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To What Degree do Retail Electricity Prices Inform Residential Solar Energy Investment Decisions?

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Abstract: The relationship between electricity price and household solar photovoltaic (PV) adoption has not been thoroughly studied. How much would a carbon tax, and increase in electricity price, spur growth in residential solar? This paper adds to the literature with a utility-level panel analysis. Consumer choice provides the framework for the empirical models. I use electricity price and net metered solar PV capacity data from the Energy Information Administration (EIA). Through a variety of specifications, I control for both utility and state-year effects. My findings suggest that electricity price is significantly positively correlated with solar adoption, with an estimated price elasticity of 1.85. These results are limited by endogeneity bias.

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I. Introduction

Over the last decade, solar photovoltaic (PV) installations grew 40 to 60% annually (SEIA and GTM 2016). This growth is expected to continue as the U.S. Department of Energy (2016) projects rooftop solar could power up to 39% of U.S. electricity. Compared to grid-level solar, distributed solar, or residential PV systems, expand community energy sovereignty and allow households to get off the grid and know from where their electricity is generated. Rapidly falling solar prices and new renewable energy incentives have made residential solar PV a more affordable option for the average household. But in a possible future with fewer policy incentives, it is important for policymakers and economists to understand what other factors drive demand for solar PV and what are the best ways to incentivize investments? We can look at the alternative cost of solar, electricity prices, which are expected to rise due to decommissioning coal, renewable mandates, and unpredictable natural gas price trends, in the case of California (Vartabedian 2014). To what extent do *electricity prices* inform and incentivize residential solar energy investments? From a policy perspective, how much would a carbon tax, and subsequent increase in electricity price, spur growth in residential solar energy investments? This paper empirically analyzes these questions.

The literature examines a wide range of factors that influence residential solar energy demand. First, the upfront cost of the solar PV system is critical to the household's investment decision. Solar panel prices have dropped 63% since 2011 due to increased competition in the U.S. market, technological improvements, and growth in Chinese silicon-based solar panel manufacturing (SEIA and GTM 2016). Across the U.S. solar prices vary; greater installer density decreases solar prices, while higher consumer value of solar increases solar prices (Gillingham et al. 2016). Federal and state incentive programs, like subsidies and tax credits, significantly reduce the upfront cost of solar PV, directly affecting household investment decisions and making residential solar economically efficient (Borenstein 2015). Sarzynski et al. (2012) find that states with renewable portfolio standards, or clean energy goals and strategies, have 95% higher solar adoption rates than those without; and, states with cash incentives have 248% higher solar deployment than those without.

Another program that reduces costs and incentivizes household solar investment is net metering. With these programs, households connect their solar PV systems to the grid, and receive compensation for the excess electricity generated and transmitted to that grid. States either mandate all utilities to offer these programs, do not mandate at all, or enact red tape policies like extra charges or system size caps that limit the maximum value of program benefits for the household. The literature does not find much influence of net metering *policy* in adoption rates (Sarzynski et al. 2012, DOE 2014), but net metering programs do increase returns on investment. In one study, 1/3 of the electricity generated in the sample was not consumed by the generators but flowed to the grid, so the returns on net metering are potentially influential (Borenstein 2015). These returns are directly related to electricity prices, as the household is compensated at a similar or equivalent rate. Thus, with higher electricity prices net metering compensation and overall benefits increase over the life of the solar PV investment.

Wealthier households may have greater rates of adoption, as they can cover the upfront cost (Borenstein 2015), but other authors find no effects of household income on adoption (Durham et al. 1988), and others identify weak correlation between income and adoption (DOE 2014). Other state-level demographic characteristics, including number of household residents and education, are significantly influential in solar adoption (Durham et al. 1988), with education presumably increasing the knowledge and awareness required to determine the benefits of investment.

The "energy efficiency paradox" is the observed phenomenon that energy-efficient investments with high rates of return, like solar PV, are routinely passed by investors.[1] This occurs due to lack of financial support or credit, perceived technological risk, transaction costs, information asymmetry, and above all, high discount rates (Alberini et al. 2013, Qiu et al. 2014, Faiers & Naeme 2006). In the presence of uncertainty, households value the high upfront cost more heavily than the slowly accumulating benefits in the future. Bauner & Crago (2015) find that in order to trigger household investment, discounted benefits must exceed investment costs by 60%. Hassett & Metcalf (1993) also find a high hurdle rate, or minimum savings, before investment in solar energy is profitable. The authors claim that policies geared to reduce initial investment costs, such as subsidies or a federal investment tax credit, must be matched with policies to increase benefits, such as taxes on energy consumption and electricity to raise costs of the alternative. Carbon taxes, for example, increase electricity prices, which raise the benefits of the solar panel over the lifetime of the investment, and encourage a household to invest. To examine the benefits of such a policy, we would need to know the extent to which changes in electricity price inform a household's investment decision.

[1] In another area of the literature, authors study household willingness to pay for renewable energy sources through premiums in their electricity bill. Authors find that these options are not significantly valued by consumers, with the exception of solar and locally generated power premiums (Gracia et al. 2012). Survey results suggest consumers value air emissions reductions and renewable energy, but this value is difficult to quantify (Roe et al. 2001).

Few papers examine how perceptions of electricity price and changes in price affect investment in residential solar.[2] According to panel data analysis (Sarzynski et al. 2012) and cross-sectional analysis (DOE 2014), states with higher electricity prices have higher rates of solar adoption. Durham et al. (1988) find that a 1% increase in conventional energy prices increases probability of solar water heater adoption by 1.28%, of significance comparable to tax credits. In a study of state financial incentives, Sarzynski et al. (2012) estimate that a 1% increase in electricity price increases grid-tied solar capacity by 2.27%. Chan et al. (2016) exploit the natural case study of an exogenous electricity price shock to measure household response in solar adoption. Nuclear power, which comprised 11% of Japan's energy production in 2011, dropped to zero following the Fukushima nuclear disaster, causing 70% of companies to raise prices 20 to 30%. The authors find a one yen/kWh (equivalent to less than $0.01/kWh) increase, or 4% of observed electricity price, leads to 7900 more residential solar installations; this is about equal to a 39.5 MW increase in solar capacity per $0.01 increase in electricity price. They estimate a price elasticity, of 1.4 to 1.97, or a 1% increase in price yields a 1.4% to 1.97% increase in solar capacity, compared to Sarzynski et al. (2012) estimate of 2.03 to 2.27. Finally, Kwan (2012) analyzes the spatial distribution of solar PV arrays with a zip code level cross-section. The author observes a 21.7% increase in residential solar PV share (%) for every $1.00 increase in the price of electricity.

[2] Economists have, however, studied the degree to which households change their electricity consumption in response to changes in price. Alberini et al. (2011) estimate price elasticities over a ten-year period and find a nationwide -0.67 to -0.86 elasticity, a weak demand response to price of electricity in short and long term. Many authors find low price elasticities of demand for electricity ranging in the short-term of -0.21 and long-term of -0.61 (Labandeira et al. 2017), and one author identifies an even lower elasticity of -0.029, when estimating real-time price elasticities (Lijeson 2006). Wolak (2011) tests three dynamic pricing models: hourly pricing with a demand warning, critical peak pricing (CPP) with the same high price for 4 to 6 hours, and CPP with a rebate. The author finds that consumers show sizable demand reductions and react similarly to all three pricing schemes.

These papers have a number of shortcomings. The effect of electricity prices is only the focus of one author's empirical analysis (Chan et al. 2016), while others study electricity price as a control variable in a broader analysis. Thus, their model specifications and observation levels for analysis are not ideal for studying the influence of electricity prices. Cross-sectional analyses (DOE 2014, Kwan 2012) fail to account for differences in adoption across time. Second, studies that observe data at the state level (DOE 2014, Sarzynski et al. 2012) fail to incorporate the heterogeneity in electricity price within states, and across counties and utilities. For example, in my sample, with a national average electricity price of $0.12/kWh, prices in New York range from $0.03/kWh to $0.42/kWh. State-level analyses would be biased if the average state electricity price is not equivalent to the price the average household faces.

My empirical analysis will address these shortcomings in four ways. First, with panel data analysis, my model will account for time variance, compared to cross-sectional studies. Given the variation in electricity prices within U.S. states, by observing data at the level of the electric utility, I can more closely reflect the prices households face and capture heterogeneity in electricity price within states. I will compare the results of my utility-level analysis to results of my aggregated state-level analysis to test for potential biases in studies using state level data. Third, using utility level data enables me to employ state and state-time effects to control for unobserved determinants of adoption that are potentially correlated with electricity prices and are specific to states, including state-level policies. If for example, a renewable energy mandate was enacted during my period of analysis, which was correlated with a subsequent rise in electricity prices due to higher utility costs, I can control for this effect on solar adoption without biasing my estimates.

Fourth, using a large sample of utilities enables me to generalize about the elasticity of electricity price on adoption of solar PV. The main contribution of my thesis will be to offer the advantages and disadvantages of using aggregated utility level data to study the influence of electricity prices on solar adoption.

My findings suggest that electricity price is significantly positively correlated with solar adoption. In the preferred specification, a log-level utility fixed effects model with state-year interaction terms, a $0.01/kWh increase in electricity price (national average is $0.12/kWh) increases installed capacity by 5.54%; the price elasticity of demand is 1.85. These estimates assume I have addressed omitted variable bias and endogeneity problems; however, my utility level analysis fails to account for the omitted variable, solar price, which strongly influences solar adoption and is negatively correlated with electricity price, causing endogeneity bias.

