

Willingness to Pay for Reliable Electricity: Analyzing the Role of Market Structures in California and Texas

Mariam Raheem

Abstract

Power outages are a significant concern for households and businesses across the United States, with far-reaching economic and social implications. According to the 2023 American Housing Survey (AHS), one in four households nationwide experienced at least one complete power outage in the previous year, affecting approximately 33.9 million households. The scale of this issue highlights the vulnerability of the nation's electrical infrastructure and its impact on daily life. This paper focuses on California and Texas, two states with vastly different energy market structures and regulatory approaches. In Texas, the Electric Reliability Council of Texas (ERCOT) operates an energy-only market, where power generators are paid solely for the electricity they produce. In contrast, the California Independent System Operator (CAISO) employs a capacity-focused strategy, compensating generators for both energy produced and the capacity they promise to provide. The vastly different market frameworks in California and Texas are likely to influence consumers' willingness to pay (WTP) for reliable electricity.

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1. Introduction

Power outages pose a significant challenge for households and businesses across the United States, leading to extensive socioeconomic disruptions and economic losses. According to the 2023 American Housing Survey (AHS), approximately one in four households experienced at least one complete power outage in the previous year, impacting around 33.9 million households (Madamba, 2024). This alarming statistic underscores the vulnerabilities inherent in the nation's electrical infrastructure and its profound effects on daily life.

This paper focuses on California and Texas, two states that exemplify contrasting energy market structures and regulatory frameworks. It aims to explore whether households with higher electricity consumption and income levels assign a higher Value of Lost Load (VoLL), reflecting their willingness to pay for reliable electricity service. Intuitively, it seems plausible that households indicating a greater willingness to pay for uninterrupted electricity would also demonstrate a higher VoLL. Conversely, participation in energy assistance programs is anticipated to correlate with a lower VoLL, suggesting reduced economic burdens during power outages.

The significance of VoLL as an economic indicator cannot be overstated; it quantifies the monetary value associated with interruptions in power supply, thereby facilitating a better understanding of the economic consequences of blackouts. VoLL has been extensively studied, with methodologies varying from customer damage functions (CDFs) that predict losses based on outage duration and customer type to macroeconomic approaches that consider electricity as a vital input in production processes (de Nooij et al., 2007; Munasinghe and Gellerson, 1979). Furthermore, the increasing interconnection of electrical networks heightens the risk of cascading failures, where minor disruptions can lead to widespread outages, as evidenced by significant events such as the European blackouts in 2003 and 2006 (Buldyrev et al., 2010).

The present paper investigates the economic evaluation of power supply security using an estimate of customer's valuation of lost load. In Section 2, we explore the distinct energy markets of Texas and California, highlighting their regulatory frameworks and market structures. Section 3 presents our data sources and methodology, detailing the quantitative and qualitative approaches used to assess VoLL in relation to household characteristics. For this analysis, we rely on public datasets to serve as a proxy for the relations between electricity consumption, income levels, and

participation in energy assistance programs. Section 4 then presents a thorough examination of our findings about VoLL and its relationship with various socioeconomic factors in both states. Our main research hypothesis posits that consumers in California demonstrate a higher willingness to pay for reliable electricity due to the stability provided by CAISO's capacity-based approach. However, given the nature of both states, we also explore trends within each state to identify factors that influence customers' willingness to pay for electricity. Finally, Section 5 concludes with a discussion of our findings and their policy implications, considering how insights from this preliminary analysis can inform strategies for enhancing grid resilience and minimizing economic losses associated with power outages in California and Texas.

2. Context Setting

Before delving into a formal analysis, an understanding of electricity markets in California and Texas is necessary. While there may be variations in regulations within local municipalities within each state, this paper looks at each state as a holistic unit. The idea is that any strong trends present a direction for future research to explore in more detail. California operates under a hybrid electricity market model that combines regulated and deregulated elements, while Texas features a fully deregulated market, allowing consumers to select their electricity providers. This dichotomy provides a unique framework for analyzing how market design affects pricing, reliability, and consumer willingness to invest in reliable energy sources.

2.1. Market Structure and Providers

California's hybrid model has three major investor-owned utilities (IOUs)¹ that serve about 75% of the state's electricity demand. The rest is served by publicly owned utilities and community choice aggregators (DeVore, 2018). The market is also characterized by substantial regulatory oversight primarily through the California Independent System Operator (CAISO), which manages the grid and wholesale electricity markets. Additionally, the state's commitment to ambitious renewable energy targets has led to challenges in integrating intermittent resources while maintaining reliability, as evidenced by recent rolling blackouts (Borenstein & Bushnell, 2018). Furthermore, California's regulatory environment is known to have significant influence on market operations. Hence, due to limited competitive pressures on utilities, prices are generally higher for consumers (Hledik et al., 2019).

¹ The three IOUs are Pacific Gas & Electric, Southern California Edison, and San Diego Gas & Electric.

Texas, on the other hand, has a more extensive deregulated market. Approximately 85% of the Texas power market is deregulated, allowing most Texans to choose their energy provider (Hirs, 2021). Texas' deregulation process separated generation, transmission, and distribution functions to create competition in generation and retail while maintaining regulated monopolies for transmission and distribution (Omerhodzic, 2022). As of 2024, there are over 130 Retail Electric Providers (REPs) operating in Texas. This structure allows electricity prices to be driven by consumer choice by allowing room for adjustment due to fluctuations in commodity prices, particularly natural gas (Mackin et al., 2020). It is worth noting that the structure of Texas' electricity market may allow more flexibility for consumers, but it also poses threats and hence, there is a need for stronger accountability and measures to help curtail deceptive practices.

2.2. Consumer's Willingness to Pay

The contrasting market structures in California and Texas significantly influence consumer willingness to pay (WTP) for reliable electricity. In Texas, the deregulated market offers lower electricity prices, with consumers benefiting from a 32% decline in inflation-adjusted retail prices from 2008 to 2017 (DeVore, 2018). However, the abundance of choices among over 130 REPs as of 2024 requires consumers to carefully compare plans, which can be complex and time-consuming (Gexa Energy, 2013). This complexity may deter some consumers from fully optimizing their choices, potentially leading to higher costs or dissatisfaction. Alternatively, in California, higher electricity prices, averaging 19.90¢ per kWh (versus 11.36¢ per kWh in Texas) as of December 2024, reflect the regulatory constraints and ambitious renewable energy goals that shape the market. These higher costs may make consumers more risk-averse and willing to pay a premium for uninterrupted service and reliability. Additionally, California's hybrid market structure limits competitive pressures on utilities, further influencing WTP by reducing consumer choice.

Individual preferences also play a critical role. Risk-averse consumers in both states may prioritize reliability over cost savings, opting for plans or providers that guarantee uninterrupted service (Saad et al., 2016; Munoz et al., 2017; Stover et al., 2023). Conversely, cost-sensitive consumers in Texas may focus on finding the lowest price, even if it means accepting variability in service reliability (Newell et al., 2012). These contrasting market structures have significant implications for consumer willingness to pay for reliable electricity.

2.3. Environmental and Regulatory Considerations

Environmental concerns are increasingly shaping consumer attitudes toward electricity markets in both states. In California, ambitious renewable energy targets have led to a 40% renewables penetration rate as of 2024, supported by policies such as carbon pricing and Resource Adequacy (RA) requirements (Plautz, 2024; Prabhu et al., 2024). These initiatives encourage investment in clean energy solutions but also contribute to higher electricity rates due to compliance costs and the need for backup power sources during periods of renewable intermittency (DeVore, 2018).

