The Impact of CCAs on Decarbonization in California

by Alison Ong, Bruce E. Cain, Roger G. Noll and Rayan Sud

Abstract

California's Community Choice Aggregators (CCAs) bill allows a local government to form a load serving entity to compete for retail customers and electricity supply with the investor-owned electric utility (IOU) that operates within its jurisdiction. In theory, CCAs could reduce the costs and/or enhance the speed of decarbonization of electricity supply. In reality, a flawed market design, the transfer of regulatory burdens from the IOUs to the CCAs, and the wide variability in community capacities and motivations imperil achieving either goal. IOU ownership and state regulation of distribution and transmission effectively eliminate meaningful price competition. Transferring financial responsibility past electricity procurement and system reliability from IOUs to CCAs creates a ceiling on the greenness and a floor on the price of CCA power. Devolution of electricity procurement to local communities that differ in intensities of preferences for green energy, local investment in generation, and lower end-user prices results in variation in energy portfolios and financial stability among CCAs. We call this energy sorting, i.e. a self-selected grouping of energy consumers by income and commitment to decarbonization. This process has implications for decarbonization because CCAs often bear the responsibility for designing and implementing residential, transportation and commercial electrification programs. Some of these problems, such as finding the right scale for CCAs through creation of joint power agreements, are being solved. Others, such as problematic regulation of the relationship between IOUs and CCAs, will require more extensive reforms.

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I. Introduction

CCAs are a relatively new mechanism for introducing retail competition in electricity. While CCAs are present in eight states, they are particularly noteworthy in California due to their rapid growth and high market penetration. Between 2010, when the first California CCA, Marin Clean Energy (MCE), began to offer service, and 2022, 26 CCAs became operational (21 after 2016), and eight more are in the planning stages. By the end of 2020, the number of CCA customers in California exceeded 11 million, and in 2023 CCA customers are expected to consume 37 percent of the electricity that is distributed by investor-owned utilities (IOUs).

A dizzying array of "load serving entities" (LSEs) provide retail electricity in California. The most important electricity retailers are IOUs and publicly owned (municipal) utilities (POUs). In addition, several irrigation districts, a type of local government, also generate and retail electricity, primarily in agricultural areas. The state classifies these entities as POUs, but organizationally and politically special purpose districts are very different entities than cities and counties that have a department that operates a local electric utility. Another relatively new form of LSE is a "direct access provider" (DAP), a privately owned entity that generates electricity, acquires transmission and distribution from an IOU and sells electricity directly to customers

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(almost exclusively large commercial and industrial entities) in the IOU's service territory.

A CCA is a new form of LSE that has unique characteristics. First, CCAs are owned by local governments (cities and counties), like a POU. In most cases, multiple CCAs then band together through a Joint Power Agreement (JPA) to form a multijurisdictional CCA to capture economies of scale in procuring electricity and dealing with state government. Both an entity that is created by a single city or county and the multijurisdictional JPA to which it belongs are called CCAs. Second, a CCA operates in the service territory of, and competes with, the IOU that has a monopoly franchise to distribute electricity in the CCA's community. Third, a CCA obtains transmission, distribution, backup reliability (supplier of last resort), and billing services from its IOU competitor. Fourth, a CCA procures electricity from generation and storage facilities that are financed by the CCA, perhaps jointly with other CCAs, other private or public generation entities, or both. To summarize, a CCA is a publicly owned (municipal) utility that competes with an IOU on the basis of retail prices and sources of electricity. Thus, CCAs are similar to DAPs, with the main difference being that the latter are private entities.[2]

Until the 1980s, most electricity in the United States was generated, transmitted, distributed, and sold to end-users via a vertically integrated IOU that was intensively regulated by a state public utility commission and the Federal Power Commission (later the Federal Energy Regulatory Commission). In the wake of the 1970s energy crises and the broader deregulation movement that began in the same decade, policy makers in federal and many state governments, including California, sought to introduce competition in electricity generation. In 1996

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[2] For more details about CCAs and DAPs in California, see the California Public Utilities Commission (CPUC) web page on LSEs at https://www.cpuc.ca.gov/consumer-support/consumer-programs-and-services/electrical-energy-and-energy-efficiency/community-choice-aggregation-and-direct-access-.

California spread competition to retail sales by passing legislation that allowed DAPs to enter. After the 2001 California energy crisis, incremental electricity supply from DAPs was suspended and, when resumed in 2009, was strictly limited. In 2002, to create a substitute for DAPs, municipal governments were given the authority to create CCAs.

Initially, growth of CCAs was slow. No local government took advantage of the opportunity to create a CCA until Marin Clean Energy (MCE) began operation in 2010. By the end of 2016, only four more CCAs had entered. Growth of CCAs accelerated thereafter, with four CCAs entering in 2017 and eight more in 2018.

I. A. The Rationale for CCAs

The creation of CCAs was a reaction to the disruptive challenges faced by the electricity industry and its regulators during the past quarter century. These challenges include: (1) climate change and its harmful effects, including wildfires caused by power lines; (2) high and rising retail prices of power; and (3) controversies over siting generation and transmission facilities.

One rationale for CCAs is that direct competition for customers might speed progress in attaining the state's ambitious plan to decarbonize the California economy by 2045. This plan implicates electric utilities in two ways. First, generating electricity by burning hydrocarbon fuels accounts for about 16 percent of greenhouse gas (GHG) emissions in California.[3] Hence, to achieve total decarbonization, electric utilities must find clean power sources for roughly half of current sales. Second, an even greater challenge arises because decarbonization requires substituting electricity for most fossil fuel uses in transportation, appliances, heating, and

[3] GHG emissions data from California Air Resources Board, "Current California GHG Emission Inventory Data," 2022 Edition, available at: https://ww2.arb.ca.gov/ghg-inventory-data.

industrial processes. Satisfying the increase in demand from the transition away from fossil fuels requires increasing electricity output by about 80 percent by 2045.[4] Thus, a potential benefit of CCAs is to facilitate decarbonization by increasing investment in clean generation.

A second potential benefit of CCAs is to reduce the costs and increase the reliability of electricity compared to IOUs. While Californians are not unique in their concern that regulated monopoly utilities do not aggressively minimize the cost of procuring an adequate supply of electricity, recent history has made this issue especially salient in California. Electricity prices in California are the second highest in the U.S. (lower than only Hawaii).[5] Moreover, after restructuring created a vertically segmented and less regulated electricity generation industry, California's IOUs decided not to procure a substantial fraction of their electricity through long-term contracts – a decision that regulators did not challenge.[6] As a result, California experienced a series of energy crises in which IOUs, to equate supply and demand, were forced to institute rolling blackouts and brownouts, to procure a substantial fraction of electricity in deregulated spot markets at extremely high prices, and to rely on state subsidies for purchasing electricity.[7]

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[4] California Air Resources Board, *Draft 2022 Scoping Plan Update*, May 10, 2022, p. 161, at: https://ww2.arb.ca.gov/sites/default/files/2022-05/2022-draft-sp.pdf.

[5] Energy Information Administration, *Energy Power Monthly*, December 22, 2022, Table 5.6.A, at: https://www.eia.gov/electricity/monthly/epm_table_grapher.php?t=epmt_5_6_a.

[6] For a discussion of how and why the California energy crises of 1998 through 2001 was made worse by FERC and CPUC regulation, see Wolak (2003).

[7] In the short run, energy supply and demand are both highly price-inelastic, which means that in the wake of a demand or supply shock reliance on the spot market can cause wholesale prices to soar. The extent to which this threatens the financial viability of a utility depends on the fraction of its power that is acquired through long-term contracts. After restructuring IOUs procured a small fraction of their electricity through long-term contracts. Hence, the combination of excess demand and transmission bottlenecks created an opportunity for some electricity suppliers to withdraw supply to force prices even higher. Due to these and other factors, between the summer of 1999 and the summer of 2000, wholesale purchases of electricity in California rose

A third potential benefit of a CCA to a local community is to steer procurement of electricity to generation and storage facilities that are located locally. While the main political attraction of this possibility is to stimulate local investment and employment, another potential benefit is to reduce reliance on strained long-distance transmission capacity. Of course, the potential magnitude of this benefit depends on the extent to which the CCA is in or near an area where local climate and geography are favorable for clean generation and storage facilities.

The feasibility of these benefits depends on the ability of a CCA to supply power at lower cost than the IOU against which it competes for customers. Only then can a CCA offer cost savings to its customers or generate rents that can be used to procure more clean power – or more locally generated power – than would minimize total costs. But CCAs may not outperform IOUs in procuring clean energy for three reasons.

First, like some POUs, even if CCAs may be able to supply clean energy at lower costs than an IOU, they may not spend this saving on setting lower prices, accelerating procurement of clean energy, or encouraging local energy investments. Instead, the cost saving may be passed back to the local government to pay for other government activities.

Second, most cities that create a CCA may be too small to capture economies of scale in procuring power and in dealing with state regulators. To achieve minimum efficient scale, CCAs can join a JPA, but doing so attenuates their ability to control the composition and location of their portfolio of power sources and their retail prices.

Third, even if the first two challenges are overcome, CCAs still must procure services from a monopoly IOU at rates that are determined by the CPUC. Ultimately, the rate-setting

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from $2 billion to $9 billion, mostly due to an increase in the market power of generators (Borenstein, Bushnell and Wolak 2002).

process of the CPUC and IOU will determine whether cost-savings are available for advancing the CCA's objectives or are simply captured by the IOU in its charges to the CCA.

I. B. Overview of CCA Performance

The early performance of CCA procurement is widely regarded as having accelerated the transition to clean electricity. CCAs signed renewable energy procurement contracts that helped to finance many renewable generation and storage facilities. The supply portfolios of some CCAs have higher proportions of renewable energy than the portfolios of their IOU competitor. A few CCAs offer 100 percent green energy as their default plan. Nevertheless, the effect of CCAs on the performance of the California electricity industry is not clear for two reasons.

First is heterogeneity among CCAs. In 2018, for example, MCE's default service offered 61 percent clean energy, while King City's default plan had 27 percent clean energy. Thus, some but not all CCAs sell cleaner power. Below we document diversity among CCAs in providing clean electricity and explore its implications as more CCAs enter the industry.

Second, CCAs appear to have adversely affected renewable procurement by IOUs. The exodus of customers from IOUs to CCAs initially left IOUs with excess procurement of renewable energy. Between 2017 and 2018, PG&E's default portfolio rose from 33 percent to 39 percent renewable and SCE's from 32 percent to 36 percent. Both were far above the state average of 31 percent, causing IOUs to deliver cleaner power than some CCAs. By 2020, both IOUs had reduced the percentages of renewables in their default portfolios to 31 percent, compared to the statewide average of 33 percent. Evidently, as explored in detail below, some CCAs surged ahead in decarbonization, but they may have slowed progress by IOUs.

Aside from the issue of CCAs contributions to renewable procurement, flaws and vulnerabilities in their design have become apparent. While many CCAs initially had lower rates than their IOU competitors, this price advantage has disappeared. Mounting reliability concerns due to recurring crises from excess demand for power have prompted imposition of more demanding long-term contract obligations, which limit CCA procurement options. As a result, some CCAs have become financially precarious. Western Community Energy went bankrupt in 2020, two of the three original members of Desert Community Energy pulled out amidst cost concerns, and two cities accounting for more than half of electricity delivery by the Orange County Power Authority are considering leaving it because its power is neither green nor cheap.

I. C. Contribution to the Literature

Past research on California CCAs largely focused on their use of green power, and concluded that CCAs have procured more clean electricity than is required by California's renewable portfolio standard (RPS), which in turn has led to IOU overcompliance (Trumbull et al. 2019). In addition, previous work explores some sociopolitical aspects of the formation of CCAs, such as coalition-building (Hess 2019) and diverse community motivations for CCA formation (Gunther and Bernell 2019).

This paper extends prior research by examining in greater detail the effect of the growth of CCAs on the speed and efficiency of decarbonization. We address this issue by asking the following questions: what types of communities form a CCA, how are CCAs organized, how do CCAs procure electricity, and how have CCAs performed with respect to the cost and extent of decarbonization of electricity supply?

In assessing the track record of CCAs during their first decade of operations, we find that CCAs have serious performance and financial problems that are the result of flawed state policies, including the design of both retail and wholesale power markets and the economic regulation of transactions between IOUs and CCAs. Specifically, CCAs are disadvantaged by the structure of their relationships with IOUs and the CPUC because: (1) IOUs are monopoly suppliers of essential inputs to competing CCAs; (2) the CPUC is required by law not to undermine the financial viability of IOUs, but not CCAs; and (3) the CPUC's regulatory process is designed to give substantial influence to other organized private interests, such as the electric generation industry and large industrial and commercial customers.

Another contribution of the paper is to identify the factors that influence the formation and operation of CCAs. CCAs are most likely to be created in communities that are wealthier, more liberal, and more supportive of environmental policy. We refer to this stratification as *energy sorting*. The significance of energy sorting is that, under current policies, CCAs are risky and perhaps unsustainable ventures for many communities. This has important consequences for overall progress toward statewide decarbonization goals as well as for environmental justice. Energy sorting implies less inclusion of disadvantaged communities in decarbonization efforts and raises a question about the fairness of the distribution of legacy financial burdens between (more privileged) CCA customers and (less privileged) residual IOU customers.

The rest of the paper proceeds as follows. Section II explains how CCAs are a product of the institutional and economic conditions that were present when they were formed, culminating in a comprehensive explication of the energy sorting concept. Section III develops empirical tests for the presence and consequences of energy sorting. Section IV introduces the data, and Section V presents results of the tests. Section VI discusses social/policy implications as they relate to the broader energy transition.

II. Retail Competition in California

The introduction of retail competition was the final step in restructuring the electric power industry. In California, DAPs were authorized to enter the industry in 1996 (P.U. Code Section 365.1). Although some policy makers expected that many customers would quickly switch from IOUs to retail competitors, by 2000 only about 3 percent of retail customers (accounting for 12 percent of load) had chosen an alternative provider (Joskow 2001).

II. A. Retail Competition after the Energy Crisis

During the California energy crisis of 2000–2001, the state's largest IOUs faced bankruptcy because of their reliance on spot market purchases of wholesale electricity and the enormous gap between unregulated wholesale prices and regulated retail prices. California responded by authorizing the state Department of Water Resources to issue bonds to finance long-term contracts for electricity for distribution by IOUs. To assure that large customers would not undermine the ability of the IOUs to pay off these bonds, the state passed legislation to suspend the authority of DAPs to add new customers or otherwise to increase their sales.[8] State officials declared: "To sell the bonds with the investment grade ratings required by law, it will be necessary to control the conditions under which ratepayers (generally large users, such as industrial customers) `exit the system,' and such controls and conditions are needed to ensure those who depart pay their `fair share' of costs incurred on their behalf, and thus to prevent the remaining ratepayers (generally small commercial and residential users) from being left to shoulder a disproportionate share of the costs incurred by DWR on behalf of all existing

[8] See https://docs.cpuc.ca.gov/publishedDocs/published/NEWS_RELEASE/14112.htm.

ratepayers."[9] According to the CPUC, allowing DAPs to grow would lead to an unstable IOU customer base, and because customers of DAPs were not previously liable for DWR surcharges, allowing continued switching would lead to cost shifts. Therefore, "It is not in the public interest to permit customers to switch from utility bundled electric service to direct access service."[10]

The decision to suspend DAPs was controversial, so a year later the legislature passed AB117, which permitted the formation of CCAs. In implementing AB117, the CPUC was primarily concerned with establishing measures to ensure that CCA customers continue to pay for recovering legacy costs, including the DWR bonds (CPUC D. 04-12-046). Rather than re-authorize competitive private suppliers of electricity, AB117 enabled local governments to become new participants in energy procurement, defined as: "Any city, county, or city and county" or "Any group of cities, counties, or cities and counties… through the formation of a joint powers agency" (AB117 SEC 2, also Public Utilities Code section 331.1).

In 2006 some communities in San Joaquin County attempted to form the first CCA, but the entity never became operational. The organizers alleged that unlawful marketing efforts by PG&E caused potential members to drop out and prevented a successful launch (CPUC D. 08-06-016). The entry of MCE in 2010 prompted the passage of SB790 in 2011 to establish a code of conduct for interactions between IOUs and CCAs. The bill aimed to mitigate behavior by IOUs that would deter CCA formation. Passage of this law had no discernible immediate effect as the second CCA, Sonoma Clean Power, was not launched until 2014.

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[9] CPUC Decision 01-10-036, *Order Modifying Decision (D.) 01-09-060, And Denying Rehearing, As Modified*, October 10, 2001, Section II.B.2, at: https://docs.cpuc.ca.gov/published/Final_decision/28204-01.htm.

[10] CPUC Decision 01-09-060, *Interim Opinion Suspending Direct Access*, September 20, 2001, at: https://docs.cpuc.ca.gov/PublishedDocs/WORD_PDF/FINAL_DECISION/9812.PDF.

II. B. CCA Formation and Energy Sorting

Borenstein and Bushnell (2015) note that since 2002, "the policy focus for the electricity industry has turned… mostly towards environmental concerns – and the loud debates from the early 2000s over the merits of restructuring have been reduced to a background murmur." In 2002, soon after the energy crisis, California enacted SB1078, the first of a series of bills that established ever more ambitious targets for renewable energy sales by electric utilities.[11]

The entry of CCAs was encouraged by the change in state policy objectives from reducing costs to accelerating decarbonization. MCE explicitly cited decarbonization as the driving force behind its founding. "Recognizing the opportunity to increase access to renewable energy and combat climate change on a local level, Rebekah Collins, co-Founder of Sustainable Fairfax, brought AB117 to the attention of the Marin County Board of Supervisors and Fairfax Town Council."[12] Now that over a decade has passed since CCAs began to operate, we can begin to evaluate how CCAs perform as alternative providers of electricity.

As California's commitment to decarbonization strengthened, several CCAs became operational between 2016 and 2020. As explored in greater detail in the next section, cities and counties varied substantially in their enthusiasm for creating a CCA, leading to socioeconomic sorting of communities according to whether they created a CCA.

Socioeconomic (including racial) sorting is a long-standing feature of California's neighborhoods and local jurisdictions due in part to the legacy of past municipal incorporation patterns and real estate redlining practices (Miller, 1981; Rothstein, 2017). More recently,

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[11] For the history of California's renewable energy standards for electric utilities, see California Public Utilities Commission, "Renewables Portfolio Standard Program," accessed at https://www.cpuc.ca.gov/rps/.

[12] Marin Clean Energy, "Our History," accessed at: https://www.mcecleanenergy.org/about-us/.

NIMBYism regarding all forms of public infrastructure, residual racism, and Tiebout-like ("voting with your feet") political sorting tended to preserve and extend socio-economic stratification. Allowing communities to act unilaterally or multilaterally through Joint Power Authorities for the purposes of energy procurement is likely to produce local variation in energy consumption that reflects the underlying pattern of political and socioeconomic clustering.

This form of clustering has consequences for energy policy. Predominantly liberal Democratic communities tend to favor more aggressive decarbonization policies than conservative Republican communities. Wealthier jurisdictions have fewer residents who default on their energy bills and more technical capacity to negotiate energy contracts, to manage a plan to investment in generation and storage, and to apply for state and federal government grants to support decarbonization. Wealthier municipalities also tend to have more influence in state politics, including lobbying to secure favorable terms and conditions for state subsidies (Payson 2020). As a result of these realities, the consequence of energy sorting is widening gaps among communities in energy portfolios and fiscal stability.

Placing CCAs under the jurisdiction of the CPUC also means that, unlike POUs, CCAs are constrained by the goals and practices of state regulatory laws and policies. The CPUC has a longstanding relationship with IOUs and its rules are designed to minimize a utility's financial risks. The foundation of this policy is the regulatory bargain between the state and an IOU: the CPUC adopts policies that essentially guarantee the long-term financial viability of IOUs in return for IOUs agreeing to be the supplier of last resort in its service territory, including for customers of the CCA. CPUC rules are designed to protect the investments of IOUs, not their upstart competitors. While IOUs are guaranteed that their costs will be recovered, CCAs have no such regulatory safety net but are burdened with costs incurred by the IOU, such as legacy costs from the energy crisis or liability for wildfire damage. Thus, even if a CCA is nimble enough to enjoy a permanent cost advantage in procuring electricity, the CPUC would not be willing to allow competition from CCAs to cause an IOU to suffer significant losses.

A CCA is likely to be further disadvantaged because it has less experience and relevant technical expertise than its IOU competitor in arranging for adequate power supplies. CCAs face the same statewide technical requirements that IOUs must follow (e.g., long term procurement contracts, reliance on instate generation, resource adequacy goals). These complex matters outstrip the technical capacities of small local governments, which causes all but the largest CCAs to contract out for technical services. Relying on outside experts to address technical issues creates a potentially severe agency problem because a CCA's top executives are elected politicians who typically have little or no relevant experience.

As a result of structural features baked into the design of the market for retail electricity, CCA cost competitiveness can be undercut in two ways: vertical leveraging by the IOU, and regulated rates for IOU services that transfer revenues from CCAs to an IOU if the financial viability of the latter is not secure.

The first problem arises from the dependence of a CCA on an IOU for essential services. A core tenet of successful restructuring in competitive power markets is the "vertical separation of potentially competitive segments…from segments that will continue to be regulated" (Joskow 2008). This is clearly violated here. A CCA depends on an IOU for transmission, distribution, reliability, and billing. Thus, the IOU potentially can engage in vertical foreclosure of its CCAs.

The second problem arises from CPUC price policies. The CPUC requires that CCA customers reimburse the IOU for unrecovered IOU legacy costs (via the Power Charge Indifference Adjustment, or PCIA), the IOU's liability for disasters for which the IOU has been found to be responsible, and the costs of providing adequate resiliency as the provider of last resort. Because a CCA's customers can return to the IOU at any time, the CCA must remain price competitive with the IOU despite these costs or risk financially destabilizing defections.

As a result of these factors, CCAs in wealthier communities that favor stronger environmental policies are more able to retain customers. Communities that formed CCAs primarily to achieve cost savings will experience greater financial vulnerability as the price advantage of CCAs erodes.

II. C. CCA Costs and Prices

One measure of the performance of CCAs is their prices in comparison with the prices of IOUs. For three reasons, one would not expect CCAs to have much effect on electricity prices. First, the retail markets in which CCAs operate are duopolies, which do not normally exhibit vigorous price competition. Second, a CCA has the advantage of being the default supplier of electricity within its jurisdiction. Switching to the competing IOU is costly in the sense that it requires time and effort. As a result, a CCA need not undercut or even match the price of an IOU to retain most of its customers. Third, as discussed above, an IOU is the monopoly supplier of essential inputs to the CCA and so, if the CPUC approves, can extract the CCAs cost advantage through its prices for these inputs. For these reasons a CCA is not likely to pass through a cost saving in procuring electricity.

