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 potential and time-varying levelized costs of wind 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.

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 evidence that renewables drive 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).

Figure 1 motivates this tension more broadly by plotting the change in inflation-adjusted average retail prices against changes in the renewable share of balancing authority energy mixes by utility between 2004 and 2023. A simple fitted line of these points reveals 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. From this figure, it follows that the net effect of renewable energy generation on electricity prices is a fundamentally empirical question. Understanding this relationship is of particular interest to policymakers balancing the renewable energy transition and broad public concern for energy affordability.[2] Motivated by these concerns, this study employs rigorous econometric methods to quantify the impact of increasing wind and solar generation on real retail electricity prices in the United States.

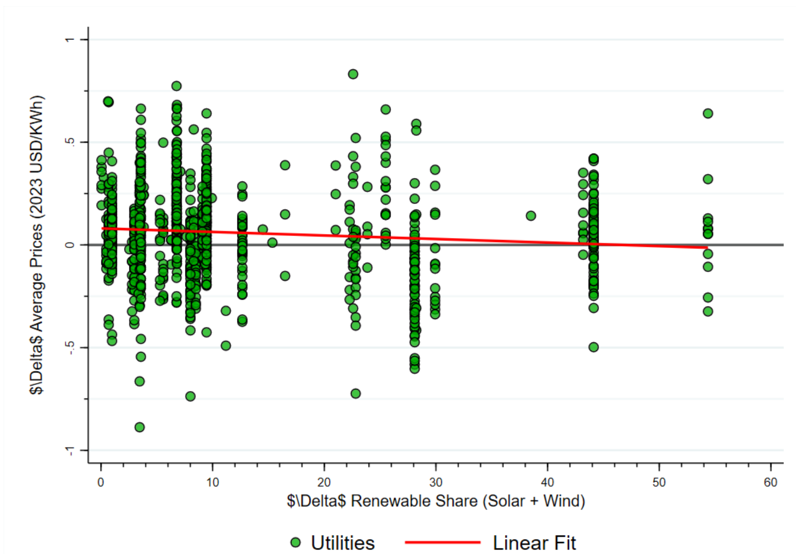
This analysis draws on annual sales data from the EIA-861 and generation data from the EIA-923, covering 47 states and Washington, D.C., from 2004 to 2023. Retail prices are represented at the utility level by state and year to align with real variation in consumer bills. Renewable generation, represented as shares of the total generation mix, is calculated at the balancing authority level which is a useful analogue for a functional 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[3] between prices and renewable shares

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

[2] A Gallup survey in March of 2025 found that 71% of Americans worried at least "a fair amount" about energy prices and 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).

Figure 1: Difference in Retail Prices and Renewable Generation Share (2004-2023)



Note: Utility observations at balancing authority by state level. Average prices calculated across residential, commercial, and industrial customers. Source: author's calculations.

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. 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 acrsos 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.

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.

A small, but complementary, thread of literature investigates the role of system costs in determining price effects of renewable generation (e.g., Petersen et al. (2024), Ciarreta et al. (2014)). The present work offers new evidence for system costs for both wind and solar generation within the American context. 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 from uncertainty and 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 provides background information that is crucial to understanding the empirical designs of this paper. It begins by discussing the unique features of solar and wind energy as well as their background in the United States. The second part describes the complex set of institutions that govern electricity across the nation.

2.1 Renewable Energy in the United States

While sources of renewable energy in the United States are diverse and were historically dominated by hydroelectric power, this paper focuses on wind and solar energy. There are several reasons for choosing this emphasis. First, since the turn of the century wind, and eventually solar, have overtaken hydroelectric power as the dominant sources of renewable energy both in terms of capacity and in new constructions. Second, while areas differ in their suitability for these technologies, there are fundamentally fewer restrictions on their placement than for hydroelectric, which is tightly constrained by geography, and so there is greater scope for inefficiencies in placement. Lastly, the intermittent nature of wind and solar power generates economically distinct challenges from other renewable sources which, combined with their widespread adoption, have led to concerns that these technologies are driving increases in electricity prices around the country.