In Texas, while the deregulated market has fostered significant growth in wind energy, making it the nation's leader in wind power generation, renewables penetration remains lower at 27% (Prabhu et al., 2024). The state's scarcity pricing mechanism incentivizes shorter-duration batteries and other solutions to address renewable intermittency but does not yet fully support longer-duration storage technologies necessary for grid stability (EPSA, 2021).

Consumers' willingness to pay for environmentally friendly energy varies by state. In California, where environmental policies are deeply integrated into the market structure, many consumers are willing to pay a premium for clean energy options due to strong environmental awareness and state mandates (EPSA, 2021). In Texas, while some consumers prioritize cost savings over environmental considerations, others are increasingly drawn to green energy plans offered by REPs as part of the competitive market landscape (Prabhu et al., 2024).

Additionally, regulatory frameworks also impact WTP. California's stringent environmental regulations drive up costs for utilities, which are passed on to consumers. In contrast, Texas's lighter regulatory approach keeps costs lower but places greater responsibility on consumers to navigate the complexities of the market effectively (Omerhodzic, 2022). Understanding these dynamics is crucial for designing policies that balance affordability, reliability, and environmental sustainability in both states.

Environmental concerns are also influencing factors in consumers' willingness to pay for reliable electricity. As renewable energy becomes increasingly integrated into the market, consumers may be inclined to support providers that invest in clean energy solutions even at a premium price. Policies such as renewable energy targets and carbon pricing are driving this shift, compelling consumers to consider not only reliability but also the environmental impact of their energy choices (Sullivan et al., 2021). Additionally, increased compliance costs associated with new

environmental regulations can lead utility companies to raise rates, thereby influencing consumer willingness to pay for reliable service amidst rising prices (Gillingham & Stock, 2018).

3. Data and Methodology

3.1. Data Sources

This study utilizes two primary data sources to analyze the Value of Lost Load (VoLL) and its implications for residential energy consumption in California and Texas:

1. **U.S. Energy Information Administration (EIA) State Energy Data System (SEDS):**

The EIA provides a comprehensive state-level dataset that includes estimates of energy production, consumption, prices, and expenditures broken down by energy source and sector. This dataset allows for annual comparisons across states and over time, making it a valuable resource for analyzing energy trends in the United States. Notably, the EIA collects this data through various surveys and reporting mechanisms, including the Monthly Energy Review, the Annual Energy Outlook, and specific surveys like the Residential Energy Consumption Survey (RECS).

2. **Residential Energy Consumption Survey (RECS) 2020:** Conducted by the EIA, the RECS dataset includes detailed information on residential energy consumption patterns, household demographics, and economic characteristics across various income levels. The survey captures responses from thousands of households across the United States, allowing for a robust analysis of energy usage and consumer behavior.

- The RECS collects data from a nationally representative sample of housing units, including household demographics, energy use patterns, and housing unit characteristics. The survey is conducted in two phases:
 - i. The first phase involves a cross-sectional household survey that collects energy-related characteristics and usage data.
 - ii. The second phase is through the Energy Supplier Survey (ESS), where corresponding energy suppliers are surveyed for billing data used by EIA to estimate energy consumption and expenditure.

3. **American Community Survey (ACS) 2018-2022:** The American Community Survey (ACS) 2018-2022 data is used to construct the Low-Income Energy Affordability Data (LEAD) tool, which provides insights into energy affordability for low-income households

across various geographic levels. A visual of energy burden bifurcated by area median income in both states is shown in Appendix A (see Figure A4) to highlight the percentage of gross household income spent on energy costs in both California and Texas.

4. **System Average Interruption Duration Index (SAIDI):** The SAIDI represents the average duration of power interruptions experienced by customers over a specified period. The EIA has published annual measures in minutes per year. For this study, SAIDI values for 2020 are utilized to extract the average number of hours power was disrupted in Texas and California. Specifically, Texas had an average outage duration of approximately 6.99 hours (419.4 minutes), while California experienced an average of 4.68 hours (280.7 minutes)².

3.2. Methodology

3.2.1. Preparation of Key Variables

The key variables used throughout the analysis are listed in Tables 2.1 and 2.2 below. SEDS data is used for a time series analysis of patterns in electricity consumption, price, and expenditure over the last decade. There is also a variable that measures total energy losses in the electrical system. Before analysis, we standardize these variables by taking the natural log. Variable descriptions are added in Appendix B.

Table 2.1a: Summary Statistics for Key Variables from SEDS

Variable	Obs	Mean	Std. Dev.	Min	Max
electricity_consumption	10	344655.1	99762.2	247250.0	475401.0
electricity_price	10	40.7	15.7	24.8	65.6
electricity_expenditure	10	42576.8	6685.9	35055.3	55917.7
electricity_losses	10	1557318.0	621396.3	932761.0	2196346.0

Table 2.1b: Summary Statistics for Key (Standardized) Variables from SEDS

Variable	Obs	Mean	Std. Dev.	Min	Max
ln_electricity_consumption	10	12.71	0.30	12.42	13.07
ln_electricity_price	10	3.64	0.39	3.21	4.18
ln_electricity_expenditure	10	10.65	0.15	10.46	10.93
ln_electricity_losses	10	14.18	0.42	13.75	14.60

² These values are based on the IEEE 1366-2003 or the IEEE 1366-2012 standard.

Table 2.2a: Summary Statistics for Key Variables from RECS – California

Variable	Obs	Mean	Std. Dev.	Min	Max
dollarel	1016	1596.54	884.97	0.00	12036.36
kwh	1016	13990.48	7825.35	42.01	104637.00
income_midpoint	1016	102229.30	65000.19	2500.00	200000.00
elec_rate	1016	0.12	0.02	0.00	0.25
hourly_wage	1016	11.67	7.42	0.29	22.83
saidi2020	1016	6.99	0.00	6.99	6.99
daily_kwh	1016	1.60	0.89	0.00	11.94
average_kwh_lost	1016	11.16	6.24	0.03	83.49
value_of_lost_load	1016	81.57	51.87	1.99	159.59
total_cost_of_outage	1016	82.85	52.10	2.16	169.19
has_child_under17	1016	0.33	0.47	0.00	1.00
has_adult_under65	1016	0.79	0.41	0.00	1.00
has_adult_over65	1016	0.38	0.48	0.00	1.00
has_solar	826	0.01	0.12	0.00	1.00
has_highschool	1016	0.94	0.23	0.00	1.00
has_college	1016	0.72	0.45	0.00	1.00
has_bachelors	1016	0.42	0.49	0.00	1.00
had_help	125	0.22	0.41	0.00	1.00
has_highceil	964	0.61	0.49	0.00	1.00
has_employment	1016	0.57	0.50	0.00	1.00
reduce_bill_once_or_more	1016	0.24	0.43	0.00	1.00
keep_unhealthy_temp	1016	0.10	0.29	0.00	1.00
disconnection_notice	1016	0.12	0.33	0.00	1.00
ln_totaldol	1016	7.41	0.53	3.63	9.40
ln_kwh	1,016	9.39	0.60	3.74	11.56
ln_sqft_en	1016	7.36	0.58	5.83	9.30