CCAs likely had a cost advantage over IOUs when CCAs first entered the market. Technological advances caused the cost of renewable generation to fall substantially since the energy crisis of 2000-2001, and especially after 2010. During and immediately after the energy crisis, IOUs signed expensive long-term contracts for renewable energy that reflected the much higher cost of renewables in the first few years of the 21st century. When CCAs entered starting in 2010, they were able to sign contracts to procure renewable electricity at much lower prices. Lower wholesale electricity costs allowed CCAs to set retail prices slightly below IOU prices; however, this advantage was inherently temporary. As old IOU contracts expired and were replaced by contracts of recent vintage, CCAs lost this cost advantage.

The CPUC also has imposed stricter long-term contracting requirements on both IOUs and CCAs, cutting into the cost advantage that CCAs had enjoyed from having greater flexibility to make short-term purchases. In addition, the PCIA surcharge on electricity sold by CCAs and DAPs rose significantly in the years of rapid CCA growth. Thus, even if a CCA's energy charge was below the IOU's, its total charges often were greater.

As a result of these factors, by 2022 CCAs generally did not have lower prices than IOUs. Table 1 shows the price differences in recent years for basic residential rates between a CCA and its competing IOU.[13] (The number of years covered differs among CCAs due to differences in formation dates and, in some cases, data availability.) The table reveals a shift in relative prices in favor of IOUs. In 2022, the prices charged by the vast majority of CCAs differed from prices for the corresponding IOU by one percent or less. Table 2 compares IOU and CCA rate increases in 2021 and 2022, with the column on the far right showing the fraction of the IOU's price increase that was not matched by the CCA. In 15 of the 21 cases, the CCA's rate change was at least 80 percent of the IOU's rate change, indicating that CCAs tend to be price followers of the corresponding IOU.

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[13] A CCA's total rate is the sum of the rates for generation, transmission and distribution, PCIA, and franchise fee. For IOUs, the total rate is the sum of the generation rate and the transmission & distribution rate. (Before 2022, the IOU's generation rate included PCIA and Franchise Fees bundled together. Beginning in 2022, IOUs report unbundled generation and PCIA rates.)

The most plausible explanation for CCA price performance is rising costs, including regulated input prices. An increasing number of CCAs are in precarious financial positions. In addition to one bankruptcy and threats to abandon a few other CCAs, a recent CPUC staff report states that no new CCAs are expected to launch in 2023. Between 2018 and 2022, seven CCAs either postponed their launches indefinitely or deregistered. This is a stark contrast to the period from 2016 to 2019, when the number of CCAs increased rapidly.

III. Empirical Approach

This section describes two regression models. First is a model for predicting which communities form a CCA, which is used for gaining insight into the motives for creating CCAs and for detecting the presence of energy sorting in the formation of CCAs. Second is a model for explaining the intensity of procurement of electricity from renewable sources among IOUs and CCAs.

III. A. The Decision to Form a CCA

The first empirical task is to ascertain whether CCA formation is a function of the underlying demographic characteristics of its community. Energy sorting implies that CCA formation will be affected by demographic, socioeconomic and ideological characteristics of a community. such as wealthy communities with atypically high support for environmental regulation. Data were collected for both incorporated cities and towns and unincorporated areas in a county. A binomial logit model was used to ascertain the factors that led a community to form a CCA by the year 2020.

For the binomial logit regression, the outcome variable (type of LSE operating in a community in 2020) takes the value one if a CCA entered the community in any year between 2010 and 2020. Communities that, in 2020, were in the process of forming a CCA are recorded as served only by an IOU. This group includes communities in which a CCA became operational after 2020 and other communities that abandoned the process of CCA formation in that period. (A community in which a CCA was formed but then went bankrupt is coded as having a CCA.)

If CCA formation rates are unaffected by demographic and political factors, none of the demographic variables should be a significant predictor of CCA formation. If, however, the decision to form a CCA reflects sorting, then some demographic variables should have a significant association with CCA membership. The model specification tests the importance of a variety of demographic features including community wealth, socio-political characteristics, local industry, presence of renewable resources, and geography. If the specification omits important demographic variables, the results may fail to detect that an included factor affects formation, or falsely conclude that a factor influences CCA formation when in fact formation is influenced instead by its omitted correlate.

Initially a CCA enrolls all customers within an area in which it offers service; however, a CCA may offer service initially only in part of its jurisdiction, then gradually expand service as it negotiates agreements for more power. Once a CCA offers service in a neighborhood, all the IOU's customers automatically switch to CCA service unless they proactively opt to stay with the IOU. Because data are not available for neighborhoods in the same local jurisdiction that were offered service at different times, all political, socioeconomic, and demographic variables are recorded at the community level. This procedure results in two limitations to our findings. First, the model captures variation among communities within a multi-city LSE but cannot measure the effects of variation in these variables within the same community. Therefore, our results are likely to be biased against detecting the presence of sorting, some of which occurs at the neighborhood level. Second, some customers opt-up to a CCA's premium portfolio (a higher proportion of renewable energy) and some opt-out to return to IOU service. We cannot identify the specific households that elect to opt-up or opt-out due to data privacy restrictions. The problems arising because of this data limitation are limited by the fact that opt-outs and opt-ups tend to be a small percentage of customers.

The logistic regression estimates the odds that a community will have formed a CCA by 2020. Extending our analysis to characterize CCA formation in the years since 2020 requires a different approach. We assess changes in CCA formation during the pandemic by comparing the descriptive statistics for the last pre-pandemic set of CCA launches with the characteristics of communities that formed CCAs in 2021 or 2022, as well as those that indefinitely postponed or deregistered their CCAs.

III. B. Socioeconomic Determinants of CCA Clean Electricity Procurement

Perhaps the paramount issue in the policy debate over the value of CCAs pertains to whether clean energy procurement varies systematically between CCAs and IOUs. Also important for determining the likely future impact of the formation of additional CCAs is whether the intensity of clean energy varies among established CCAs. Proponents of CCAs claim that they increase consumption of clean energy by their customers. But among CCAs, the percentage of clean energy in procurement portfolios varies widely. If existing CCAs exhibit sorting, the level of clean energy procurement by a CCA that has not yet been formed may be predictable based on the community's demographic characteristics. To test for whether this might be possible, we regress the composition of a CCA's energy portfolio composition on the characteristics of the community in which the CCA is located, in similar fashion to the regressions on CCA formation.

Existing studies of CCAs from UCLA's Luskin Center (see DeShazo, Gattaciecca and Trumbull, 2018; Trumbull, Gattaciecca, and DeShazo, 2020) examined renewable procurement by CCAs and IOUs, with a focus on CCA contributions to procurement above minimum state standards for procurement of electricity from renewable sources (RPS). The 2020 report acknowledges that there are income and partisanship differences with respect to renewable and other clean energy sources in CCA portfolios but characterize the bivariate relationships as "not strongly correlated" (p. 14). They conclude that "the size and median income of a community are not predictors of success," suggesting that the CCA model "can be successful in a variety of communities with differing sizes and incomes." The 2020 study also reported single variable regressions showing that income and, separately, political party registration, did not significantly impact the CCA's default renewable or carbon-free energy share.

We examine these conclusions first in a multi-variate model using data from 2020 and then in disaggregated comparisons more recently. Both reveal a more complex picture of CCAs. CCAs exhibit considerable heterogeneity with respect to renewable procurement, median income, party and scale.

To ascertain whether prior findings were affected by specification error (omitted variables and incorrect functional form), we performed multivariate linear and piecewise linear regressions estimating the composition of a CCA's electricity portfolio as determined by several demographic and socioeconomic variables. In this regression procurement information for 2020 is measured in two ways. "Renewable" means Category 1 generators (RPS eligible) and

Category 2 (specified import) renewables. These renewable fuel sources are biofuel, small hydro, geothermal, wind, and solar. "Carbon Free" refers to the sum of electricity from renewable, nuclear, and large hydro facilities.

Data on electricity procurement by type of generation facility are from the Power Source Disclosure filings by each CCA, from which are calculated weighted averages of the percent of electricity from sources that are renewable and the percent from carbon-free sources. For example, MCE is a multi-jurisdiction entity composed of CCAs in several communities in Contra Costa, Marin, Napa, and Solano counties. If MCE had a 30 percent renewable portfolio that supplies 90 percent of its sales and a 100 percent renewable portfolio that supplies the other 10 percent, we assign each community in MCE a renewable energy percentage of 37 percent (0.9x.30 +0.1x1.0).

Some cities within a JPA CCA select a higher renewable portfolio as their default. When this information is known, each city within a CCA is assigned the renewable and carbon-free energy percentages that correspond to its default portfolio. For example, Calabasas has "Lean Power" as its default option, while Beverly Hills has "100 percent Green Power" as its default option. Then Calabasas is assigned 40 percent renewable, while Beverly Hills is assigned 100 percent. This procedure does not account for the fact that some customers opt for a choice other than the default rate.

IV. Descriptive Statistics

This section summarizes the data described above on the structure and performance of the retail electricity industry in California.

IV. A. LSE Scale

Prior to the creation of CCAs, three large IOUs (PG&E, SCE, and SDG&E) served approximately 80 percent of California's load. Throughout the analysis, "IOU" generally refers to these three and not to the three much smaller IOUs (Bear Valley, Liberty Utilities, and Pacificorp). As of 2020, CCAs served 183 communities containing 11.3 million customers. The smallest is King City Community Power, a single city CCA of 13,800 people; the largest is Clean Power Alliance of Southern California, spanning 32 communities over two counties and serving 2.7 million people. Table 3 shows that CCAs vary substantially in size. Figure 1 further illustrates the heterogeneity among CCAs in terms of annual revenue, annual sales, and number of customer accounts.

Throughout the empirical analysis, we restrict our attention to IOUs and CCAs. We are principally interested in characterizing which communities join CCAs and how community characteristics affect the performance of the CCA. As specified in AB 117, CCAs may be formed within the existing service territory of an IOU but not a POU or Co-Op.

IV.B. Community Characteristics

Data were compiled for 18 parameters describing socioeconomic, demographic, and other characteristics of each community. Regression tables contain a subset of these variables, as covariates that did not improve the explanatory power of the regression were removed. Table 4 lists the variables that are used in the regressions.

The top executive authority of a CCA rests in a city or town council or a county board of supervisors. Because the unit of observation is one of these communities, data were collected for each city, town, and unincorporated community in each county (n = 539). Communities that are not served by an IOU were removed from the data set (n = 475). Summary statistics for these communities are shown in Table 5.

The variables that are used to test for ideological sorting are four measures of the political preferences of citizens: two indicators of general political ideology (party identification and vote share for Donald Trump in 2020), and two indicators of relevant policy preferences as measured by votes on ballot propositions (one that would have disfavored public provision of electricity and another that would have suspended California's cap-and-trade program for controlling GHG emissions). The variables that test for socioeconomic sorting are median income and measures of educational attainment. Variables that potentially affect the demand for electricity, besides income, are measures of the structure of the local economy (shares of agriculture and manufacturing) and local climate (winter and summer temperatures). Indicators that the community might perceive a benefit from a CCA that purchased power locally are megawatts of power production from nearby photovoltaic and hydro installations. We also add an indicator for communities that are not in either PG&E or SCE's original service territory. The politics of the other four IOUs (SDG&E and the three small utilities) are more likely to be dominated by a single city or county, whereas PG&E and SCE have service territories that include many large political jurisdictions.

IV. C. Procurement

Data to analyze heterogeneity in procurement come from the California Energy Commission's (CEC) Power Source Disclosure (PSD) program. This program is intended to provide consumers "accurate, reliable, and simple to understand information on the sources of energy that are used to provide electric services."[14] PSD filings for CCAs, IOUs, and POUs were obtained via a data request to the CEC, for years 2011–2020. Each document contains information on MWh procured from each generation source and total retail sales. Data for 2021 come from a summary of PSD filings published on the CEC website, which contains total retail sales and percentages procured from each generation source for all portfolios.[15]

The analysis of procurement focuses on the years 2017–2020, reflecting the relatively recent entry of most CCAs. As shown in Table 6, more than three-quarters of CCAs commenced operation after 2016. The period 2017–2020 also aligns with the most recent RPS compliance period. RPS methodology differs somewhat from PSD accounting, creating discrepancies between the values presented in this analysis (reflective of actual retail sales each year) versus those found in the CEC staff's RPS reports (reflective of RPS credit accounting).

Table 7a summarizes relevant procurement data from the PSD filings for the CCAs and IOUs in question. The table shows the estimated fraction of total procurement attributable to each fuel category as defined by the CEC. Table 7b groups these fuels among renewable, other carbon-free, and fossil, following CEC definitions.[16] Unspecified power, also called system power, is the difference between an LSE's retail sales and specified (contracted) power. Unspecified power is assumed to have the average characteristics of the California grid.

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[14] California Senate Bill 1305 (Stats. 1997, ch. 796). See: http://www.leginfo.ca.gov/pub/97-98/bill/sen/sb_1301-1350/sb_1305_bill_19971009_chaptered.html.

[15] California Energy Commission, 2021 Power Content Labels Sortable Table, accessed at: https://www.energy.ca.gov/media/7746.

[16] Renewable includes biomass and biowaste, geothermal, eligible (small) hydro, solar, and wind. Carbon-free includes large hydro and nuclear power.

V. Results

This section presents the results of several econometric models that explore the factors that affect the formation of CCAs and their procurement of electricity from renewable sources.

V. A. Factors Affecting the Presence of a CCA in 2020

The first regression is a binomial logit model that estimates the odds that a city, town or county formed a CCA by 2020, based on its socioeconomic, demographic, political and climate characteristics. The regression takes the form:

$$is\_CCA_i = X'\beta + \epsilon_i$$

where the vector X consists of variables measuring the characteristics of the community as discussed above.

This regression indicates that CCA formation is related to community characteristics in a manner that implies socioeconomic and political energy sorting. Table 8 reports statistically significant regression coefficients for median income, political support for local power, and political support for state regulation of GHG emissions. The results support the hypothesis that CCA membership reflects energy sorting based on income and politics.

Possible structural breaks in the causal relationships may be detected using a piecewise linear specification. We test for structural breaks by separating each variable into two segments at the optimal breakpoint, defining a dummy variable that takes value zero if below the breakpoint and the value of the existing data if above the breakpoint, and re-running our generalized linear model to obtain two coefficients per independent variable. Thus, the reported coefficient for the segment above the breakpoint is the difference in slopes for the two segments. For example, our coefficient for median income is 3.612 for communities with median income below the breakpoint of $108,000 and 3.612 - 4.750 = -1.138 for communities with median income above $108,000 (the median household income for our entire sample is $87,000).

A simple ANOVA test confirms whether the addition of each dummy variable significantly improves explanatory power. We find that the effects of income, political support for local power, and climate are all better described by piecewise linear relationships; we report these improvements to model fit alongside the fully linear model. (A more detailed explanation of our model selection process and robustness tests are included in the Appendix.)

Larger regression coefficients do not necessarily mean larger effects on the outcome. We measure the effect of changing each variable in isolation within its range of variance in the sample to assess the relative importance of each covariate on propensity for CCA formation. We begin by creating a hypothetical community with average characteristics for all covariates and determine the model's prediction of the probability of CCA formation. We then perturb a covariate by one standard deviation, holding all other variables constant, and measure the difference in predicted probability of CCA formation. This exercise, summarized in Table 9, shows that one standard deviation changes in income, political support for local power and for state regulation of GHG emissions, and August temperature (hot summer) have large effects on the probability that a CCA had been formed by 2020. (The effect of January temperature is smaller.) For example, an otherwise-average community with income one standard deviation below the sample mean (from $87,000 to $44,000) has an estimated probability of CCA formation that is 27.5 percent lower (from 39.7 percent to 12.2 percent).

Examining instances in which an existing CCA has a low predicted formation probability and in which a community without a CCA has a high predicted formation probability provides some insight into which communities may seek to form CCAs in the future and which may be candidates to discontinue an existing CCA. Table 10a lists all communities with a modeled propensity for CCA formation above 60 percent that did not belong to a CCA in 2020. Most of these places did indeed become CCA communities in 2021 and 2022. Further, the model results imply that the majority of communities with high propensity for CCA formation have already done so, leaving few likely candidates for further CCA expansion. Table 10b lists all communities with a modeled propensity for CCA formation below 40 percent that did belong to a CCA in 2020. Three communities with CCAs that deregistered in 2021 appear on this list. Most single-city CCAs, which plausibly lack sufficient scale for efficient operations, also appear.

V. B. Examining Post-2020 Trends

The onset of the Covid-19 pandemic appears to have affected CCA formation since 2020. We compile information about all California communities that changed their CCA status (joining or abandoning a CCA) in 2021 and 2022 to assess changes in the propensity to form a CCA during the pandemic era. Table 11 summarizes these findings. We first display average demographic characteristics for the last cohort of pre-pandemic CCA launches (communities that began operation in 2018, 2019, and 2020). We also show average demographic characteristics for the cohort of communities that *intended* to begin operating a CCA in 2021 or 2022. This category is comprised of three groups: communities that successfully launched a single-jurisdiction CCA, communities that joined existing JPA CCAs, and communities that either indefinitely postponed launch plans or deregistered their CCA to return all customers to IOU service. The "Postponed/Deregistered" category contains five indefinite postponements (four single cities and one multi-community) and two deregistered CCAs (the city of Baldwin Park and Western Community Energy, which served six communities in Riverside County).

The overall characteristics of the communities that intended to be part of operational CCAs in 2021–2022 do not appear much different from CCAs that launched in 2018–2020. However, the group of communities that postponed or deregistered their CCAs as of 2022 are markedly less wealthy and smaller than the groups that launched during 2018–2020 or that joined during 2021–2022. New CCAs in 2021–2022 were associated with large communities such as the city of Santa Barbara. Expansion of existing CCAs in this time period included many smaller communities. This suggests that smaller communities looking to form a CCA find that joining an existing JPA is more attractive than attempting to launch a single-jurisdiction CCA.

V. C. Procurement of Renewable Electricity

The last set of regressions examines the relationship between the average percentage of renewable energy in each LSE's portfolio and the characteristics of the community. The LSEs that are included in the first regression are the six IOUs plus the CCAs. The second regression includes data only for CCAs.

In both cases, the regression takes the form:

$$pct\_renewable_i = X'\beta + \epsilon_i$$

where each i is an LSE and the vector X contains variables measuring community characteristics and size of the LSE. The CCA only model takes the same form.

Having shown that the probability of CCA formation is affected by community characteristics, we now examine whether this leads to sorting in renewable energy procurement. The results for CCAs and IOUs combined are shown in Table 12 while the results for CCAs only are shown in Table 14. As with the logit results for CCA formation, inclusion of piecewise linear terms improved model fit. The combined results in Table 12 do not include income but do include a variety of other socioeconomic and political indicators, including variables around educational attainment. The CCA only results in Table 14 include a strong income effect as well as significant coefficients for other socioeconomic indicators.

In both the combined and CCA-only regressions, the size of the LSE is important. In the combined analysis the coefficient is positive until the breakpoint then becomes slightly negative, reflecting the fact that, compared to CCAs, IOUs are much larger and procured a lower share of electricity from renewable sources. Table 13 shows that among the significant variables, LSE size is the most influential in predicting renewable energy share. In the CCA-only regression, the breakpoint to segment this variable occurs around the 10^{th} percentile, so although the coefficient on size is negative for the smallest 10 percent (about 18 observations), it is otherwise positive. This indicates that larger CCAs (usually agglomerations of multiple communities) procure a larger fraction of their power from renewable sources. Table 15 confirms that within CCAs, LSE size is one of the most important variables for predicting the percentage of renewable energy use in a community.

But do communities that consume more clean energy reflect the communities who most desire it? One argument for CCAs is that they enable communities that want to leap ahead of state standards to realize greater renewable procurement. If support for Prop 23 (the ballot measure about suspending AB32) is a good indicator of a preference for clean energy, then a lower "yes" vote should correspond to higher levels of renewables. Table 13 shows that Prop 23 is not a significant variable for the combined regression. Table 15 shows that the coefficient for Prop 23 is significant in the CCA-only regression. However, among the set of significant variables it has the smallest quantitative effect (whether in the positive or negative direction) on the predicted percentage of renewable energy.

The regression analysis shows that CCA formation leads to sorting by income. The regressions reported in this section indicate that the percentage of renewable energy in a CCA's portfolio in 2020 also is affected by income and the size of the CCA. We now examine trends in procurement over time among various retail suppliers in California to assess the implications of energy sorting for overall progress towards decarbonized energy procurement.

Although *total* CCA renewable procurement showed large year-on-year gains during the period 2017–2020, the trajectories of individual CCAs vary widely. Table 16 groups CCAs into three categories that reveal the heterogeneity in CCA renewable procurement. The first group exhibits consistent, sustained voluntary renewable procurement; the second group struggles to procure stable, sustained amounts of clean energy, resulting in volatile portfolios; the last group exhibits declining renewable procurement. For comparison we also note the trajectories of select IOUs and POUs as well as aggregated procurement by DAPs.

As noted above, customers leaving IOUs for CCAs left IOUs with excess renewable procurement. In subsequent years, IOUs decreased renewable procurement, which also reduced their percentage of retail sales supplied by renewable resources. Table 17 shows total CCA and total IOU renewable procurement. Although CCAs consistently increased provision of renewable energy during 2017–2020, these increases were more than offset by the fall in renewable procurement by IOUs.

In addition to the difference between IOUs and CCAs in overall renewable procurement, CCAs also differ substantially in the share of renewables in their electricity supply. CCAs can be separated into two equal groups according to median income (here labeled as "rich" and "poor." Likewise, CCAs can be divided into two equal groups according to MWh of electricity sales in 2020, here labeled as "large" and "small." Differences between these groups, and between each and other types of LSEs, for the period 2017–2021 are shown in Table 18 and Table 19. We extend the analysis to 2021 using publicly available summaries of the Power Source Disclosure data. Both stratifications show a substantial difference between the two groups in renewable procurement.

Wealthier CCAs have indeed achieved high voluntary renewable procurement, although their renewable share has declined substantially since 2017. Meanwhile, in 2021 less wealthy CCAs procured a lower fraction of renewable electricity than the average of the three big IOUs, and this group's share of renewables in procurement is steadily declining.

