The Evidence from California on the Economic Impact of Inefficient Distribution Network Pricing and a Framework for a Proposed Solution

by

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Abstract

Charging full requirements customers for distribution network services using the traditional cents per kilowatt hour (KWh) approach creates economic incentives for consumers to invest in distributed generation technologies, such as rooftop solar photovoltaics, despite the fact that marginal cost of grid-supplied electricity is lower. This paper first assesses the economic efficiency properties of this approach to transmission and distribution network pricing and whether current approach distribution network pricing implies that full-requirement customers cross-subsidize distributed solar customers. Using data on quarterly residential distribution network prices from California's three largest investor-owned utilities I find that larger amounts of distributed solar capacity and more geographically concentrated solar capacity predict higher distribution network prices and average distribution network costs. Moreover, this result continues to hold even after controlling for average distribution network costs for the utility, Using these econometric model estimates, I find that 2/3 of the increase in residential distribution network costs for each of the three utilities between 2003 and 2016 can attributed to the growth distributed solar capacity. The paper also investigates the legal obligation that distributed solar generation customers have to pay for sunk costs of investments in the transmission and distribution networks. The paper closes with a description of an alternative approach to distribution network pricing that is likely to increase the economic signals for efficient electricity consumption and the incentive for cost effective installation of distributed solar generation capacity. A straightforward approach to implementing this mechanism for regions where residential customers have interval meters. Suggestions for how to implement mechanism in regions with mechanical meters is also discussed.

1. Introduction

The falling cost of rooftop solar photovoltaic (PV) installations and generous solar support mechanisms in many states have led to a rapid increase in the amount of solar capacity installed by residential customers in these regions. The retail price a household pays for the last unit of grid-supplied electricity consumed is another important driver of the decision to install a rooftop solar system because it is the cost avoided from consuming a kilowatt-hour (KWh) from the distributed solar system. This retail price is typically significantly above the marginal cost of providing that KWh, because historically state regulators set the average retail electricity price equal to the vertically-integrated utility's average total cost of generating, transmitting, distributing, and retailing electricity. In regions of the United States with formal wholesale electricity markets, such as the California Independent System Operator (ISO), the PJM Interconnection, the New England ISO, and New York ISO, state public utilities commissions (PUCs) continue to recover the vast majority of the costs of the transmission and distribution networks and the cost of serving regulated retail customers through per unit charges in excess of the marginal cost of providing these services. The resulting retail prices for grid-supplied electricity increase the attractiveness of installing a rooftop solar system.

A number of PUCs have further increased the magnitude of the difference between the retail price for the last unit consumed and the marginal cost of supplying this KWh for high-demand users by charging retail customers according to increasing block price schedules. For example, the three largest investor-owned utilities in California all charge residential consumers according to steeply increasing block price schedules. Borenstein (2015) argues that for Pacific Gas and Electric—the utility with the largest number of distributed solar residential customers in the United States—the financial incentive to

adopt distributed solar during his sample period is due as much to California's increasing block rates as it is to the 30 percent federal tax credit for a distributed solar installation.

In the language of interconnection pricing, retail electricity prices that recover fixed and sunk costs through a per unit KWh charge encourage inefficient bypass in the sense that residential customers find it privately profitable to install a distributed solar system because the levelized cost (net of the government support received by the household) of electricity from their distributed solar system is less than the retail price, but not less than the marginal cost of an additional KWh of grid-supplied electricity. Consequently, although it is privately profitable for the consumer to install the distributed solar system (ignoring the cost of the government support provided to the household to purchase the solar system), it is socially inefficient for this investment to occur because it is cheaper to supply this customer with wholesale energy from the grid rather than pay for the cost of the solar system. In the former vertically-integrated geographic monopoly regime, this approach to retail pricing do not lead to inefficient bypass because the price of distributed generation implied that customers effectively only had the choice to consume grid-supplied electricity or not consume grid-supplied electricity.

Retail electricity prices that recover fixed and sunk costs on a per KWh basis when customers have the option to install distributed solar capacity has created what many electric utilities argue is an unsustainable dynamic where high marginal prices for grid-supplied electricity encourage customers to install distributed solar PV systems, which then requires the regulator to set higher retail prices to recover the same fixed and sunk costs from a smaller volume of sales of grid-supplied electricity. This higher retail price encourages more customers to install distributed solar PV systems, which then requires higher retail prices if the utility is going to recover these sunk and fixed costs.

The significantly larger monthly bills for grid-suppled electricity by distributed solar customers under the existing retail tariffs before versus after they install a rooftop solar system have caused many utilities to claim that these customers are cross-subsidized by full-requirements customers. This is often referred to as a "cost-shift" from the utility's distributed solar customers to its full requirements customers. Solar installers often counter these claims by arguing that distributed solar installations allow utilities to reduce their distribution network costs because a declining share of the electricity households consume is supplied from the grid. Solar installers also claim that this fact implies rooftop solar customers make much less use of the distribution grid and should therefore pay for less of the fixed and sunk costs. Utilities counter that they made sunk investments in the distribution grid to serve all customers and should therefore receive full cost recovery from all customers. There is an ongoing debate to resolve these issues in a number of states with significant distributed solar potential such as Arizona, California and Nevada.