Table 2.2b: Summary Statistics for Key Variables from RECS – Texas

Variable	Obs	Mean	Std. Dev.	Min	Max
dollarel	1016	1596.54	884.97	0.00	12036.36
kwh	1016	13990.48	7825.35	42.01	104637.00
income_midpoint	1016	102229.30	65000.19	2500.00	200000.00
elec_rate	1016	0.12	0.02	0.00	0.25
hourly_wage	1016	11.67	7.42	0.29	22.83
saidi2020	1016	6.99	0.00	6.99	6.99
daily_kwh	1016	1.60	0.89	0.00	11.94
average_kwh_lost	1016	11.16	6.24	0.03	83.49
value_of_lost_load	1016	81.57	51.87	1.99	159.59
total_cost_of_outage	1016	82.85	52.10	2.16	169.19
has_child_under17	1016	0.33	0.47	0.00	1.00
has_adult_under65	1016	0.79	0.41	0.00	1.00
has_adult_over65	1016	0.38	0.48	0.00	1.00
has_solar	826	0.01	0.12	0.00	1.00
has_highschool	1016	0.94	0.23	0.00	1.00
has_college	1016	0.72	0.45	0.00	1.00
has_bachelors	1016	0.42	0.49	0.00	1.00
had_help	125	0.22	0.41	0.00	1.00
has_highceil	964	0.61	0.49	0.00	1.00
has_employment	1016	0.57	0.50	0.00	1.00
reduce_bill_once_or_more	1016	0.24	0.43	0.00	1.00
keep_unhealthy_temp	1016	0.10	0.29	0.00	1.00
disconnection_notice	1016	0.12	0.33	0.00	1.00
ln_totaldol	1016	7.41	0.53	3.63	9.40
ln_kwh	1,016	9.39	0.60	3.74	11.56
ln_sqft_en	1016	7.36	0.58	5.83	9.30

3.2.2. Understanding the Value of Lost Load

From a socioeconomic perspective, the value of lost load (VoLL) is an important indicator addressing the economic consequences of power blackouts and the monetary evaluation of uninterruptedness of power supply (Schröder & Kuckshinrichs, 2015). Typically, this estimate is

measured in dollars per megawatt-hour and serves as an estimation of the maximum electricity price customers are willing to pay to avoid an outage (SEM Committee, 2023). Schröder and Kuckshinrichs (2015) provide a comprehensive overview of the Value of Lost Load (VoLL) as an economic indicator that reflects the costs associated with electricity supply interruptions. The authors discuss several key methods for measuring VoLL, including consumer surveys, market-based approaches, production function approaches, cost of service approaches, and household income methods. They note that while the literature categorizes these techniques differently, a general distinction can be made between those that directly survey consumers for their experiences and those that utilize statistical data to infer costs. This distinction is crucial for understanding the methodologies used to estimate the Value of Lost Load (VoLL) and its implications for electricity reliability assessments. Direct methods gather information about the costs of power interruptions directly from end users, while indirect methods rely on external data sources, such as statistical analyses. This classification is supported by multiple studies dating back to the 1990s, including those by Caves et al. (1990), Woo and Pupp (1992), Sullivan and Keane (1995), Ajodhia (2006), and de Nooij et al. (2007).

This paper uses the household income approach to construct a measure of VoLL. Schröder and Kuckshinrichs (2015) emphasize that while various measurement methods exist, reliance on household income methods provides valuable insights into individual consumer experiences and economic realities during power interruptions. The idea is to quantify the value of lost leisure time and productivity during power outages, based on the premise that individuals derive utility not just from goods but also from time. In line with Becker's theory of valuing leisure in monetary terms this approach highlights how the reliability of power supply impacts overall well-being and economic activity (Becker, 1965; Gorman, 2022; Gorman & Callaway, 2024).

The approach of determining the interruption costs using household income is based on the logic of evaluating leisure in terms of money. The Agency for the Cooperation of Energy Regulators (ACER) emphasizes the importance of using survey data and macroeconomic analysis in VoLL calculations, which aligns with the use of RECS survey data in this paper (ACER, 2020; Schröder & Kuckshinrichs, 2015).

The London Economics International study for ERCOT (2013) emphasizes the importance of considering income levels in VoLL calculations, supporting our approach of segmenting by income categories. Additionally, we note that the RECS data has some limitations. Household income is a categorical variable. Schröder and Kuckshinrichs (2015) discuss challenges associated with using categorical income data in VoLL estimations and suggest using midpoints as a reasonable approximation.

3.2.3. Measuring the Value of Lost Load (VoLL)

In line with the literature above, the calculation of VoLL in this paper is as follows. The key variables include total electricity consumption (*kWh*), total electricity bills (*dollarel*), income midpoints (*moneyppy*), and state-specific data on power interruptions, specifically the System Average Interruption Duration Index (SAIDI) for 2020.

- Extract Key Variables (from RECS)
 - **Gross Household Income:** In line with Schröder & Kuckshinrichs (2015), the midpoint of RECS' categorical income is assumed to be a decent approximation.
 - **Annual Cost of Electricity:** Cost of electricity is determined by the household's total electricity bill (in dollars) for the year.
 - **Annual kWh Usage:** Total kilowatt-hours consumed for the year.

- Determine Hourly Wage

- Divide the annual household income by the total number of working hours.³

$$\text{Hourly wage} = \frac{\text{Gross household income (annual)}}{\text{Total working hours}}$$

- Estimate Value of Leisure

- According to Becker (1965), the value of leisure can be equated to the hourly wage.

Hence, we use the calculated hourly wage as a proxy for the value of an hour of leisure

- Determine Daily kWh Usage

$$\text{daily_kwh} = \frac{\text{Annual killowatt-hours of electricity}}{365}$$

³ Note that the caveat with using RECS data is that employment status of households is also a categorical variable. In the absence of accurate data on households, we assume that the average household income divided by the total number of hours in a year will give us a standard approximation for an hourly wage estimate. For future research, it is preferable to find a data source with the number of hours worked (or a reasonable estimate for each state).

- Evaluate Impact of Dsirutions (SAIDI)
 - For each hour of interruption, assume that there is a loss of leisure time or productivity. Therefore, we assume that any interruption lasting t hours, affects productivity and so, the VoLL is as follows

$$\text{Value of Lost Load} = t * \text{Hourly Wage}$$

Based on this calculation, the final statistic is our estimate of the economic value that households place on reliable electricity service, expressed in dollars per kilowatt-hour (\$/kWh). Tables 3.1 and 3.2 show how our estimates of consumer valuations (VoLL) varies by income levels between the two states, California and Texas.

Table 3.1: Value of Lost Load Estimates for Texas

Annual Gross Household Income	Min	Mean	Median	Max
Less than \$5,000	1.99	1.99	1.99	1.99
\$5,000 - \$7,499	5.98	5.98	5.98	5.98
\$7,500 - \$9,999	9.97	9.97	9.97	9.97
\$10,000 - \$12,49	13.96	13.96	13.96	13.96
\$12,500 - \$14,99	17.95	17.95	17.95	17.95
\$15,000 - \$19,99	21.94	21.94	21.94	21.94
\$20,000 - \$24,99	25.93	25.93	25.93	25.93
\$25,000 - \$29,99	29.92	29.92	29.92	29.92
\$30,000 - \$34,99	35.91	35.91	35.91	35.91
\$35,000 - \$39,99	43.89	43.89	43.89	43.89
\$40,000 - \$49,99	53.86	53.86	53.86	53.86
\$50,000 - \$59,99	69.82	69.82	69.82	69.82
\$60,000 - \$74,99	89.77	89.77	89.77	89.77
\$75,000 - \$99,99	109.72	109.72	109.72	109.72
\$100,000 - \$149,	139.64	139.64	139.64	139.64
\$150,000 or more	159.59	159.59	159.59	159.59
Total	1.99	76.03	69.82	159.59

The Value of Lost Load (VoLL) in Texas demonstrates a strong correlation with household income, ranging from \$1.99 per outage hour for the lowest income bracket to \$159.59 for the highest. The mean VoLL across all income groups is \$76.03 per outage hour, indicating a significant economic impact of power interruptions on Texas consumers. Notably, even middle-

income households (\$50,000 - \$59,999) value uninterrupted power at \$69.82 per outage hour, underscoring the importance of reliable electricity supply across various socioeconomic levels. The consistently high VoLL values, particularly for higher income brackets, suggest that Texans place a premium on avoiding power outages, possibly influenced by factors such as climate dependence on air conditioning and recent experiences with major grid failures.