In the previous two decades, the growth in renewables has been facilitated largely facilitated by public policy which has urged their deployment to combat environmental risks. These policies included mandates such as the well-studied renewable portfolio standards as well as market based instruments like tax breaks and subsidies. Across the 2010's, these policies were effective at increasing the deployment of wind which, with government incentives, was cost competitive with most traditional generators throughout the period. Solar, however, remained prohibitively costly with correspondingly low deployment into the next decade where its costs began to fall precipitously with technological improvement. By 201X, solar had achieved cost parity with the lowest cost, traditional generator, combined cycle gas. A few years later, it achieved parity with wind which had decreased in cost, albeit much slower, over the past decade. This time line is important as most studies, especially those focused on policy implications, restrict analysis to the pre-201X period when before renewable adoption could be competitively optimal.

2.2 Institutional Context

The purpose of this section is to discuss the necessary underlying strata of American energy institutions. It can be useful to conceptualize these institutions under two broad categories: those that generate, provide, and ensure quality of electrical power and those that make policy for and regulate the electrical system.

While I treat these groups as distinct in purpose, they are not disjoint in practice. Understanding and disentangling their complex interactions is a crucial problem to address empirically. For this paper, the important energy institutions are electrical utilities and balancing authorities (BAs); on the policy side, there is shared federal regulation but state governments are the key entity in regards to retail prices.

2.2.1 The Regulatory Environment

The primary policy setting in the American energy context is the state. Each state is responsible for the structure of its electricity market and regulation of entities operating within it. Importantly, regulation related to the retail pricing of electricity falls under state jurisdiction. There are several key mechanisms that affect prices at the state level and incredible diversity in these mechanisms amongst the states.

The first crucial state mechanism is the structure of its electrical market. Prior to the late nineties, state electricity markets operated under a vertically integrated, natural monopoly model. Under this system, large entities controlled generation, transmission, and distribution of electricity within the state under strict regulation from policy makers.[4] Around the turn of the century, many states began to restructure their energy markets, specifically by deregulating the generation of electricity. The push for deregulation followed standard economic arguments that competitively generating firms would do so at lower cost and thus reduce electricity prices. In practice, this created a secondary market for electricity, the wholesale market, in which utilities bid for electricity offered by deregulated generators. The price paid by utilities in this market is the wholesale price of electricity and is analogous to the cost of generation.

In each state, Public Utility Commissions (PUCs) regulate electric utilities (among others) through a board of governor-appointed commissioners.[5]. The PUC primarily regulates investor-owned utilities (IOUs) while municipal and cooperative utilities face either limited regulation or full exemption. In traditional markets, the PUC oversees each component of the market while in restructured markets, they only regulate distribution while independent system operators (ISOs) or regional transmission organizations (RTOs) oversee generation and transmission. the retail price of electricity is determined quite similarly. A key function of the PUC is to set utility's retail electricity prices through a "rate-case" proceeding. In this process, a utility submits key organizational information to the regulator regarding proposed investments, estimated demand, and operating costs for review. The PUC assess the validity of the utility's estimates as well as the necessity of proposed investments, then sets a revenue requirement for the utility which covers these costs plus a reasonable return on investment. While the process is generalizable, the mechanics can vary widely across states and there is no uniform time frame between a rate-case and price determination. As a result, retail electricity prices are relatively sticky overtime.

Not all prices are determined by regulators, however. In some states, the restructuring effort went further, deregulating their distribution markets as well. These markets allow retail choice for some or all electricity consumers in their footprint.[6] Retail electricity providers (REPs) offer electricity plans to consumers which may differ in contract structure, source of electricity, etc. While these providers are not regulated, they often compete with municipal utilities for customers, as such, it is useful to frame their pricing decisions as analogous to the rate-case process. Another entity outside the purvey of PUCs are independent power providers (IPPs). These are private generators who can build generation capacity and sell power without

[4] Generation is the physical act of generating electrical energy from another source. Transmission moves electricity from generation to demand centers, typically medium to long distance over high-voltage lines. Distribution involves converting transmitted electricity into retail voltages and distributing that electricity to end-use consumers.