This paper is organized as follows: First, I use consumer choice theory, and literature on forecasting and discounting, to provide a framework for understanding residential solar demand. Section III provides the empirical models for my utility and state-level analyses. Section IV examines my data, including retail electricity prices and net metered solar PV capacity from Energy Information Administration (EIA). Section V uses a variety of specifications to estimate the effect of electricity prices on the growth of residential solar PV. Finally, I conclude in Section VII and VIII with a discussion of my results and remarks on future research and policy implications.

II. Theory

To measure the degree to which electricity prices inform residential solar energy investment decisions, we must first understand the household's decision. Economic theory models households' decisions as utility maximization. Households choose among bundles of goods and services based on benefits and costs, and consume the bundle that provides the greatest utility given their income. In the case of the decision to invest in solar PV, the household first chooses their optimal consumption of energy, in relation to all other goods. Next, households choose to consume this energy from one of two sources: solar energy, from investing and installing a PV system, or grid electricity, from paying electric utility bills. The decision is determined by comparing the present value of costs of grid electricity in equation [1] with the present value of costs of solar PV in equation [2].

The cost of grid electricity from the electric utility, $C_{electric}$, is the retail rate, P_{grid} in dollars per kilowatt hour (kWh), multiplied by the consumption of electricity, Q^*, in kilowatt hours. The retail rate of electricity varies across U.S. states, and across U.S. utilities *within* states. This rate is determined both by state regulations through Public Service Commissions, and by market forces that affect demand and supply. Supply forces include generation, transmission, and distribution costs, like weather or fuel costs, while demand depends on the demographics of the utility's customers, such as income level and rural versus urban home sizes (EIA 2015).

The cost of solar PV, C_{solar}, is the cost of the residential solar PV system minus the benefits of bill savings, net metering, and additional utility. The cost of the solar PV panels, C_{panel}, is the cost of installing and purchasing the PV system, which is affected by subsidies, tax credits, solar panel prices, and installation costs which vary by location.

After installing the PV system, the household generates their own electricity, G, and incurs a benefit of no longer paying utility bills for household energy consumption. This benefit, B_{bill}, is equal to the price of electricity times quantity consumed, $P_{grid} \times Q^*$. The energy that is not consumed, G-Q^*, is fed to the grid and compensated through state net metering programs. Utilities pay the household credits equal to the price of grid electricity, P_{grid}, for this excess energy, which has a total benefit, B_{nem}, equal to $P_{grid} \times (G-Q^*)$. The total benefits are thus equal to $P_{grid} \times G$. In addition, some households receive an intangible benefit, or utility, from getting off the grid and being more sustainable; this is indicated by U.

The present discounted cost of grid electricity [1] and present discounted cost of solar [2] are the sum of costs over 25 years, the average lifespan of solar PV system and what many manufacturers cover under warranty (DOE 2012, Sherwani et al. 2010), and functions of discounting and forecasting. The two cost equations are as follows:

$$C_{electric} = E\left[\sum_{t}^{t=25} \frac{P_{grid} x\ Q^*}{(1+r)^t}\right] \quad [1]$$

and

$$C_{solar} = C_{panel} - E\left[\sum_{t}^{t=25} \frac{Benefits}{(1+r)^t} + U\right] \quad [2]$$

Where, $Benefits = B_{bill} + B_{nem} = P_{grid} \cdot Q^* + P_{grid} \cdot (G - Q^*) = P_{grid} \cdot G$

Where, $C_{panel} = f\ (subsidy, tax\ credit, price\ of\ system, installation\ cost)$

These equations model the alternative approach to risk accounting created by Thompson (1997). Instead of incorporating risk into models simply by raising the discount rate, the author models the household decision as between two future cash streams filled with uncertainty. In the electricity cash stream [1], households pay electricity bills according to their electricity consumption and the utility's electricity price. In the solar cash stream [2], households pay the upfront cost and receive uncertain benefits of bill savings and net metering over the life of the solar panel. Because all of these costs and benefits are paid or received in the future, the household *discounts* by dividing future values by $(1+r)^t$ where r is the discount rate and t is the number of years since installation.

Estimates of discount rates vary in the literature. In the absence of asymmetric information and uncertainty, discount rates should be equal to the real interest rate; they measure the return on investment or opportunity cost. In this case, discount rates would differ between households depending on access to credit. One of the first papers to identify high implicit discount rates in energy-using durables investments, Hausman (1979), models individual air conditioner purchase decisions. The author estimates a consumer discount rate between 15% to 25%, comparable to the average interest rate for credit cards at the time, 18%. This rate accounts for the tradeoff between *present* purchase price and *future* operating costs, energy efficiency benefits, and durability benefits. Enzler et al. (2014) measure subjective discount rates and identify rates as high as 60%, but they do not find convincing evidence that these discount rates impact energy saving behavior. In contrast, Alberini et al. (2013) identify a low discount rate of 1.5 to 2.9%, after removing uncertainty from survey scenarios. Overall, discount rates vary in the literature;

yet, the underlying consumer beliefs and perceptions that determine a discount rate are important to understand when theorizing solar adoption.

The costs described in equation [1] and [2] are *expected* (E) in that the household must predict future electricity prices over the 25-year time period to estimate the sum of present benefits and costs before making the investment. Anderson et al. (2011) find that the average consumer expects future real gasoline prices to be the same as the current price. This suggests that the undervaluation of fuel economy investments, or energy efficiency investments, does not stem from energy price biases. Allcott (2011) finds that consumers incorrectly calculate energy costs and savings due to imperfect information. Of the author's surveyed consumers, 40% did not think about fuel costs at all, while 89% of those who did calculated imprecisely. This study agrees with Alberini et al. (2013) which suggests that households uncertain about future energy prices weigh the cost of energy efficiency retrofits more heavily than the benefits. Although these studies focus on consumer forecasting of *gasoline* prices, they are the best available reference as few studies examine consumer forecasting of *electricity* prices.

Provided these cost equations, as long as households value the future benefits to the same degree as the costs, an increase in the price of electricity, P_{grid}, causes benefits of solar to rise, and the cost of solar, C_{solar}, to become relatively cheaper. At the same time, the cost of electricity, $C_{electric}$, becomes relatively more expensive. The likelihood the cost of solar will be lower than the cost of electricity rises; that is, the household's demand for solar rises. Market demand for solar is the sum of all individual demands at all prices.

To measure the influence of the price of electricity, the focus of this thesis, my empirical models must control for other factors within the solar market that affect how the equilibrium quantity of solar changes. Price changes occur based on the availability of state and federal subsidies and tax credits, and changing costs of PV systems. Demand for solar shifts due to changes in income, preferences, or education of solar energy, population, and expectations. The supply of solar shifts due to changes in input prices, technologies that affect installation or production procedures, firm entry or exit. Both supply and demand are also affected by insolation that measures potential capacity of solar given amount of sunlight.

III. Empirical Models

The ideal empirical model for my analysis measures adoption of residential solar energy as a function of all the factors influencing supply, demand, and price changes in the market for solar energy. Many of these factors are recorded at the state or household level, but I am observing data at the *utility* level to best match the electricity prices households face. Because of this, I control for state-level factors, utility-level factors, and time effects with dummy variables and state-year interaction terms. As a result, I have four empirical models:

$$Q_{ijt} = \beta_0 + \beta_1 P_{it} + \beta_2 T_t + \beta_3 \delta_j + \varepsilon_{it} \qquad [3]$$

$$Q_{ijt} = \beta_0 + \beta_1 P_{it} + \beta_2 T_t + \beta_3 \delta_j + \beta_4 \delta_j T_t + \varepsilon_{it} \qquad [4]$$

$$Q_{ijt} = \beta_0 + \beta_1 P_{it} + \beta_2 T_t + \beta_3 \lambda_i + \varepsilon_{it} \qquad [5]$$

$$Q_{ijt} = \beta_0 + \beta_1 P_{it} + \beta_2 T_t + \beta_3 \lambda_i + \beta_4 \delta_j T_t + \varepsilon_{it} \qquad [6]$$

In the equations above, Q is installed residential solar capacity (MW) and P is the utility's retail electricity price ($/kWh). Each year, t, is represented by a dummy variable,

T, in all models [3,4,5,6]. Each state, j, is represented with a dummy variable, δ, in the OLS models [3,4]. The observation level, i, represents the utility, and each utility is represented with a dummy variable, λ, in the fixed effects models [5,6]. State-year interaction terms, $\delta_j T_t$, are included in both the OLS [4] and fixed effects [6] models. The error terms, ε_{it}, measure the residual error and demand not accounted for by the variables in the model.

In the first specification, I have a utility panel with state and year dummies. Year dummies control for solar adoption factors that vary over time, but do not vary across states or utilities, such as nationwide solar awareness or general declines in solar prices. State dummies in the OLS models control for solar adoption factors that vary across states, but do not vary within states or across time, such as subsidies, tax credits, net metering policy, and insolation. The only instance state dummies are sufficient to control for all state-level factors is if these factors do not change over time differently across states. For example, if New York enacted a policy to offer solar PV financing during the time period of my study – 2010 to 2015, and other states did not, or did so differently, the New York dummy could not control for this policy change, and the consequent effect on solar adoption (this is the case for a New York 2012 policy). That is why in my next model [4], I use state-year interaction terms to control for state factors that differ in each year. These state-year interaction terms would be able to control for the 2012 New York policy, for example.