Table 3.2: Value of Lost Load Estimates for California

Annual Gross Household Income	Min	Mean	Median	Max
Less than \$5,000	1.34	1.34	1.34	1.34
\$5,000 - \$7,499	4.01	4.01	4.01	4.01
\$7,500 - \$9,999	6.68	6.68	6.68	6.68
\$10,000 - \$12,49	9.35	9.35	9.35	9.35
\$12,500 - \$14,99	12.02	12.02	12.02	12.02
\$15,000 - \$19,99	14.69	14.69	14.69	14.69
\$20,000 - \$24,99	17.36	17.36	17.36	17.36
\$25,000 - \$29,99	20.03	20.03	20.03	20.03
\$30,000 - \$34,99	24.04	24.04	24.04	24.04
\$35,000 - \$39,99	29.38	29.38	29.38	29.38
\$40,000 - \$49,99	36.06	36.06	36.06	36.06
\$50,000 - \$59,99	46.75	46.75	46.75	46.75
\$60,000 - \$74,99	60.10	60.10	60.10	60.10
\$75,000 - \$99,99	73.46	73.46	73.46	73.46
\$100,000 - \$149,	93.49	93.49	93.49	93.49
\$150,000 or more	106.85	106.85	106.85	106.85
Total	1.34	59.02	60.10	106.85

California's VoLL analysis reveals a similar income-based trend, albeit with generally lower values compared to Texas. The VoLL ranges from \$1.34 per outage hour for the lowest income group to \$106.85 for the highest, with a mean of \$59.02 across all income levels. This lower average compared to Texas (\$59.02 vs \$76.03) suggests that Californians, while still valuing reliable power highly, may be somewhat less sensitive to outages or have different expectations of grid reliability. The VoLL for middle-income households (\$50,000 - \$59,999) in California is \$46.75 per outage hour, significantly lower than the corresponding group in Texas. This disparity

could reflect differences in energy consumption patterns, climate-related needs, or overall grid reliability perceptions between the two states.

3.2.4. Analyzing the Value of Lost Load (VoLL)

For all additional analyses, the paper looks at simple linear regressions. The initial model investigates whether electricity consumption (in kilowatt-hours) is a significant predictor of VoLL.

- **Model 1:**

$$[\text{Value of Lost Load}] = \beta_0 + \beta_1[\text{kilowatt} - \text{hours used}] + \epsilon_0$$

- **Model 2:**

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon_0$$

where $X_1 = \text{kilowatt} - \text{hours used}$ and $X_2 = \text{vector of demographic variables}$

- **Model 3** includes financial assistance variables⁴
- **Model 4** includes additional variables on household energy efficiency measures⁶
- **Model 5** goes further to add additional household characteristics⁶

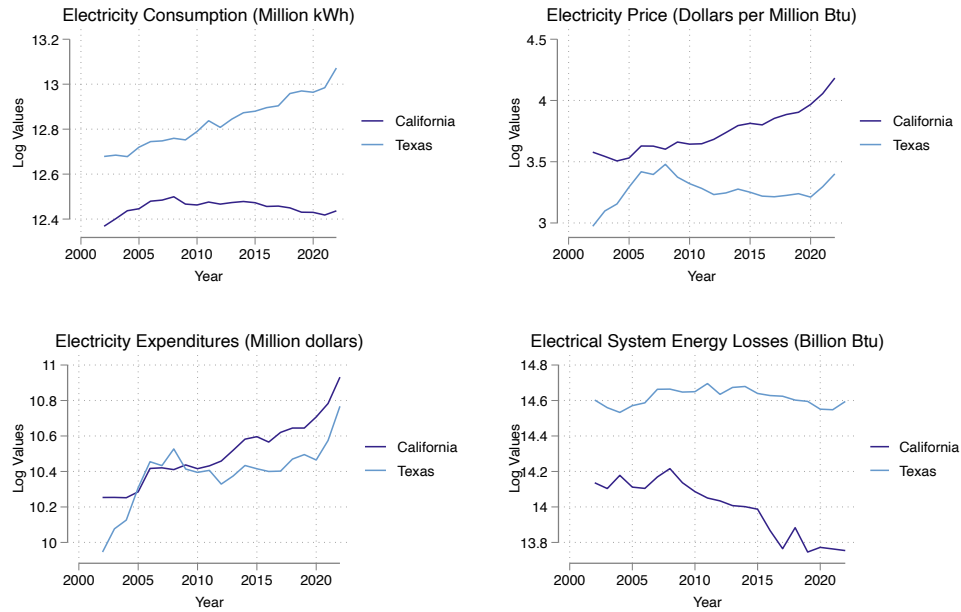
4. Analysis

4.1. Comparison of Electricity Markets

Figure 4.1.1 below shows the general trend of electricity consumption, price, and expenditures.. The trends observed in this data reveal distinct patterns in the electricity markets of California and Texas, reflecting their different regulatory approaches. California, with its hybrid market structure, shows more dynamic changes across various metrics. Notably, estimated demand and estimated value in California are both on an upward trajectory, indicating growing electricity consumption and increasing market valuations. However, California also exhibits a declining trend in lot characteristics, which could suggest changes in land use or property configurations related to energy infrastructure. Interestingly, estimated expenditure in California remains relatively stable over the period, possibly indicating that the hybrid market structure is moderating price fluctuations despite increasing demand.

⁴ A full list of variables is given in Appendix B and regression results are shown in Appendix C

Figure 4.1.1: Comparison of Electricity Markets in California and Texas



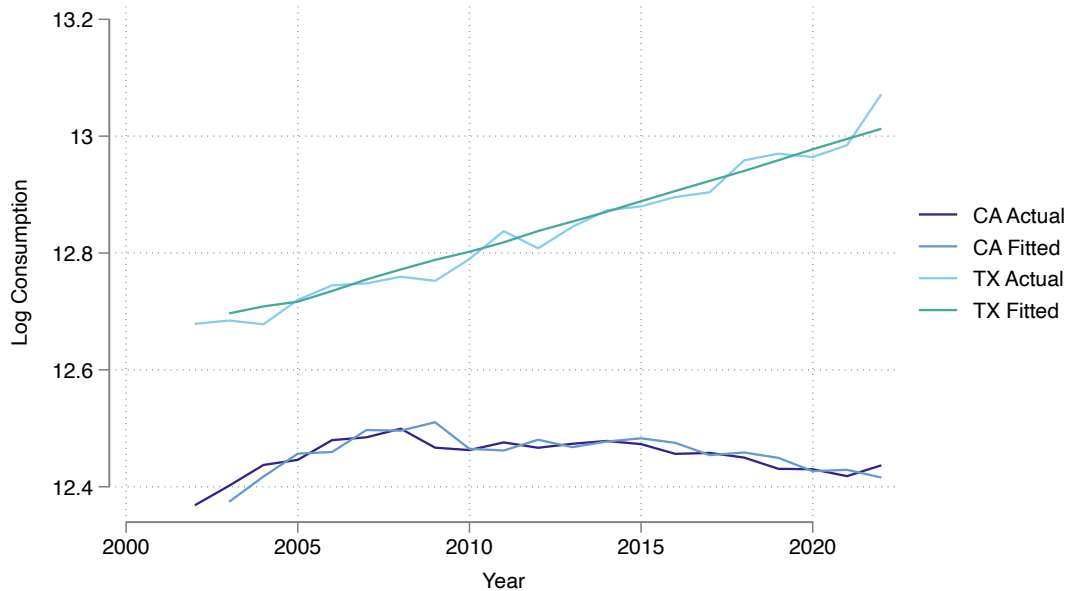
On the other hand, Texas, with its fully deregulated market structure, displays more stability in most metrics, aligning with the expected outcomes of a market-driven system. The most notable trend in Texas is the increase in estimated expenditure, which could reflect the competitive nature of the deregulated market where providers may be adjusting pricing strategies or offering new services. Estimated value in Texas is also increasing, though less sharply than in California, while estimated demand and lot characteristics remain relatively stable. This overall stability in Texas might indicate that the deregulated market is responding to changes in demand and value through price mechanisms, without significant shifts in consumption patterns or infrastructure characteristics.