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

[6] Retail choice is not necessarily complete, however, and many states offer this choice only to industrial and commercial consumers of electricity, while residential households still rely on local utilities.

explicit licensing from the PUC. However, a regulated utility that purchases power from an IPP may have its decision reviewed by the PUC.

State regulations can also directly affect the adoption of renewables. Renewable portfolio standards (RPSs) mandate that a minimum set share of electricity sold to residents come from renewable sources. Over half of states have an RPS on the books, varying widely in their requirement from as little as 10% to over 50%. Generally the established RPS is designed to ramp up over time with a goal of 100% renewably sourced electricity in the next two decades in most cases. RPS's are known to increase the price of electricity (Greenstone et al. (2024)) and to accelerate the adoption of renewables when the policies are binding (Deschenes et al. (2023), Yin and Powers (2010)). Net metering policies are tariff or billing programs that allow certain consumers to offset their billed amount of electricity during a period with electricity sold back to the grid when self-generation exceeds consumption. While net-metering may encompass other forms of generation, it is most often associated with renewables and, in particular, solar power. This policy provides incentive for consumers to build small-scale renewables behind the meter that can reduce the volume of electricity a utility recovers its costs from. While a relatively small portion of generation, net-metering and other behind the meter generation that is not utility scale (>1 MWh capacity) has been shown to increase retail electricity rates (Argosino and Knittel (2025), Wiser et al. (2025)).

Interstate regulation is handled by the Federal Energy Regulatory Commission (FERC). One of it's primary functions is to oversee the interstate transmission of electricity. This includes enforcement of reliability standards, consideration of environmental concerns, and limited oversight of transmission siting in some circumstances. Other functions, secondary to this paper, include the oversight of interstate natural gas operations and the siting or abandonment of natural gas pipelines. Additionally, FERC licenses and inspects hydroelectric projects.

2.2.2 The Electrical System

Electric utilities are the entities that handle distribution of electricity to end-use consumers including investor-owned, municipal, cooperative, and retail electricity operators. As distributors, they may own small-scale infrastructure including power lines, transformers, and storage systems to facilitate their services. Through the rate-case process described above, they are also the billing-entity for retail customers.

Within a state, there are typically many utilities which may vary dramatically in size and structure. Based on these differences, utilities are often subject to different regulations as noted in Section 2.2.1. While common state-level analyses of electrical prices can control for the regulatory environment broadly, they do not explicitly capture the differential experience of the environment by individual utilities. To the extent that these differences inform price determination, focusing on utility by state level prices provides a more accurate picture of retail prices than state-level simple averages.

Furthermore, a single utility's footprint may extend into many states, subjecting it to different regulations within its own operation. Crucially, this includes price-determination. To address this problem, I make three assumptions regarding the scope of considerations by the state PUC. Specifically, I assume (I.) the rate-base of investments attributed to the firm and used to determine the revenue requirement, (II.) the operational costs of providing electricity, and (III.) the serviced load of billable electricity over which these costs are recouped are restricted to the regulating state's boundaries.

Balancing authorities oversee the generation and transmission of electricity within their footprint. Their primary purpose is to ensure real time equilibrium between electricity supply and demand to maintain grid reliability and integrity. In restructured markets, the ISOs and RTOs that operate the markets generally serve as the balancing authority too. BAs may also take part in planning or facilitating infrastructural investments, especially regarding transmission. There is substantial variation in the geographic footprint of balancing authorities: the smallest BAs operate within a single state while larger ones cross state boundaries and can encompass whole states. 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, each oversee several states and distinct geographic regions. To ensure they match the intent of BA level data, these entities are split into distinct sub-regions aligning with known energy-model and intra-organizational divisions.[7]