The first two models only capture variation across states, and across time. However, some factors that affect solar adoption, like electricity prices or demographics, vary within states at a more granular level, and are captured best with a fixed effects specification, or utility dummies, in model [5,6]. The preferred specification [6] incorporates both the state-year interaction terms and utility dummies.

To assess the advantages of utility-level analysis, I compare my results to the results of an aggregated state-level analysis. This state analysis follows two models:

$$Q_{jt} = \beta_0 + \beta_1 P_{jt} + \beta_2 T_t + \varepsilon_{jt} \qquad [7]$$

$$Q_{jt} = \beta_0 + \beta_1 P_{jt} + \beta_2 T_t + \beta_3 \delta_j + \varepsilon_{jt} \qquad [8]$$

The observational level, *j*, represents the state. Electricity price, *P*, is the state average of retail electricity prices across utilities, and installed residential solar capacity, *Q*, is the state's total installed capacity, or sum of utility-recorded solar capacity.

IV. Data Description

This section will provide background on my data sources and choice of measures for dependent variable, solar adoption, and key independent variable, electricity price.

For the dependent variable, I follow Sarzynski et al. (2012) and choose cumulative installed residential solar capacity installed in megawatts (MW) as the measure of solar adoption. Alternatives include number of installations (Kwan 2012, Chan et al. 2016) and capacity per capita (DOE 2014). These are all relatively similar measurements, but total installed capacity is the *only* available metric at the *utility* level. Smart Electric Power Association (SEPA), the best-known source for recording utility-level solar capacity, also collects data with this metric.

Electricity price is measured as price per kilowatt hour (kWh) and calculated by dividing utility revenues (dollars) by sales (MWh) and converting to dollar per kilowatt hour units. All authors in the literature follow suit with this electricity price metric, with variation in energy unit (Sarzynski et al. 2012, Kwan 2012, Chan et al. 2016). Alberini et al. (2011) assert that average prices are not necessarily equal to the prices faced by the household; the ideal price measurement would be the price the household actually faces which would require household-level data.

Residential solar data is available from Open PV, which records individual installations and the zip code. Although this is the ideal observational level, the installations cannot be associated with electricity price data. SEPA[3] collects utility-level data, but does not a large sample size, and their database is not accessible to the public. Thus, the Energy Information Administration (EIA) is the best source of data for this project with both residential solar and electricity price data.

Data for both the dependent and independent variable are provided publicly by the Energy Information Administration (EIA)[4] through responses to survey form EIA-861 – Annual Electric Power Industry Report. Law requires electric power industry participants, energy service providers, wholesale power marketers, and electric utilities to respond to Form EIA-861; [5] this makes this form and its data very reliable. The EIA-861

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[3] SEPA (Smart Electric Power Association) is recognized as the most reliable source of solar capacity data by utility, because they collect solar-specific adoption data from individual utilities; however, the data provided in their "Utility Solar Database" is very difficult to use for the purposes of my paper. The main problem with these data is a shorter time period, missing observations across time period, and lack of *residential* solar capacity estimates for many utilities, and the sample size of 1098 is comparable to the EIA data with more reliable estimates.

[4] Kwan (2012) also uses EIA data for electricity price estimates and Alberini et al. (2011) uses EIA-861 form data.

[5] In 2012, a shorter form, EIA-861S, was set up to reduce respondent burden and speed up EIA processing. This form only requires data in the aggregate, not by customer sector, and does *not* request solar capacity data, but asks in if net metering is available. As a result, from 2012 to 2015, data for 1,124 of the total 3,170 utilities are not available for my analysis. To assess whether the sample is systematically biased without

form asks for information on sales, electricity purchases, customer counts, demand-side management, peak load generation, green pricing, advanced metering, distributed generation capacity, and net metering. All data is split by customer sector – residential, industrial, commercial, and transportation. For the purposes of this analysis, I focus on data from the residential sector; because I want to study the household response to price in the adoption of residential solar. I take data from two "schedules" on the EIA-861 form – "Net Metering" (Schedule 7-Part A) and "Sales to Ultimate Customers" (Schedule 4).

The observational level is an electric utility. These can range geographically from 2 to 20 counties. Some utilities cross state lines, but data on sales and net metering are recorded separately for each state within the utility. For this reason, data are at the utility level, but split by state.[6]

There are several limitations of these data. The EIA admits that the reports on net metering are a lower bound of residential installed PV capacity, because not all systems are captured on EIA-861 forms. For one, net metering capacity data only includes residential solar systems connected to the grid and part of utility net metering programs. Although some states mandate net metering and require utilities to connect solar PV

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these utilities who use the short form, I compare the summary statistics of price from 2007 to 2011, utilities that use, and those that do not use the short form. The mean price of those that do not use the short form is on average $0.015/kWh lower than those that do. However, those using the short form, have much higher standard deviations in price. A member of the EIA-861 survey team said there was no significant trend in utilities that do the short form, but noticed that utilities in states with higher fluctuations in electricity price, like Alaska and Colorado, tend to use the short form. If this is the case, and utilities not included in my sample have on average, higher electricity prices, then this would be a form of selection bias. If these utilities have higher electricity prices and *lower* capacity values on average, this would push my elasticity estimates lower. If these utilities have higher electricity prices and higher capacity values, as hypothesized, this would push my estimates higher or simply make them more significant.

[6] In my sample, 16 utilities cross state lines, 15 of which cross two states and 1 crosses three. As a result, there are 33 observations that have duplicates in utility characteristics, but prices and capacity differ.

systems to the grid free of charge, other states have restrictions, which may influence the capacity of solar PV reported on the form. Second, although the form is mandatory, filling in this particular section or schedule to record capacity is voluntary and so many utilities do not report. The EIA advises that these unreported values should not be interpreted as 0 MW solar PV capacity. This creates an unbalanced panel in my data set, where not every utility records capacity for all years in the time period,[7] and others start recording late in the sample period.[8] The EIA goes through a rigorous quality assurance process with all data, but some errors slip through. For instance, there are 48 to 86 instances each year in which capacity falls or drops to zero from one year to the next. [9] This is highly unlikely unless some or all customers were disconnected from grid, or the 25-year-old solar panels ran out of life. Ultimately, my data set is the subset of utilities that fill out the net metering schedule merged with their matched price data from the sales schedule.

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[7] In one test, I assumed that all missing values of capacity for utilities that recorded in at least one year were equal to zero, thereby creating a balanced panel. The mean price was 0.89 MW lower, as it was pulled down by zeros, but there was no significant difference in mean price. Because this assumption is not valid, my paper's results use an unbalanced panel.

[8] Because capacity is only an optional segment of the form, there are discrepancies in the capacity data, where many utilities start to record net metering solar capacity later in the 2010 to 2015 time period than others. The largest difference in mean price change between utilities that started recording later and those that recorded throughout the time period was only $0.00027/kWh. I could not identify any significance or price change trend for those that started recording capacity later.

[9] There was a slight decline in capacity from year to year for some observations. In these cases, the solar panels were no longer connected to the grid or the capacity of solar panels declined over time, given the natural rate of depreciation. Price change was compared between those that had a decline in capacity, 283 observations, with those that either showed no change or increases in capacity, 5,092 observations. The median price change was only $0.0008 lower and mean was $0.008 lower for those that had a capacity decline. There was no pattern of utilities with capacity decline and declines in price.

V. Summary Statistics

My sample contains 4,615 observations from 1075 utilities. The state distribution of utilities can be found in Table 3. Retail electricity price has a mean of $0.12/kWh, ranging from $0.03/kWh to $0.54/kWh between 2010 to 2015 (see Table 1). The mean of the sample is consistent with the national average of $0.125/kWh (EIA 2015). As shown in Figure 1, electricity price, on average, rises over time. Average electricity price varies across utilities from county to county (see Figure 2). For my aggregated state analysis, the mean average electricity price for 51 states, including DC, is $0.13/kWh, ranging from $0.08/kWh to $0.40/kWh (see Table 2). As shown in Figure 4, average electricity price varies across states.

The dependent variable, cumulative installed residential solar PV capacity, has a mean of 3.13 MW, ranging from 0 to 1058 MW between 2010 to 2015 (see Table 1). Of the 4,615 observations, 2166 had capacity values less than 0.05 MW, 739 less than 0.01 MW, and 371 less than .005 MW, with 32 values equal to 0. This suggests there is quite a spread in capacity, and many utilities have observations of 0 MW capacity either at the beginning of the time period or throughout. The high maximum implies there are outliers in the sample; however, these high values are consistent with the "population" of utilities.[10] As shown in Figure 1, average solar capacity increases exponentially over time, so the number of installations per year increases over time, as reports suggest (SEIA 2016). Residential installed solar capacity varies across utilities as seen in Figure 3

[10] SEPA's database suggests a high of 1058.38 MW cumulative residential PV capacity for Pacific Gas & Electric in California, 791.2 MW for Southern California Edison, and 507.200 MW for San Diego Gas & Electric. The Arizona utility that records the maximum value of capacity sample does not report their data to SEPA, but the California competition justifies this large capacity (MW).

mapped by county. For my aggregated state level analysis, I measure total installed solar capacity as the sum of utility capacity observations for 51 states, including DC. Average total installed capacity is 47.55 MW, ranging from 0.004 MW to 2448 MW (see Table 2). In Figure 5, we see residential solar capacity varies significantly across U.S. states.