To further validate the trends, Autoregressive Integrated Moving Average (ARIMA) models are commonly employed for time series forecasting and analysis of economic and energy data. The ARIMA(1,1,1) specification indicates the use of one autoregressive term, one differencing term, and one moving average term. We use the following steps for consumption. The results are visualized in Figure 4.1.2 below.

- Fitting separate ARIMA(1,1,1) models to the logged values of electricity consumption for California and Texas.
- Generating fitted values from these models to predict consumption trends.

- Creating a time series plot comparing actual and fitted log consumption values.

Figure 4.1.2: Comparison of Electricity Consumption in California and Texas

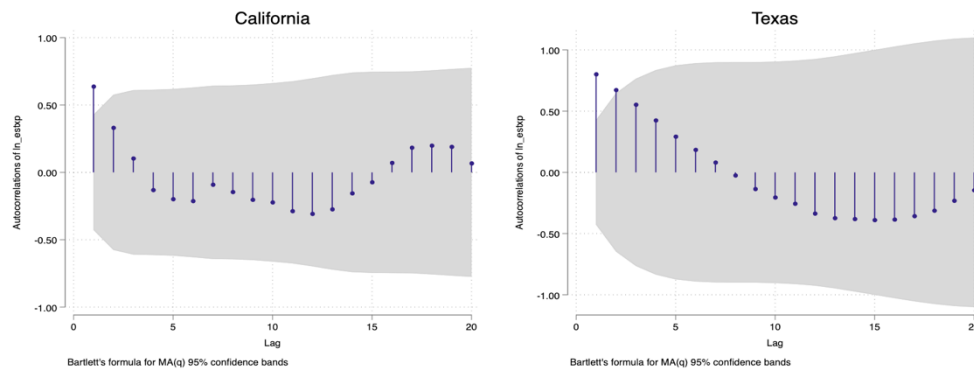


Fitted lines represent ARIMA(1,1,1) model predictions
Source: EIA State Energy Data System.

The resulting visualization shows that the ARIMA(1,1,1) model fit closely tracks the actual electricity consumption patterns for both California and Texas. This close alignment between the fitted and actual values indicates that the model effectively captures the underlying trends and dynamics of electricity consumption in both states. Finally, we look at correlograms for consumption, price, and expenditure to ensure that there is no autocorrelation. The correlograms for all three variables - consumption, price, and expenditure - show that the residuals exhibit no significant autocorrelation (see Figure 4.2).

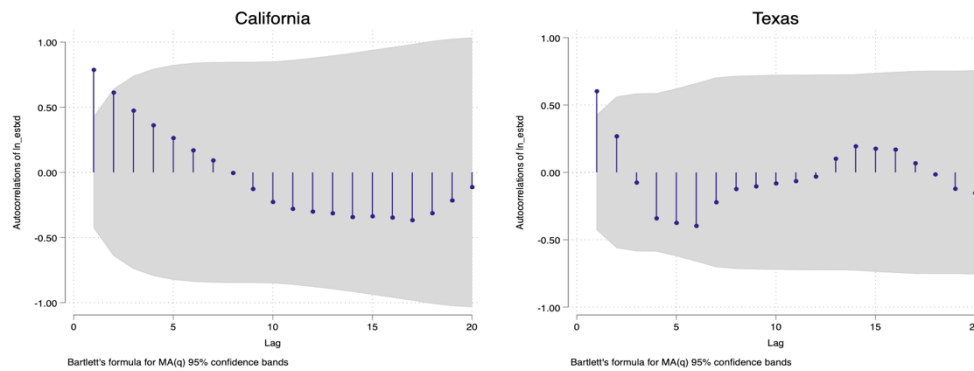
Figure 4.2: Correlograms for consumption, price, and expenditure

Correlograms for Log Electricity Consumption
California and Texas, 2002-2022



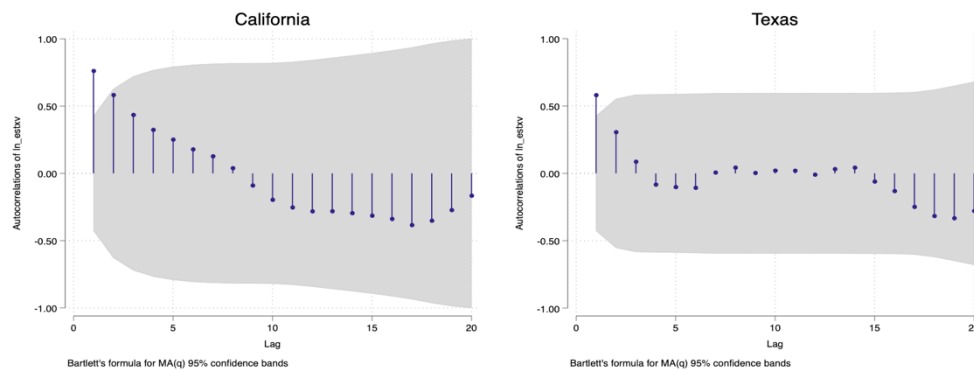
AC: Autocorrelation

Correlograms for Log Electricity Price
California and Texas, 2002-2022



AC: Autocorrelation

Correlograms for Log Electricity Expenditure
California and Texas, 2002-2022



AC: Autocorrelation

4.2. Willingness to Pay Analysis

The regression results, presented in Appendix C, provide insights into the determinants of the Value of Lost Load (VoLL) for California and Texas. In addition to linear regression, a robust regression was conducted to address potential heteroscedasticity and ensure the reliability of the results. While these models offer valuable findings, future research could enhance explanatory power by integrating data from the American Housing Survey and other comprehensive datasets. The following subsections detail the results and key insights for California and Texas, highlighting the distinct factors influencing VoLL in each state.

- **California**

The regression analyses for California reveal several important insights about the factors influencing the Value of Lost Load (VoLL). In the simplest model, we observe a significant positive relationship between electricity consumption (\ln_kwh) and VoLL. For a 1% increase in electricity consumption (kWh), the Value of Lost Load (VoLL) is expected to increase by approximately 0.15 units. This indicates that households that consume more electricity tend to place a higher value on uninterrupted power supply. This positive relationship aligns with economic theory, as larger consumers of electricity are likely to experience greater economic losses during power outages. For instance, a consumer with high electricity consumption might face significant productivity losses or potential damage to equipment during an interruption, thus valuing reliability more highly (Bentham et al., 2022; Frayer, 2013).

It is important to note that this relationship is logarithmic, meaning the absolute increase in VoLL diminishes as consumption increases. While higher consumers value reliability more, there may be a point of diminishing returns in terms of the “perceived” value of uninterrupted supply.

When incorporating demographic variables, we find that employment status has a substantial impact on VoLL. Households with employed members have a VoLL that is \$22.96 higher on average, indicating that working individuals place a greater value on reliable electricity, possibly due to the potential for lost productivity during outages. Interestingly, the presence of children under 17 does not significantly affect VoLL. The full model (model 5), which includes additional variables, shows that the presence of adults under 65 increases VoLL by \$24.09, while other factors like solar panel ownership and energy assistance programs do not have statistically significant effects.