Similar results hold for large versus small CCAs. The renewables share has gradually declined for large CCAs, but the fall has been precipitous for small CCAs. Moreover, in 2021 small CCAs had a lower renewable share than any other LSE type except for DAPs.

These data have troubling implications regarding the future of CCAs. IOUs have made gains in renewable procurement, while some CCAs have stagnated or even regressed. Moreover, the gap between large/wealthy and smaller/poorer CCAs is growing, and the latter are losing ground to the IOUs as suppliers of electricity from renewable sources. As a result, many CCA customers receive less green electricity than the IOU that serves their community. If these CCAs provide neither greener power nor lower prices, the rationale for their existence is unclear.

VI. Discussion

Initially CCAs enabled some communities to attain levels of voluntary renewable procurement that exceeds state standards; however, excess voluntary renewable procurement is realized and sustained only by wealthier and/or larger CCAs, and their performance advantage is shrinking. Less wealthy and smaller CCAs have lower shares of renewable energy procurement than IOUs. Evidently, CCAs have created greater dispersion but not substantially greater overall progress. Simply focusing on the successes of some CCAs—or even apparent overall gains in statewide total procurement—ignores the evidence of stagnation or unevenness among CCAs.

Energy sorting also implies stratification in the performances and broader abilities of California's electricity retailers. Wealthier and larger CCAs have greater capacity to take on matters requiring technical expertise, such as the mandates to procure long-term contracts, as well as greater reserves to weather adverse economic conditions. While such CCA communities can sustain progress, stratification also created a class of communities tasked with electricity retailing duties that may outstrip their financial and technical capacity. The seven CCAs who indefinitely postponed launch or deregistered are all either single-jurisdiction CCAs or are in less wealthy areas. Thus, CCAs not only allowed some communities to surge ahead towards 100 percent renewable electricity, they also potentially exposed other communities to financial vulnerability as they invested time and effort in unsustainable ventures.

The ability of some communities to surge forward must be contrasted with the challenges of fractured governance of decarbonization. Wealthy first movers benefitted from favorable conditions for inexpensive renewable contracts and were able to sort themselves into CCAs; now, the challenges to starting and maintaining a viable CCA are greater. CCAs face greater difficulty in achieving cost savings or in offering a path to acquiring greener electricity. Some customers are receiving less electricity from renewable sources under CCA service than they would have received from their IOU.

The remaining value of CCAs is in the other local decarbonization programs they offer, which vary widely depending on city capacity. Wealthy and better-organized communities tend to dominate the policy agenda and win a larger share of funds. Energy sorting by income, therefore, implies stratification in access, funding, and capacity to further decarbonize. CCAs have indeed allowed some communities to progress faster—but these are the wealthy ones.

The first decade of operations for CCAs reveals a system in flux. The number of electric service providers expanded rapidly, as did renewable energy procurement. What might an eventual equilibrium between CCAs, incumbent providers, and the regulator look like? The future remains deeply uncertain. In the past few years, California's energy system has seen significant shocks ranging from summer reliability challenges to disastrous wildfires to bill debt from the Covid-19 pandemic.

Notwithstanding these disruptions, one plausible equilibrium is becoming apparent: a future in which CCAs agglomerate to capture economies of scale and to achieve financial stability, leaving fewer but larger independent CCA JPAs that approach IOUs in scale. A plausible indicator of the future is the creation of a "super JPA" by the Bay Area CCAs to procure energy storage. Larger CCAs have been more successful in achieving and sustaining high levels of renewable energy while remaining cost-competitive with IOUs, although even the larger CCAs have regressed on renewable procurement. Smaller CCAs that are not part of large JPAs have been more likely to experience financial instability. The recent performance of CCAs indicates that achieving greater scale is likely to improve performance, but whether scale alone can overcome the growing challenges faced by CCAs remains uncertain.

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Table 1: Selected CCA Residential Electricity Rate Comparisons

CCA Name	IOU	Year	$P_{t,IOU}$ ($/kWh)	$P_{t,IOU}$-$P_{t,CCA}$ ($/kWh)	Source
CPSF (CleanPowerSF)	PG&E	2016	-	0.00024	CPSF rates effective May 1, 2016, taken from tariff book provided by CCA through PRA request.
		2017	0.23992	0.00543	Rates from archived Joint Rate Comparison, effective July 1, 2017.
		2020	0.26981	-0.00079	Rates from archived Joint Rate Comparison. PG&E rates effective as of May 1, 2020. CPSF rates effective as of May 15, 2020
		2021	0.28518	-0.00253	Rates from archived Joint Rate Comparison. PG&E rates effective as of March 1, 2021. CPSF rates effective as of January 15, 2021
		2022	0.34262	0	Rates from archived Joint Rate Comparison, effective March 2022
SCP (Sonoma Clean Power)	PG&E	2017	0.24138	0.00213	Rates from archived Joint Rate Comparison, effective March 1, 2017.
		2018	0.25055	0.00431	Rates from archived Joint Rate Comparison, July 1, 2018
		2020	0.27444	-0.01249	Rates from archived Joint Rate Comparison, January 1, 2021
		2021	0.28461	-0.01295	Rates from archived Joint Rate Comparison, April 1, 2021
		2022	0.34748	0.00073	Rates from archived Joint Rate Comparison, effective July 1, 2022
RCEA (Redwood Coast Energy Authority)	PG&E	2017	-	0.00266	Rates effective Jan 23, 2017, taken from tariff book provided on CCA website (link)
		2018	0.25786	0.00323	Rates from archived Joint Rate Comparison, March 15, 2018
		2021	0.29456	0.00057	Rates from archived Joint Rate Comparison, June 21, 2021
		2022	0.35005	0.00076	Rates from archived Joint Rate Comparison, effective July 1, 2022
MCE (Marin Clean Energy)	PG&E	2017	0.23887	0.00061	Rates from archived Joint Rate Comparison, effective June 1, 2017.
		2018	0.24928	0.00579	Rates from archived Joint Rate Comparison, March 1, 2018
		2021	0.27904	-0.0209	Rates from archived Joint Rate Comparison, May 1, 2021
		2022	0.34599	0.02394	Rates from archived Joint Rate Comparison, effective June 1, 2022

VCE (Valley Clean Energy)	PG&E	2018	0.23997	0.00269	Rates from archived Joint Rate Comparison, June 1, 2018
		2021	0.28368	0	Rates from archived Joint Rate Comparison, June 21, 2021
		2022	0.33991	0	Rates from archived Joint Rate Comparison, effective June 1, 2022
SVCE (Silicon Valley Clean Energy)	PG&E	2018	0.24554	0.00647	Rates from archived Joint Rate Comparison, March 1, 2018
		2021	0.28551	0.00114	Rates from archived Joint Rate Comparison, March 1, 2021
		2022	0.34405	0.00152	Rates from archived Joint Rate Comparison, effective June 1, 2022
SJCE (San Jose Clean Energy)	PG&E	2018	0.24352	0.00108	Rates from archived Joint Rate Comparison, September 2018
		2019	-	0.00112	Rates effective May 1, 2019, from tariff book provided on CCA website (link)
		2020	-	0.00118	Rates effective May 27, 2020, from tariff book provided on CCA website (link)
		2021	0.28250	0.00029	Rates from archived Joint Rate Comparison, March 1, 2021
		2022	0.34020	0.00074	Rates from archived Joint Rate Comparison, effective July 1, 2022
Pioneer Community Energy	PG&E	2021	0.28812	-0.01109	Rates from archived Joint Rate Comparison, June 21, 2021
		2022	0.34450	0.01566	Rates from archived Joint Rate Comparison, effective June 1, 2022
PCE-San Mateo County (Peninsula Clean Energy)	PG&E	2018	0.24673	0.00539	Rates from archived Joint Rate Comparison, March 15, 2018
		2021	0.27685	0.00571	Rates from archived Joint Rate Comparison, March 2021
		2022	0.34473	0.00759	Rates from archived Joint Rate Comparison, PCE rates effective July 2022, PG&E rates effective June 2022
EBCE (East Bay Clean Energy)	PG&E	2018	0.24513	0.00162	Rates from archived Joint Rate Comparison. EBCE rates are current as of April 18, 2018. PG&E rates are current as of March 1, 2018
		2020	0.26853	-0.00079	Rates from archived Joint Rate Comparison. EBCE Rates are current as of July 2020 PG&E Rates are current as of May 2020

		2021	0.28164	0.00114	Rates from archived Joint Rate Comparison, March 2021
		2022	0.34132	0.00455	Rates from archived Joint Rate Comparison, effective July 2022
3CE (Central Coast Community Energy)	PG&E	2018	0.24906	0	Rates from archived Joint Rate Comparison, March 2018
		2019	-	0	Rates from archived MBCP rates, May 7, 2019 from tariff book provided on Wayback Machine archive of CCA website (link)
		2020	-	0.00611	Rates from archived MBCP rates, March 1, 2020 from tariff book provided on Wayback Machine archive of CCA website (link)
		2021	0.28545	0.00029	Rates from archived Joint Rate Comparison, March 1, 2021
		2022	0.34557	0.02716	Rates from archived Joint Rate Comparison, June 1, 2022
KCCP (King City Community Power)	PG&E	2020	0.27821	0.00134	Rates from archived Joint Rate Comparison. Rates Current as of May 1, 2021
		2021	0.27821	0.00134	Rates from archived Joint Rate Comparison, May 1, 2021
		2022	0.33323	0	Rates from archived Joint Rate Comparison, July 1, 2022
3CE-SCE	SCE	2022	0.32566	0.00205	Rates from archived Joint Rate Comparison. SCE rates are current as of October 1, 2022. CCCE rates are current as of October 10, 2022.
SJP (San Jacinto Power)	SCE	2020	0.23526	0.00037	Rates from archived Joint Rate Comparison. Rates are current as of October 1, 2020
		2021	0.25142	-0.01347	Rates from archived Joint Rate Comparison. SCE rates are current as of October 1, 2021. SJP rates are current as of June 1, 2021.
		2022	0.31273	0.00169	SCE rates are current as of October 10, 2022. SJP rates are current as of March 1, 2022.
RMEA (Rancho Mirage Energy Authority)	SCE	2020	0.23131	0.00229	Rates from archived Joint Rate Comparison. SCE rates are current as of October 1, 2020. RMEA rates are current as of April 13, 2020
		2021	0.24805	0.00096	Rates from archived Joint Rate Comparison. SCE rates are current as of Feb 1, 2021. RMEA rates are current as of April 1, 2020.
		2022	0.30563	0.00057	SCE rates are current as of October 1, 2022, RMEA rates are current as of March 1, 2022.

PRIME (Pico Rivera Innovative Municipal Energy)	SCE	2020	0.23063	0	Rates from archived Joint Rate Comparison. Rates are current as of October 1, 2020
		2021	0.25340	-0.0149	Rates from archived Joint Rate Comparison. SCE rates are current as of October 1, 2021. PRIME rates are current as of September 1, 2021.
		2022	0.30532	0.00113	SCE rates are current as of October 1, 2022. PRIME rates are current as of March 1, 2022.
Pomona Choice Energy	SCE	2020	0.23063	0	Rates from archived Joint Rate Comparison, effective as of October 1, 2020.
		2021	0.25587	0.00013	Rates from archived Joint Rate Comparison. SCE rates are current as of June 1, 2021. POME rates are current as of April 1, 2020.
		2022	0.30532	0.00338	SCE rates are current as of October 1, 2022. POME rates are current as of March 1, 2022.
LCE (Lancaster Clean Energy)	SCE	2020	0.22901	0.00362	Rates from archived Joint Rate Comparison. Rates current as of June 1, 2020 for SCE and April 13, 2020 for LCE
		2021	0.25317	-0.00869	Rates from archived Joint Rate Comparison. SCE rates are current as of June 1, 2021. LCE rates are current as of March 1, 2021.
		2022	0.31391	-0.00632	SCE rates are current as of October 1, 2022. LCE rates are current as of May 20, 2022.
DCE (Desert Clean Energy)	SCE	2020	0.22185	0.00375	Rates from archived Joint Rate Comparison. Rates are current as of April 13, 2020
		2021	0.25177	0.00096	Rates from archived Joint Rate Comparison. SCE rates are current as of June 1, 2021. DCE rates are current as of July 15, 2021
		2022	0.31047	0.00116	Rates from archived Joint Rate Comparison. SCE rates are current as of October 1, 2022. DCE rates are current as of October 1, 2022.
CPA (Clean Power Alliance)	SCE	2020	0.23063	0.00197	Rates from archived Joint Rate Comparison. Rates are current as of October 1, 2020
		2021	0.25340	0	Rates from archived Joint Rate Comparison. SCE rates are current as of October 1, 2021. CPA rates are current as of July 1, 2021.
		2022	0.30532	0.00308	SCE rates are current as of October 1, 2022. CPA rates are current as of October 1, 2022.

BPROUD (Baldwin Park Resident-Owned Utility District)	SCE	2020	0.23063	0	Rates from archived Joint Rate Comparison. Rates are current as of October 1, 2020
		2021	0.25587	-0.01777	Rates from archived Joint Rate Comparison. SCE rates are current as of October 1, 2021. BPROUD rates are current as of September 1, 2021.
AVCE (Apple Valley Choice Energy)	SCE	2020	0.23719	0.00037	Rates from archived Joint Rate Comparison. SCE rates are current as of October 1, 2020. AVCE rates are current as of April 13, 2020.
		2021	0.27971	-0.00709	Rates from archived Joint Rate Comparison. SCE rates are current as of October 1, 2021. AVCE rates are current as of April 13, 2020.
		2022	0.31391	0.00338	SCE rates are current as of October 1, 2022. AVCE rates are current as of March 1, 2022
SBCE (Santa Barbara Clean Energy)	SCE	2022	0.32566	0	SCE rates are current as of October 1, 2022. SBCE rates are current as of October 1, 2022.
OCPA (Orange County Power Authority)	SCE	2022	0.32566	0	SCE rates are current as of October 1, 2022. OCPA rates are current as of October 1, 2022.
EPIC (Energy for Palmdale’s Independent Choice)	SCE	2022	0.31129	-0.01536	SCE rates are current as of October 1, 2022. EPIC rates are current as of October 1, 2022.
SEA (Solana Energy Alliance)	SDG&E	2021	0.33714	-0.00288	Rates from archived Joint Rate Comparison, March 1, 2021
CEA (Clean Energy Alliance)	SDG&E	2021	0.33391	0.00322	Rates from archived Joint Rate Comparison, June 1, 2021
		2022	0.38201	-0.00252	CEA rates effective February 1, 2022. SDG&E rates effective June 1, 2022
SDCP (San Diego Clean Power)	SDG&E	2022	0.36298	-0.002750	SDCP rates effective February 1, 2022. SDG&E rates effective June 1, 2022

Sources:
For most CCA-year pairs, electricity prices of IOUs and CCAs are taken from Joint Rate Comparison documents provided on IOU websites. Joint Rate Comparisons for 2017, 2018, 2020, and 2021 are from Wayback Machine archives of IOU websites. For several other CCA-year pairs, electricity prices were sourced from tariff books found online or provided through Public Records Act requests. For 2022, Joint Rate Comparisons were sourced from IOU websites. Joint Rate Comparison tables for the year 2019 were not available.
Notes:
1. No. of Customers for a year calculated by taking the maximum number of customers reported in that year
2. From 2018-2020, 3CE was called Monterey Bay Community Power (MBCP). Tariffs for MBCP are used and reported as 3CE.
3. From 2021 onwards, 3CE includes SCE service territory. Separate 3CE-SCE prices are reported for 2022.
4. For 2022, PCE rates are calculated using the larger San Mateo County service territory, and the newer Los Banos prices are excluded.
5. For 2022, BPROUD prices are not available as the CCA deregistered in 2021.
6. For PG&E, the basic residential rate is E-1. For SCE, it is D. For SDG&E, it is DR.
7. When a CCA or IOU offered premium rates of higher renewable content, the lowest-tier rate with the minimum renewables content (the default rate) was used for comparison purposes
8. For certain years for CPSF, RCEA, SJCE, and 3CE, Joint Rate Comparisons were not available, but Pt,IOU(generation), Pt,CCA(generation), and Pt,IOU(PCIA+FF) were reported by the CCA. For those years, the total Pt,IOU could not be estimated in a way consistent with the rest of the dataset. However, for those CCA-year pairs, Pt,IOU-Pt,CCA is still available. This difference is calculated with P_(T,IOU (generation))-[P_(T,CCA (generation))+P_(T,CCA (PCIA+FF))]. This difference is consistent with other differences calculated since the residual components of the rate, including transmission and distribution, are equal for IOU and CCA customers, and so are not relevant to the difference in their rates.

Table 2: Effect of IOU Rate Increases on CCA Rates

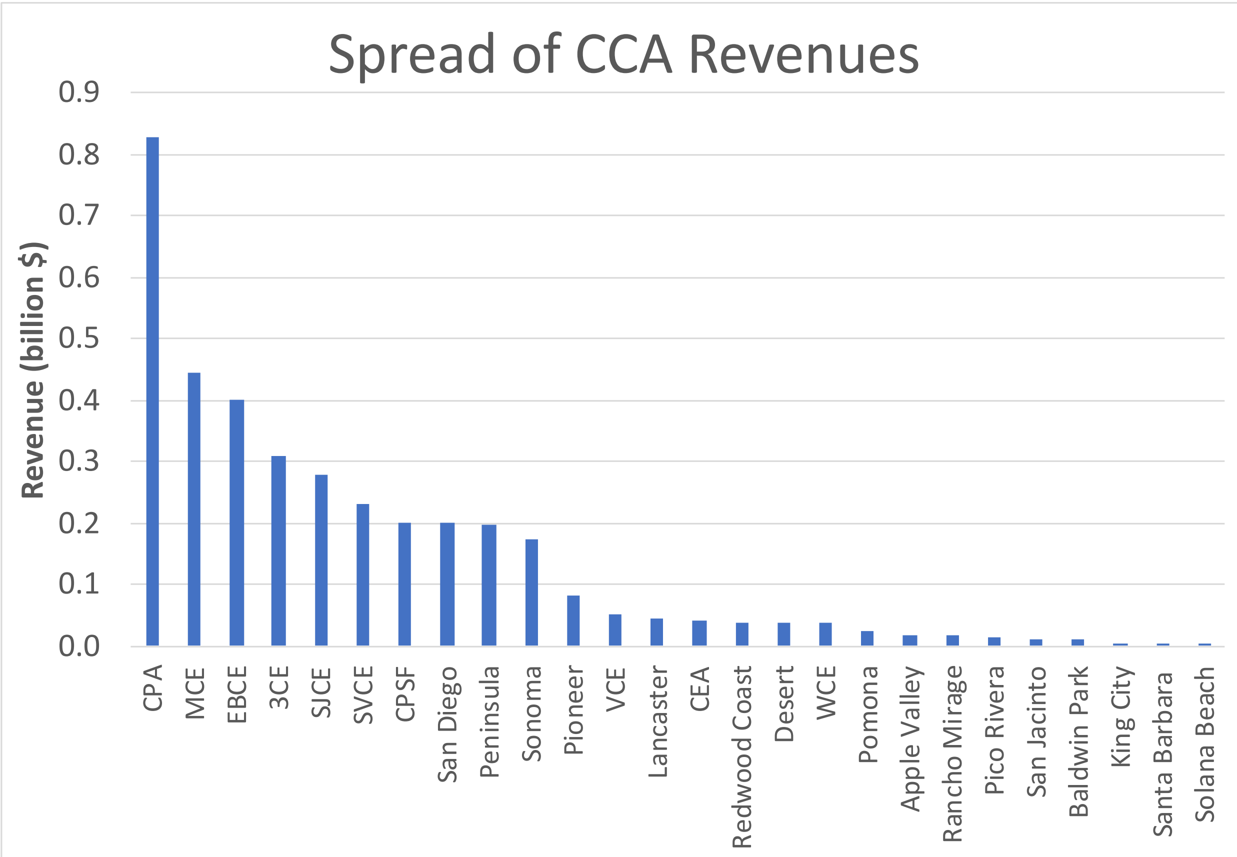
CCA Name	IOU	Change in IOU Rate, 2021-22 $P_{2022,IOU} - P_{2021,IOU}$	Change in IOU-CCA Rate Difference, 2021-22 $(P_{2022,IOU} - P_{2022,CCA}) - (P_{2021,IOU} - P_{2021,CCA})$	Ratio of Change in IOU-CCA Rate Difference To Change in IOU Rate $[(P_{2022,IOU} - P_{2022,CCA}) - (P_{2021,IOU} - P_{2022,CCA})]/[P_{2022,IOU} - P_{2021,IOU}]$
3CE	PG&E	0.060120	0.026870	0.446939
CPSF		0.057440	0.002530	0.044046
EBCE		0.059680	0.003410	0.057138
KCCP		0.055020	-0.001340	-0.024355
MCE		0.066950	0.043430	0.648693
PCE-SM		0.067880	0.001990	0.029316
PIO		0.056380	0.026750	0.474459
RCEA		0.055490	0.000190	0.003424
SCP		0.062870	0.013680	0.217592
SJCE		0.057700	0.000450	0.007799
SVCE		0.058540	0.000380	0.006491
VCE		0.056230	0.000000	0.000000
AVCE	SCE	0.034200	0.010470	0.306140
CPA		0.051920	0.008330	0.160439
DCE		0.058700	0.000200	0.003407
LCE		0.060740	0.002500	0.041159
POME		0.049450	0.003250	0.065723
PRIME		0.051920	0.007660	0.147535
RMEA		0.057580	-0.000390	-0.006773
SJP		0.061310	0.007850	0.128038
CEA	SDG&E	0.048100	-0.005740	-0.119