VI. Analysis and Results

I hypothesize that a rise in retail electricity price will increase installed residential solar capacity. This hypothesis will first be tested on a panel of utilities in 8 models with increasing complexity: 1) Level-level pooled OLS with state dummies, 2) Level-level pooled OLS with state dummies and state-year interaction terms, 3) Log-level[11] pooled OLS with state dummies, 4) Log-level Pooled OLS with state-year interaction terms, 5) Level-level Fixed Effects, 6) Level-level Fixed Effects with state-year interaction terms, 7) Log-Level Fixed Effects, 8) Log-level Fixed Effects with state-year interaction terms. The four pooled OLS models have state dummies for 51 states, including DC, with Alaska as the reference level. All eight models incorporate year dummies for 2010 to 2015, 2010 as the reference level, and use the same sample of observations. Coefficient estimates can be found in Table 4 and elasticity estimates in Table 5.

It is important to note when examining these results, 1 MW of solar powers, on average, 200 homes; the average home's residential solar PV system is 5 kW or 0.005 MW (SEIA 2016). For reference, the average electricity price in my sample, and nationwide, is \$0.12/kWh and average capacity for my sample of utilities is 3.13 MW, but as high as 1057.9 MW.

[11] In log-level models, capacity is normalized with a log(x+1) transformation due to many observations of zero capacity.

The first model, a simple pooled OLS model with state and year dummies estimates that every \$0.01 increase in electricity price results in 0.33 MW increase in capacity, or 66 households. As explained in Section 3, state dummies can only control for state-level factors, like state policies, that remain the same over the time period. That is why in my next model, and in Model 4, 6, and 8, I use state-year interaction terms to control for state factors that may vary over time, such as state policies. Model 2 estimates an elasticity of 1.451, up from 1.289 in Model 1. Model 1 and 2 are the only models with elasticity estimates not significant at the 0.01 level, but are significant at the 0.2 level.

In the next model, and in the fixed effects models, a log-level specification log normalizes capacity to better fit the capacity data.[12] Model 3, a log-level model with the same specification as Model 1, estimates a coefficient of 1.75. A \$0.01 increase in price increases capacity by 1.75%. The elasticity is 0.585, much lower than Model 1 and 2. In Figure 6 and 7, there is a pronounced pattern in the residuals, but the log-level Model 3 condenses the spread in residuals, as logging capacity is a better fit for the data. Model 4 is the same as Model 3 but incorporates state-year interaction terms. The model estimates a \$0.01 increase in electricity price increases capacity by 2.01%, compared to 1.8%. In both the log-level and level-level OLS models, the elasticity and coefficient estimates increase with the incorporation of state-year interaction terms. Thus, the greater controls increase the impact of electricity price on solar adoption due to omitted variable bias without state-year interaction terms.

[12] The spread of electricity price does not justify a log transformation. A log-log specification estimated an elasticity of 2.56 for OLS with state-year interaction terms and an elasticity of 2.02 for fixed effects with state-year interaction terms. Both elasticities are higher than the log-level specification results; however, the residual plot looked similar to the latter model (see Figure 7).

Next, I will analyze the fixed effects models, which control for utility-level effects, or differences across utilities. In Model 5, I estimate a price coefficient of 147, so that a $0.01 increase in price will increase capacity by about 1.47 MW, or 294 homes. In Model 6, with state-year interaction terms, a $0.01 increase in price increases capacity by 2.37 MW, or 474 home installations. This coefficient is 7 times the magnitude of the Model 1 coefficient.

In the log-level Model 7, the elasticity estimate is 1.05, but the addition of state-year interaction terms in Model 8 increases the estimate to 1.85. The coefficient estimate of Model 8 is interpreted as a $0.01 increase in electricity price increases capacity by 5.54%. This final model is the preferred specification as it is the most complex, controlling for utility, state-year, and year effects, and best fit with logged capacity. However, this model's residual plot (see Figure 8) and other log-level model residual plots show a pattern of values following a 1:1 downward slope. These fitted values line up with capacity observations very close to 0 MW.[13] Also, the residual plot shows some states with high positive residuals, including Hawaii, where one utility increases in capacity from 3 MW to 47 MW in the time period.[14] Due to this clear trend in my residual plot, I will explore problems and possible solutions in my discussion.

[13] When the capacity values less than .005 MW are dropped from Model 5, level-level fixed effects, the residual plot looks the same and the price coefficient is 5.873 compared to slightly lower, 5.539, with zeros. This leads me to believe the zero values are not necessarily the problem.

[14] These residuals prompted me to test if modeling change in price to change in capacity, would better fit the price-capacity relationship. With a log-level fixed effects with state-year interactions specification, I find a 1% increase in year to year price change increases the growth in capacity by 0.03%. The residual plot of this model shows even stronger patterns in residuals, suggesting this specification does not solve the problem of residual patterns.

Next, I perform a state-level analysis to compare my prior results and establish benefits and costs of utility-level analysis. The same hypothesis will be tested with a 51-state panel in 4 models, matching the utility-level analysis specifications: 1) Level-level pooled OLS with year dummies, 2) Log-level pooled OLS with year dummies, 3) Level-level fixed effects with year dummies, and 4) Log-level fixed effects with year dummies. In order to compare the results of these models to my utility-level results, I will compare elasticity estimates in Table 7, but coefficient estimates can be found in Table 6. The log-level OLS model results in an elasticity estimate of 1.04, compared to 0.59 to 0.67 elasticity in Model 3 and 4 of my utility-level analysis. The state log-level fixed effects model results in an elasticity of 1.281, compared to the utility-level model of 1.05 to 1.85 in Model 7 and 8. So, state level elasticity estimates range both higher and lower than my utility level estimates. The residual plot of Figure 9, shows a more uniform spread in residuals, compared to the pattern of residuals in Figure 8. This is most likely due to larger capacity values, and fewer capacity values close to 0 MW. It is unclear if there is significant bias from analyzing this relationship at the state-level; the estimation errors in my utility level analysis are also present in my state-level analysis.

VII. Discussion

In summary, in the preferred specification, log-level fixed effects with state-year interaction terms, I find a price elasticity of 1.85, compared to literature estimates of 1.4 to 1.97 (Chan et al. 2016) and 2.03 to 2.27 (Sarzynski et al. 2012). These results and policy implications must be interpreted with caution. There are certain limitations of my analysis, including omitted variable bias and endogeneity, as evidenced by the pronounced pattern in my residual plot (see Figure 8) and high elasticity estimates.

This paper contributes to the literature in two ways. First, panel data analysis takes into account changes over time and allows use of fixed effects to capture sources of variation that are correlated with electricity price. Second, studying this relationship at the utility level captures heterogeneity in electricity prices within states and more closely matches the prices households face, compared to state-level analysis (Sarzynski et al. 2012, Durham et al. 1988). Although this is not as granular as household-level or zip-code level data (Kwan 2012), I am able to assess the benefits and costs of this aggregated approach.

The greatest disadvantage of observing data at the utility level to study this relationship is that data for control variables is unavailable at the utility level. My use of state dummies, state-year interaction terms, and utility dummies, is useful, but some factors vary at a more granular level. If these factors, not controlled for in my models, are correlated with electricity prices, I have omitted variable bias.

In particular, a very important determinant in solar demand is solar prices. Although electricity price, the price of a substitute, may explain solar demand, as theory suggests, solar demand is more significantly caused by *price* of solar. Although it would seem customers would be guaranteed the same price, according to Gillingham et al. (2016) solar prices differ *within* U.S. states based on system characteristics, market structure, and greater demand. So, solar prices may differ across households within utilities, and are not controlled for in my models with utility dummies.

Over the last decade, solar prices have been falling exponentially as electricity prices have been rising incrementally; this makes solar prices and electricity prices negatively correlated. In this case, I have endogeneity bias due to simultaneous causality and omitted variables. In a granger causality test, price granger causes capacity with significance at the 0.002 level, but solar capacity granger causes price at an even higher significance of less than 0.0001. This proves my cross-price elasticity estimates are higher than the actual value, and including solar prices in my models would reduce my estimates. Although these estimates accord with literature estimates, these papers also fail to control for solar prices. The solution would be to use instrumental variables or to do a simultaneous regression in which solar prices determine solar capacity and then capacity explains the capacity, controlling for solar price.

I performed a robustness test to check if the variation in levelized cost of electricity (LCOE) accounts for the variation in residuals across utilities within a state. In other words, does the absence of LCOE in my models explain the residual error. Besides electricity price, LCOE is determined by solar potential and the amount of sunlight, quantified as insolation. In states with high variation in insolation, like Washington which varies east to west, and California which varies north to south, I would expect greater standard deviation in residuals. In my sample, Washington, with 37 utilities, has a standard deviation of 0.67, and California (31 utilities) has a deviation of 1.4, compared to a higher value of 1.8 in Arizona (15 utilities) where LCOE is relatively homogenous.

The peer effect,[15] where neighbors influence your willingness to adopt solar, is also not controlled in the current model. Over time, households are exposed to solar

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[15] Others study spatial patterns of solar adoption and find a strong relationship between adoption and previous installations, providing evidence of peer effects in the adoption of residential solar (Graziano & Gillingham 2015). One paper estimates an additional installation increases the probability of adoption in

panels as their "neighbors" adopt, and they are in turn made aware of the benefits of solar energy. This is evident in the exponential growth in solar capacity over time. The year dummies control for general trends that occur over time, but do not vary within states or across states. The network effect would not differ across states, but could between rural and urban regions within a state. If, for example, the network effect were greater in urban locations where people are closer to their neighbors and have more neighbors, this would not bias my estimates as the variation is not influenced by electricity price.