The final model (model5) provides a nuanced picture of VoLL determinants. It reveals that larger homes (as measured by *ln_sqft_en*) are associated with higher VoLL, with each unit increase in log square footage corresponding to a \$14.78 increase in VoLL. Employment remains a strong positive factor. Notably, energy assistance program participation is associated with a substantial decrease in VoLL (-\$29.94), suggesting that households receiving aid may be less sensitive to outages or have lower overall electricity dependence. Factors such as keeping unhealthy temperatures to save on energy bills and receiving disconnection notices are also associated with lower VoLL, possibly indicating that these households prioritize cost savings over uninterrupted service. These findings highlight the complex interplay of economic, demographic, and behavioral factors in determining the value Californians place on reliable electricity supply.

- **Texas**

The results from the regression analyses for Texas provide valuable insights into the factors influencing the Value of Lost Load (VoLL) among households. In the simplest model, we observe a significant positive relationship between electricity consumption (*ln_kwh*) and VoLL, with a coefficient of 28.23538. This means that for a 1% increase in electricity consumption, the VoLL is expected to increase by approximately 0.2824 units. This indicates that households that consume more electricity tend to place a higher value on uninterrupted power supply, reflecting the greater economic impact they would face during outages.

Incorporating demographic variables reveals further nuances in VoLL determinants. The presence of employed individuals in a household significantly increases VoLL by \$26.24, suggesting that working households value reliable electricity more highly due to the potential for lost productivity during outages. Conversely, having children under 17 does not show a significant effect on VoLL, indicating that other factors may play a more critical role in determining how much value households place on reliable electricity.

The most comprehensive model (model5) highlights several additional factors influencing VoLL in Texas. A notable finding is that larger homes (as measured by *ln_sqft_en*) are associated with higher VoLL, with each 1% increase in square footage corresponding to an increase of approximately \$16.16 in VoLL. Employment remains a strong positive factor, reinforcing the idea that working households prioritize reliable electricity supply. Interestingly, participation in energy assistance programs is linked to a substantial decrease in VoLL (-\$31.50), suggesting that households receiving aid may have different priorities or lower overall dependence on electricity.

reliability. These findings underscore the complex interplay of economic and demographic factors in shaping how Texas households value uninterrupted electricity service.

5. Practical Implications of VoLL Estimates

Texas's VoLL figures reflect the state's unique market dynamics and consumer expectations regarding electricity reliability. The recent emphasis on establishing a regulatory estimate of VoLL highlights the need for better visibility into consumer valuation of electric reliability as Texas continues to enhance its grid infrastructure following past challenges. The PUCT's analysis revealed that small commercial and industrial customers often have disproportionately high VoLL values relative to their energy consumption, necessitating careful consideration when assessing overall reliability needs.

California's VoLL figures are influenced by the state's frequent power outages due to extreme weather events and its transition towards renewable energy sources. As the state grapples with climate change impacts, consumers are increasingly aware of the economic implications of outages. This awareness is further emphasized by recent studies indicating that California's VoLL estimates should be tailored to account for regional factors such as outage duration and consumer reliance on electricity for critical needs. Overall, the data underscores the importance of understanding consumer perspectives in shaping energy policy and ensuring grid reliability.

The comparison between California and Texas reveals striking differences in how consumers value lost electricity, reflective of broader trends in energy policy and consumer behavior even before significant events like Winter Storm Uri occurred in Texas. California's higher VoLL values indicate a more acute awareness among consumers regarding the economic implications of power outages, driven by frequent outages related to wildfires and extreme weather conditions. In contrast, while Texas has established a higher overall VoLL compared to its previous estimates, many households still exhibit lower valuations on average across most income categories.

Both states demonstrate a clear correlation between income levels and VoLL. However, California's figures are consistently higher across all categories, suggesting that Californians are more likely to prioritize electricity reliability in their economic assessments. As both states navigate ongoing challenges related to grid stability and energy policy reforms, California focusing on renewable integration and Texas addressing regulatory changes, the understanding of consumer perspectives on VoLL will be crucial for shaping effective energy policies that enhance grid reliability and address diverse consumer needs effectively.

6. Conclusion

The comparison of California and Texas reveals slightly contrasting dynamics in electricity consumption, expenditures, and consumer valuations, shaped by their distinct market structures and policy approaches. California demonstrates an upward trajectory in electricity demand and expenditures, highlighting the growing importance of reliable electricity amidst challenges like climate change and renewable integration. This is complemented by higher VoLL estimates which potentially reflect heightened consumer awareness of the economic and societal impacts of outages, further emphasized by the state's vulnerability to extreme weather events and frequent outages.

In contrast, Texas' fully deregulated market showcases some stability in consumption and expenditures, but with a notable increase in VoLL, particularly among small commercial and industrial consumers. This indicates a shift (or room for a shift) in consumer priorities. Considering the limitations of this data and the fact that significant grid events like Winter Storm Uri occurred after the RECS dataset was compiled, these findings seem crucial. However, lower VoLL valuations among Texas households suggest that while reliability of electricity may be valued, consumer expectations may differ due to historical grid performance and pricing dynamics. There could be some effects based on local REPs and the type of plans available in local cities or municipalities within Texas.

However, these preliminary results from both states underline the critical role of income, employment, and certain household characteristics in shaping VoLL. Further, energy assistance programs in both states emerge as a significant factor in moderating VoLL, underscoring the need for equitable energy policies that account for varying consumer capacities and expectations. As California and Texas continue to reform their energy policies, especially with the transition of the government in the next few months, understanding consumer perspectives on VoLL will remain pivotal. Policymakers must balance reliability, affordability, and equity to ensure that grid enhancements align with diverse consumer needs while fostering resilience against future challenges.

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Appendix A: Electricity Markets in California and Texas

Figure A1: Net generation of electricity by source in California (million megawatt-hours)

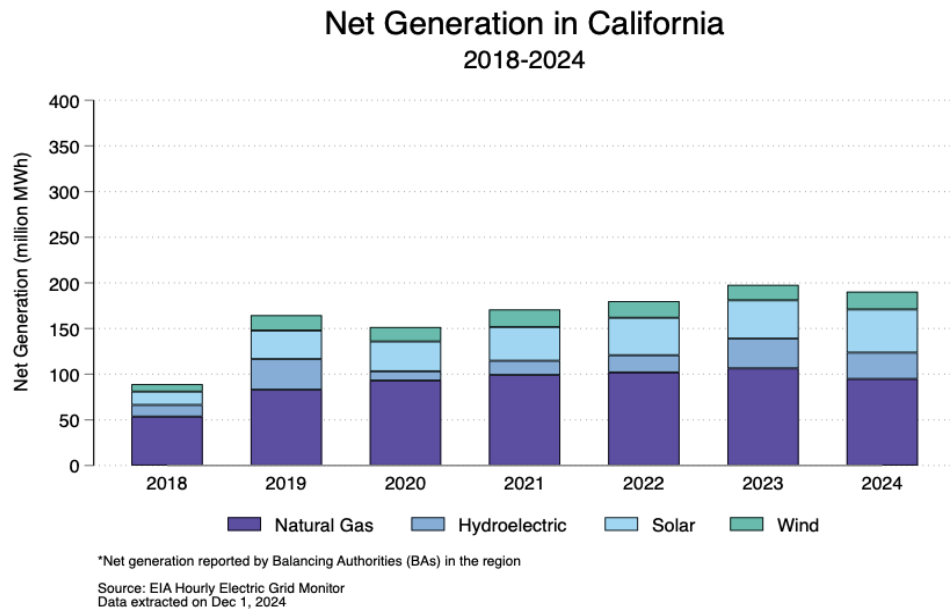


Figure A2: Net generation of electricity by source in Texas (million megawatt-hours)