Table 3: Size of California's CCAs and IOUs, 2020

	Type	Name	No. of Communities	MWh
1	CCA	Apple Valley Choice Energy	1	257,974
2	CCA	Baldwin Park Resident Owned Utility District	1	20,421
3	CCA	Central Coast Community Energy (3CE)	21	3,272,051
4	CCA	Clean Power Alliance of Southern California	32	11,045,771
5	CCA	CleanPowerSF	1	2,923,716
6	CCA	Desert Community Energy	1	339,927
7	CCA	East Bay Community Energy	12	5,877,863
8	CCA	King City Community Power	1	–
9	CCA	Lancaster Choice Energy	1	588,054
10	CCA	Marin Clean Energy	34	5,262,191
11	CCA	Peninsula Clean Energy	21	3,402,000
12	CCA	Pico Rivera Innovative Municipal Energy	1	224,237
13	CCA	Pioneer Community Energy	6	1,135,234
14	CCA	Pomona Choice Energy	1	49,040
15	CCA	Rancho Mirage Energy Authority	1	279,664
16	CCA	Redwood Coast Energy Authority	8	641,433
17	CCA	San Jacinto Power	1	166,506
18	CCA	San Jose Clean Energy	1	4,008,652
19	CCA	Silicon Valley Clean Energy	13	3,877,796
20	CCA	Solana Energy Alliance	1	56,113
21	CCA	Sonoma Clean Power Authority	13	2,343,097
22	CCA	Valley Clean Energy Alliance	3	706,403
23	CCA	Western Community Energy	6	–
24	IOU	Bear Valley Electric Service	1	–
25	IOU	Liberty Utilities (Calpeco Electric) LLC	5	559,360
26	IOU	PacifiCorp	12	758,823
27	IOU	PG&E	117	35,940,697
28	IOU	SCE	138	58,870,798
29	IOU	SDG&E	21	14,398,202

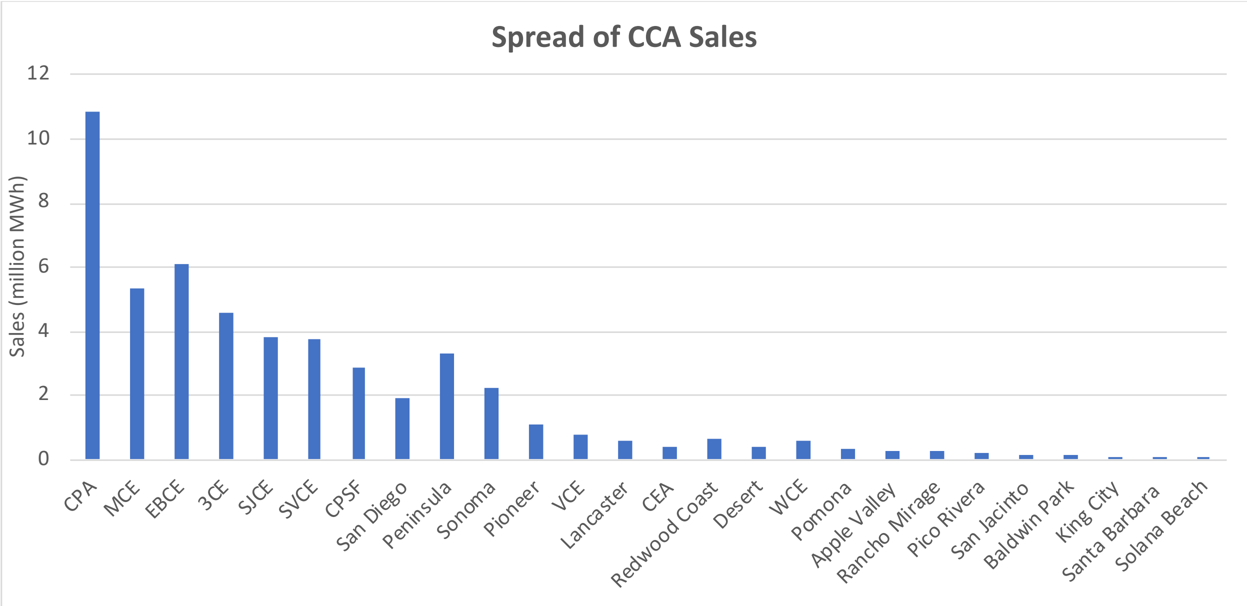
Sources: websites of each LSE, CEC Power Source Disclosure program.
Notes:
1. At the time of the data request to the CEC, the filings for King City Community Power, Bear Valley Electric Service, and Western Community Energy were confidential and unavailable to the authors.
2. A "Community" is a city, town, or unincorporated area of a county that has formed a CCA or joined a multijurisdictional CCA.
3. Baldwin Park and Pomona began serving load in October 2020.

Figure 1a: Spread of CCA annual revenue, billions of dollars



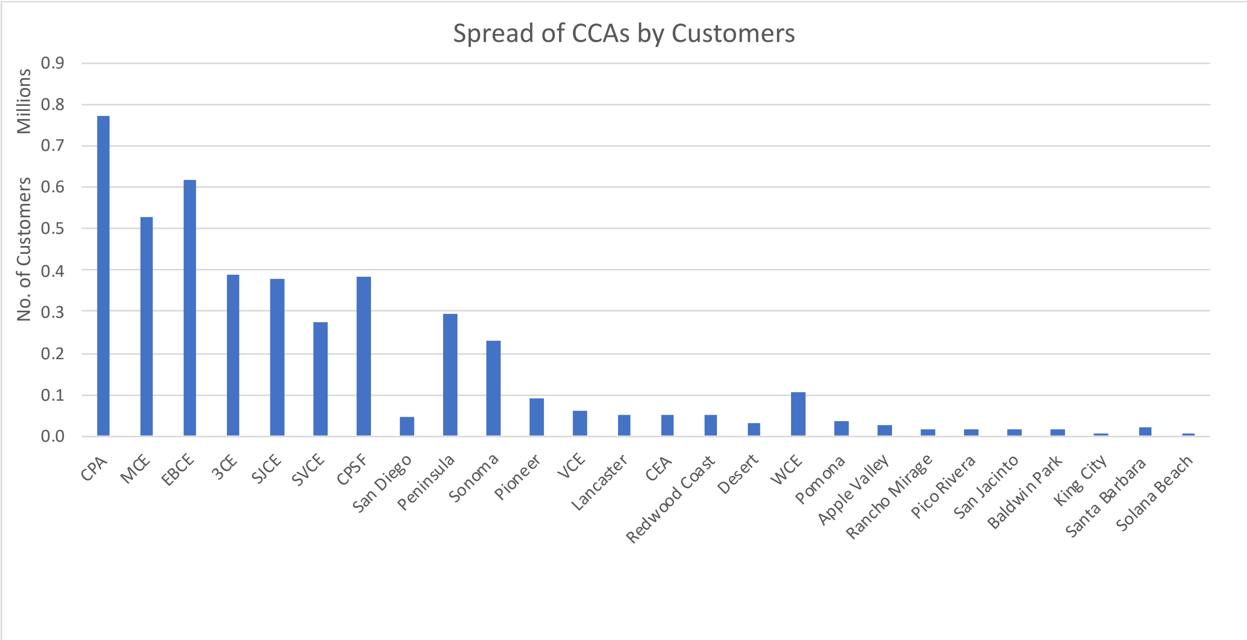
Source: EIA Form 861

Figure 1b: Spread of CCA annual sales, millions of MWh



Source: EIA Form 861

Figure 1c: Spread of CCA customers, millions of accounts



Source: EIA Form 861

Table 4: Community Characteristics: Names, Descriptions, Units of Measurement

Variable Name	Description	Units
med_income[1]	Median household income	$100,000's
pct_white[1]	Percentage identifying as non-Latino White	%
pct_asian[1]	Percentage identifying as Asian	%
pct_some_college[1]	Percentage with at least a high school diploma, some college but no bachelor's	%
pct_bachelors[1]	Percentage with at least a bachelor's)	%
pct_democrat[2]	Percentage registered with Democratic Party	%
population[1]	Population size	Million people
med_age[1]	Median age	Decades
pct_yes_prop_16[2]	Voting Yes on Prop 16, a ballot measure where yes indicated opposition to local/public power	%
pct_yes_prop_23[2]	Voting Yes on Prop 23, a ballot measure that would have suspended AB 32	%
pct_trump[2]	Vote for Donald Trump in the 2020 presidential election	%
pct_manufacturing[1]	Manufacturing share of employment	%
pct_agri[1]	Agricultural share of employment	%
hydro[4]	Hydro production within same county	MW
pv[4]	PV production within same city/county	MW
temp_jan[3]	Average temperature in January	Tens of Degrees Fahrenheit
temp_aug[3]	Average temperature in August	Tens of Degrees Fahrenheit
lse_size[5]	LSE size (Only used for procurement-related regressions)	Billion MWh sales in 2020
not_PGE_SCE	Indicates if the community is outside PG&E or SCE's original service territories	Binary indicator

Notes to Table 4.

[1] Data for income, race, education, age, population, and employment category come from ACS 5-year tables, 2020 vintage. Census data was pulled with Place (i.e., city/town/CDP) as the granularity, so all CDPs in a given county were aggregated to yield a single value for the unincorporated county.

[2] Data for political party affiliation, presidential vote, vote on Prop 16, and vote on Prop 23 come from the CA Secretary of State's database. These report a single value for the unincorporated counties so no additional mapping was needed. There were six entries missing for Prop 16 (mostly unincorporated counties), so those entries were dropped from the dataset.

[3] Temperature data comes from NOAA Monthly Temperature Normals (1980–2010). Weather

stations were matched to cities where this mapping was straightforward (taking simple averages where multiple stations serviced the same city). Otherwise, for smaller cities/towns, the county average value was simply applied.

[4] Local hydro and local PV production come from the CEC arcGIS (https://cecgis-caenergy.opendata.arcgis.com/) and CEC Energy Almanac (https://www.energy.ca.gov/data-reports/energy-almanac/data-renewable-energy-markets-and-resources). For PV, all CEC-registered solar plants were mapped to the city or unincorporated county where they are physically located. For hydro, all cities within a given county were assigned the value of total hydro production in that county.

[5] Finally, LSE size is based on the total MWh of retail sales for that LSE in 2020, which was calculated by summing up sales across all portfolios offered by each LSE as reported in the 2020 Power Source Disclosure filings. This variable is only used for the regression analyses concerning renewable and carbon-free procurement. It is not included in the logit regression about CCA membership, since the size of a community's LSE is clearly dependent on whether it formed a CCA or not.

Table 5: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
med_income	475	0.871	0.431	0.256	2.500
pct_white	475	0.457	0.251	0.009	0.899
pct_asian	475	0.113	0.139	0.000	0.690
pct_some_college	475	0.505	0.142	0.109	0.840
pct_bachelors	475	0.343	0.210	0.010	0.876
pct_democrat	475	0.435	0.118	0.155	0.745
population	475	0.059	0.114	0.0002	1.415
med_age	475	3.978	0.761	2.400	7.530
pct_yes_prop_16	470	0.489	0.107	0.059	0.811
pct_yes_prop_23	474	0.403	0.111	0.075	0.662
pct_trump	475	0.340	0.154	0.040	0.801
pct_manufacturing	475	0.083	0.038	0.000	0.233
pct_agri	475	0.046	0.093	0.000	0.636
hydro	475	0.505	0.831	0.000	2.594
pv	475	0.026	0.171	0.000	2.717
temp_jan	475	4.918	0.551	2.748	5.980
temp_aug	475	7.278	0.591	5.690	9.290
lse_size	461	0.029	0.023	0.00004	0.059

Table 6: Number of CCAs with PSD filings by year

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Number of CCAs	1	1	1	2	3	5	9	19	19	22

Source: CEC Power Source Disclosure program

Table 7a: Average Percent of Overall Retail Sales by Fuel Type, 2017–2020

Category	CCA				IOU			
	2017	2018	2019	2020	2017	2018	2019	2020
Biomass & biowaste	4.3%	3.3%	3.1%	2.5%	1.8%	2.0%	1.6%	1.2%
Geothermal	6.1%	5.6%	6.9%	6.3%	5.2%	5.4%	3.7%	3.8%
Eligible hydro	4.9%	1.9%	3.1%	1.8%	1.7%	1.2%	1.3%	0.8%
Solar	9.1%	11.0%	15.5%	21.2%	13.0%	14.8%	15.1%	15.9%
Wind	27.0%	27.0%	21.1%	18.3%	9.7%	12.2%	10.9%	9.2%
Coal	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Large hydro	35.2%	34.0%	30.5%	27.9%	11.3%	7.0%	13.1%	5.3%
Natural Gas	1.2%	0.0%	0.2%	0.0%	22.9%	18.1%	12.0%	17.0%
Nuclear	0.0%	0.0%	0.4%	2.4%	14.3%	15.9%	18.7%	18.6%
Other	0.3%	2.7%	0.1%	0.2%	0.1%	0.1%	0.1%	0.2%
Unspecified Power	11.8%	14.4%	19.1%	19.5%	20.1%	23.4%	23.6%	27.9%
Total	100%	100%	100%	100%	100%	100%	100%	100%

Table 7b: Electricity Sources Aggregated by Type

Category	CCA				IOU			
	2017	2018	2019	2020	2017	2018	2019	2020
Renewable	51.5%	48.9%	49.7%	50.0%	31.3%	35.6%	32.6%	30.9%
Other carbon-free	35.2%	34.0%	31.0%	30.3%	25.6%	22.9%	31.8%	23.9%
Carbon	1.4%	2.7%	0.3%	0.2%	23.0%	18.2%	12.1%	17.2%
Unspecified Power	11.8%	14.4%	19.1%	19.5%	20.1%	23.4%	23.6%	27.9%
Total	100%	100%	100%	100%	100%	100%	100%	100%

Source: CEC Power Source Disclosure program
Note: Unspecified power is treated as a separate category from renewable energy and carbon-free energy, regardless of how much renewable/carbon-free energy contributed to system power throughout the year.

Table 8: CCA Formation

	Linear	Piecewise Linear
med_income	1.035***	3.612***
	(0.394)	(0.845)
med_income.seg		−4.750***
		(1.233)
pct_yes_prop_16	−6.465***	−9.193***
	(1.976)	(2.527)
pct_yes_prop_16.seg		71.038***
		(17.796)
pct_yes_prop_23	−9.347***	−9.537***
	(1.807)	(2.268)
temp_jan	0.231	0.742*
	(0.316)	(0.400)
temp_jan.seg		−9.282***
		(2.979)
temp_aug	−1.033***	−1.842***
	(0.301)	(0.392)
temp_aug.seg		3.721***
		(0.913)
not_PGE_SCE	−3.084***	−3.336***
	(1.081)	(1.142)
Constant	11.791***	14.524***
	(2.238)	(2.885)
Observations	470	470
Log Likelihood	−177.044	−147.402
Akaike Inf. Crit.	368.088	316.805
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 9: Impact of Each Variable on Predicted Probability of CCA Formation

	Pr(is_CCA)	**Change in Probability**
All Average	39.7%	0.0%
+1 SD, med_income	51.8%	12.1%
+1 SD, pct_yes_prop_16	19.8%	-19.9%
+1 SD, pct_yes_prop_23	18.5%	-21.2%
+1 SD, temp_jan	35.4%	-4.3%
+1 SD, temp_aug	27.0%	-12.6%
-1 SD, med_income	12.2%	-27.5%
-1 SD, pct_yes_prop_16	63.7%	24.0%
-1 SD, pct_yes_prop_23	65.6%	25.9%
-1 SD, temp_jan	30.4%	-9.3%
-1 SD, temp_aug	66.1%	26.5%

Table 10a: Non-CCA Communities in 2020 with a High Propensity for CCA Formation

Place_Name	**LSE_name**	**Pr(is_CCA)**	**Notes**
Del Rey Oaks	PG&E	96.8%	Subsequently joined 3CE
Goleta	SCE	95.0%	Subsequently joined 3CE
Santa Barbara	SCE	94.6%	Subsequently launched own CCA
Pleasant Hill	PG&E	92.3%	Subsequently joined MCE
Pismo Beach	PG&E	90.4%	Subsequently joined 3CE
Newark	PG&E	89.9%	Subsequently joined EBCE
Pleasanton	PG&E	85.4%	Subsequently joined EBCE
Hercules	PG&E	84.9%	
Orinda	PG&E	84.8%	
Hermosa Beach	SCE	82.8%	Subsequently joined 3CE
Unincorporated Santa Barbara County	PG&E	72.3%	Subsequently joined 3CE
Carpinteria	SCE	72.1%	Subsequently joined 3CE
Compton	SCE	71.9%	
Inglewood	SCE	69.9%	
Nevada City	PG&E	68.1%	
Blythe	SCE	65.8%	
Clayton	PG&E	65.5%	
Unincorporated San Luis Obispo County	PG&E	60.7%	

Table 10b: CCA Member Communities in 2020 with a Low Propensity for CCA Formation

Place_Name	**LSE_name**	**Network IOU**	**Pr(is_CCA)**	**Notes**
Arcadia	Clean Power Alliance of SoCal	SCE	39.2%	
Rocklin	Pioneer Community Energy	PG&E	38.7%	
Temple City	Clean Power Alliance of SoCal	SCE	38.4%	
Unincorporated Placer County	Pioneer Community Energy	PG&E	34.9%	
Fortuna	Redwood Coast Energy Authority	PG&E	34.2%	
Alhambra	Clean Power Alliance of SoCal	SCE	34.0%	
Unincorporated Los Angeles County	Clean Power Alliance of SoCal	SCE	33.8%	
Rio Dell	Redwood Coast Energy Authority	PG&E	32.3%	
Pico Rivera	Pico Rivera Innovative Municipal Energy	SCE	32.3%	Single-city CCA
Rancho Mirage	Rancho Mirage Energy Authority	SCE	31.2%	Single-city CCA
Unincorporated Yolo County	Valley Clean Energy Alliance	PG&E	30.7%	
Hawthorne	Clean Power Alliance of SoCal	SCE	29.4%	
Rolling Hills Estates	Clean Power Alliance of SoCal	SCE	28.6%	
Baldwin Park	Baldwin Park Resident Owned Utility District	SCE	25.0%	Deregistered in 2021
Lincoln	Pioneer Community Energy	PG&E	24.6%	
Whittier	Clean Power Alliance of SoCal	SCE	23.6%	
Downey	Clean Power Alliance of SoCal	SCE	23.5%	
Unincorporated Solano County	Marin Clean Energy	PG&E	20.0%	
Norco	Western Community Energy	SCE	18.9%	Deregistered in 2021
Paramount	Clean Power Alliance of SoCal	SCE	18.8%	
San Jacinto	San Jacinto Power	SCE	18.1%	Single-city CCA
Palm Springs	Desert Community Energy	SCE	15.9%	Single-city CCA
Hawaiian Gardens	Clean Power Alliance of SoCal	SCE	14.0%	
Auburn	Pioneer Community Energy	PG&E	13.0%	
Hemet	Western Community Energy	SCE	12.0%	Deregistered in 2021
Apple Valley	Apple Valley Choice Energy	SCE	10.1%	Single-city CCA
Solana Beach	Solana Energy Alliance	SDG&E	8.7%	
Loomis	Pioneer Community Energy	PG&E	7.5%	
Colfax	Pioneer Community Energy	PG&E	5.8%	
Pomona	Pomona Choice Energy	SCE	4.7%	Single-city CCA
Lancaster	Lancaster Choice Energy	SCE	2.0%	Single-city CCA

Table 11: Analysis of Pre- and Post-Pandemic CCA Formation

	Active LSEs, 2018–2020		**Intended LSEs, 2021–22**		**New Launch, 2021–2022**		**Expansion, 2021–2022**		**Postponed/ Deregistered**	
Num communities	83		51		16		21		14	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
med_income	$93,395	$23,936	$86,486	$21,246	$88,651	$16,892	$93,481	$28,000	$69,692	$22,518
pct_white	32.5%	21.6%	40.1%	18.0%	42.6%	15.1%	38.3%	19.7%	31.7%	25.0%
pct_asian	19.6%	15.9%	14.8%	10.6%	16.4%	10.5%	14.7%	11.8%	8.3%	8.4%
pct_some_college	45.5%	9.3%	48.7%	10.5%	45.1%	9.6%	52.9%	9.8%	58.7%	6.5%
pct_bachelors	38.7%	16.1%	38.0%	16.0%	43.8%	13.5%	32.6%	15.6%	20.0%	10.4%
pct_democrat	51.6%	9.7%	43.1%	7.6%	42.0%	6.7%	46.9%	6.8%	43.2%	10.8%
population	375,329	401,266	494,649	584,471	708,181	629,113	82,577	38,919	71,587	26,104
med_age	37.8	4.7	36.4	3.8	36.6	3.1	37.1	5.1	34.7	4.6
pct_yes_prop_16	44.6%	10.7%	53.8%	12.2%	54.5%	5.9%	49.5%	5.9%	55.7%	31.8%
pct_yes_prop_23	32.6%	8.7%	42.3%	9.8%	42.2%	7.2%	39.8%	6.4%	46.6%	22.8%
pct_trump	25.5%	10.2%	34.5%	10.5%	35.2%	9.2%	28.8%	11.1%	37.8%	13.6%
pct_manufacturing	10.2%	3.9%	9.6%	2.4%	9.9%	2.1%	9.2%	3.2%	9.1%	2.6%
pct_agri	2.2%	5.5%	1.7%	4.3%	0.6%	0.5%	5.0%	8.8%	2.5%	3.3%
hydro	672.0	921.8	191.6	499.0	129.4	417.8	30.9	127.4	629.1	801.6
pv	8.3	16.5	31.8	95.6	42.2	116.1	16.7	46.8	5.4	8.6
temp_jan	51.4	3.3	53.6	3.7	55.2	2.5	49.1	2.2	52.0	4.5
temp_aug	70.5	4.6	73.5	4.4	72.8	2.5	70.3	4.5	79.8	4.8

Table 12: Percent Renewable Regression Coefficients, CCAs and IOUs

	Linear	Piecewise Linear
pct_white	0.060	0.080*
	(0.037)	(0.042)
pct_white.seg.r		$-$0.337***
		(0.110)
pct_some_college	$-$0.172***	$-$0.180***
	(0.046)	(0.043)
pct_democrat	0.179***	0.299***
	(0.064)	(0.061)
med_age	0.008	0.056***
	(0.010)	(0.014)
med_age.seg.r		$-$0.075***
		(0.024)
pct_manufacturing	$-$0.249	$-$0.256*
	(0.154)	(0.140)
hydro	0.006	21.700***
	(0.007)	(6.487)
hydro.seg.r		$-$21.711***
		(6.490)
temp_jan	0.058***	0.028**
	(0.012)	(0.012)
temp_aug	0.030**	0.022*
	(0.012)	(0.012)
lse_size	$-$3.612***	18.568***
	(0.320)	(2.841)
lse_size.seg.r		$-$23.925***
		(3.039)
not_PGE_SCE	$-$0.183***	$-$0.200***
	(0.022)	(0.021)
Constant	$-$0.037	$-$0.185
	(0.121)	(0.120)
Observations	461	461
Log Likelihood	361.782	406.060
Akaike Inf. Crit.	$-$701.563	$-$782.121
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 13: Impact of Each Variable on Predicted Percentage Renewable, CCAs and IOUs

	pct_renewable	Change in Predicted Percentage
All Average	47.4%	0.0%
+1 SD, pct_white	46.1%	-1.3%
+1 SD, pct_some_college	44.8%	-2.6%
+1 SD, pct_democrat	50.9%	3.5%
+1 SD, med_age	49.4%	2.0%
+1 SD, pct_manufacturing	46.4%	-1.0%
+1 SD, hydro	46.5%	-0.9%
+1 SD, temp_jan	48.9%	1.6%
+1 SD, temp_aug	48.7%	1.3%
+1 SD, lse_size	35.0%	-12.4%
-1 SD, pct_white	45.4%	-2.0%
-1 SD, pct_some_college	49.9%	2.6%
-1 SD, pct_democrat	43.8%	-3.5%
-1 SD, med_age	43.1%	-4.3%
-1 SD, pct_manufacturing	48.3%	1.0%
-1 SD, hydro	NA	NA
-1 SD, temp_jan	45.8%	-1.6%
-1 SD, temp_aug	46.1%	-1.3%
-1 SD, lse_size	55.5%	8.1%

