 1, instruments are lagged a single year behind generation while in Column 2 the lag is increased to five years. In both cases, there is a small loss reduction in first stage power relative to the preferred timing but well above weak-IV thresholds. There is loss of significance in Column 1, but in both cases, the magnitude of the estimates are not significantly different from those in Table 2. Another concern may be that the price impacts of renewable generation could take longer than a single year to manifest in retail prices. The third and fourth columns explore this question by changing the lag on renewable share in relation to the dependent variable, keeping the timing between renewable share and the instruments at three years. While the estimates apparently increase in magnitude with increasing lags, each estimate remains within the confidence interval of the preferred estimate.

Table 3: Alternative Instrument Structures

	Instrument Lags		Renewables Lags		Non-linear
	(1)	(2)	(3)	(4)	(5)
	1 Year	5 years	2 Years	3 years	Quadratic
Renewable Share_{t-1}	-0.00184	-0.00362**	-0.00372**	-0.00408**	-0.00938
	(0.00102)	(0.00129)	(0.00126)	(0.00155)	(0.00616)
Quadratic Share					0.00014
					(0.00013)
KP-F	56.45	51.67	50.91	40.55	11.20
β_1 95% CI	[-0.0040,0.0004]	[-0.0063,-0.0002]	[-0.0064,-0.0005]	[-0.0073,-0.0001]	[-0.0245,0.0034]
β_2 95% CI					[-0.0001,0.0005]
Obs.	50917	39395	41517	37942	45177

P-values and confidence intervals derived by wild-bootstrap. Standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Finally, it is possible that the price effect varies by the level of renewable penetration. Column 5 estimates the model with quadratic renewable shares. While the first stage borders on weak identification, the confidence intervals suggest opposing dominant signs and it may be instructive to consider inflection points in the net and marginal effects. The estimates indicate that marginally increasing renewables reduces prices up until 33.5% renewable penetration. The net price effect does not become positive, however, until nearly 52% penetration. Using the upper bound of the quadratic estimate, the net price effect is only positive above 18% renewable penetration - over three times the sample mean from penetration in Table 1. Overall, this exercise provides some weak, suggestive evidence of increasing marginal system costs at higher penetrations of renewables.

5.1 Heterogeneity Analyses

Within the U.S. electrical system, there are several potential vectors for heterogeneity that are explored within this section. The first of these separates the sample by the energy market regime of the state. In the preferred specification, controls are interacted by market structure, but renewable shares are not. Following the discussion in Section 2, one might expect that the price effect of renewables may manifest differentially by market structure as pricing and investment mechanisms differ. Columns 1 and 2 of Table 4 fully split the sample on market differences, resulting in a fully-interacted model. In both cases, there is a reduction in first stage power and estimates are not significantly different from zero and. In the "traditional" market case, the provided estimate falls within the confidence interval of the preferred specification, however the same is not true for "restructured" markets though there is substantial overlap of confidence intervals.

Table 4: Markets and Time

	(1) Traditional	(2) Restructured	(3) Time-Split
Renewable Share$_{t-1}$	-0.0017	-0.0063	-0.0210**
	(0.0011)	(0.0027)	(0.0082)
Post-2015			0.0139**
			(0.0065)
KP-F	32.87	19.61	11.01
β_1 95% CI	[-0.0040,0.0015]	[-0.0152,0.0096]	[-0.0503,-0.0040]
β_2 95% CI			[0.0003,0.0370]
Obs.	35078	10098	45177

P-values and confidence intervals derived by wild-bootstrap.
Standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Figure 2 suggests that allowing the effect to differ across time periods may be important as both wind and solar were least cost technologies by 2015. In Column 3, renewable shares are interacted with a dummy for post-2015 years to explore this.[15] Notably, the signs of the effects differ about the split and are statistically significant, but are, perhaps, contrary to expectation. If post-2015 renewable investments were cost-minimizing on average then, all else being equal, equilibrium prices should decrease. However, we observe the opposite. A possible explanation follows from the discussion of non-linearities from Table 3. In the earlier time period, when renewable penetration was lower, cost-savings from increased renewable generation outweighed system costs of integration, decreasing prices after controlling for policy effects. After 2015, if system costs increase at higher baseline generation levels, further increases in renewable shares would be more costly and the net effect could flip sign. However, the net marginal effect of newer generation is a 0.71% decrease in prices for every percentage point increase in penetration, which is comparable in magnitude to other estimates in this paper.