Another area of bias is the use of average electricity prices for each utility, although households in a single utility may face different retail rates because of different pricing structures. Many authors have studied the impact of retail rate design or electricity pricing structure on the cost-competitiveness and adoption of solar.[16] However, the authors fail to consider how the household *perceives* the solar investment. With asymmetric information, the household may believe and incorrectly calculate the bill savings and net metering benefits that time-of-use, flat-rate tariff, or peak demand rates provide. I believe, according to my theory, the total cost on each electricity bill is more

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the same zip code by 0.78%, and peer effects lead to greater capacity installed (Bollinger & Gillingham 2012).

[16] Procter & Tyner's (1984) simulation model find that solar PV systems with the federal solar tax credit, were *not* cost-competitive with peak load pricing, where consumers are charged different rates based on the time of day, but were competitive with block pricing. Their findings tell us that pricing *structure* impacts the cost-competitiveness of solar in the presence of subsidies. However, with the simulation model, they are not able to assess the consumer's response to price changes, or whether the consumer would correctly estimate and consider the cost-competitiveness and retail rate structure in their decision to invest. Borenstein (2007) similarly assesses the incentives for PV under different pricing structures, by comparing net metering under time of use (TOU) rates, which charge higher prices at peak demand times, and flat-rate tariffs, which charge a constant price, analyzing data from 2 utilities. With a statistical comparison of electricity bills, the author finds that TOU rates do *not* make PV less attractive than the flat rate tariff, and even in some cases TOU rates were better than flat-rate. Darghouth et al. (2011) analyzes the same two utilities to assess variations in bill savings according to retail rate design.

influential, not *how* this cost is determined; so, households charged with different electricity rate designs would not differ in their response. However, the use of average prices is still a concern for my model.

Another variable, central to the theoretical equations, is the discount rate, which is influenced by demographic variables, such as education and wealth. Higher education levels may enhance the household's ability to evaluate the investment on a benefit-cost basis. Wealthier households tend to consume more, and are more negatively impacted by rises in electricity price, yet these same households may not look at their electricity bills or react as strongly to changes in electricity price as lower-income households. Both of these factors are best measured at the household level. Neither education nor wealth are correlated with electricity price, as retail electricity prices neither vary household to household within the same utility nor change due to income or education. Yet, both factors may influence how electricity prices affect a household's response to changes in electricity price and consequent adoption of solar.

Many of these problems are due to my choice of observing data at the utility level. Estimates for demographic variables, solar prices, or policy specifics are not available at this observational level. For this reason, I provide a word of caution for researchers: Although utility level analysis accounts for the variation in electricity price across states, compared to state-level analysis, survey data would be more appropriate. This survey would measure actual electricity prices faced by the household, the degree to which households considered net metering and bill savings benefits prior to their investment decision, and all other factors of the household's investment decision that are the core of my theoretical model. The closest available source to this ideal data is Open PV project, which does not yet include electricity prices faced by the household prior to installation.

Future researchers should expand my study with a more extensive sample across more years, and by controlling for all factors correlated with electricity price, like solar prices, that affect a household's willingness to invest in residential solar. It would be important to evaluate how the type of pricing plan, block pricing, fixed tariff, informs solar investment, and how absence of net metering programs, a component of my theoretical model, would alter these results. Additionally, authors should explore the effect of lagging electricity price on regression model results. Does a household evaluate electricity prices over a longer period of time up to their investment? If so, by lagging electricity price and extending electricity data back before 2010, it may improve the fit of these models. I would be interested to see how long it takes for households to respond to electricity price increases in the presence of a carbon tax. The best method to perform this research is with household-level data that accounts for demographics and a household's true electricity price.

VIII. Conclusion

My findings suggest that electricity price is significantly positively correlated with solar adoption. In the preferred specification, log-level fixed effects with state-year interaction terms, I find a price elasticity estimate of 1.85, in the range of literature estimates (Chan et al. 2016, Sarzynski et al. 2012). My results suggest that if a carbon tax were to increase electricity prices by 8.5%, as suggested by Rivers (2012), capacity would increase by 15.73%. These results are limited by endogeneity bias. My study is the first to focus on the influence of electricity price on the residential adoption of solar PV with data at the utility level. Currently, the U.S. has the fastest developing market of residential solar in the world, so understanding causes of this growth will help other countries choose the most effect policy measure to incentivize solar. With the possibility of carbon taxes on grid electricity, researchers and policymakers must understand how will households respond, and at what rate will they choose to invest in solar?

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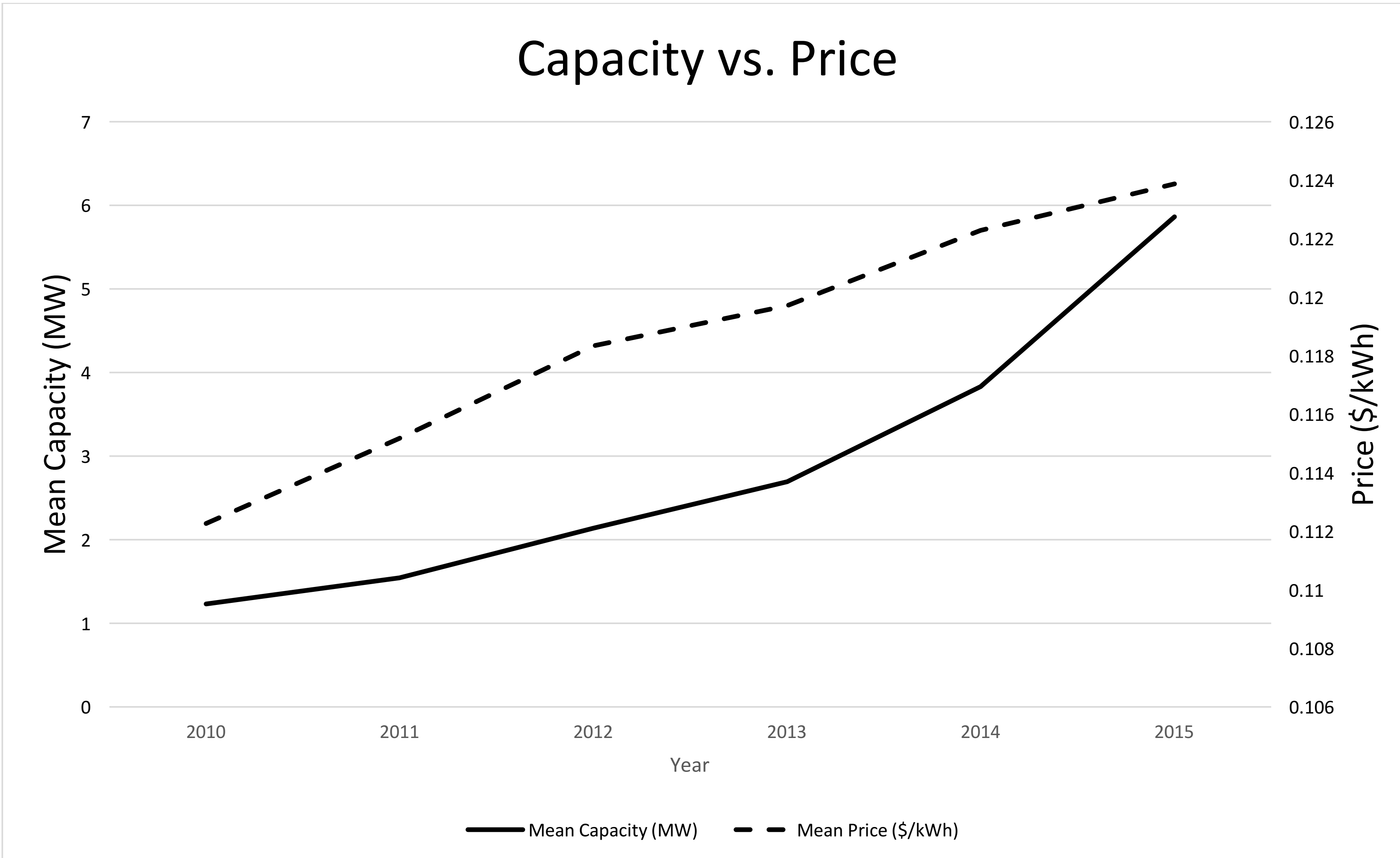

Figure 1. Sample's Average Price ($/kWh) and Average Capacity (MW) over Time Period of Analysis (2010-2015)