Table 14: Percent Renewable Regression Coefficients, CCAs Only

	Linear	Piecewise Linear
med_income	0.095**	0.147***
	(0.047)	(0.044)
pct_white	0.408**	0.829***
	(0.172)	(0.174)
pct_white.seg.r		−0.953***
		(0.225)
pct_asian	0.287	0.529***
	(0.178)	(0.159)
pct_some_college	−0.454	−0.717**
	(0.313)	(0.284)
pct_bachelors	−0.520*	−0.971***
	(0.310)	(0.287)
pct_democrat	0.986**	1.129***
	(0.420)	(0.373)
pct_yes_prop_23	0.715	4.370***
	(0.455)	(1.072)
pct_yes_prop_23.seg.r		−4.141***
		(0.993)
pct_manufacturing	−0.703**	−0.817***
	(0.337)	(0.291)
hydro	−0.030	−0.038*
	(0.024)	(0.021)
temp_jan	−0.018	−0.188***
	(0.049)	(0.050)
lse_size	34.632***	−547.573***
	(5.199)	(104.846)
lse_size.seg.r		605.536***
		(108.731)
Constant	−0.145	0.499
	(0.455)	(0.491)
Observations	173	173
Log Likelihood	91.439	118.752
Akaike Inf. Crit.	−158.877	−207.505
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 15: Impact of Each Variable on Predicted Percentage Renewable, CCA Only

	pct_renewable	Change in Predicted Percentage
All Average	52.9%	0.0%
+1 SD, med_income	59.9%	7.0%
+1 SD, pct_white	62.2%	9.4%
+1 SD, pct_asian	61.0%	8.2%
+1 SD, pct_some_college	42.3%	-10.5%
+1 SD, pct_bachelors	32.2%	-20.7%
+1 SD, pct_democrat	64.1%	11.2%
+1 SD, pct_yes_prop_23	55.0%	2.2%
+1 SD, pct_manufacturing	49.6%	-3.3%
+1 SD, hydro	50.2%	-2.7%
+1 SD, temp_jan	46.9%	-6.0%
+1 SD, lse_size	72.1%	19.2%
-1 SD, med_income	45.8%	-7.0%
-1 SD, pct_white	33.1%	-19.8%
-1 SD, pct_asian	44.7%	-8.2%
-1 SD, pct_some_college	63.4%	10.5%
-1 SD, pct_bachelors	73.5%	20.7%
-1 SD, pct_democrat	41.7%	-11.2%
-1 SD, pct_yes_prop_23	50.7%	-2.2%
-1 SD, pct_manufacturing	56.2%	3.3%
-1 SD, hydro	NA	NA
-1 SD, temp_jan	58.8%	6.0%
-1 SD, lse_size	33.7%	-19.2%

Table 16a: Percent Renewable, Constant or Increasing Levels

LSE	2017	2018	2019	2020
Central Coast Community Energy (3CE)	N/A	31.0%	31.2%	31.5%
Clean Power Alliance of Southern California	N/A	53.2%	50.5%	60.2%
CleanPowerSF	45.6%	50.8%	50.6%	56.6%
Marin Clean Energy	62.4%	62.1%	61.5%	62.5%
Peninsula Clean Energy	54.0%	54.3%	55.6%	55.2%
Sonoma Clean Power Authority	45.2%	49.0%	50.7%	49.6%
LADWP	30%	32%	34%	37%
SMUD	23%	25%	29%	37%

Table 16b: Percent Renewable, Inconsistent Levels

LSE	2017	2018	2019	2020
East Bay Community Energy	N/A	41.7%	62.5%	39.3%
Pioneer Community Energy	N/A	32.8%	29.6%	32.4%
Redwood Coast Energy Authority	44.4%	47.0%	43.4%	38.7%
San Jose Clean Energy	N/A	42.4%	34.5%	47.1%
Silicon Valley Clean Energy	48.8%	49.9%	48.4%	44.8%
PG&E	31.3%	36.3%	28.7%	30.8%
SCE	29.1%	33.6%	35.1%	30.9%
Direct Access (Averaged)	31%	26%	30%	29%

Table 16c: Percent Renewable, Decreasing Levels

	2017	2018	2019	2020
Apple Valley Choice Energy	38.0%	37.5%	28.4%	29.2%
Lancaster Choice Energy	37.4%	37.1%	28.6%	30.5%
Pico Rivera Innovative Municipal Energy	63.9%	58.8%	29.4%	32.1%
Rancho Mirage Energy Authority	N/A	36.2%	35.4%	32.2%
San Jacinto Power	N/A	40.9%	30.8%	31.2%
Solana Energy Alliance	N/A	48.0%	50.6%	35.6%
Valley Clean Energy Alliance	N/A	47.9%	45.4%	44.0%
SDG&E	41.2%	42.9%	31.9%	31.6%

Source: CEC Power Source Disclosure program

Table 17: Annual renewable resource procurement by LSE type (MWh)

	2017	2018	2019	2020
Total CCA	6,247,745	12,092,281	21,285,299	23,241,477
Total IOU	50,419,513	51,838,946	36,584,678	33,791,541
Total POU	17,537,270	18,188,537	18,426,213	20,150,899
Total DA	5,715,686	6,297,761	5,918,025	6,752,559
Combined	79,920,213	88,422,454	82,214,215	83,936,477

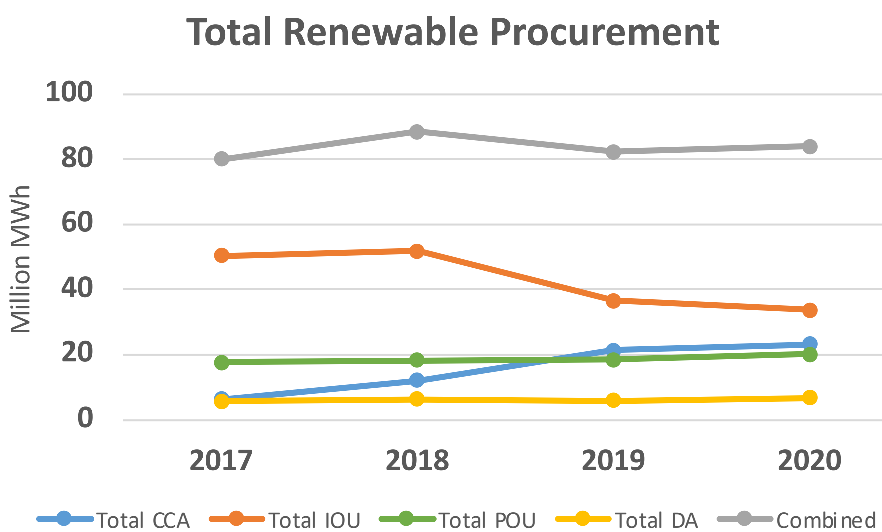


Table 18: Renewable Procurement for Large versus Small (<2 million MWh per year) CCAs

	2017	2018	2019	2020	2021
Small CCAs	40%	40%	35%	37%	31%
Large CCAs	53%	50%	51%	51%	50%
PG&E	31%	36%	29%	31%	49%
SCE	29%	34%	35%	31%	31%
SDG&E	41%	43%	32%	32%	45%
IOU average	31%	36%	33%	31%	39%
POU average	28%	29%	31%	34%	34%
DA average	31%	26%	30%	29%	23%

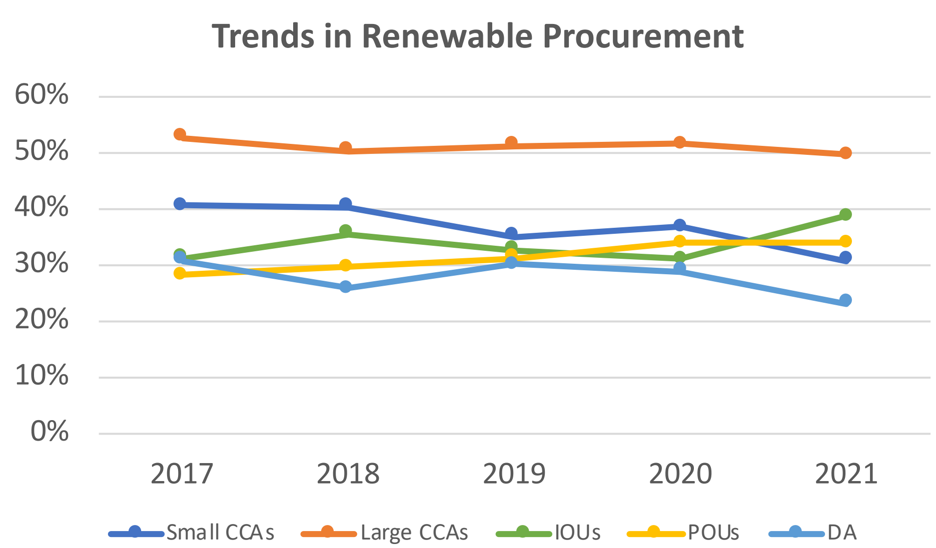
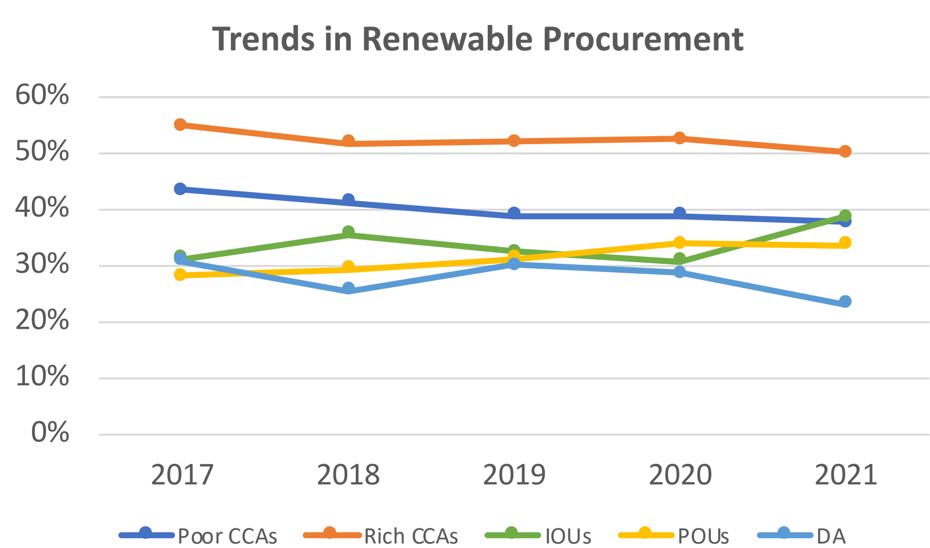


Table 19: Trends in Renewable Procurement for High versus Low Income (<$82k median income) CCAs

	2017	2018	2019	2020	2021
Poor CCAs	44%	41%	39%	39%	38%
Rich CCAs	55%	52%	52%	53%	50%
PG&E	31%	36%	29%	31%	49%
SCE	29%	34%	35%	31%	31%
SDG&E	41%	43%	32%	32%	45%
IOU average	31%	36%	33%	31%	39%
POU average	28%	29%	31%	34%	34%
DA average	31%	26%	30%	29%	23%



Appendices to The Impact of CCAs on Decarbonization in California

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Appendix A - Energy Sorting

Initially, a straightforward binomial logit specification was estimated. Because the functional form of the underlying equation cannot be derived from theory, a different functional form plausibly may be a better representation of the underlying relationship. To test whether the functional form is non-linear, piecewise linear specifications also were estimated. Appendix Tables A1—A17 display the results of regressions in which one of the continuous covariates is divided into two segments while leaving all other variables unchanged.

Segmenting the data adds an additional variable, a tradeoff that is worthwhile if the resulting piecewise specification adds explanatory power. This was determined by using ANOVA. The variables found to improve explanatory power when segmented were added on to the original binomial logit. Then, variable selection was performed to eliminate the worst-performing terms. This yielded the specification shown in the main text.