Table 5 separates the analysis by technology. While both wind and solar are resource constrained, the nature of these relationships and thus their potential impact on prices differ. In this table, specifications use technology specific shares of generation as the key independent variable (e.g. wind generation's share of total generation). The instruments constructed similarly following the preferred specification. Column 1 estimates the effect of increased wind generation over the entire sample. It finds a marginally significant decrease in prices of 0.24% when wind penetration increases one percentage point. Column 2 uses the temporal split from Table 4 and observes similar patterns and magnitudes of effects. Early wind generation strongly reduced prices but this effect has been reduced in later years, though remains negative.

[15] Analyses using different threshold years are presented in Appendix X. Across candidate years, effects are quantitatively similar.

Table 5: Renewable Technology

	Wind		Solar	
	(1)	(2)	(3)	(4)
Renewable Share$_{t-1}$	-0.0024*	-0.0192**	-0.0200*	-0.0457
	(0.0011)	(0.0076)	(0.0117)	(0.0511)
Post - 2015		0.0131**		0.0241
		(0.0058)		(0.0445)
KP-F	135.08	12.10	7.09	1.80
β_1 95% CI	[-0.0046,0.0002]	[-0.0387,-0.0052]	[-0.0517,0.0004]	[-0.2064,0.0541]
β_1 95% CI		[0.0024,0.0289]		[-0.0783,0.1657]
Obs.	45177	45177	45177	45177

P-values and confidence intervals derived by wild-bootstrap. Standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Columns 3 and 4 present the analogous models for solar technology. While the estimates appear qualitatively similar to previous specifications, low first F-statistics precludes any definitive analysis. While the loss of power may appear jarring, there are a few plausible explanations from the data. First, there is very little variation in solar shares prior to 2010 owing in part to high costs of the technology and the relatively limited role of RPSs in the period. Second, the instrument in this paper uses market features to predict renewable generation, but prior to 2015 solar generation was, on average, not cost-competitive and resulted more from policy mandates. As such, a market based predictor would have little power in the earlier time period.

Table 6: Customer Type

	(1) Residential	(2) Commercial	(3) Industrial
Renewable Share$_{t-1}$	-0.0008	-0.0023	-0.0015
	(0.0010)	(0.0014)	(0.0019)
KP-F	70.51	65.50	49.44
95% CI	[-0.0027,0.0014]	[-0.0051,0.0010]	[-0.0057,0.0032]
Obs.	43813	43432	33326

P-values and confidence intervals derived by wild-bootstrap.
Standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Electricity markets typically categorize consumers as residential, commercial, or industrial. Usually, each type is considered separately in rate-cases and policy, resulting in different rate limits and structures. From a demand side, price elasticities are known to vary across types which may also affect individual prices. Taken together, it is possible that changes to the energy mix may affect these consumer type differently.

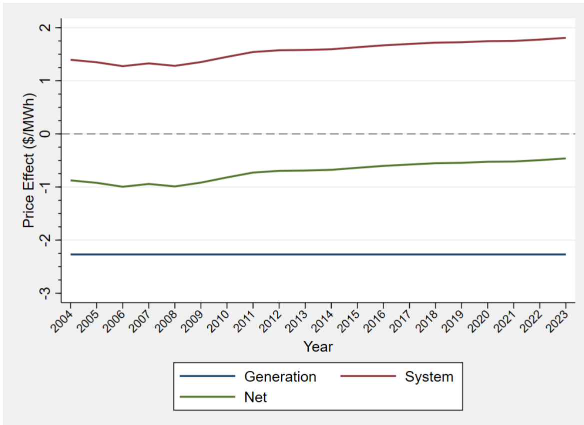
Table 6 reports results for the main specification when restricted to each customer type. Note that none of these splits reflect the full sample of utilities in Table 2 as many utilities do not provide service to each customer type. Across columns, results are modestly negative and statistically insignificant. Importantly, they are statistically indistinguishable from each other as well as from the main estimate in column 5 of Table 2.