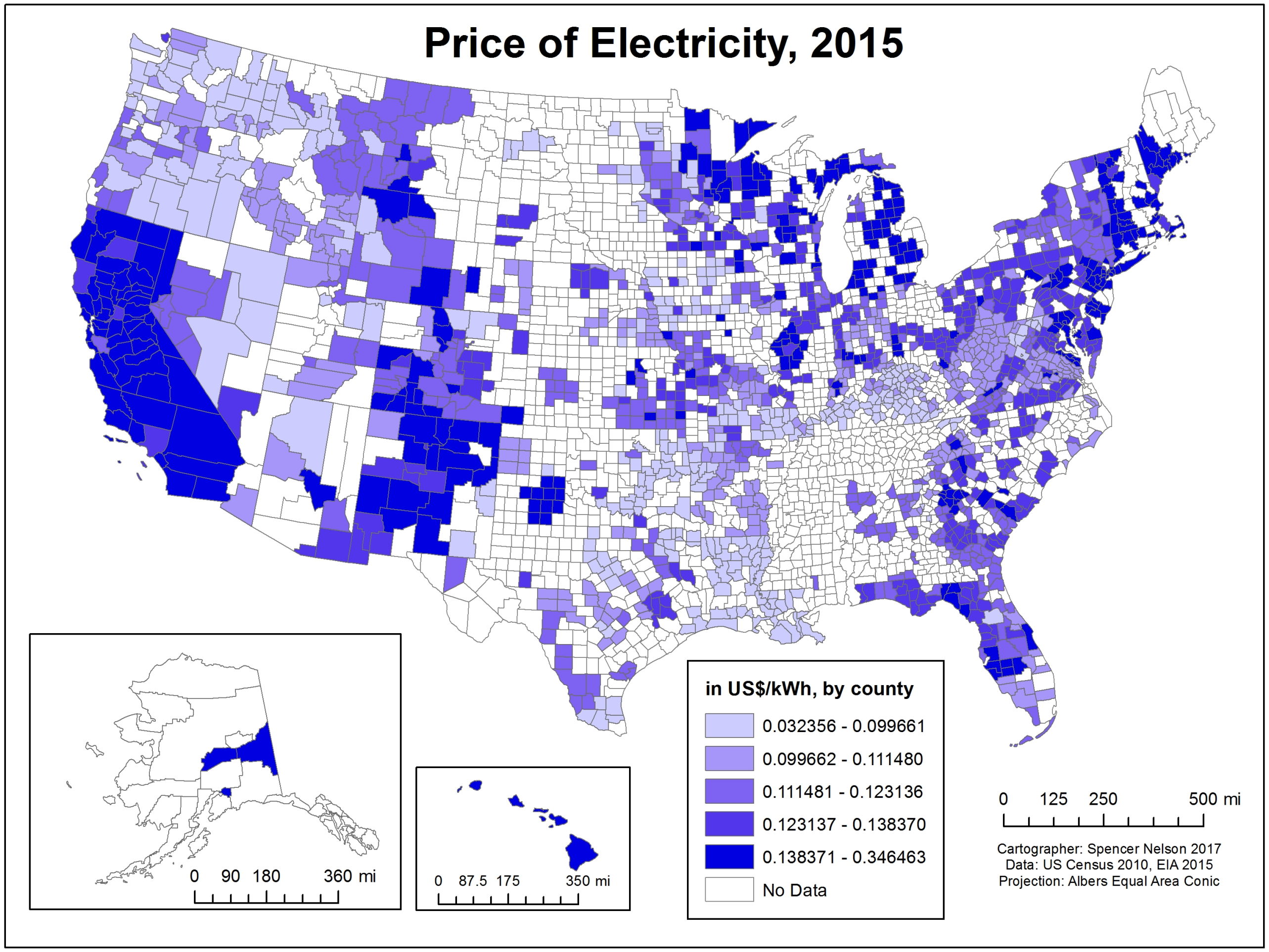

Figure 2. Price of Electricity in 2015 by County using Utility-Level Price Data (EIA 2015)

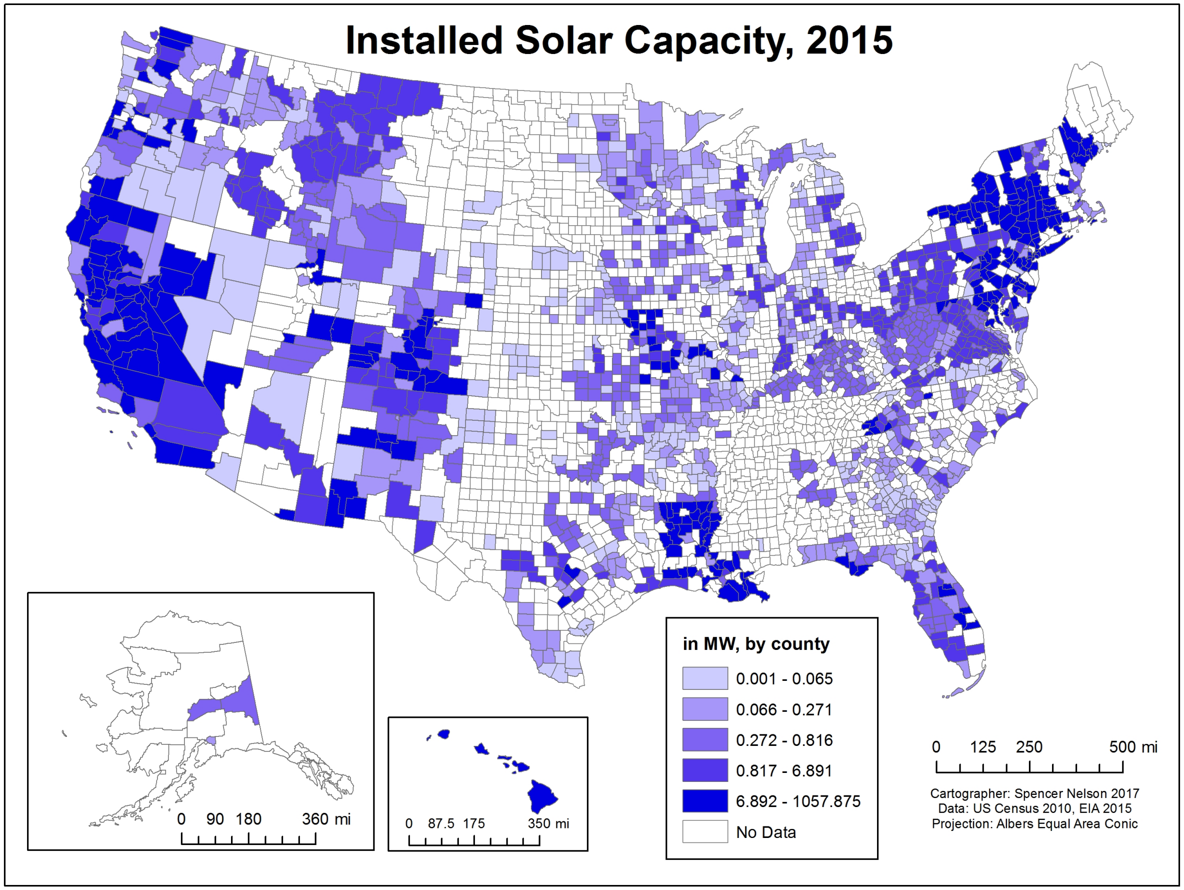

Figure 3. Total Residential Solar Capacity (MW) in 2015 by County using Utility-Level Net Metering Data (EIA 2015)

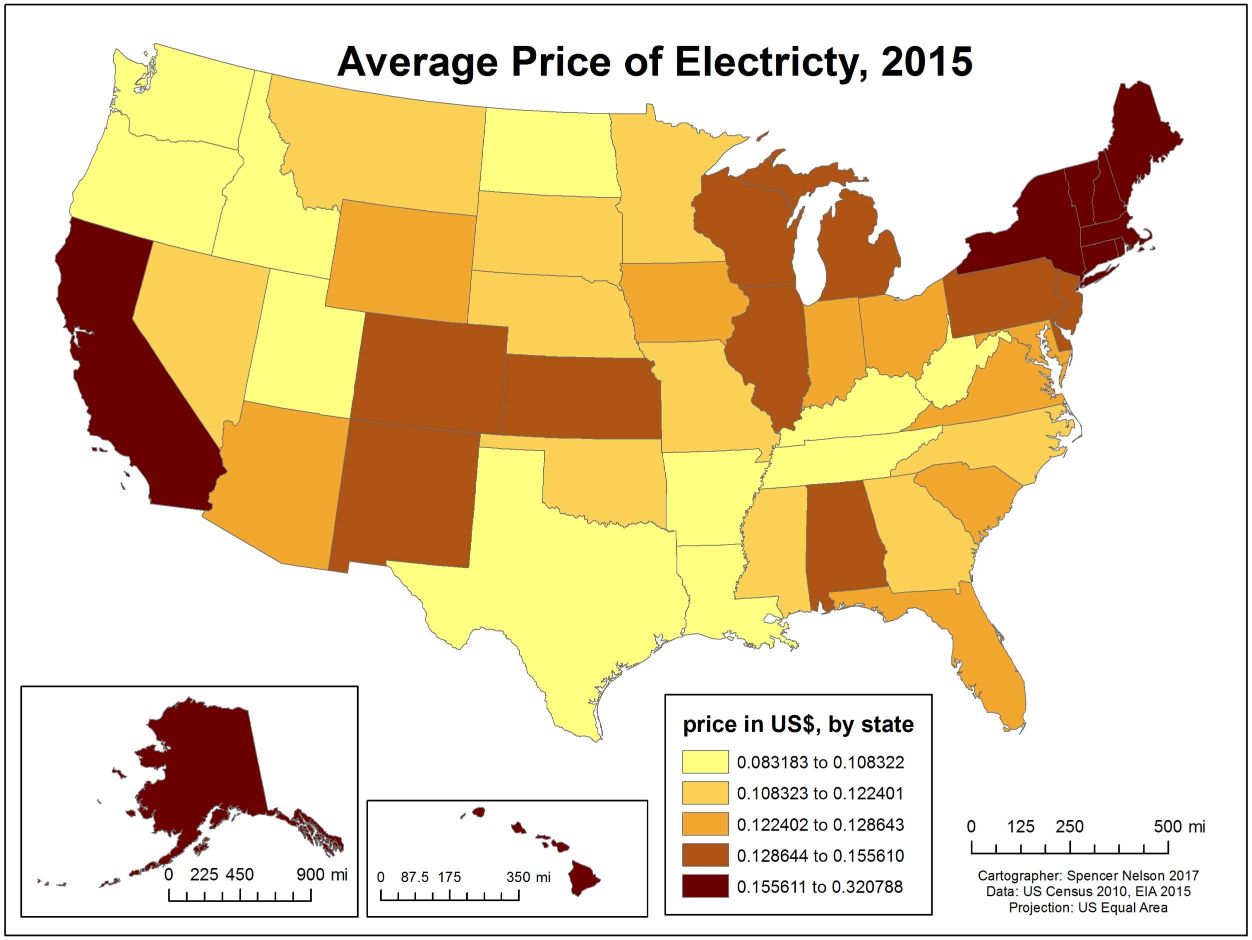

Figure 4. Average Price of Electricity by State in 2015 using Aggregated Utility-Level Price Data (EIA 2015)