Table A1: Med_income Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	4.757***
	(0.732)	(1.259)
med_income.seg		−4.711***
		(1.431)
pct_white	1.167	1.971
	(2.136)	(2.187)
pct_asian	0.799	1.032
	(1.990)	(2.043)
pct_some_college	1.892	−2.683
	(3.523)	(3.865)
pct_bachelors	−0.558	−5.987
	(3.686)	(4.076)
pct_democrat	2.192	−0.427
	(5.152)	(5.342)
population	1.222	1.149
	(1.260)	(1.357)
med_age	−0.008	0.116
	(0.294)	(0.300)
pct_yes_prop_16	−5.841**	−6.310**
	(2.698)	(2.753)
pct_yes_prop_23	−11.490**	−15.430***
	(5.492)	(5.804)
pct_trump	1.256	2.051
	(1.714)	(1.749)
pct_manufacturing	−1.486	−3.507
	(4.407)	(4.576)
pct_agri	−0.324	−1.224
	(3.043)	(3.181)
hydro	−0.439**	−0.404*
	(0.210)	(0.214)
pv	1.032	1.096
	(1.248)	(1.265)
temp_jan	0.512	0.308
	(0.398)	(0.408)
temp_aug	−0.636*	−0.477
	(0.331)	(0.342)
not_PGE_SCE	−3.194***	−3.329***
	(1.133)	(1.139)
Constant	5.258	8.797
	(5.175)	(5.449)
Observations	470	470
Log Likelihood	−169.797	−164.360
Akaike Inf. Crit.	377.593	368.720
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A2: Pct_white Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.579**
	(0.732)	(0.757)
pct_white	1.167	143.844**
	(2.136)	(67.744)
pct_white.seg		−141.784**
		(67.513)
pct_asian	0.799	0.895
	(1.990)	(1.992)
pct_some_college	1.892	−2.918
	(3.523)	(3.868)
pct_bachelors	−0.558	−5.268
	(3.686)	(4.002)
pct_democrat	2.192	1.822
	(5.152)	(5.215)
population	1.222	0.802
	(1.260)	(1.313)
med_age	−0.008	0.016
	(0.294)	(0.300)
pct_yes_prop_16	−5.841**	−5.939**
	(2.698)	(2.825)
pct_yes_prop_23	−11.490**	−12.613**
	(5.492)	(5.585)
pct_trump	1.256	1.056
	(1.714)	(1.705)
pct_manufacturing	−1.486	0.912
	(4.407)	(4.562)
pct_agri	−0.324	−3.388
	(3.043)	(3.385)
hydro	−0.439**	−0.352*
	(0.210)	(0.213)
pv	1.032	0.994
	(1.248)	(1.229)
temp_jan	0.512	0.517
	(0.398)	(0.403)
temp_aug	−0.636*	−0.612*
	(0.331)	(0.332)
not_PGE_SCE	−3.194***	−3.125***
	(1.133)	(1.115)
Constant	5.258	2.292
	(5.175)	(5.914)
Observations	470	470
Log Likelihood	−169.797	−165.128
Akaike Inf. Crit.	377.593	370.257
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A3: Pct_asian Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.362*
	(0.732)	(0.746)
pct_white	1.167	1.903
	(2.136)	(2.198)
pct_asian	0.799	52.616***
	(1.990)	(20.354)
pct_asian.seg		−52.171**
		(20.381)
pct_some_college	1.892	0.067
	(3.523)	(3.627)
pct_bachelors	−0.558	−2.805
	(3.686)	(3.796)
pct_democrat	2.192	1.889
	(5.152)	(5.276)
population	1.222	0.694
	(1.260)	(1.273)
med_age	−0.008	0.086
	(0.294)	(0.298)
pct_yes_prop_16	−5.841**	−5.849**
	(2.698)	(2.757)
pct_yes_prop_23	−11.490**	−12.467**
	(5.492)	(5.609)
pct_trump	1.256	1.388
	(1.714)	(1.719)
pct_manufacturing	−1.486	−0.203
	(4.407)	(4.503)
pct_agri	−0.324	0.528
	(3.043)	(3.105)
hydro	−0.439**	−0.388*
	(0.210)	(0.210)
pv	1.032	0.917
	(1.248)	(1.272)
temp_jan	0.512	0.385
	(0.398)	(0.411)
temp_aug	−0.636*	−0.692**
	(0.331)	(0.339)
not_PGE_SCE	−3.194***	−2.771**
	(1.133)	(1.102)
Constant	5.258	6.324
	(5.175)	(5.274)
Observations	470	470
Log Likelihood	−169.797	−166.231
Akaike Inf. Crit.	377.593	372.462
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A4: Pct_some_college Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.947**
	(0.732)	(0.771)
pct_white	1.167	0.954
	(2.136)	(2.155)
pct_asian	0.799	0.537
	(1.990)	(2.016)
pct_some_college	1.892	19.694*
	(3.523)	(10.058)
pct_some_college.seg		−18.746*
		(10.039)
pct_bachelors	−0.558	−1.211
	(3.686)	(3.724)
pct_democrat	2.192	0.443
	(5.152)	(5.250)
population	1.222	1.140
	(1.260)	(1.282)
med_age	−0.008	0.026
	(0.294)	(0.293)
pct_yes_prop_16	−5.841**	−6.091**
	(2.698)	(2.745)
pct_yes_prop_23	−11.490**	−13.380**
	(5.492)	(5.649)
pct_trump	1.256	1.184
	(1.714)	(1.708)
pct_manufacturing	−1.486	−1.609
	(4.407)	(4.411)
pct_agri	−0.324	−0.522
	(3.043)	(3.074)
hydro	−0.439**	−0.478**
	(0.210)	(0.213)
pv	1.032	1.057
	(1.248)	(1.263)
temp_jan	0.512	0.451
	(0.398)	(0.402)
temp_aug	−0.636*	−0.561*
	(0.331)	(0.335)
not_PGE_SCE	−3.194***	−3.170***
	(1.133)	(1.126)
Constant	5.258	2.131
	(5.175)	(5.400)
Observations	470	470
Log Likelihood	−169.797	−168.255
Akaike Inf. Crit.	377.593	376.510
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A5: Pct_bachelors Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.944**
	(0.732)	(0.780)
pct_white	1.167	0.993
	(2.136)	(2.157)
pct_asian	0.799	0.527
	(1.990)	(2.019)
pct_some_college	1.892	0.989
	(3.523)	(3.586)
pct_bachelors	−0.558	−1.205
	(3.686)	(3.735)
pct_bachelors.seg		−17.543*
		(9.583)
pct_democrat	2.192	0.598
	(5.152)	(5.240)
population	1.222	1.136
	(1.260)	(1.276)
med_age	−0.008	0.021
	(0.294)	(0.294)
pct_yes_prop_16	−5.841**	−6.027**
	(2.698)	(2.743)
pct_yes_prop_23	−11.490**	−13.254**
	(5.492)	(5.646)
pct_trump	1.256	1.185
	(1.714)	(1.708)
pct_manufacturing	−1.486	−1.699
	(4.407)	(4.416)
pct_agri	−0.324	−0.516
	(3.043)	(3.071)
hydro	−0.439**	−0.474**
	(0.210)	(0.213)
pv	1.032	1.054
	(1.248)	(1.261)
temp_jan	0.512	0.454
	(0.398)	(0.401)
temp_aug	−0.636*	−0.560*
	(0.331)	(0.335)
not_PGE_SCE	−3.194***	−3.117***
	(1.133)	(1.123)
Constant	5.258	6.891
	(5.175)	(5.286)
Observations	470	470
Log Likelihood	−169.797	−168.321
Akaike Inf. Crit.	377.593	376.642
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A6: Pct_democrat Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.340*
	(0.732)	(0.724)
pct_white	1.167	1.192
	(2.136)	(2.142)
pct_asian	0.799	0.869
	(1.990)	(2.016)
pct_some_college	1.892	2.156
	(3.523)	(3.538)
pct_bachelors	−0.558	0.120
	(3.686)	(3.734)
pct_democrat	2.192	−4.789
	(5.152)	(6.861)
pct_democrat.seg		9.174
		(6.376)
population	1.222	1.231
	(1.260)	(1.263)
med_age	−0.008	−0.036
	(0.294)	(0.296)
pct_yes_prop_16	−5.841**	−5.901**
	(2.698)	(2.728)
pct_yes_prop_23	−11.490**	−10.996**
	(5.492)	(5.411)
pct_trump	1.256	1.241
	(1.714)	(1.644)
pct_manufacturing	−1.486	−1.239
	(4.407)	(4.431)
pct_agri	−0.324	−0.253
	(3.043)	(3.034)
hydro	−0.439**	−0.449**
	(0.210)	(0.210)
pv	1.032	1.209
	(1.248)	(1.257)
temp_jan	0.512	0.540
	(0.398)	(0.398)
temp_aug	−0.636*	−0.664**
	(0.331)	(0.332)
not_PGE_SCE	−3.194***	−3.153***
	(1.133)	(1.133)
Constant	5.258	7.205
	(5.175)	(5.283)
Observations	470	470
Log Likelihood	−169.797	−168.828
Akaike Inf. Crit.	377.593	377.657
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A7: Population Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.623**
	(0.732)	(0.738)
pct_white	1.167	1.668
	(2.136)	(2.161)
pct_asian	0.799	0.744
	(1.990)	(1.981)
pct_some_college	1.892	1.121
	(3.523)	(3.580)
pct_bachelors	−0.558	−1.649
	(3.686)	(3.749)
pct_democrat	2.192	2.498
	(5.152)	(5.198)
population	1.222	20.729**
	(1.260)	(10.495)
population.seg		−20.298*
		(10.833)
med_age	−0.008	0.137
	(0.294)	(0.304)
pct_yes_prop_16	−5.841**	−6.075**
	(2.698)	(2.781)
pct_yes_prop_23	−11.490**	−11.686**
	(5.492)	(5.544)
pct_trump	1.256	1.799
	(1.714)	(1.771)
pct_manufacturing	−1.486	−2.518
	(4.407)	(4.461)
pct_agri	−0.324	0.518
	(3.043)	(3.080)
hydro	−0.439**	−0.371*
	(0.210)	(0.213)
pv	1.032	0.856
	(1.248)	(1.289)
temp_jan	0.512	0.416
	(0.398)	(0.402)
temp_aug	−0.636*	−0.712**
	(0.331)	(0.338)
not_PGE_SCE	−3.194***	−3.053***
	(1.133)	(1.103)
Constant	5.258	5.453
	(5.175)	(5.173)
Observations	470	470
Log Likelihood	−169.797	−167.999
Akaike Inf. Crit.	377.593	375.997
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A8: Med_age Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.354*
	(0.732)	(0.753)
pct_white	1.167	0.862
	(2.136)	(2.173)
pct_asian	0.799	0.442
	(1.990)	(2.038)
pct_some_college	1.892	1.524
	(3.523)	(3.549)
pct_bachelors	−0.558	−0.533
	(3.686)	(3.683)
pct_democrat	2.192	2.449
	(5.152)	(5.157)
population	1.222	1.281
	(1.260)	(1.266)
med_age	−0.008	0.303
	(0.294)	(0.509)
med_age.seg		−0.600
		(0.809)
pct_yes_prop_16	−5.841**	−5.889**
	(2.698)	(2.716)
pct_yes_prop_23	−11.490**	−11.278**
	(5.492)	(5.497)
pct_trump	1.256	1.419
	(1.714)	(1.726)
pct_manufacturing	−1.486	−1.214
	(4.407)	(4.422)
pct_agri	−0.324	−0.210
	(3.043)	(3.047)
hydro	−0.439**	−0.473**
	(0.210)	(0.216)
pv	1.032	0.945
	(1.248)	(1.263)
temp_jan	0.512	0.469
	(0.398)	(0.401)
temp_aug	−0.636*	−0.604*
	(0.331)	(0.335)
not_PGE_SCE	−3.194***	−3.201***
	(1.133)	(1.132)
Constant	5.258	4.302
	(5.175)	(5.319)
Observations	470	470
Log Likelihood	−169.797	−169.516
Akaike Inf. Crit.	377.593	379.032
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A9: Pct_yes_prop_16 Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.502**
	(0.732)	(0.755)
pct_white	1.167	0.276
	(2.136)	(2.182)
pct_asian	0.799	0.104
	(1.990)	(2.005)
pct_some_college	1.892	3.190
	(3.523)	(3.678)
pct_bachelors	−0.558	0.346
	(3.686)	(3.820)
pct_democrat	2.192	0.696
	(5.152)	(5.239)
population	1.222	1.390
	(1.260)	(1.289)
med_age	−0.008	0.103
	(0.294)	(0.309)
pct_yes_prop_16	−5.841**	−8.778***
	(2.698)	(3.222)
pct_yes_prop_16.seg		67.438***
		(16.733)
pct_yes_prop_23	−11.490**	−12.195**
	(5.492)	(5.761)
pct_trump	1.256	0.827
	(1.714)	(1.746)
pct_manufacturing	−1.486	−1.308
	(4.407)	(4.509)
pct_agri	−0.324	0.460
	(3.043)	(3.150)
hydro	−0.439**	−0.366*
	(0.210)	(0.210)
pv	1.032	0.745
	(1.248)	(1.308)
temp_jan	0.512	0.572
	(0.398)	(0.404)
temp_aug	−0.636*	−0.765**
	(0.331)	(0.344)
not_PGE_SCE	−3.194***	−3.295***
	(1.133)	(1.143)
Constant	5.258	7.275
	(5.175)	(5.445)
Observations	470	470
Log Likelihood	−169.797	−163.130
Akaike Inf. Crit.	377.593	366.261
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A10: Pct_yes_prop_23 Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.436**
	(0.732)	(0.724)
pct_white	1.167	0.981
	(2.136)	(2.152)
pct_asian	0.799	0.714
	(1.990)	(2.006)
pct_some_college	1.892	2.626
	(3.523)	(3.585)
pct_bachelors	−0.558	0.106
	(3.686)	(3.739)
pct_democrat	2.192	1.890
	(5.152)	(5.144)
population	1.222	1.301
	(1.260)	(1.269)
med_age	−0.008	−0.006
	(0.294)	(0.299)
pct_yes_prop_16	−5.841**	−5.754**
	(2.698)	(2.746)
pct_yes_prop_23	−11.490**	−14.747**
	(5.492)	(5.997)
pct_yes_prop_23.seg		8.737
		(6.373)
pct_trump	1.256	1.288
	(1.714)	(1.641)
pct_manufacturing	−1.486	−1.802
	(4.407)	(4.424)
pct_agri	−0.324	0.211
	(3.043)	(3.086)
hydro	−0.439**	−0.428**
	(0.210)	(0.211)
pv	1.032	0.965
	(1.248)	(1.217)
temp_jan	0.512	0.509
	(0.398)	(0.398)
temp_aug	−0.636*	−0.648*
	(0.331)	(0.333)
not_PGE_SCE	−3.194***	−3.178***
	(1.133)	(1.138)
Constant	5.258	6.089
	(5.175)	(5.229)
Observations	470	470
Log Likelihood	−169.797	−168.880
Akaike Inf. Crit.	377.593	377.761
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A11: Pct_trump Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.391*
	(0.732)	(0.734)
pct_white	1.167	1.050
	(2.136)	(2.159)
pct_asian	0.799	0.931
	(1.990)	(2.003)
pct_some_college	1.892	1.508
	(3.523)	(3.551)
pct_bachelors	−0.558	−0.205
	(3.686)	(3.704)
pct_democrat	2.192	6.066
	(5.152)	(5.596)
population	1.222	1.103
	(1.260)	(1.280)
med_age	−0.008	−0.042
	(0.294)	(0.299)
pct_yes_prop_16	−5.841**	−6.476**
	(2.698)	(2.787)
pct_yes_prop_23	−11.490**	−12.923**
	(5.492)	(5.616)
pct_trump	1.256	−61.621**
	(1.714)	(27.964)
pct_trump.seg		67.590**
		(30.421)
pct_manufacturing	−1.486	−0.903
	(4.407)	(4.426)
pct_agri	−0.324	−0.329
	(3.043)	(3.070)
hydro	−0.439**	−0.432**
	(0.210)	(0.211)
pv	1.032	1.487
	(1.248)	(1.152)
temp_jan	0.512	0.556
	(0.398)	(0.399)
temp_aug	−0.636*	−0.725**
	(0.331)	(0.338)
not_PGE_SCE	−3.194***	−3.047***
	(1.133)	(1.132)
Constant	5.258	10.171*
	(5.175)	(5.568)
Observations	470	470
Log Likelihood	−169.797	−167.051
Akaike Inf. Crit.	377.593	374.102
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A12: Pct_manufacturing Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.443*
	(0.732)	(0.739)
pct_white	1.167	1.456
	(2.136)	(2.142)
pct_asian	0.799	1.123
	(1.990)	(1.986)
pct_some_college	1.892	1.069
	(3.523)	(3.594)
pct_bachelors	−0.558	−1.300
	(3.686)	(3.723)
pct_democrat	2.192	1.790
	(5.152)	(5.155)
population	1.222	1.054
	(1.260)	(1.259)
med_age	−0.008	−0.002
	(0.294)	(0.296)
pct_yes_prop_16	−5.841**	−5.886**
	(2.698)	(2.716)
pct_yes_prop_23	−11.490**	−12.400**
	(5.492)	(5.553)
pct_trump	1.256	1.298
	(1.714)	(1.711)
pct_manufacturing	−1.486	4.232
	(4.407)	(6.452)
pct_manufacturing.seg		−16.849
		(13.751)
pct_agri	−0.324	−0.598
	(3.043)	(3.084)
hydro	−0.439**	−0.470**
	(0.210)	(0.211)
pv	1.032	1.036
	(1.248)	(1.247)
temp_jan	0.512	0.438
	(0.398)	(0.403)
temp_aug	−0.636*	−0.613*
	(0.331)	(0.335)
not_PGE_SCE	−3.194***	−3.201***
	(1.133)	(1.127)
Constant	5.258	6.175
	(5.175)	(5.248)
Observations	470	470
Log Likelihood	−169.797	−169.044
Akaike Inf. Crit.	377.593	378.087
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A13: Pct_agri Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.454**
	(0.732)	(0.731)
pct_white	1.167	0.985
	(2.136)	(2.143)
pct_asian	0.799	0.459
	(1.990)	(2.030)
pct_some_college	1.892	2.337
	(3.523)	(3.557)
pct_bachelors	−0.558	−0.536
	(3.686)	(3.684)
pct_democrat	2.192	1.290
	(5.152)	(5.229)
population	1.222	1.205
	(1.260)	(1.269)
med_age	−0.008	0.009
	(0.294)	(0.294)
pct_yes_prop_16	−5.841**	−6.309**
	(2.698)	(2.720)
pct_yes_prop_23	−11.490**	−11.943**
	(5.492)	(5.504)
pct_trump	1.256	1.108
	(1.714)	(1.714)
pct_manufacturing	−1.486	−0.808
	(4.407)	(4.462)
pct_agri	−0.324	−12.573
	(3.043)	(13.647)
pct_agri.seg		13.814
		(15.005)
hydro	−0.439**	−0.478**
	(0.210)	(0.214)
pv	1.032	1.171
	(1.248)	(1.260)
temp_jan	0.512	0.495
	(0.398)	(0.395)
temp_aug	−0.636*	−0.664**
	(0.331)	(0.332)
not_PGE_SCE	−3.194***	−3.207***
	(1.133)	(1.134)
Constant	5.258	6.375
	(5.175)	(5.293)
Observations	470	470
Log Likelihood	−169.797	−169.371
Akaike Inf. Crit.	377.593	378.741
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A14: Hydro Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	0.849
	(0.732)	(0.775)
pct_white	1.167	1.760
	(2.136)	(2.141)
pct_asian	0.799	0.803
	(1.990)	(1.998)
pct_some_college	1.892	0.501
	(3.523)	(3.583)
pct_bachelors	−0.558	−0.993
	(3.686)	(3.642)
pct_democrat	2.192	1.184
	(5.152)	(5.193)
population	1.222	1.291
	(1.260)	(1.275)
med_age	−0.008	−0.034
	(0.294)	(0.292)
pct_yes_prop_16	−5.841**	−5.192*
	(2.698)	(2.750)
pct_yes_prop_23	−11.490**	−10.662*
	(5.492)	(5.584)
pct_trump	1.256	1.114
	(1.714)	(1.707)
pct_manufacturing	−1.486	−2.074
	(4.407)	(4.468)
pct_agri	−0.324	−1.551
	(3.043)	(3.161)
hydro	−0.439**	−221.306**
	(0.210)	(91.290)
hydro.seg		221.173**
		(91.415)
pv	1.032	0.913
	(1.248)	(1.219)
temp_jan	0.512	0.583
	(0.398)	(0.416)
temp_aug	−0.636*	−0.384
	(0.331)	(0.345)
not_PGE_SCE	−3.194***	−2.846**
	(1.133)	(1.132)
Constant	5.258	4.881
	(5.175)	(5.245)
Observations	470	470
Log Likelihood	−169.797	−166.904
Akaike Inf. Crit.	377.593	373.807
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A15: PV Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.453**
	(0.732)	(0.734)
pct_white	1.167	1.225
	(2.136)	(2.137)
pct_asian	0.799	0.786
	(1.990)	(1.990)
pct_some_college	1.892	1.812
	(3.523)	(3.535)
pct_bachelors	−0.558	−0.515
	(3.686)	(3.692)
pct_democrat	2.192	2.240
	(5.152)	(5.148)
population	1.222	1.081
	(1.260)	(1.305)
med_age	−0.008	−0.002
	(0.294)	(0.294)
pct_yes_prop_16	−5.841**	−5.595**
	(2.698)	(2.764)
pct_yes_prop_23	−11.490**	−11.459**
	(5.492)	(5.501)
pct_trump	1.256	1.242
	(1.714)	(1.721)
pct_manufacturing	−1.486	−1.499
	(4.407)	(4.399)
pct_agri	−0.324	−0.413
	(3.043)	(3.056)
hydro	−0.439**	−0.419*
	(0.210)	(0.214)
pv	1.032	1,091,095.000
	(1.248)	(2,558,244.000)
pv.seg		−1,091,094.000
		(2,558,244.000)
temp_jan	0.512	0.529
	(0.398)	(0.401)
temp_aug	−0.636*	−0.672**
	(0.331)	(0.343)
not_PGE_SCE	−3.194***	−3.168***
	(1.133)	(1.132)
Constant	5.258	5.246
	(5.175)	(5.166)
Observations	470	470
Log Likelihood	−169.797	−169.706
Akaike Inf. Crit.	377.593	379.412
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A16: Temp_jan Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	0.646
	(0.732)	(0.764)
pct_white	1.167	1.754
	(2.136)	(2.215)
pct_asian	0.799	1.443
	(1.990)	(2.050)
pct_some_college	1.892	1.159
	(3.523)	(3.647)
pct_bachelors	−0.558	0.689
	(3.686)	(3.733)
pct_democrat	2.192	5.174
	(5.152)	(5.508)
population	1.222	1.445
	(1.260)	(1.331)
med_age	−0.008	−0.027
	(0.294)	(0.310)
pct_yes_prop_16	−5.841**	−5.302*
	(2.698)	(2.741)
pct_yes_prop_23	−11.490**	−6.393
	(5.492)	(5.967)
pct_trump	1.256	0.945
	(1.714)	(1.786)
pct_manufacturing	−1.486	−0.548
	(4.407)	(4.473)
pct_agri	−0.324	−0.618
	(3.043)	(3.173)
hydro	−0.439**	−0.576***
	(0.210)	(0.220)
pv	1.032	0.571
	(1.248)	(1.294)
temp_jan	0.512	1.254**
	(0.398)	(0.488)
temp_jan.seg		−9.552***
		(2.805)
temp_aug	−0.636*	−0.688**
	(0.331)	(0.345)
not_PGE_SCE	−3.194***	−3.156***
	(1.133)	(1.157)
Constant	5.258	−0.909
	(5.175)	(5.753)
Observations	470	470
Log Likelihood	−169.797	−162.143
Akaike Inf. Crit.	377.593	364.285
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A17: Temp_aug Sensitivity

	Linear	Piecewise Linear
med_income	1.480**	1.628**
	(0.732)	(0.747)
pct_white	1.167	1.527
	(2.136)	(2.202)
pct_asian	0.799	1.352
	(1.990)	(2.069)
pct_some_college	1.892	1.802
	(3.523)	(3.594)
pct_bachelors	−0.558	−1.013
	(3.686)	(3.703)
pct_democrat	2.192	3.390
	(5.152)	(5.352)
population	1.222	1.269
	(1.260)	(1.295)
med_age	−0.008	−0.054
	(0.294)	(0.298)
pct_yes_prop_16	−5.841**	−6.791**
	(2.698)	(2.763)
pct_yes_prop_23	−11.490**	−9.442*
	(5.492)	(5.663)
pct_trump	1.256	1.337
	(1.714)	(1.738)
pct_manufacturing	−1.486	1.700
	(4.407)	(4.610)
pct_agri	−0.324	−0.178
	(3.043)	(3.177)
hydro	−0.439**	−0.131
	(0.210)	(0.230)
pv	1.032	−0.018
	(1.248)	(1.220)
temp_jan	0.512	0.443
	(0.398)	(0.392)
temp_aug	−0.636*	−1.641***
	(0.331)	(0.454)
temp_aug.seg		3.655***
		(1.088)
not_PGE_SCE	−3.194***	−3.216***
	(1.133)	(1.145)
Constant	5.258	11.374**
	(5.175)	(5.685)
Observations	470	470
Log Likelihood	−169.797	−164.016
Akaike Inf. Crit.	377.593	368.033
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix B - Percent Renewable

Appendix B follows a similar structure to Appendix A. We show the effect of adding piecewise linear terms to the generalized linear model predicting the percentage of electricity from renewable sources as a function of various community characteristics. The tables below display results for two samples: the first includes all communities that are served by CCAs and only by IOUs, and the second includes only communities that are served by a CCA.

Table B1: Effect of Segmenting med_income on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.090^{**}	0.125^{**}	-0.608^{*}
	(0.025)	(0.045)	(0.051)	(0.316)
med_income.seg.r		−0.073		0.748^{**}
		(0.051)		(0.319)
pct_white	0.023	0.034	0.318	0.228
	(0.075)	(0.076)	(0.209)	(0.210)
pct_asian	−0.065	−0.063	0.238	0.176
	(0.075)	(0.075)	(0.193)	(0.192)
pct_some_college	−0.002	−0.064	0.089	0.256
	(0.134)	(0.141)	(0.465)	(0.464)
pct_bachelors	0.137	0.055	−0.206	0.004
	(0.136)	(0.147)	(0.435)	(0.438)
pct_democrat	0.041	0.001	0.233	0.390
	(0.175)	(0.177)	(0.509)	(0.506)
population	0.018	0.013	0.037	0.057
	(0.048)	(0.048)	(0.096)	(0.095)
med_age	−0.001	0.0005	0.006	0.014
	(0.011)	(0.011)	(0.023)	(0.023)
pct_yes_prop_16	0.272^{***}	0.261^{***}	0.194	0.210
	(0.097)	(0.097)	(0.197)	(0.194)
pct_yes_prop_23	−0.162	−0.215	−0.146	−0.005
	(0.190)	(0.193)	(0.589)	(0.583)
pct_trump	-0.116^{**}	-0.110^{**}	−0.275	−0.268
	(0.051)	(0.051)	(0.176)	(0.174)
pct_manufacturing	-0.327^{**}	-0.348^{**}	-0.907^{**}	-0.869^{**}
	(0.163)	(0.164)	(0.355)	(0.350)
pct_agri	0.008	−0.003	0.575	0.656^{*}
	(0.107)	(0.107)	(0.355)	(0.352)
hydro	0.008	0.009	−0.042	-0.050^{*}
	(0.007)	(0.007)	(0.028)	(0.028)
pv	−0.047	−0.045	0.047	0.038
	(0.045)	(0.045)	(0.149)	(0.147)
temp_jan	0.047^{***}	0.040^{***}	−0.011	−0.015
	(0.014)	(0.015)	(0.052)	(0.051)
temp_aug	0.036^{***}	0.038^{***}	0.065^{*}	0.075^{**}
	(0.013)	(0.013)	(0.035)	(0.034)
lse_size	-3.881^{***}	-3.800^{***}	34.451^{***}	36.686^{***}
	(0.345)	(0.350)	(5.654)	(5.652)
not_PGE_SCE	-0.194^{***}	-0.189^{***}	0.051	0.061
	(0.024)	(0.024)	(0.159)	(0.157)
Constant	−0.081	−0.014	−0.363	−0.273
	(0.188)	(0.194)	(0.518)	(0.512)
Observations	458	458	172	172
Log Likelihood	368.399	369.474	95.348	98.433
Akaike Inf. Crit.	−696.797	−696.948	−150.696	−154.867

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B2: Effect of Segmenting pct_white on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.042^{*}	0.125^{**}	0.132^{***}
	(0.025)	(0.025)	(0.051)	(0.050)
pct_white	0.023	0.153^{*}	0.318	0.636^{***}
	(0.075)	(0.082)	(0.209)	(0.222)
pct_white.seg.r		-0.445^{***}		-0.914^{***}
		(0.121)		(0.266)
pct_asian	−0.065	−0.049	0.238	0.347^{*}
	(0.075)	(0.074)	(0.193)	(0.189)
pct_some_college	−0.002	−0.080	0.089	−0.342
	(0.134)	(0.134)	(0.465)	(0.466)
pct_bachelors	0.137	0.042	−0.206	−0.589
	(0.136)	(0.136)	(0.435)	(0.435)
pct_democrat	0.041	0.088	0.233	0.462
	(0.175)	(0.173)	(0.509)	(0.496)
population	0.018	0.020	0.037	0.040
	(0.048)	(0.048)	(0.096)	(0.092)
med_age	−0.001	0.010	0.006	0.024
	(0.011)	(0.011)	(0.023)	(0.023)
pct_yes_prop_16	0.272^{***}	0.312^{***}	0.194	0.282
	(0.097)	(0.096)	(0.197)	(0.192)
pct_yes_prop_23	−0.162	−0.182	−0.146	−0.056
	(0.190)	(0.187)	(0.589)	(0.570)
pct_trump	-0.116^{**}	-0.127^{**}	−0.275	−0.205
	(0.051)	(0.051)	(0.176)	(0.171)
pct_manufacturing	-0.327^{**}	-0.345^{**}	-0.907^{**}	-0.967^{***}
	(0.163)	(0.161)	(0.355)	(0.344)
pct_agri	0.008	0.008	0.575	0.480
	(0.107)	(0.105)	(0.355)	(0.344)
hydro	0.008	0.013^{*}	−0.042	−0.022
	(0.007)	(0.007)	(0.028)	(0.028)
pv	−0.047	−0.055	0.047	0.028
	(0.045)	(0.044)	(0.149)	(0.145)
temp_jan	0.047^{***}	0.039^{***}	−0.011	−0.039
	(0.014)	(0.014)	(0.052)	(0.051)
temp_aug	0.036^{***}	0.038^{***}	0.065^{*}	0.056^{*}
	(0.013)	(0.013)	(0.035)	(0.034)
lse_size	-3.881^{***}	-3.832^{***}	34.451^{***}	33.701^{***}
	(0.345)	(0.341)	(5.654)	(5.467)
not_PGE_SCE	-0.194^{***}	-0.189^{***}	0.051	0.058
	(0.024)	(0.023)	(0.159)	(0.154)
Constant	−0.081	−0.112	−0.363	−0.216
	(0.188)	(0.186)	(0.518)	(0.502)
Observations	458	458	172	172
Log Likelihood	368.399	375.442	95.348	101.823
Akaike Inf. Crit.	−696.797	−708.883	−150.696	−161.646