6 Mechanism Analysis

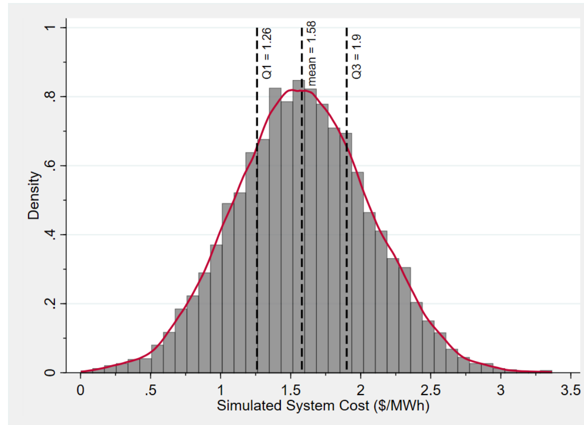
6.1 System Costs

TBD

Figure 4: Relative Magnitude and Distribution of System Costs (ERCOT)



A.) Separation of Price Effects



B.) Kernel Distribution of System Costs

Panel A: This figure shows the marginal net, generation cost, and system cost effects, in dollars per megawatthour, over time for ERCOT. Net effects are converted from the estimate in column 5 of Table 2. The generation cost effect is borrowed from Weber and Woerman (2024). Following the stylized model from Section 2, system costs are given as the difference between the net effect and generation costs. For a more detailed discussion, refer to Appendix B.
Panel B: This panel depicts the Monte Carlo simulated distribution of per megawatthour system costs for ERCOT in 2019. Standard errors for net and generation costs are taken from column 5 of Table 2 and Weber and Woerman (2024), respectively. Black dashed lines depict the bounds of the lower and upper quartile as well as the distribution mean. The red line gives the kernel density.

7 Conclusion

This paper presents an empirical analysis of the role of increasing intermittent renewable generation on retail electricity prices in the United States. The empirical strategy identifies estimates based on within utility variation and addresses simultaneity between prices and generation quantity. Overall, it finds that increased renewable penetration led to reductions in the real price of electricity on average. The preferred specification estimates a 0.3% reduction in prices per percentage point of renewables in the mix or a net decrease of 3.5% at the sample mean change in penetration. These results are robust to alternative instrument structures and sample splits. Across specifications, the marginal effect is tightly bounded between roughly −0.7% and 0.7%, suggesting that, if anything, the true effect of renewables on prices is modest.

These findings may serve to allay present concerns that renewable technologies are increasing electricity prices dramatically. In so doing, this paper hopes to inform clearer discourse about the effects of renewable investments and policies.

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A Instrumental Variables Strategy

A.1 Summary Statistics

Table A.1: Balancing Authority Capacity Factors

Balancing Authority	Wind	Solar	Balancing Authority	Wind	Solar
AEC	0.32	0.15	NSB	0.32	0.16
AECI	0.35	0.15	NWMT	0.39	0.15
AVA	0.34	0.14	NYIS	0.33	0.13
AZPS	0.32	0.2	OKGE	0.4	0.16
BPAT	0.34	0.14	OPPD	0.44	0.16
CHPD	0.34	0.13	OVEC	0.32	0.13
CPLE	0.33	0.15	PACE	0.34	0.17
CSWS	0.38	0.16	PACW	0.28	0.12
DOPD	0.34	0.13	PGE	0.34	0.15
DUK	0.33	0.15	PJM Atlantic	0.34	0.14
EDE	0.37	0.15	PJM Central	0.33	0.14
EPE	0.39	0.19	PNM	0.38	0.2
ERCO	0.39	0.17	PSCO	0.38	0.18
FMPP	0.32	0.16	PSEI	0.34	0.13
FPC	0.32	0.16	SCEG	0.31	0.16
FPL	0.32	0.16	SCL	0.34	0.13
GCPD	0.34	0.13	SEC	0.32	0.16
GLHB	0.35	0.14	SOCO	0.33	0.15
GRDA	0.41	0.16	SPS	0.39	0.17
GVL	0.32	0.16	SRP	0.32	0.2
HST	0.32	0.16	SWPP North	0.42	0.16
IPCO	0.33	0.15	SWPP South	0.39	0.16
ISNE	0.35	0.14	TAL	0.32	0.16
JEA	0.32	0.16	TEC	0.32	0.16
KCPL	0.38	0.16	TEPC	0.33	0.2
LES	0.44	0.16	TPWR	0.34	0.13
LGEE	0.33	0.14	TVA	0.33	0.15
MISO Central	0.34	0.14	WACM	0.39	0.17
MISO North	0.41	0.14	WALC	0.17	0.1
MISO South	0.32	0.15	WAUE	0.43	0.15
MPS	0.34	0.15	WAUW	0.4	0.16
NEVP	0.26	0.15	WFEC	0.41	0.16
NPPD	0.44	0.16	WR	0.43	0.16