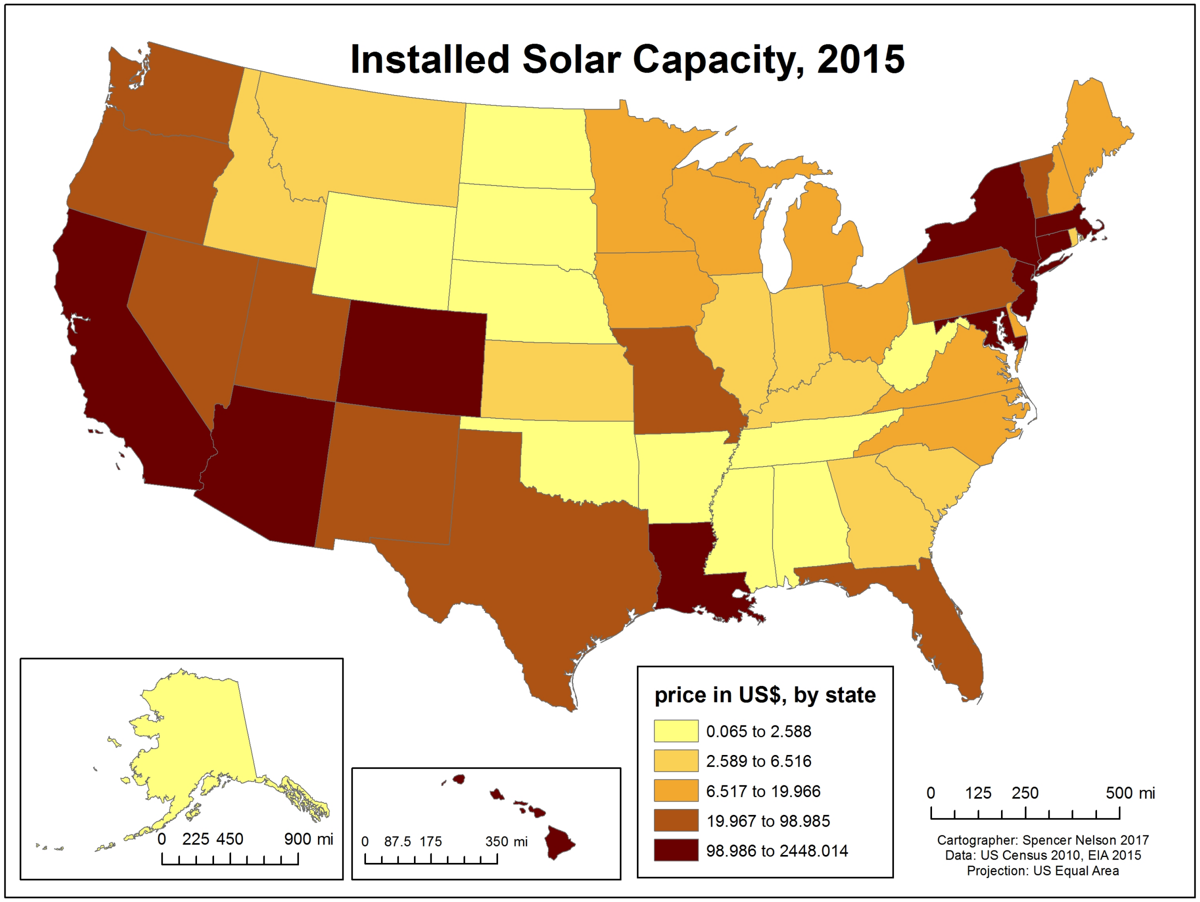

Figure 5. Total Residential Solar Capacity (MW) by State in 2015 using Aggregated Utility-Level Net Metering Data (EIA 2015)

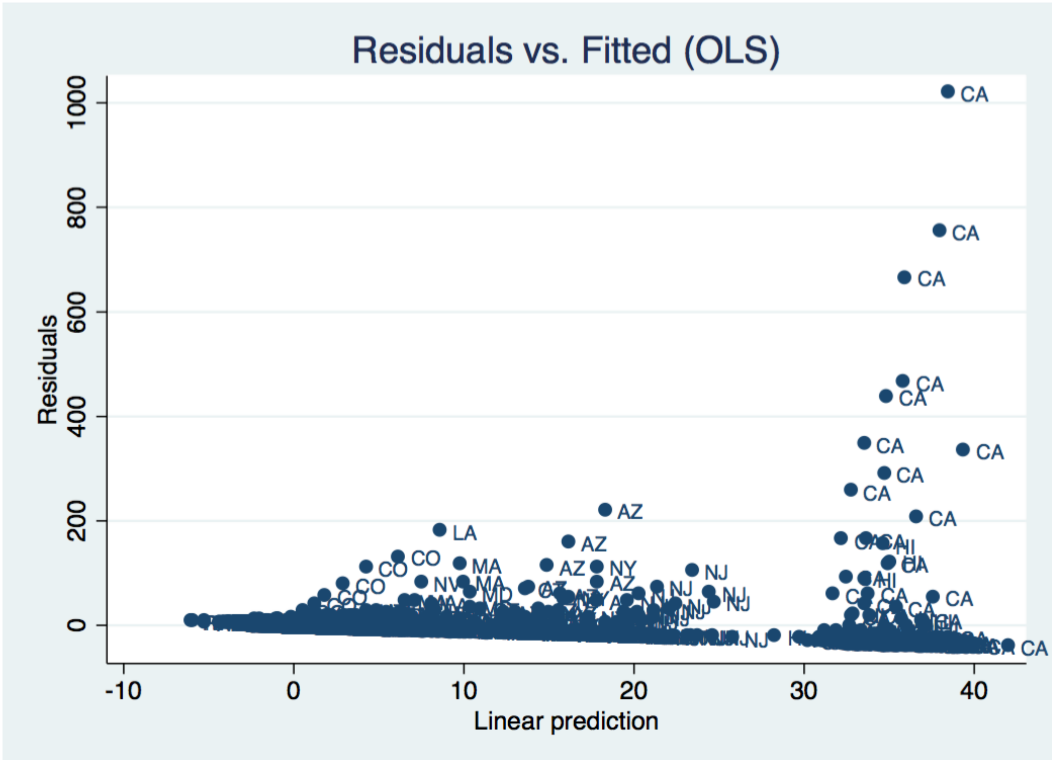

Figure 6. Residual Plot of Level-Level OLS with State Labels

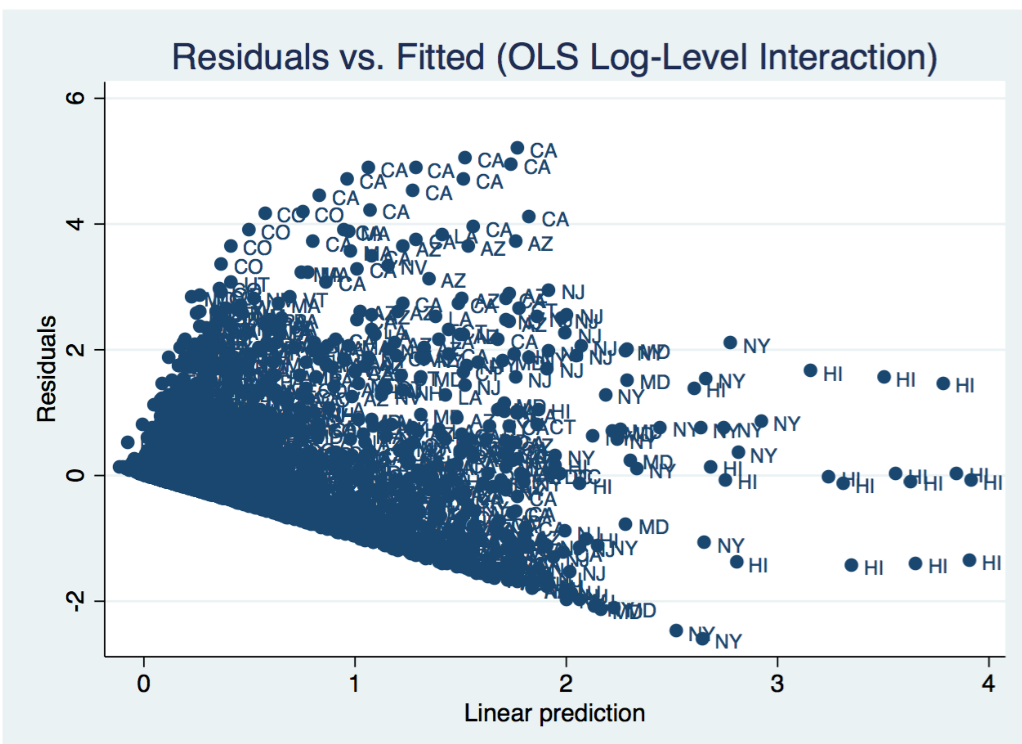

Figure 7. Residual Plot of Log-Level OLS with State-Year Interactions and State Labels