Note: *p<0.1; **p<0.05; ***p<0.01

Table B3: Effect of Segmenting pct_asian on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.037	0.125**	0.114**
	(0.025)	(0.025)	(0.051)	(0.052)
pct_white	0.023	0.041	0.318	0.382*
	(0.075)	(0.076)	(0.209)	(0.215)
pct_asian	−0.065	12.459	0.238	0.558*
	(0.075)	(8.184)	(0.193)	(0.321)
pct_asian.seg.r		−12.510		−0.451
		(8.175)		(0.361)
pct_some_college	−0.002	0.008	0.089	−0.002
	(0.134)	(0.134)	(0.465)	(0.470)
pct_bachelors	0.137	0.137	−0.206	−0.323
	(0.136)	(0.135)	(0.435)	(0.444)
pct_democrat	0.041	0.079	0.233	0.175
	(0.175)	(0.177)	(0.509)	(0.510)
population	0.018	0.018	0.037	0.021
	(0.048)	(0.048)	(0.096)	(0.096)
med_age	−0.001	−0.001	0.006	0.011
	(0.011)	(0.011)	(0.023)	(0.024)
pct_yes_prop_16	0.272***	0.288***	0.194	0.232
	(0.097)	(0.097)	(0.197)	(0.199)
pct_yes_prop_23	−0.162	−0.147	−0.146	−0.222
	(0.190)	(0.190)	(0.589)	(0.591)
pct_trump	−0.116**	−0.115**	−0.275	−0.279
	(0.051)	(0.051)	(0.176)	(0.176)
pct_manufacturing	−0.327**	−0.320*	−0.907**	−0.811**
	(0.163)	(0.163)	(0.355)	(0.363)
pct_agri	0.008	0.063	0.575	0.631*
	(0.107)	(0.113)	(0.355)	(0.357)
hydro	0.008	0.011	−0.042	−0.039
	(0.007)	(0.007)	(0.028)	(0.028)
pv	−0.047	−0.047	0.047	0.056
	(0.045)	(0.045)	(0.149)	(0.149)
temp_jan	0.047***	0.044***	−0.011	−0.014
	(0.014)	(0.014)	(0.052)	(0.052)
temp_aug	0.036***	0.035***	0.065*	0.064*
	(0.013)	(0.013)	(0.035)	(0.035)
lse_size	−3.881***	−3.848***	34.451***	34.008***
	(0.345)	(0.346)	(5.654)	(5.654)
not_PGE_SCE	−0.194***	−0.186***	0.051	0.057
	(0.024)	(0.024)	(0.159)	(0.159)
Constant	−0.081	−0.157	−0.363	−0.288
	(0.188)	(0.194)	(0.518)	(0.520)
Observations	458	458	172	172
Log Likelihood	368.399	369.622	95.348	96.234
Akaike Inf. Crit.	−696.797	−697.245	−150.696	−150.468

Note: *p<0.1; **p<0.05; ***p<0.01

Table B4: Effect of Segmenting pct_some_college on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.063^{**}	0.125^{**}	0.157^{***}
	(0.025)	(0.028)	(0.051)	(0.058)
pct_white	0.023	0.019	0.318	0.311
	(0.075)	(0.075)	(0.209)	(0.209)
pct_asian	−0.065	−0.072	0.238	0.221
	(0.075)	(0.074)	(0.193)	(0.194)
pct_some_college	−0.002	0.645^{*}	0.089	0.627
	(0.134)	(0.331)	(0.465)	(0.662)
pct_some_college.seg.r		-0.701^{**}		−0.651
		(0.327)		(0.571)
pct_bachelors	0.137	0.104	−0.206	−0.287
	(0.136)	(0.136)	(0.435)	(0.440)
pct_democrat	0.041	−0.022	0.233	0.134
	(0.175)	(0.177)	(0.509)	(0.516)
population	0.018	0.010	0.037	0.022
	(0.048)	(0.048)	(0.096)	(0.096)
med_age	−0.001	−0.0002	0.006	0.007
	(0.011)	(0.011)	(0.023)	(0.023)
pct_yes_prop_16	0.272^{***}	0.260^{***}	0.194	0.167
	(0.097)	(0.096)	(0.197)	(0.198)
pct_yes_prop_23	−0.162	−0.237	−0.146	−0.247
	(0.190)	(0.192)	(0.589)	(0.595)
pct_trump	-0.116^{**}	-0.119^{**}	−0.275	−0.268
	(0.051)	(0.051)	(0.176)	(0.176)
pct_manufacturing	-0.327^{**}	-0.328^{**}	-0.907^{**}	-0.929^{***}
	(0.163)	(0.163)	(0.355)	(0.355)
pct_agri	0.008	−0.001	0.575	0.521
	(0.107)	(0.106)	(0.355)	(0.358)
hydro	0.008	0.007	−0.042	−0.044
	(0.007)	(0.007)	(0.028)	(0.028)
pv	−0.047	−0.044	0.047	0.059
	(0.045)	(0.044)	(0.149)	(0.150)
temp_jan	0.047^{***}	0.040^{***}	−0.011	−0.013
	(0.014)	(0.015)	(0.052)	(0.052)
temp_aug	0.036^{***}	0.040^{***}	0.065^{*}	0.071^{**}
	(0.013)	(0.013)	(0.035)	(0.035)
lse_size	-3.881^{***}	-3.822^{***}	34.451^{***}	33.814^{***}
	(0.345)	(0.345)	(5.654)	(5.675)
not_PGE_SCE	-0.194^{***}	-0.188^{***}	0.051	0.046
	(0.024)	(0.024)	(0.159)	(0.159)
Constant	−0.081	−0.192	−0.363	−0.414
	(0.188)	(0.195)	(0.518)	(0.519)
Observations	458	458	172	172
Log Likelihood	368.399	370.788	95.348	96.087
Akaike Inf. Crit.	−696.797	−699.577	−150.696	−150.174

Note: *p<0.1; **p<0.05; ***p<0.01

Table B5: Effect of Segmenting pct_bachelors on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.058^{**}	0.125^{**}	0.128^{**}
	(0.025)	(0.028)	(0.051)	(0.052)
pct_white	0.023	0.019	0.318	0.349
	(0.075)	(0.075)	(0.209)	(0.217)
pct_asian	−0.065	−0.074	0.238	0.261
	(0.075)	(0.075)	(0.193)	(0.198)
pct_some_college	−0.002	−0.044	0.089	0.010
	(0.134)	(0.136)	(0.465)	(0.488)
pct_bachelors	0.137	0.112	−0.206	0.231
	(0.136)	(0.136)	(0.435)	(0.910)
pct_bachelors.seg.r		−0.471		−0.517
		(0.288)		(0.947)
pct_democrat	0.041	−0.002	0.233	0.272
	(0.175)	(0.177)	(0.509)	(0.515)
population	0.018	0.012	0.037	0.029
	(0.048)	(0.048)	(0.096)	(0.097)
med_age	−0.001	0.0001	0.006	0.003
	(0.011)	(0.011)	(0.023)	(0.024)
pct_yes_prop_16	0.272^{***}	0.264^{***}	0.194	0.204
	(0.097)	(0.097)	(0.197)	(0.199)
pct_yes_prop_23	−0.162	−0.216	−0.146	−0.115
	(0.190)	(0.192)	(0.589)	(0.593)
pct_trump	-0.116^{**}	-0.117^{**}	−0.275	−0.271
	(0.051)	(0.051)	(0.176)	(0.177)
pct_manufacturing	-0.327^{**}	-0.335^{**}	-0.907^{**}	-0.899^{**}
	(0.163)	(0.163)	(0.355)	(0.356)
pct_agri	0.008	−0.001	0.575	0.653^{*}
	(0.107)	(0.107)	(0.355)	(0.384)
hydro	0.008	0.007	−0.042	−0.039
	(0.007)	(0.007)	(0.028)	(0.029)
pv	−0.047	−0.045	0.047	0.034
	(0.045)	(0.045)	(0.149)	(0.152)
temp_jan	0.047^{***}	0.041^{***}	−0.011	−0.008
	(0.014)	(0.015)	(0.052)	(0.052)
temp_aug	0.036^{***}	0.039^{***}	0.065^{*}	0.066^{*}
	(0.013)	(0.013)	(0.035)	(0.035)
lse_size	-3.881^{***}	-3.833^{***}	34.451^{***}	33.756^{***}
	(0.345)	(0.346)	(5.654)	(5.807)
not_PGE_SCE	-0.194^{***}	-0.189^{***}	0.051	0.049
	(0.024)	(0.024)	(0.159)	(0.160)
Constant	−0.081	−0.018	−0.363	−0.449
	(0.188)	(0.192)	(0.518)	(0.542)
Observations	458	458	172	172
Log Likelihood	368.399	369.797	95.348	95.518
Akaike Inf. Crit.	−696.797	−697.593	−150.696	−149.036

Note: *p<0.1; **p<0.05; ***p<0.01

Table B6: Effect of Segmenting pct_democrat on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.035	0.125^{**}	0.110^{**}
	(0.025)	(0.025)	(0.051)	(0.051)
pct_white	0.023	0.023	0.318	0.382^{*}
	(0.075)	(0.075)	(0.209)	(0.208)
pct_asian	−0.065	−0.064	0.238	0.290
	(0.075)	(0.075)	(0.193)	(0.191)
pct_some_college	−0.002	0.001	0.089	−0.038
	(0.134)	(0.134)	(0.465)	(0.461)
pct_bachelors	0.137	0.144	−0.206	−0.264
	(0.136)	(0.136)	(0.435)	(0.429)
pct_democrat	0.041	−0.289	0.233	0.675
	(0.175)	(0.412)	(0.509)	(0.534)
pct_democrat.seg.r		0.368		-1.308^{**}
		(0.414)		(0.544)
population	0.018	0.017	0.037	0.044
	(0.048)	(0.048)	(0.096)	(0.094)
med_age	−0.001	−0.001	0.006	−0.003
	(0.011)	(0.011)	(0.023)	(0.023)
pct_yes_prop_16	0.272^{***}	0.268^{***}	0.194	0.107
	(0.097)	(0.097)	(0.197)	(0.198)
pct_yes_prop_23	−0.162	−0.137	−0.146	0.107
	(0.190)	(0.192)	(0.589)	(0.589)
pct_trump	-0.116^{**}	-0.118^{**}	−0.275	−0.264
	(0.051)	(0.051)	(0.176)	(0.174)
pct_manufacturing	-0.327^{**}	-0.317^{*}	-0.907^{**}	-1.023^{***}
	(0.163)	(0.164)	(0.355)	(0.353)
pct_agri	0.008	0.004	0.575	0.515
	(0.107)	(0.107)	(0.355)	(0.351)
hydro	0.008	0.008	−0.042	-0.047^{*}
	(0.007)	(0.007)	(0.028)	(0.028)
pv	−0.047	−0.044	0.047	0.050
	(0.045)	(0.045)	(0.149)	(0.147)
temp_jan	0.047^{***}	0.048^{***}	−0.011	−0.033
	(0.014)	(0.014)	(0.052)	(0.052)
temp_aug	0.036^{***}	0.035^{***}	0.065^{*}	0.074^{**}
	(0.013)	(0.013)	(0.035)	(0.034)
lse_size	-3.881^{***}	-3.876^{***}	34.451^{***}	36.513^{***}
	(0.345)	(0.346)	(5.654)	(5.633)
not_PGE_SCE	-0.194^{***}	-0.193^{***}	0.051	0.063
	(0.024)	(0.024)	(0.159)	(0.157)
Constant	−0.081	−0.013	−0.363	−0.471
	(0.188)	(0.204)	(0.518)	(0.512)
Observations	458	458	172	172
Log Likelihood	368.399	368.811	95.348	98.573
Akaike Inf. Crit.	−696.797	−695.622	−150.696	−155.146

Note: *p<0.1; **p<0.05; ***p<0.01

Table B7: Effect of Segmenting population on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.043*	0.125**	0.122**
	(0.025)	(0.025)	(0.051)	(0.051)
pct_white	0.023	0.030	0.318	0.294
	(0.075)	(0.075)	(0.209)	(0.211)
pct_asian	−0.065	−0.058	0.238	0.220
	(0.075)	(0.074)	(0.193)	(0.194)
pct_some_college	−0.002	−0.001	0.089	0.099
	(0.134)	(0.134)	(0.465)	(0.465)
pct_bachelors	0.137	0.116	−0.206	−0.188
	(0.136)	(0.136)	(0.435)	(0.435)
pct_democrat	0.041	0.073	0.233	0.237
	(0.175)	(0.176)	(0.509)	(0.509)
population	0.018	8.495*	0.037	11.083
	(0.048)	(4.868)	(0.096)	(12.113)
population.seg.r		−8.480*		−11.050
		(4.871)		(12.117)
med_age	−0.001	0.003	0.006	0.013
	(0.011)	(0.011)	(0.023)	(0.025)
pct_yes_prop_16	0.272***	0.261***	0.194	0.166
	(0.097)	(0.097)	(0.197)	(0.200)
pct_yes_prop_23	−0.162	−0.140	−0.146	−0.099
	(0.190)	(0.190)	(0.589)	(0.591)
pct_trump	−0.116**	−0.101*	−0.275	−0.277
	(0.051)	(0.052)	(0.176)	(0.176)
pct_manufacturing	−0.327**	−0.355**	−0.907**	−0.961***
	(0.163)	(0.164)	(0.355)	(0.360)
pct_agri	0.008	0.018	0.575	0.563
	(0.107)	(0.107)	(0.355)	(0.356)
hydro	0.008	0.009	−0.042	−0.041
	(0.007)	(0.007)	(0.028)	(0.028)
pv	−0.047	−0.049	0.047	0.044
	(0.045)	(0.045)	(0.149)	(0.150)
temp_jan	0.047***	0.043***	−0.011	−0.017
	(0.014)	(0.014)	(0.052)	(0.052)
temp_aug	0.036***	0.033**	0.065*	0.060*
	(0.013)	(0.013)	(0.035)	(0.035)
lse_size	−3.881***	−3.851***	34.451***	34.086***
	(0.345)	(0.345)	(5.654)	(5.671)
not_PGE_SCE	−0.194***	−0.186***	0.051	0.045
	(0.024)	(0.024)	(0.159)	(0.159)
Constant	−0.081	−0.127	−0.363	−0.382
	(0.188)	(0.190)	(0.518)	(0.519)
Observations	458	458	172	172
Log Likelihood	368.399	369.982	95.348	95.820
Akaike Inf. Crit.	−696.797	−697.963	−150.696	−149.641

Note: *p<0.1; **p<0.05; ***p<0.01

Table B8: Effect of Segmenting med_age on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.014	0.125**	0.097*
	(0.025)	(0.025)	(0.051)	(0.052)
pct_white	0.023	−0.030	0.318	0.298
	(0.075)	(0.076)	(0.209)	(0.207)
pct_asian	−0.065	−0.134*	0.238	0.175
	(0.075)	(0.076)	(0.193)	(0.193)
pct_some_college	−0.002	−0.057	0.089	−0.013
	(0.134)	(0.133)	(0.465)	(0.462)
pct_bachelors	0.137	0.154	−0.206	−0.189
	(0.136)	(0.134)	(0.435)	(0.429)
pct_democrat	0.041	0.049	0.233	0.204
	(0.175)	(0.173)	(0.509)	(0.502)
population	0.018	0.026	0.037	0.011
	(0.048)	(0.048)	(0.096)	(0.095)
med_age	−0.001	0.054***	0.006	0.123**
	(0.011)	(0.018)	(0.023)	(0.057)
med_age.seg.r		−0.103***		−0.157**
		(0.028)		(0.071)
pct_yes_prop_16	0.272***	0.264***	0.194	0.215
	(0.097)	(0.095)	(0.197)	(0.195)
pct_yes_prop_23	−0.162	−0.157	−0.146	−0.143
	(0.190)	(0.187)	(0.589)	(0.581)
pct_trump	−0.116**	−0.100**	−0.275	−0.319*
	(0.051)	(0.051)	(0.176)	(0.175)
pct_manufacturing	−0.327**	−0.300*	−0.907**	−0.882**
	(0.163)	(0.161)	(0.355)	(0.351)
pct_agri	0.008	0.034	0.575	0.673*
	(0.107)	(0.106)	(0.355)	(0.354)
hydro	0.008	0.003	−0.042	−0.049*
	(0.007)	(0.007)	(0.028)	(0.028)
pv	−0.047	−0.055	0.047	0.064
	(0.045)	(0.044)	(0.149)	(0.148)
temp_jan	0.047***	0.041***	−0.011	0.003
	(0.014)	(0.014)	(0.052)	(0.051)
temp_aug	0.036***	0.043***	0.065*	0.078**
	(0.013)	(0.013)	(0.035)	(0.035)
lse_size	−3.881***	−3.894***	34.451***	31.905***
	(0.345)	(0.341)	(5.654)	(5.700)
not_PGE_SCE	−0.194***	−0.200***	0.051	−0.0002
	(0.024)	(0.024)	(0.159)	(0.159)
Constant	−0.081	−0.244	−0.363	−0.822
	(0.188)	(0.191)	(0.518)	(0.552)
Observations	458	458	172	172
Log Likelihood	368.399	375.390	95.348	98.087
Akaike Inf. Crit.	−696.797	−708.779	−150.696	−154.174
Note:				*p<0.1; **p<0.05; ***p<0.01

Table B9: Effect of Segmenting pct_yes_prop_16 on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.036	0.125**	0.133**
	(0.025)	(0.025)	(0.051)	(0.051)
pct_white	0.023	0.032	0.318	0.268
	(0.075)	(0.075)	(0.209)	(0.209)
pct_asian	−0.065	−0.057	0.238	0.197
	(0.075)	(0.075)	(0.193)	(0.193)
pct_some_college	−0.002	−0.017	0.089	0.130
	(0.134)	(0.134)	(0.465)	(0.462)
pct_bachelors	0.137	0.126	−0.206	−0.173
	(0.136)	(0.135)	(0.435)	(0.431)
pct_democrat	0.041	0.072	0.233	0.208
	(0.175)	(0.176)	(0.509)	(0.505)
population	0.018	0.013	0.037	0.030
	(0.048)	(0.048)	(0.096)	(0.095)
med_age	−0.001	−0.002	0.006	0.004
	(0.011)	(0.011)	(0.023)	(0.023)
pct_yes_prop_16	0.272***	0.587***	0.194	0.660**
	(0.097)	(0.213)	(0.197)	(0.318)
pct_yes_prop_16.seg.r		−0.391*		−0.725*
		(0.235)		(0.390)
pct_yes_prop_23	−0.162	−0.146	−0.146	−0.207
	(0.190)	(0.190)	(0.589)	(0.585)
pct_trump	−0.116**	−0.116**	−0.275	−0.265
	(0.051)	(0.051)	(0.176)	(0.175)
pct_manufacturing	−0.327**	−0.336**	−0.907**	−0.989***
	(0.163)	(0.163)	(0.355)	(0.355)
pct_agri	0.008	−0.002	0.575	0.543
	(0.107)	(0.107)	(0.355)	(0.353)
hydro	0.008	0.006	−0.042	−0.046
	(0.007)	(0.007)	(0.028)	(0.028)
pv	−0.047	−0.045	0.047	0.073
	(0.045)	(0.045)	(0.149)	(0.149)
temp_jan	0.047***	0.047***	−0.011	−0.005
	(0.014)	(0.014)	(0.052)	(0.051)
temp_aug	0.036***	0.037***	0.065*	0.075**
	(0.013)	(0.013)	(0.035)	(0.035)
lse_size	−3.881***	−3.796***	34.451***	33.980***
	(0.345)	(0.349)	(5.654)	(5.614)
not_PGE_SCE	−0.194***	−0.189***	0.051	0.042
	(0.024)	(0.024)	(0.159)	(0.158)
Constant	−0.081	−0.203	−0.363	−0.559
	(0.188)	(0.202)	(0.518)	(0.525)
Observations	458	458	172	172
Log Likelihood	368.399	369.839	95.348	97.295
Akaike Inf. Crit.	−696.797	−697.678	−150.696	−152.591

Note: *p<0.1; **p<0.05; ***p<0.01

Table B10: Effect of Segmenting pct_yes_prop_23 on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.037	0.125**	0.101**
	(0.025)	(0.025)	(0.051)	(0.050)
pct_white	0.023	0.011	0.318	0.363*
	(0.075)	(0.076)	(0.209)	(0.203)
pct_asian	−0.065	−0.072	0.238	0.280
	(0.075)	(0.075)	(0.193)	(0.188)
pct_some_college	−0.002	0.020	0.089	0.090
	(0.134)	(0.135)	(0.465)	(0.451)
pct_bachelors	0.137	0.152	−0.206	−0.150
	(0.136)	(0.136)	(0.435)	(0.422)
pct_democrat	0.041	0.025	0.233	0.487
	(0.175)	(0.176)	(0.509)	(0.499)
population	0.018	0.019	0.037	0.030
	(0.048)	(0.048)	(0.096)	(0.093)
med_age	−0.001	0.001	0.006	−0.007
	(0.011)	(0.011)	(0.023)	(0.023)
pct_yes_prop_16	0.272***	0.285***	0.194	0.093
	(0.097)	(0.097)	(0.197)	(0.194)
pct_yes_prop_23	−0.162	−0.265	−0.146	3.715***
	(0.190)	(0.206)	(0.589)	(1.313)
pct_yes_prop_23.seg.r		0.273		−3.762***
		(0.212)		(1.152)
pct_trump	−0.116**	−0.110**	−0.275	−0.254
	(0.051)	(0.052)	(0.176)	(0.171)
pct_manufacturing	−0.327**	−0.326**	−0.907**	−0.945***
	(0.163)	(0.163)	(0.355)	(0.345)
pct_agri	0.008	0.020	0.575	0.571*
	(0.107)	(0.107)	(0.355)	(0.345)
hydro	0.008	0.009	−0.042	−0.052*
	(0.007)	(0.007)	(0.028)	(0.028)
pv	−0.047	−0.048	0.047	0.076
	(0.045)	(0.045)	(0.149)	(0.145)
temp_jan	0.047***	0.048***	−0.011	−0.023
	(0.014)	(0.014)	(0.052)	(0.050)
temp_aug	0.036***	0.036***	0.065*	0.074**
	(0.013)	(0.013)	(0.035)	(0.034)
lse_size	−3.881***	−3.874***	34.451***	36.999***
	(0.345)	(0.345)	(5.654)	(5.538)
not_PGE_SCE	−0.194***	−0.194***	0.051	0.060
	(0.024)	(0.024)	(0.159)	(0.154)
Constant	−0.081	−0.072	−0.363	−1.116**
	(0.188)	(0.188)	(0.518)	(0.553)
Observations	458	458	172	172
Log Likelihood	368.399	369.265	95.348	101.212
Akaike Inf. Crit.	−696.797	−696.530	−150.696	−160.424
Note:				*p<0.1; **p<0.05; ***p<0.01