Note: Table reports weighted average capacity factors for each balancing authority in the main sample. Values are rounded to two digits. Source: author's calculations, state capacity factors from Bento et al. (2018).

B System Costs

B.1 Calculation

The purpose of this Appendix is to formalize the back of the envelope calculations used to estimate the per-gigawatthour system costs of renewable energy in Section 6. At the core of this calculation is the stylized formula for the retail price of electricity, ρ, as defined in Section 2 and repeated here:

$$\rho = \lambda + \sigma$$

Where λ and σ are generation and system costs, respectively. Assuming that both generation and system costs depend on the level of renewable generation, r, and totally differentiating ρ with respect to r provides a simple representation of the marginal effect of renewable generation on the all-in retail price.

$$\frac{\partial \rho}{\partial \mathcal{R}} = \frac{\partial \rho}{\partial \lambda}\frac{\partial \lambda}{\partial \mathcal{R}} + \frac{\partial \rho}{\partial \sigma}\frac{\partial \sigma}{\partial \mathcal{R}} \tag{B1}$$

In this equation, the left-hand side is represented by the main estimates of this paper, albeit transformed. On the right side, the first term represents the marginal effect of renewable generation on total generation costs, while the second term defines the same marginal effect for system costs. Following this representation, it is possible to approximate the marginal effect of renewables on system costs:

$$\frac{\partial \rho}{\partial \sigma}\frac{\partial \sigma}{\partial \mathcal{R}} = \frac{\partial \rho}{\partial \mathcal{R}} - \frac{\partial \rho}{\partial \lambda}\frac{\partial \lambda}{\partial \mathcal{R}} \tag{B2}$$

In order to calculate Equation B2, I (i) convert estimates in this paper from logged prices and renewable shares to per-unit prices and renewable generation then (ii) deduct estimates of the marginal generation cost as estimated in the literature (e.g., Weber and Woerman (2024), Quint and Dahlke (2019)).

For step (i), I begin by recalling the main specification in the paper, given by Equation 5:

$$y_{usb,t} = \beta_1 \mathcal{R}_{b,t-1} + \beta_2 X_{s,t-1} + \beta_3 X_{us,t-1} + \gamma_{us} + \gamma_{r,t} + \varepsilon_{usb,t} \tag{B3}$$

Where the dependent variable, $y_{usb,t}$ is defined as $\ln \rho_{usb,t}$ and the key regressor, $\mathcal{R}_{b,t-1}$ is the renewable generation share in percentage points (0-100). Throughout the rest of this section, I will be dropping subscripts for brevity while maintaining the underlying variation defined in main specification. From here, the marginal effect of a change in renewable generation share on prices is given by:

$$\frac{\partial \ln \rho}{\partial \mathcal{R}} = \beta_1 \quad \text{and} \quad \frac{\partial \ln \rho}{\partial \mathcal{R}} = \frac{1}{\rho}\frac{\partial \rho}{\partial \mathcal{R}}$$

Where the second equivalence follows from $d \ln \rho = \frac{d\rho}{\rho}$ and application of the chain rule. Simplifying terms, the marginal effect of an increase in renewable share on prices (in levels) is given by Equation B4 with the first order approximation in Equation B5.