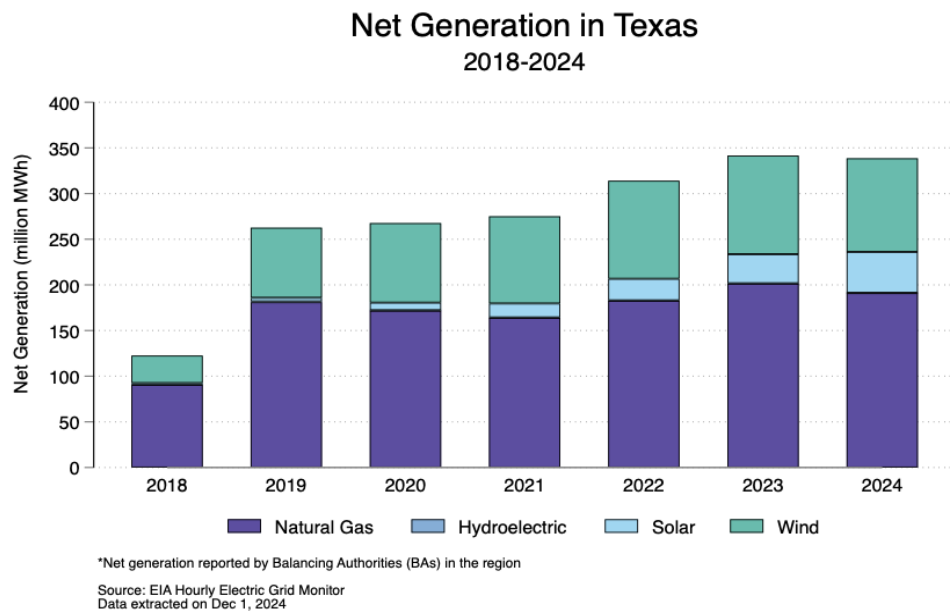


Figure A3: Electricity demand, generation and consumption in Texas vs. California (million mWh)

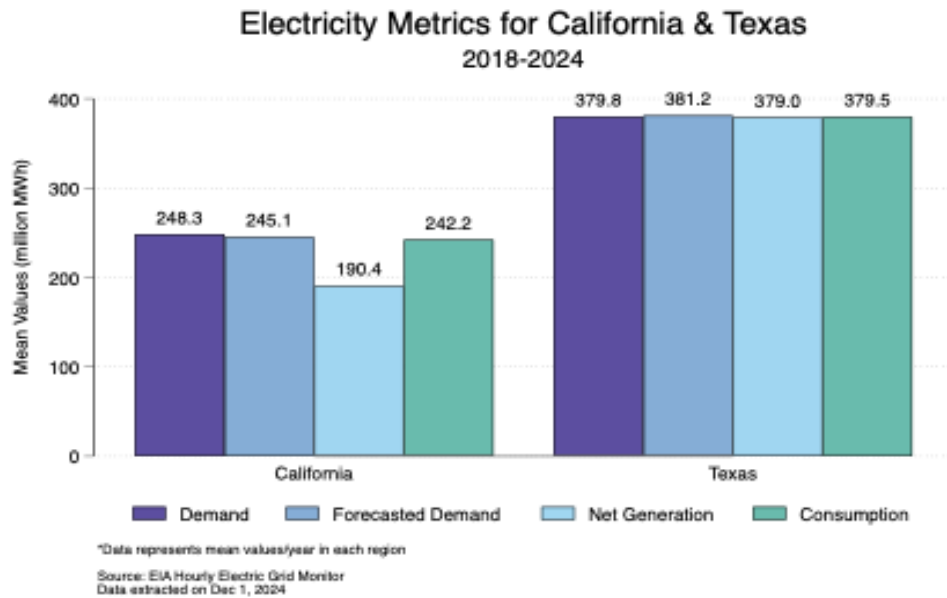
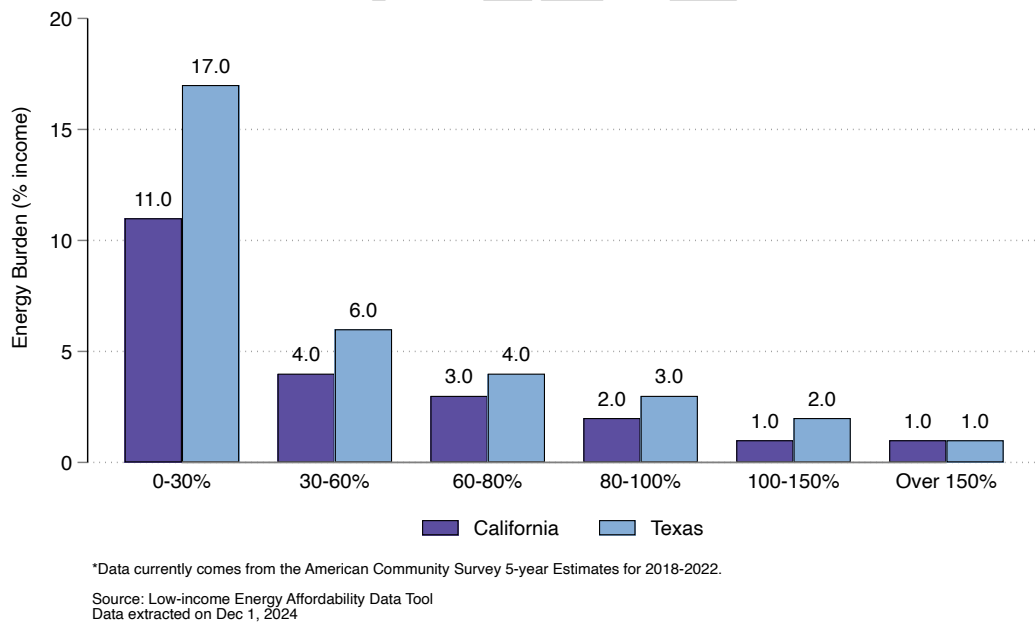


Figure A4: Energy Burden as a percentage of household income (2018-2022)



Note: In the LEAD assessment energy tool, **energy burden** is defined as the percentage of gross household income spent on energy costs. It is calculated by dividing the average annual housing energy cost by the average annual household income. Generally, a household with an energy burden $\geq 6\%$ is a high energy burden household.