This paper contributes to this debate by providing: (1) a theoretical foundation to address the cost-shift debate, (2) empirical evidence on the claims made by utilities and solar installers about the impact of solar installations on distribution network costs and prices, (3) description of the legal risks these issues create for utilities, and (4) a framework for more efficient pricing to recover to the costs of the transmission and distribution network.

The economic theory of multi-product cost functions is used to argue that full-requirements customers are unlikely to be cross-subsidizing customers with distributed solar systems even under the existing tariffs for grid-supplied electricity. The major source of economic inefficiency from the existing transmission and distribution pricing scheme is that it encourages inefficient levels of the electricity consumption and the inefficient decisions by consumers to bypass grid-supplied electricity.

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I then examine the empirical validity of the claim that distributed solar installations reduce distribution network costs using panel data on quarterly utility-level residential distribution network prices, utility-level quarterly installed distribution network-level solar PV capacity, annual utility-level distribution network regulated costs (revenue requirements), and annual utility-level electricity demand for California's three large investor-owned utilities. I estimate an econometric model of the California Public Utilities Commission (CPUC) distribution network price-setting process to quantify the extent to which increases in solar PV capacity in a utility's distribution network predicts higher residential distribution network prices.

I find that even after the accounting for the mechanical effect that more distributed solar PV capacity reduces the total withdrawals of grid-supplied electricity and therefore requires an increase residential distribution prices, more solar capacity in the distribution network predicts significantly higher distribution network prices. I find that the vast majority of the almost 100 percent increase in average residential distribution network prices between 2003 and 2017 for each of the three utilities can be explained by increases in the installation of distributed solar PV capacity. I then repeat this analysis using the annual distribution network regulated average cost for each utility as the dependent variable and find that increases in the amount distributed solar capacity the utility's service territory predicts a higher distribution network average cost for the utility. Combing this residential distribution price data with the annual distribution network average cost data, I find that residential distribution network prices are higher in utility distribution networks with more solar capacity even after controlling the annual average cost of the distribution network. These results are exactly counter to the claims of solar PV suppliers about the impact of solar PV installations on distribution costs and prices. Moreover, they are consistent with state regulators placing a greater share of the burden of the recovery of the fixed

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cost of the distribution network on residential consumers in utility service territories with more distributed solar capacity.

I then consider the legal question of whether utilities will be allowed to recover the costs of the transmission and distribution network from distributed solar PV customers that claim not to use these networks at all or as much as they did before installing rooftop solar capacity. Resolution of this legal question is particularly urgent for utilities experiencing rapid growth in the amount of distributed solar capacity given the estimated relationship between distribution network prices and costs and amount of solar PV capacity installed in that utility's distribution network. There are legal precedents in favor both sides of this debate, which provides a strong case for these utilities addressing this issue with their public utilities commissions as soon as possible.

Finally, I develop a simple economic model that provides a mechanism for increasing the efficiency of distribution network pricing and reduces the incentive for both inefficient consumption of grid-supplied electricity and inefficient decisions to install distributed solar systems. This model is first applied to the case that customers have interval meters capable of recording their consumption on an hourly basis. I then consider an extension to the case that customers have meters that can only read their monthly consumption. The paper closes with a brief discussion of how the insights from this simple model can be operationalized in an actual regulatory price-setting process to improve the efficiency of retail electricity pricing in regions with significant distributed solar resources.

2. The Theory of Multi-Output Production Applied to Electric Utility Costing

To understand of the inefficiency of the existing approach to retail electricity pricing and to provide essential input into the model used to derive more efficient of retail tariffs, I rely on the economic concept of a multiproduct cost function, $C(q_1, q_2 \ldots, q_N)$, where

q_k is the amount of electricity withdrawn by customer k from the grid and N is the total number of customers served. For each value of $(q_1,q_2\ldots,q_N)'$, the N-dimensional vector of the monthly consumption of each customer served by the utility, the function $C(q_1,q_2\ldots,q_N)$ gives the utility's total cost of providing this vector of outputs. Under the regularity conditions on utility's technology set described in Panzar (1989) this function is differentiable in all of the arguments.[1]

The marginal cost of providing customer k with an additional KWh of grid-supplied electricity is the increase in the value of $C(q_1,q_2\ldots,q_N)$ associated with a one unit change in q_k keeping the output levels of all other customers constant. Mathematically, the marginal cost of serving customer k at output vector $(q_1,q_2\ldots,q_N)'$ is equal to $\frac{\partial C(q_1,q_2,\ldots,q_N)}{\partial q_k}$. Virtually all hours of the year this marginal cost is slightly higher than the hourly wholesale price at the point of withdrawal from the transmission grid that connects that customer to their distribution grid. The cost is higher than the wholesale price because of distribution network losses between the point of injection to the customer's distribution network and the customer's dwelling where the energy is consumed.[2] However, during hours when the capacity constraints on the distribution network are close to binding, the marginal cost of customer k withdrawing an additional KWh can be substantially larger than the relevant hourly locational marginal price of wholesale electricity because marginal losses scale with the square of the flow on the distribution line.