$$\frac{\partial \rho}{\partial \mathcal{R}} = \rho \beta_1 \tag{B4}$$

$$\Delta \rho \approx \rho \beta_1 \Delta \mathcal{R} \tag{B5}$$

Setting $\Delta \mathcal{R} = 1$, equation B5 gives the price change in dollars per kilowatthour, for a 1 percentage point increase in renewable share. For comparability with existing works, this effect must be transformed. Standard interpretations in the literature define price changes in dollars per megawatthour for a gigawatthour increase in renewable generation. The first necessary transformation is straightforward. To convert dollars per kilowatthour to dollars per megawatthour, prices are multiplied by 1000:

$$\Delta \rho_{\$/MWh} = 1000 \times \Delta \rho_{\$/kWh} \tag{B6}$$

Transforming renewable shares into gigawatthours is slightly more challenging. For estimation, renewable shares , given in percentage points, are calculated as:

$$\mathcal{R} = 100 \times \frac{R}{G} \tag{B7}$$

where R is the sum of generation from renewable sources and G is the total generation across all sources, given in gigawatthours. When renewable generation increases, there are two ways it can affect total generation. The first case is that new renewable generation replaces existing generation such that total generation is unaffected. Alternatively, renewable generation may be additive, in which case the change in renewable generation is equally reflected in total generation. Under the assumption of replacement:

$$\begin{aligned} \mathcal{R}_0 = 100 \times \frac{R}{G} \quad &\text{and} \quad \mathcal{R}_1 = 100 \times \frac{R + \Delta R}{G} \\ \implies \quad \Delta\mathcal{R} &= \mathcal{R}_1 - \mathcal{R}_0 = 100 \times \frac{\Delta R}{G} \end{aligned}$$

Then, for a one gigawatthour increase in renewable generation, the change in renewable share is:

$$\Delta\mathcal{R} = \frac{100}{G} \tag{B8}$$

Alternatively, we may assume that an increase in renewable generation increases total generation proportionately. Under this assumption:

$$\begin{aligned} \mathcal{R}_0 = 100 \times \frac{R}{G} \quad &\text{and} \quad \mathcal{R}_1 = 100 \times \frac{R + \Delta R}{G + \Delta G} \\ \implies \Delta\mathcal{R} &= 100 \times \left(\frac{R + \Delta R}{G + \Delta G} - \frac{R}{G} \right) \\ \implies \Delta\mathcal{R} &= 100 \times \frac{\Delta R(G - R)}{G(G + \Delta G)} \end{aligned}$$

By assumption $\Delta R = \Delta G$, then for a one gigawatthour increase in renewables, the percentage point change in renewable share is:

$$\Delta\mathcal{R} = 100 \times \frac{G - R}{G(G + 1)} \tag{B9}$$

Combining Equations B5, B6, B8, and B9 the approximate change in the price per megawatthour of a one gigawatthour increase in renewable generation is given for the replacement and additive cases in Equations B10 and B11, respectively:

$$\Delta\rho_{\$/MWh} \approx 1000\rho_{\$/kWh} \times \beta_1 \times \frac{100}{G} \tag{B10}$$

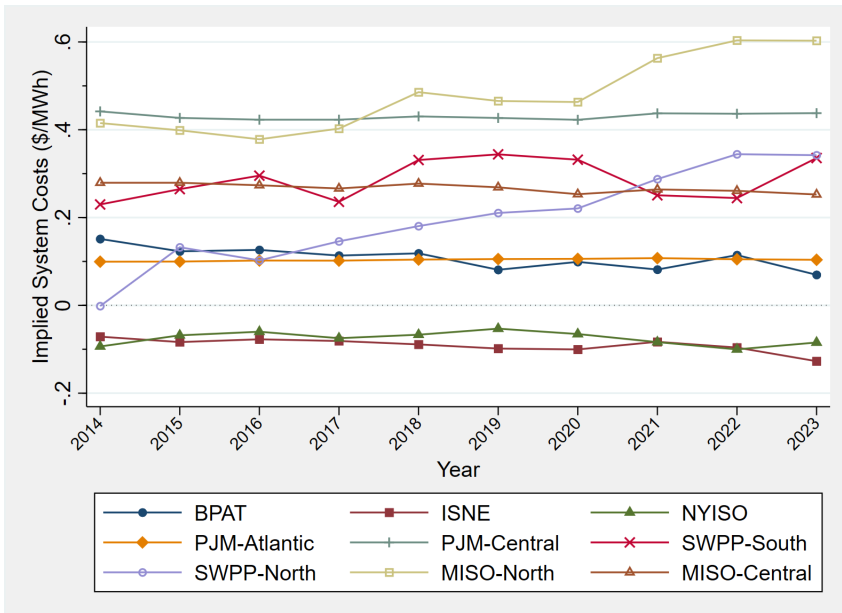
$$\Delta\rho_{\$/MWh} \approx 1000\rho_{\$/kWh} \times \beta_1 \times \frac{100(G - R)}{G(G + 1)} \tag{B11}$$