Appendix B: Description of Key Variables

Variable Name	Description	Source
ln_electricity_consumption	Natural log of total end-use electricity consumption (in million kWh)	SEDS
ln_electricity_price	Natural log of average price of electricity (in dollars per million Btu)	SEDS
ln_electricity_expenditure	Natural log of total expenditures on electricity (in million dollars)	SEDS
ln_electricity_losses	Natural log of total electrical system energy losses (in billion Btu)	SEDS
dollarel	Total electricity bill	RECS
kwh	Total electricity consumption (in kWh)	RECS
moneyyp	Household income category (coded)	RECS
income_midpoint	Midpoint of household income category	RECS
elec_rate	Average electricity rate (dollars per kWh)	RECS
hourly_wage	Hourly wage calculated from income midpoint	RECS
has_child_under17	Indicator for households with children under 17	RECS
has_adult_under65	Indicator for households with adults under 65	RECS
has_adult_over65	Indicator for households with adults over 65	RECS
has_solar	Indicator for households with solar panels	RECS
has_highschool	Indicator for households with at least a high school education	RECS
has_college	Indicator for households with at least some college education	RECS
has_bachelors	Indicator for households with a bachelor's degree	RECS
had_help	Indicator for households that received financial assistance	RECS
has_highceil	Indicator for households with high ceilings	RECS
has_employment	Indicator for employment status of household members	RECS
reduce_bill_once_or_more	Indicator for households that have reduced their bill at least once	RECS
keep_unhealthy_temp	Indicator for households keeping unhealthy temperatures	RECS
disconnection_notice	Indicator for households that received a disconnection notice	RECS
saidi2020	System Average Interruption Duration Index for 2020 (in hours)	EIA Website
ln_totaldol	Natural logarithm of total dollars spent on electricity	Constructed from RECS
ln_kwh	Natural logarithm of total kWh consumed	Constructed from RECS
ln_sqft_en	Natural logarithm of total square footage of the household	Constructed from RECS
daily_kwh	Daily electricity consumption (kWh)	Constructed from RECS
average_kwh_lost	Average kWh lost during power outages	Constructed from RECS
value_of_lost_load	Value of Lost Load (VoLL)	Constructed from RECS
cost_per_kwh	Cost of electricity per kWh	Constructed from RECS
total_cost_of_outage	Total cost of an outage	Constructed from RECS

Appendix C: Regression Results

Table C1: OLS Results for California

	(1)	(2)	(3)	(4)	(5)
	value_of_lost_load	value_of_lost_load	value_of_lost_load	value_of_lost_load	value_of_lost_load
ln_kwh	15.04*** (1.55)	14.69*** (1.488)	14.55* (5.882)	11.82 (8.169)	5.178** (1.878)
Demographics					
has_child_under17		-1.406 (2.114)		-5.758 (10.99)	2.268 (2.319)
has_adult_under65				24.09* (11.51)	6.662* (3.094)
has_adult_over65					-5.653* (2.628)
has_employment		22.96*** (1.936)			14.62*** (2.282)
Required Financial Assistance					
had_help			-15.23 (8.258)	-15.29 (9.367)	
energy_asst			-1.929 (9.296)	-3.744 (12.85)	-29.94*** (3.644)
reduce_bill_once_or_more			-19.24* (7.437)		
keep_unhealthy_temp					-15.97*** (3.089)
disconnection_notice					-15.14*** (4.376)
Energy Efficient/Household Characteristics					
has_solar				2.338 (10.28)	3.638 (2.971)
backup					9.003** (3.375)
powerout					-0.801 (2.647)
has_highceil					1.646 (2.098)
ln_sqft_en					14.78*** (2.283)
Constant	-67.37*** (13.42)	-76.96*** (12.82)	-65.19 (50.85)	-71.73 (65.52)	-95.87*** (19.34)
R-squared	0.0757	0.179	0.196	0.149	0.329
F-statistic	94.16	83.16	4.017	3.714	31.06

Standard errors in parentheses

*Note that these regressions use a robust specification.

Table C2: OLS Results for California, Robust

	(1)	(2)	(3)	(4)	(5)
	value_of_lost_load	value_of_lost_load	value_of_lost_load	value_of_lost_load	value_of_lost_load
ln_kwh	15.04*** (1.55)	14.69*** (1.527)	14.55* (5.717)	11.82 (8.169)	5.178** (1.87)
Demographics					
has_child_under17		-1.406 (2.205)		-5.758 (10.99)	2.268 (2.352)
has_adult_under65				24.09* (11.51)	6.662* (2.931)
has_adult_over65					-5.653* (2.646)
has_employment		22.96*** (1.95)			14.62*** (2.289)
Required Financial Assistance					
had_help			-15.23* (7.597)	-15.29 (9.367)	
energy_asst			-1.929 (7.318)	-3.744 (12.85)	-29.94*** (3.072)
reduce_bill_once_or_more			-19.24* (8.277)		
keep_unhealthy_temp					-15.97*** (3.382)
disconnection_notice					-15.14** (4.969)
Energy Efficient/Household Characteristics					
has_solar				2.338 (10.28)	3.638 (2.73)
backup					9.003** (3.227)
powerout					-0.801 (2.626)
has_highceil					1.646 (2.12)
ln_sqft_en					14.78*** (2.337)
Constant	-67.37*** (13.44)	-76.96*** (13.04)	-65.19 (49.77)	-71.73 (65.52)	-95.87*** (19.24)
R-squared	0.0757	0.179	0.196	0.149	0.329
F-statistic	94.15	88.99	3.887	3.714	46.89

Standard errors in parentheses

*Note that these regressions use a robust specification.

Table C3: OLS Results for Texas

	(1)	(2)	(3)	(4)	(5)
	value_of_lost_load	value_of_lost_load	value_of_lost_load	value_of_lost_load	value_of_lost_load
ln_kwh	28.24*** (2.556)	27.44*** (2.503)	25.43*** (5.671)	26.62*** (7.106)	16.16*** (3.226)
Demographics					
has_child_under17		-1.538 (3.315)		12.76 (8.188)	3.085 (3.378)
has_adult_under65				3.757 (16.23)	-0.00332 (4.624)
has_adult_over65					-14.19*** (4.005)
has_employment		26.24*** (3.11)			19.67*** (3.393)
Required Financial Assistance					
had_help			-13.61 (9.705)	-13.99 (11.38)	
energy_asst			-14.24 (13.51)	-25.18* (10.59)	-31.50*** (8.957)
reduce_bill_once_or_more			-19.35* (7.649)		
keep_unhealthy_temp					-12.06* (5.371)
disconnection_notice					-21.83*** (4.789)
Energy Efficient/Household Characteristics					
has_solar					15.52 (11.44)
backup					5.483 (4.995)
powerout					-3.911 (3.723)
has_highceil					14.01*** (3.144)
ln_sqft_en					32.07*** (3.195)
Constant	-183.7*** (24.06)	-190.7*** (23.45)	-168.0** (54.26)	-201.5** (68.06)	-315.5*** (29.13)
R-squared	0.107	0.168	0.247	0.196	0.413
F-statistic	122.1	68.34	9.865	8.261	41.19

Standard errors in parentheses

*Note that these regressions use a robust specification.

Table C4: OLS Results for Texas, Robust

	(1)	(2)	(3)	(4)	(5)
	value_of_lost_load	value_of_lost_load	value_of_lost_load	value_of_lost_load	value_of_lost_load
ln_kwh	28.24*** (4.207)	27.44*** (4.028)	25.43*** (4.747)	26.62*** (7.106)	16.16*** (3.129)
Demographics					
has_child_under17		-1.538 (3.381)		12.76 (8.188)	3.085 (3.25)
has_adult_under65				3.757 (16.23)	-0.00332 (4.602)
has_adult_over65					-14.19*** (4.051)
has_employment		26.24*** (3.131)			19.67*** (3.635)
Required Financial Assistance					
had_help			-13.61 (8.489)	-13.99 (11.38)	
energy_asst			-14.24 (7.836)	-25.18* (10.59)	-31.50*** (7.383)
reduce_bill_once_or_more			-19.35* (8.22)		
keep_unhealthy_temp					-12.06* (5.458)
disconnection_notice					-21.83*** (4.383)
Energy Efficient/Household Characteristics					
has_solar					15.52 (11.34)
backup					5.483 (4.806)
powerout					-3.911 (3.828)
has_highceil					14.01*** (3.329)
ln_sqft_en					32.07*** (3.23)
Constant	-183.7*** (39.69)	-190.7*** (37.55)	-168.0*** (43.88)	-201.5** (68.06)	-315.5*** (26.93)
R-squared	0.107	0.168	0.247	0.196	0.413
F-statistic	45.04	51.41	14.72	8.261	66.1

Standard errors in parentheses

*Note that these regressions use a robust specification.