Table B11: Effect of Segmenting pct_trump on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.033	0.125**	0.106**
	(0.025)	(0.025)	(0.051)	(0.051)
pct_white	0.023	0.012	0.318	0.343*
	(0.075)	(0.075)	(0.209)	(0.206)
pct_asian	−0.065	−0.070	0.238	0.250
	(0.075)	(0.075)	(0.193)	(0.190)
pct_some_college	−0.002	0.006	0.089	0.156
	(0.134)	(0.134)	(0.465)	(0.457)
pct_bachelors	0.137	0.162	−0.206	−0.133
	(0.136)	(0.136)	(0.435)	(0.428)
pct_democrat	0.041	0.088	0.233	0.177
	(0.175)	(0.178)	(0.509)	(0.500)
population	0.018	0.016	0.037	0.063
	(0.048)	(0.048)	(0.096)	(0.094)
med_age	−0.001	0.0004	0.006	0.001
	(0.011)	(0.011)	(0.023)	(0.023)
pct_yes_prop_16	0.272***	0.273***	0.194	0.172
	(0.097)	(0.097)	(0.197)	(0.194)
pct_yes_prop_23	−0.162	−0.106	−0.146	0.092
	(0.190)	(0.193)	(0.589)	(0.585)
pct_trump	−0.116**	−0.175***	−0.275	3.013**
	(0.051)	(0.064)	(0.176)	(1.278)
pct_trump.seg.r		0.239		−3.597**
		(0.155)		(1.385)
pct_manufacturing	−0.327**	−0.321**	−0.907**	−1.009***
	(0.163)	(0.163)	(0.355)	(0.351)
pct_agri	0.008	0.003	0.575	0.582*
	(0.107)	(0.107)	(0.355)	(0.349)
hydro	0.008	0.009	−0.042	−0.045
	(0.007)	(0.007)	(0.028)	(0.028)
pv	−0.047	−0.051	0.047	0.033
	(0.045)	(0.045)	(0.149)	(0.147)
temp_jan	0.047***	0.050***	−0.011	−0.032
	(0.014)	(0.014)	(0.052)	(0.051)
temp_aug	0.036***	0.034***	0.065*	0.068**
	(0.013)	(0.013)	(0.035)	(0.034)
lse_size	−3.881***	−3.867***	34.451***	36.358***
	(0.345)	(0.345)	(5.654)	(5.598)
not_PGE_SCE	−0.194***	−0.193***	0.051	0.049
	(0.024)	(0.024)	(0.159)	(0.156)
Constant	−0.081	−0.126	−0.363	−0.647
	(0.188)	(0.190)	(0.518)	(0.520)
Observations	458	458	172	172
Log Likelihood	368.399	369.651	95.348	99.107
Akaike Inf. Crit.	−696.797	−697.301	−150.696	−156.214

Note: *p<0.1; **p<0.05; ***p<0.01

Table B12: Effect of Segmenting pct_manufacturing on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.036	0.125**	0.111**
	(0.025)	(0.025)	(0.051)	(0.052)
pct_white	0.023	0.017	0.318	0.261
	(0.075)	(0.075)	(0.209)	(0.211)
pct_asian	−0.065	−0.070	0.238	0.192
	(0.075)	(0.074)	(0.193)	(0.194)
pct_some_college	−0.002	−0.009	0.089	0.001
	(0.134)	(0.134)	(0.465)	(0.466)
pct_bachelors	0.137	0.130	−0.206	−0.220
	(0.136)	(0.135)	(0.435)	(0.432)
pct_democrat	0.041	0.035	0.233	0.166
	(0.175)	(0.175)	(0.509)	(0.507)
population	0.018	0.016	0.037	0.028
	(0.048)	(0.048)	(0.096)	(0.095)
med_age	−0.001	0.001	0.006	0.016
	(0.011)	(0.011)	(0.023)	(0.024)
pct_yes_prop_16	0.272***	0.270***	0.194	0.145
	(0.097)	(0.096)	(0.197)	(0.198)
pct_yes_prop_23	−0.162	−0.166	−0.146	−0.124
	(0.190)	(0.189)	(0.589)	(0.586)
pct_trump	−0.116**	−0.111**	−0.275	−0.257
	(0.051)	(0.051)	(0.176)	(0.176)
pct_manufacturing	−0.327**	2.659*	−0.907**	4.176
	(0.163)	(1.438)	(0.355)	(3.110)
pct_manufacturing.seg.r		−3.106**		−5.290
		(1.486)		(3.216)
pct_agri	0.008	−0.009	0.575	0.478
	(0.107)	(0.107)	(0.355)	(0.358)
hydro	0.008	0.008	−0.042	−0.048*
	(0.007)	(0.007)	(0.028)	(0.028)
pv	−0.047	−0.050	0.047	0.056
	(0.045)	(0.044)	(0.149)	(0.149)
temp_jan	0.047***	0.044***	−0.011	−0.011
	(0.014)	(0.014)	(0.052)	(0.051)
temp_aug	0.036***	0.034***	0.065*	0.060*
	(0.013)	(0.013)	(0.035)	(0.035)
lse_size	−3.881***	−3.868***	34.451***	34.268***
	(0.345)	(0.344)	(5.654)	(5.623)
not_PGE_SCE	−0.194***	−0.195***	0.051	0.027
	(0.024)	(0.024)	(0.159)	(0.159)
Constant	−0.081	−0.144	−0.363	−0.382
	(0.188)	(0.190)	(0.518)	(0.515)
Observations	458	458	172	172
Log Likelihood	368.399	370.677	95.348	96.876
Akaike Inf. Crit.	−696.797	−699.354	−150.696	−151.752

Note: *p<0.1; **p<0.05; ***p<0.01

Table B13: Effect of Segmenting pct_agri on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.038	0.125**	0.126**
	(0.025)	(0.025)	(0.051)	(0.051)
pct_white	0.023	0.050	0.318	0.299
	(0.075)	(0.078)	(0.209)	(0.209)
pct_asian	−0.065	−0.039	0.238	0.201
	(0.075)	(0.077)	(0.193)	(0.194)
pct_some_college	−0.002	−0.022	0.089	0.161
	(0.134)	(0.135)	(0.465)	(0.466)
pct_bachelors	0.137	0.133	−0.206	−0.195
	(0.136)	(0.135)	(0.435)	(0.433)
pct_democrat	0.041	0.103	0.233	0.204
	(0.175)	(0.181)	(0.509)	(0.507)
population	0.018	0.021	0.037	0.045
	(0.048)	(0.048)	(0.096)	(0.095)
med_age	−0.001	−0.002	0.006	0.003
	(0.011)	(0.011)	(0.023)	(0.023)
pct_yes_prop_16	0.272***	0.314***	0.194	0.174
	(0.097)	(0.101)	(0.197)	(0.197)
pct_yes_prop_23	−0.162	−0.142	−0.146	−0.178
	(0.190)	(0.190)	(0.589)	(0.587)
pct_trump	−0.116**	−0.114**	−0.275	−0.288
	(0.051)	(0.051)	(0.176)	(0.176)
pct_manufacturing	−0.327**	−0.348**	−0.907**	−0.905**
	(0.163)	(0.164)	(0.355)	(0.354)
pct_agri	0.008	0.284	0.575	−17.621
	(0.107)	(0.224)	(0.355)	(12.265)
pct_agri.seg.r		−0.415		18.217
		(0.296)		(12.274)
hydro	0.008	0.011	−0.042	−0.051*
	(0.007)	(0.007)	(0.028)	(0.029)
pv	−0.047	−0.048	0.047	0.055
	(0.045)	(0.045)	(0.149)	(0.149)
temp_jan	0.047***	0.048***	−0.011	−0.015
	(0.014)	(0.014)	(0.052)	(0.052)
temp_aug	0.036***	0.036***	0.065*	0.070**
	(0.013)	(0.013)	(0.035)	(0.035)
lse_size	−3.881***	−3.883***	34.451***	35.510***
	(0.345)	(0.345)	(5.654)	(5.676)
not_PGE_SCE	−0.194***	−0.193***	0.051	0.070
	(0.024)	(0.024)	(0.159)	(0.159)
Constant	−0.081	−0.153	−0.363	−0.300
	(0.188)	(0.195)	(0.518)	(0.518)
Observations	458	458	172	172
Log Likelihood	368.399	369.424	95.348	96.594
Akaike Inf. Crit.	−696.797	−696.849	−150.696	−151.187

Note: *p<0.1; **p<0.05; ***p<0.01

Table B14: Effect of Segmenting hydro on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.057^{**}	0.125^{**}	0.120^{**}
	(0.025)	(0.026)	(0.051)	(0.052)
pct_white	0.023	−0.002	0.318	0.322
	(0.075)	(0.075)	(0.209)	(0.209)
pct_asian	−0.065	−0.062	0.238	0.232
	(0.075)	(0.074)	(0.193)	(0.194)
pct_some_college	−0.002	0.023	0.089	0.088
	(0.134)	(0.134)	(0.465)	(0.465)
pct_bachelors	0.137	0.148	−0.206	−0.191
	(0.136)	(0.135)	(0.435)	(0.435)
pct_democrat	0.041	0.058	0.233	0.187
	(0.175)	(0.174)	(0.509)	(0.512)
population	0.018	0.014	0.037	0.049
	(0.048)	(0.048)	(0.096)	(0.097)
med_age	−0.001	0.00002	0.006	0.004
	(0.011)	(0.011)	(0.023)	(0.024)
pct_yes_prop_16	0.272^{***}	0.272^{***}	0.194	0.221
	(0.097)	(0.096)	(0.197)	(0.200)
pct_yes_prop_23	−0.162	−0.187	−0.146	−0.124
	(0.190)	(0.189)	(0.589)	(0.590)
pct_trump	-0.116^{**}	-0.121^{**}	−0.275	−0.287
	(0.051)	(0.051)	(0.176)	(0.177)
pct_manufacturing	-0.327^{**}	-0.338^{**}	-0.907^{**}	-0.971^{***}
	(0.163)	(0.162)	(0.355)	(0.363)
pct_agri	0.008	0.032	0.575	0.561
	(0.107)	(0.106)	(0.355)	(0.356)
hydro	0.008	19.846^{***}	−0.042	−0.542
	(0.007)	(7.396)	(0.028)	(0.572)
hydro.seg.r		-19.847^{***}		0.552
		(7.400)		(0.633)
pv	−0.047	−0.040	0.047	0.001
	(0.045)	(0.044)	(0.149)	(0.158)
temp_jan	0.047^{***}	0.042^{***}	−0.011	−0.032
	(0.014)	(0.014)	(0.052)	(0.057)
temp_aug	0.036^{***}	0.029^{**}	0.065^{*}	0.073^{**}
	(0.013)	(0.013)	(0.035)	(0.036)
lse_size	-3.881^{***}	-4.080^{***}	34.451^{***}	32.895^{***}
	(0.345)	(0.351)	(5.654)	(5.932)
not_PGE_SCE	-0.194^{***}	-0.207^{***}	0.051	0.060
	(0.024)	(0.024)	(0.159)	(0.160)
Constant	−0.081	−0.056	−0.363	−0.281
	(0.188)	(0.187)	(0.518)	(0.527)
Observations	458	458	172	172
Log Likelihood	368.399	372.138	95.348	95.782
Akaike Inf. Crit.	−696.797	−702.275	−150.696	−149.563

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B15: Effect of Segmenting pv on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.038	0.125**	0.122**
	(0.025)	(0.025)	(0.051)	(0.051)
pct_white	0.023	0.010	0.318	0.302
	(0.075)	(0.075)	(0.209)	(0.209)
pct_asian	−0.065	−0.065	0.238	0.229
	(0.075)	(0.074)	(0.193)	(0.193)
pct_some_college	−0.002	0.005	0.089	0.078
	(0.134)	(0.133)	(0.465)	(0.463)
pct_bachelors	0.137	0.133	−0.206	−0.197
	(0.136)	(0.135)	(0.435)	(0.433)
pct_democrat	0.041	0.032	0.233	0.311
	(0.175)	(0.174)	(0.509)	(0.509)
population	0.018	0.049	0.037	0.078
	(0.048)	(0.050)	(0.096)	(0.099)
med_age	−0.001	−0.003	0.006	0.003
	(0.011)	(0.011)	(0.023)	(0.023)
pct_yes_prop_16	0.272***	0.240**	0.194	0.167
	(0.097)	(0.097)	(0.197)	(0.197)
pct_yes_prop_23	−0.162	−0.159	−0.146	−0.052
	(0.190)	(0.189)	(0.589)	(0.590)
pct_trump	−0.116**	−0.114**	−0.275	−0.253
	(0.051)	(0.051)	(0.176)	(0.176)
pct_manufacturing	−0.327**	−0.340**	−0.907**	−0.848**
	(0.163)	(0.163)	(0.355)	(0.356)
pct_agri	0.008	0.020	0.575	0.570
	(0.107)	(0.106)	(0.355)	(0.354)
hydro	0.008	0.006	−0.042	−0.051*
	(0.007)	(0.007)	(0.028)	(0.029)
pv	−0.047	−19,552,648.000**	0.047	−44.953
	(0.045)	(7,832,573.000)	(0.149)	(29.602)
pv.seg.r		19,552,648.000**		45.022
		(7,832,573.000)		(29.616)
temp_jan	0.047***	0.044***	−0.011	−0.007
	(0.014)	(0.014)	(0.052)	(0.052)
temp_aug	0.036***	0.043***	0.065*	0.074**
	(0.013)	(0.013)	(0.035)	(0.035)
lse_size	−3.881***	−3.976***	34.451***	33.447***
	(0.345)	(0.346)	(5.654)	(5.668)
not_PGE_SCE	−0.194***	−0.200***	0.051	0.027
	(0.024)	(0.024)	(0.159)	(0.159)
Constant	−0.081	−0.080	−0.363	−0.469
	(0.188)	(0.187)	(0.518)	(0.520)
Observations	458	458	172	172
Log Likelihood	368.399	371.641	95.348	96.654
Akaike Inf. Crit.	−696.797	−701.282	−150.696	−151.309

Note: *p<0.1; **p<0.05; ***p<0.01

Table B16: Effect of Segmenting temp_jan on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.062**	0.125**	0.142***
	(0.025)	(0.026)	(0.051)	(0.051)
pct_white	0.023	0.008	0.318	0.328
	(0.075)	(0.075)	(0.209)	(0.207)
pct_asian	−0.065	−0.067	0.238	0.263
	(0.075)	(0.074)	(0.193)	(0.192)
pct_some_college	−0.002	0.016	0.089	0.028
	(0.134)	(0.133)	(0.465)	(0.461)
pct_bachelors	0.137	0.091	−0.206	−0.278
	(0.136)	(0.136)	(0.435)	(0.432)
pct_democrat	0.041	−0.013	0.233	0.286
	(0.175)	(0.175)	(0.509)	(0.504)
population	0.018	0.012	0.037	0.032
	(0.048)	(0.048)	(0.096)	(0.095)
med_age	−0.001	−0.003	0.006	0.0004
	(0.011)	(0.011)	(0.023)	(0.023)
pct_yes_prop_16	0.272***	0.225**	0.194	0.173
	(0.097)	(0.097)	(0.197)	(0.195)
pct_yes_prop_23	−0.162	−0.282	−0.146	−0.136
	(0.190)	(0.193)	(0.589)	(0.583)
pct_trump	−0.116**	−0.101**	−0.275	−0.254
	(0.051)	(0.051)	(0.176)	(0.175)
pct_manufacturing	−0.327**	−0.364**	−0.907**	−0.881**
	(0.163)	(0.163)	(0.355)	(0.352)
pct_agri	0.008	0.023	0.575	0.537
	(0.107)	(0.106)	(0.355)	(0.352)
hydro	0.008	0.003	−0.042	−0.050*
	(0.007)	(0.007)	(0.028)	(0.028)
pv	−0.047	−0.040	0.047	0.063
	(0.045)	(0.044)	(0.149)	(0.148)
temp_jan	0.047***	0.002	−0.011	−0.084
	(0.014)	(0.021)	(0.052)	(0.062)
temp_jan.seg.r		0.141***		0.497**
		(0.051)		(0.242)
temp_aug	0.036***	0.043***	0.065*	0.050
	(0.013)	(0.013)	(0.035)	(0.035)
lse_size	−3.881***	−4.175***	34.451***	34.573***
	(0.345)	(0.359)	(5.654)	(5.595)
not_PGE_SCE	−0.194***	−0.216***	0.051	0.081
	(0.024)	(0.025)	(0.159)	(0.158)
Constant	−0.081	0.168	−0.363	0.121
	(0.188)	(0.207)	(0.518)	(0.564)
Observations	458	458	172	172
Log Likelihood	368.399	372.381	95.348	97.713
Akaike Inf. Crit.	−696.797	−702.763	−150.696	−153.426

Note: *p<0.1; **p<0.05; ***p<0.01

Table B17: Effect of Segmenting temp_aug on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.033	0.125**	0.110**
	(0.025)	(0.025)	(0.051)	(0.052)
pct_white	0.023	0.011	0.318	0.339
	(0.075)	(0.075)	(0.209)	(0.209)
pct_asian	−0.065	−0.078	0.238	0.253
	(0.075)	(0.074)	(0.193)	(0.193)
pct_some_college	−0.002	−0.043	0.089	0.076
	(0.134)	(0.133)	(0.465)	(0.463)
pct_bachelors	0.137	0.102	−0.206	−0.188
	(0.136)	(0.135)	(0.435)	(0.433)
pct_democrat	0.041	−0.001	0.233	0.322
	(0.175)	(0.174)	(0.509)	(0.509)
population	0.018	0.017	0.037	0.040
	(0.048)	(0.048)	(0.096)	(0.095)
med_age	−0.001	−0.00002	0.006	0.011
	(0.011)	(0.011)	(0.023)	(0.023)
pct_yes_prop_16	0.272***	0.268***	0.194	0.227
	(0.097)	(0.096)	(0.197)	(0.197)
pct_yes_prop_23	−0.162	−0.198	−0.146	0.004
	(0.190)	(0.188)	(0.589)	(0.594)
pct_trump	−0.116**	−0.107**	−0.275	−0.293*
	(0.051)	(0.051)	(0.176)	(0.176)
pct_manufacturing	−0.327**	−0.505***	−0.907**	−1.056***
	(0.163)	(0.171)	(0.355)	(0.366)
pct_agri	0.008	−0.017	0.575	0.541
	(0.107)	(0.106)	(0.355)	(0.354)
hydro	0.008	0.005	−0.042	−0.032
	(0.007)	(0.007)	(0.028)	(0.029)
pv	−0.047	−0.024	0.047	0.089
	(0.045)	(0.045)	(0.149)	(0.151)
temp_jan	0.047***	0.051***	−0.011	0.061
	(0.014)	(0.014)	(0.052)	(0.069)
temp_aug	0.036***	0.113***	0.065*	0.142**
	(0.013)	(0.028)	(0.035)	(0.059)
temp_aug.seg.r		−0.120***		−0.188
		(0.038)		(0.119)
lse_size	−3.881***	−3.904***	34.451***	27.164***
	(0.345)	(0.342)	(5.654)	(7.284)
not_PGE_SCE	−0.194***	−0.205***	0.051	−0.026
	(0.024)	(0.024)	(0.159)	(0.166)
Constant	−0.081	−0.527**	−0.363	−1.303
	(0.188)	(0.234)	(0.518)	(0.788)
Observations	458	458	172	172
Log Likelihood	368.399	373.544	95.348	96.750
Akaike Inf. Crit.	−696.797	−705.089	−150.696	−151.500

Note: *p<0.1; **p<0.05; ***p<0.01

Table B18: Effect of Segmenting lse_size on Model Fit

	Linear (CCA & IOU)	Piecewise (CCA & IOU)	Linear (CCA Only)	Piecewise (CCA Only)
med_income	0.037	0.032	0.125**	0.155***
	(0.025)	(0.024)	(0.051)	(0.050)
pct_white	0.023	0.034	0.318	0.399**
	(0.075)	(0.071)	(0.209)	(0.201)
pct_asian	−0.065	−0.040	0.238	0.327*
	(0.075)	(0.071)	(0.193)	(0.186)
pct_some_college	−0.002	−0.079	0.089	−0.012
	(0.134)	(0.128)	(0.465)	(0.445)
pct_bachelors	0.137	0.055	−0.206	−0.397
	(0.136)	(0.129)	(0.435)	(0.418)
pct_democrat	0.041	0.137	0.233	0.356
	(0.175)	(0.167)	(0.509)	(0.487)
population	0.018	−0.011	0.037	0.041
	(0.048)	(0.046)	(0.096)	(0.091)
med_age	−0.001	0.004	0.006	0.003
	(0.011)	(0.010)	(0.023)	(0.022)
pct_yes_prop_16	0.272***	0.231**	0.194	0.080
	(0.097)	(0.092)	(0.197)	(0.191)
pct_yes_prop_23	−0.162	−0.120	−0.146	−0.064
	(0.190)	(0.180)	(0.589)	(0.563)
pct_trump	−0.116**	−0.049	−0.275	−0.308*
	(0.051)	(0.050)	(0.176)	(0.169)
pct_manufacturing	−0.327**	−0.331**	−0.907**	−0.738**
	(0.163)	(0.155)	(0.355)	(0.342)
pct_agri	0.008	−0.071	0.575	0.349
	(0.107)	(0.102)	(0.355)	(0.344)
hydro	0.008	0.002	−0.042	−0.047*
	(0.007)	(0.007)	(0.028)	(0.027)
pv	−0.047	−0.028	0.047	0.064
	(0.045)	(0.042)	(0.149)	(0.143)
temp_jan	0.047***	0.035**	−0.011	−0.120**
	(0.014)	(0.014)	(0.052)	(0.057)
temp_aug	0.036***	0.023*	0.065*	0.002
	(0.013)	(0.012)	(0.035)	(0.037)
lse_size	−3.881***	17.172***	34.451***	−518.096***
	(0.345)	(3.027)	(5.654)	(140.028)
lse_size.seg.r		−22.532***		571.490***
		(3.221)		(144.721)
not_PGE_SCE	−0.194***	−0.198***	0.051	−0.189
	(0.024)	(0.023)	(0.159)	(0.164)
Constant	−0.081	−0.039	−0.363	0.996
	(0.188)	(0.179)	(0.518)	(0.603)
Observations	458	458	172	172
Log Likelihood	368.399	392.704	95.348	103.800
Akaike Inf. Crit.	−696.797	−743.408	−150.696	−165.600

Note: *p<0.1; **p<0.05; ***p<0.01