For comparability with existing estimates, $\Delta\rho$ in Equations B10 and B11 are multiplied by 8760 to report the effect of a sustained one GW increase in renewables over a given year. Price effects, such as in Weber and Woerman (2024), are estimated from hourly shocks on contemporaneous hourly prices. Assuming a sustained one GW increase in renewable generation, the implied annual average marginal effect remain unchanged from their reported estimates. Letting $\Delta\lambda$ represent the price effect, the average marginal system cost per MWh of a sustained one GW increase in renewable generation is:

$$\Delta\sigma = 8760 \times \Delta\rho - \Delta\lambda \tag{B12}$$

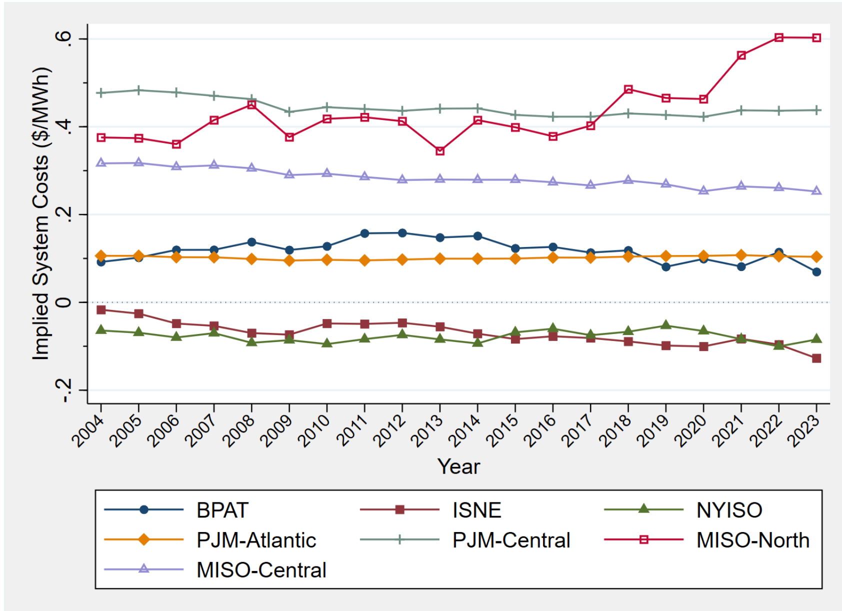
B.2 Tables and Figures

Figure B.1: Calculated System Cost Trends (2014-2023)



Note: Figure displays trends in system costs in dollars per megawatthour over time for balancing authorities in the top quartile of net and wind generation, excluding ERCOT. Time period omits outlier system costs for SWPP-South and SWPP-North pre-expansion.

Figure B.2: Calculated System Cost Trends (2004-2023)



Note: Figure displays trends in system costs in dollars per megawatthour over time for balancing authorities in the top quartile of net and wind generation. Figure excludes ERCOT, SWPP-South, and SWPP-North.

Table B.1: System Costs: Summary Statistics

BA	Mean	SD	Min	Max
Aggregate	0.731	0.475	-0.127	1.808
Aggregate (No ERCOT)	0.318	0.196	-0.127	0.604
BPAT	0.122	0.025	0.070	0.158
ERCO	1.682	0.179	1.275	1.808
ISNE	-0.087	0.027	-0.127	-0.017
MISO Central	0.268	0.020	0.253	0.318
MISO North	0.477	0.076	0.345	0.604
NYIS	-0.078	0.013	-0.100	-0.053
PJM Atlantic	0.102	0.004	0.095	0.108
PJM Central	0.433	0.020	0.423	0.483
SWPP North	0.237	0.109	-0.002	0.344
SWPP South	0.291	0.046	0.230	0.344

Note: Table displays summary statistics for implied marginal system costs for balancing authorities in the top quartile of average yearly total generation and wind generation. Units are dollars per megawatthour. In all aggregations and their respective rows, SPP figures include only the years from 2014 to 2023 to avoid pre-expansion outlier values.