A balancing authority covers many utilities, ensuring sufficient electricity is supplied to meet their demand. Conversely, most utilities operate entirely within a single balancing authority.[8] Intra-authority generation is the primary source of electricity in a BA, with generators dispatched according to merit-order. Most BA's also obtain electricity through trades with directly connected balancing authorities, but this trade represents a comparatively small share of total demand. Trade between BA regions is restricted by differences in coordination and market structure as well as physical limitations of intertie transmissions.[9]It follows that the supply and composition of electricity available to a given utility is predominately determined by the BA in which they reside. This presents another potential issue with analyzing state level prices and renewable deployment, namely that the existence of renewable capacity in a state is not sufficient to determine a utility's exposure to renewable generation and the impacts it may have on their costs. By representing renewable generation shares at the balancing authority level, this study more accurately measures this exposure by reflecting the tangible constraints of the electricity system.

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:

[7] 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.

[8] There are some cases where a utility spans several balancing authorities (e.g., Excel Energy which operates in eight states and two BAs), but operational connection is largely limited to organization and not physical electrical connections.

[9] These barriers are exacerbated at the interchange level, which subdivides some states, as intertie limits become particularly restrictive.

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

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

	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

[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.

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 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.

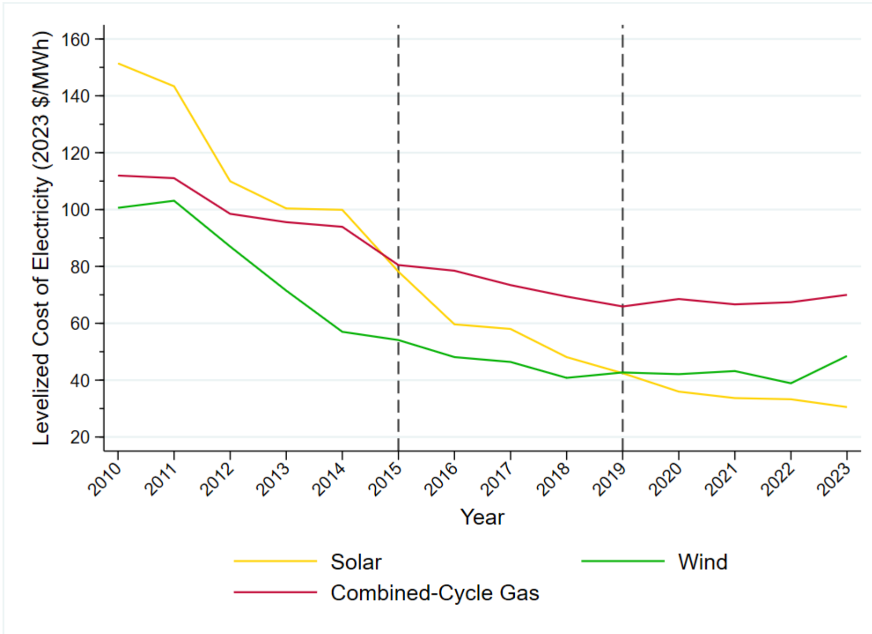
3.2 Instrumental Variables Data

Additional data for the instrumental variables specification presented in section 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 borrowed 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

Figure 2: Levelized Costs of Electricity Over Time



Notes: Figure depicts the levelized costs of electricity when generated by solar, wind, and gas energy. Start year corresponds to the first year where solar and gas data are observable. Data sources: (Seel et al., 2024); wind (Wiser et al., 2024); gas, author's calculations, nominal values from (Lazard, 2024)

total number of counties served by the balancing authority.

4 Empirical Strategy

In this section, I develop a 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, the generation of electricity and retail price are simultaneously determined equilibrium outcomes and, as such, are subject to endogeneity biases.

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 a plausibly 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. This process is what determines the prices that utilities operating in a specific state are able to legally charge consumers in that state for electrical services. While not a universal policy for setting prices, rate-cases are the dominant form of price determination in the United States' context. Furthermore, in cases where competitive forces determine market prices, this paper argues that the rate-case

Table 2: 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).

model is a close parallel of the market factors that inform price decisions by forward-planning electrical firms.