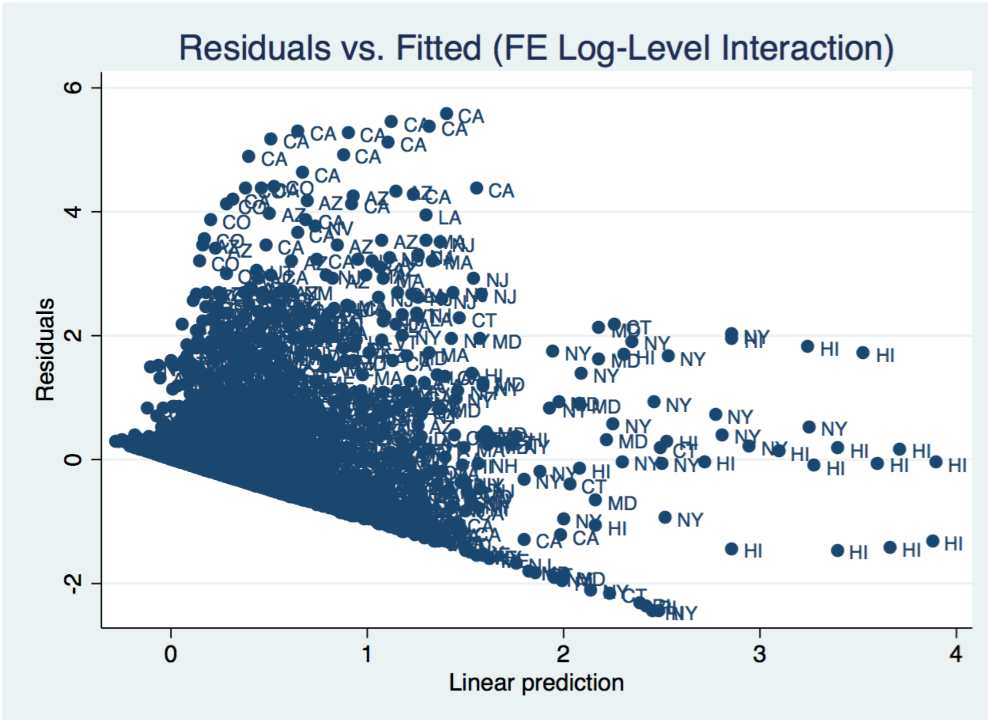

Figure 8. Residual Plot of Log-Level Fixed Effects with State-Year Interactions and State Labels

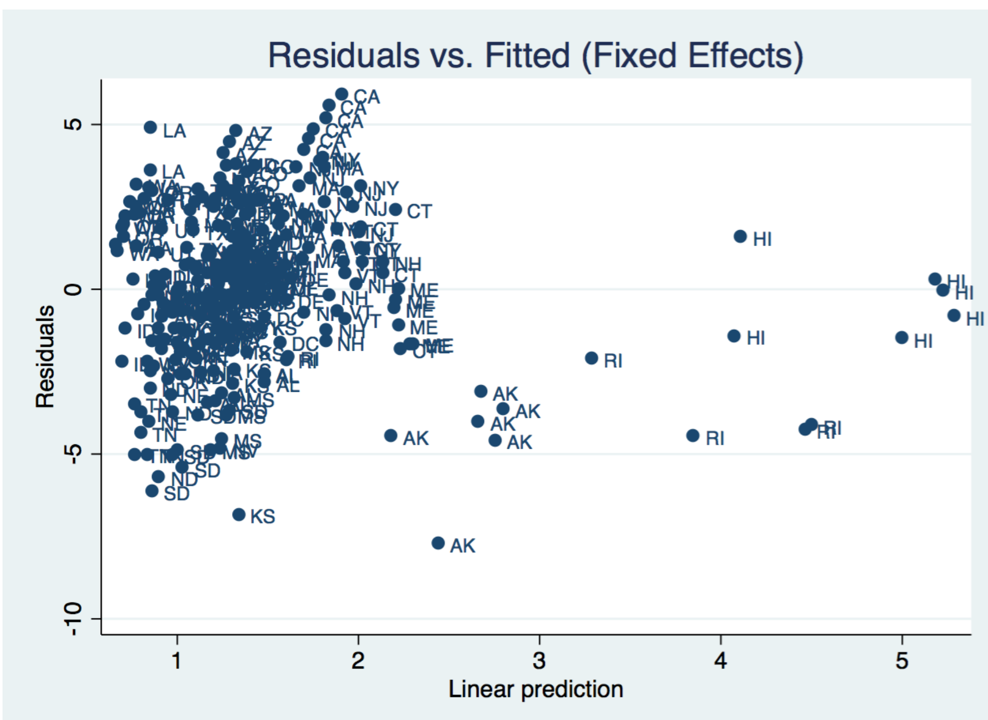

Figure 9. Residual Plot of STATE-level Log-Level Fixed Effects with State Labels

Summary Statistics of Price and Capacity – Utility Panel

Variable	Years	Utilities	Observations	Mean	Std. Dev.	Min	Max
Price ($/kWh)	2010-2015	1,075	4,615	0.121	0.0368	0.0293	0.540
Capacity (MW)	2010-2015	1,075	4,615	3.132	28.839	0	1057.875

Table 1. Summary Statistics – Unbalanced Panel

Summary Statistics of Price and Capacity – State Panel

Variable	Years	States	Observations	Mean	Std. Dev.	Min	Max
Average Price ($/kWh)	2010-2015	51	304	0.131	0.0496	0.0760	0.404
Total Capacity (MW)	2010-2015	51	304	47.550	191.656	0.004	2448.014

Table 2. Summary Statistics – Includes DC (2010 TN and MS missing)

State Distribution of Utility Sample

STATE	NUMBER OF UTILITIES
AK	8
AL	5
AR	19
AZ	18
CA	35
CO	34
CT	6
DC	1
DE	7
FL	41
GA	37
HI	4
IA	39
ID	7
IL	24
IN	37
KS	28
KY	23
LA	19
MA	21
MD	8
ME	3
MI	29
MN	66
MO	51
MS	5
MT	14
NC	22
ND	6
NE	36
NH	5
NJ	8
NM	20
NV	7
NY	9
OH	30
OK	19
OR	33
PA	24
RI	3
SC	26
SD	7
TN	2
TX	54
UT	20
VA	20
VT	11
WA	40
WI	66
WV	4
WY	14

Table 3. Number of Utilities within each State for my Sample

Regression Results – Coefficient Estimates

	1	2	3	4	5	6	7	8
VARIABLE	OLS	OLS Interaction	OLS Log-Level	OLS Log-Level Interaction	Fixed Effects	Fixed Effects Interaction	Fixed Effects Log-Level	Fixed Effects Log-Level Interaction
Price ($/kWh)	33.46*	37.67*	1.752***	2.011***	147.0***	237.0***	3.132***	5.539***
	18.58	19.38	0.449	0.466	39.9	49.04	0.37	0.666
Observations	4,615	4,615	4,615	4,615	4,615	4,615	4,615	4,615
R-squared	0.077	0.107	0.3	0.329	0.023	0.135	0.234	0.498
Number of id					982	982	982	982
State × Year Interaction		YES		YES		YES		YES
Log Capacity			YES	YES			YES	YES
Fixed Effects					YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.2

Table 4. Regression Model Results – Coefficient Estimates (state and year dummies, and state-year interaction terms included in regressions but not reported here)

Regression Results – Elasticity Estimates

	1	2	3	4	5	6	7	8
VARIABLE	OLS	OLS Interaction	OLS Log-Level	OLS Log-Level Interaction	Fixed Effects	Fixed Effects Interaction	Fixed Effects Log-Level	Fixed Effects Log-Level Interaction
Price ($/kWh)	1.289*	1.451*	0.585***	0.672***	5.664***	9.130***	1.046***	1.850***
	0.735	0.771	0.151	0.157	1.603	2.021	0.211	0.223
Observations	4,615	4,615	4,615	4,615	4,615	4,615	4,615	4,615
State × Year Interaction		YES		YES		YES		YES
Log Capacity			YES	YES			YES	YES
Fixed Effects					YES	YES	YES	YES
	Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.2							

Table 5. Regression Model Results – Elasticity Estimates (state and year dummies, and state-year interaction terms included in regressions but not reported here)

State-Level Regression Results - Coefficients

Variable	1 OLS	2 Log-Level OLS	3 Fixed Effects	4 Log-Level Fixed Effects
Mean Price ($/kWh)	532.2**	11.45***	421.6	14.10***
	(220.3)	(2.736)	(473.6)	(4.186)
Constant	-21.89	-0.0569	-7.464	-0.403
	(30.74)	(0.382)	(62.16)	(0.549)
Observations	304	304	304	304
R-squared	0.019	0.055	0.003	0.043
Observations	51	51	51	51

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.2

Table 6. STATE Regression Model Results – Coefficient Estimates (year dummies included in regressions but not reported here)

State-Level Regression Results - Elasticities

Variable	1 OLS	2 Log-Level OLS	3 Fixed Effects	4 Log-Level Fixed Effects
Mean Price ($/kWh)	1.460**	1.040***	1.157	1.281***
	(0.691)	(0.267)	(1.31)	(0.384)
Observations	304	304	304	304

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.2

Table 7. STATE Regression Model Results – Elasticity Estimates (year dummies included in regressions but not reported here)