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

In Equation 5, retail prices y are determined at the utility (u) by state (s) by balancing authority (b) level in year t. $\mathcal{R}$ represents the share of BA electricity generation from renewable sources. Shares are used instead of nominal generation to reflect the fact 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.

$X_{s,t-1}$ is a vector of state by year level controls that may correlate with prices and renewable generation. These include factors which may affect supply such as natural gas prices and policy controls for renewable portfolio standards and quantity of net metering contracts. $X_{us,t-1}$ provides additional controls for the utility's demand.[13] To ensure correct representation, 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 properly account for industrial and commercial sales which may be large in volume but may be linked to few 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] Additionally, it allows for the stickiness of energy prices. Owing in part to both regulation and contracting of service, retail electricity prices are known to be sticky over short time periods.

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. The lags in Equation 5 may be helpful in reducing this bias but they are unlikely sufficient to remove it even if the lagged period is increased. This is because energy markets are known to emphasize strategic planning such that expected future prices usually inform current operations. Therefore, this paper employs an instrumental variables (IV) approach to address this endogeneity.

The proposed instruments leverage spatial variation in resource suitability and national trends in the costs of renewable energy in a Bartik construction. In this setting, resource suitability acts as the share while cost trends are the exogenous shift. Mechanically, national changes in the cost of electricity vary only by time and uniformly affect each balancing authority, while geographic characteristics that determine

[12] In Section 5, alternative fixed effect structures are tested. These include the common alternative of state and year FE as well as census division by year.

[13] Alternate specifications in Section 5 include broader sets of controls to test robustness of this parsimonious model

[14] Robustness checks include alternative lag periods and show quantitatively similar results.

resource suitability are fixed and plausibly exogenous to renewable generation. Intuitively, the instruments predict that decreases in the cost of generating electricity through a specific technology will induce greater investment in that technology for areas better suited to the technology.

Each balancing authority's capacity factors as defined in Section 3 are used to gauge resource suitability over its footprint. In this context, a BA's capacity factors ($\mathcal{C}_b$) are engineering estimates of the potential generation from a given technology, $g \in \{\text{wind}, \text{solar}\}$, attainable under maximum model estimates of usage and efficiency. Higher $\mathcal{C}_b^g$ indicates a greater potential for energy generation from g or greater suitability for the technology.

The technology specific levelized cost of electricity (LCOE) is used to capture trends in the cost of renewables. LCOE figures are standard industry estimates of the cost of generating one unit of electricity for a technology conditional on a set of assumptions which may include costs of capital, applicable subsidies or taxes, potential operating costs, among others. Because these assumptions are sometimes subjective, there are broad concerns for its validity. For this paper, I argue that it its usefulness in the instrument depends on its explicit use in investment decisions and not its accuracy. An additional concern with the LCOE is that some of the included assumptions (e.g., subsidies) may affect prices through channels other than renewable generation, robustness checks using only capital expenditures (CAPEX) are considered in Section 5(TBD).

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

For each technology, the instrument is constructed as the ratio of the capacity factor to LCOE as described in Equation 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 X depicts variation in the instruments...

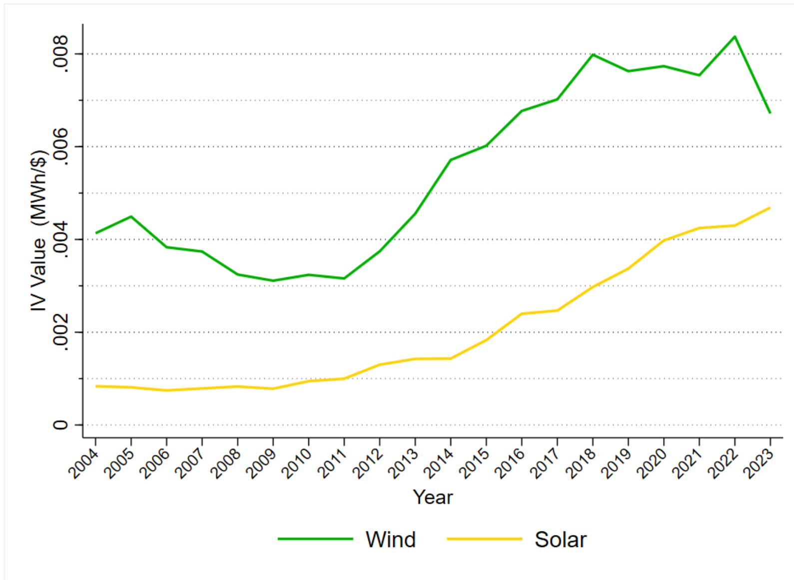
These proposed instruments affect renewable generation shares through their role in renewable investment decisions. Specifically, the instruments should affect siting decisions of firms, but there is considerable time between siting a generator and commercial operation. For on-shore wind projects, the process between siting and operation takes roughly three years while solar takes three to six years (I-SPARK (2025a), I-SPARK (2025b)). I take the lower bound of these lengths and lag the instruments three years from generation (four years from prices). Because this timing is derived from estimates that may differ from practice, alternative lags are considered in Section 5. The first and second stage models are given below:

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

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

The construction and timing of the instruments presents an intuitive case for first stage power. For the exclusion restriction to hold, however, requires that the instrument affects prices only through generation shares. If the instrument were contemporaneous with prices (or even lagged one year), inclusions in the LCOE could be problematic if they are also considered in the rate-case. The extended lag of the instrument is also beneficial here. While the rate-case process is slow and rates are sticky, it is generally not a multi-year process. It follows that technological, policy, or operational costs that may be in the LCOE four years ago are unlikely to be part of a rate-case today.

Figure 3: Instrument Trends



5 Results

Table 3 reports estimates β_1 from Equation 8 interpreted 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. It's 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 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 3: Main Results: Renewable Share and Average Retail Prices

	OLS (1)	(2)	(3)	IV (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 4 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 3. 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 lays within the confidence interval of the preferred estimate.

Table 4: Alternative Instrument Structures

	Instrument Lags (1) 1 Year	(2) 5 years	Renewables Lags (3) 2 Years	(4) 3 years	Non-linear (5) 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 possible that the price effect varies by the level of penetration. Column 5 estimates the model with quadratic renewable shares. Notably, the first stage borders on weak identification. Nevertheless, confidence intervals suggest different dominant signs, so it may be instructive to consider points of inflection in the net and marginal effects. The estimates here suggest that the marginal effect of increasing renewables is a reduction in prices up to 33.5% penetration. However, the the net effect does not amount to increased prices until nearly 52% penetration. Even at the upper bounds of the quadratic effect, the net effect of renewable penetration on prices becomes positive only above 18% penetration, over three times the sample mean penetration from Table 1.

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 is 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. One might expect that the price effect of renewables may manifest differently in different markets as pricing and investment mechanisms differ. Columns 1 and 2 of Table 5 fully split the sample on market differences, resulting ina 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 lays 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 5: 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] The first thing of note is that the sign of effect differs about the split and is statistically significant in both cases. But signs of effect are perhaps contrary to prior expectations. We would expect that post-2015 renewable investments were cost-minimizing on average (i.e. market-efficient) and, under standard assumptions, equilibrium prices would decrease. However, we observe the opposite. One possible explanation for this follows from the discussions of non-linearities from Table 4. In the earlier time period, levels of penetration were lower and so increasing lower-cost renewable generation decreased prices after controlling for policy effects. After 2015, higher baseline generation levels may result in further increases in renewable shares becoming costly. Despite this shift, however, the marginal effect of newer generation in this simple split remains negative at -0.71% for every percentage point increase in penetration which is comparable in magnitude to other estimates.

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

Table 6: 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

Table 6 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 5 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.

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 7: 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

Electrical markets typically consider three types of consumers: residential, commercial, and industrial. Each type is usually considered separately in rate-cases and in 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.

Table 7 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 3 as many utilities do not provide service to each customer type. Across columns, results are modest and statistically insignificant. Importantly, they are statistically indistinguishable from each other as well as from the main estimate in column 5 of Table 3.

6 Mechanism Analysis

In Progress

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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