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[1] The technology set, T, is composed of pairs of input vectors, x, and output vectors, y, such that the output vector y is technologically feasible to produce from the input vector x.
[2] According to the United States Energy Information Administration annual transmission and distribution network losses average about 6 percent of the total electricity produced nationally. (https://www.eia.gov/tools/faqs/faq.cfm?id=105&t=3)

The next cost concept is the incremental cost of q_k, which is equal to difference between the value of $C(q_1,q_2\ldots,q_N)$ and the value of $C(q_1,q_2\ldots,q_{k-1},0,q_{k+1},\ldots,q_N)$, or the amount that total costs are reduced as a result not selling anything to customer k. Mathematically, this is equal to $IC(q_k|Q_{-k}) = C(q_1,q_2\ldots,q_N) - C(q_1,q_2\ldots,q_{k-1},0,q_{k+1},\ldots,q_N)$, where $Q_{-k} = (q_1,q_2\ldots,q_{k-1},q_{k+1},\ldots,q_N)$. Dividing $IC(q_k|Q_{-k})$ by q_k yields the average incremental cost of q_k, $AIC(q_k|Q_{-k}) = IC(q_k|Q_{-k})/q_k$, which is also small, because the fixed costs of the installed generation capacity, transmission and distribution grid, metering and billing systems must be incurred to serve the remaining customers. Therefore, these costs are not eliminated by setting customer k's consumption to zero. One reason for the difference between the marginal cost of q_k and $AIC(q_k|Q_{-k})$ is the existence of fixed costs associated with providing service to customer k, such as the cost to connect the customer to the grid (although most these costs directly charged to the customer at the time they connect) and the monthly fixed cost of metering and billing the customer. If the marginal cost of serving customer k varies with the value of the q_k then the marginal cost of serving customer k at output level q_k given Q_{-k} can differ from $AIC(q_k|Q_{-k})$. For the reasons discussed above, it is extremely unlikely that the incremental cost of providing q_k units of electricity exceeds customer k's monthly bill, even if customer k has a distributed solar system.

The final cost concept is the stand-alone cost of q_k. This is equal to $SAC(q_k) = C(0,0\ldots,0,q_k,0,\ldots,0)$, which is equal to the total cost of providing q_k units to just customer k and nothing to all other customers. Dividing $SAC(q_k)$ by q_k yields the stand-alone average cost of q_k which much greater than average incremental cost of q_k, because the stand-alone average cost contains all of the fixed costs of the generation, transmission, distribution, and retailing segments as well as the monthly fixed cost of providing service to customer k.

It is profitable for the utility to serve a customer if the incremental cost of serving that customer is less than the revenue the firm earns by providing service to that customer. Because of the existence of the fixed costs of providing service to any customer, such as the sunk cost of the transmission and distribution network, it is possible for a utility to find it unilaterally profitable to serve each of its customers, but not earn sufficient revenues to cover its total costs. Specifically, given its existing tariff and existing vector of monthly outputs, $(q_1, q_2, \ldots, q_N)'$ the utility could find itself in the position of wanting to continue to provide service to each of its customers, even though the total revenues received from these customers is considerably less than the total cost of producing this vector of outputs.

As Faulhaber (1975) explains, as long as all groups of customers are paying more in revenues for their total consumption than the incremental cost of serving them and none of the groups of customers are paying more than the stand-alone cost of serving them, there are no cross-subsidies between customers. However, under these circumstances, the utility may not recover enough revenues from all of its customers under the existing tariff to cover its total production costs.

This set of circumstances can arise when a utility that was formerly recovering its total cost of production has a number of customers that install distributed solar systems. Under the existing tariff these distributed solar customers are still paying more in revenue to the utility than the incremental cost of providing them with this reduced amount of grid-supplied electricity. However, because their consumption of grid-supplied electricity has fallen they are making less of a contribution to fixed cost recovery than they were as full-requirement customers.

This logic suggests that it is highly unlikely that distributed solar customers are receiving cross- subsidies from full-requirements customers. Distributed solar customers are

simply making less of a contribution to fixed cost recovery as a result of their decision to incur the expense of investing in distributed solar capacity. The fixed-cost recovery problem created by a customer investing in a distributed solar system is no different from the fixed-cost recovery problem created by a customer reducing their monthly consumption of grid supplied electricity as a result of an energy efficiency investment or simply becoming more aware of their electricity consumption. In all of these cases, the utility is still recovering at least the incremental cost of serving these customers under the existing tariff, but the customer's total contribution to fixed cost recovery is lower.

Although cross-subsidies between full-requirements and distributed solar customers are very unlikely to exist under the current retail pricing regime, this regime does create incentives for inefficient consumption of electricity and inefficient bypass of grid-supplied electricity because the prices a customer pays for grid supplied electricity so far above the marginal cost of grid supplied electricity (excluding unpriced environmental externalities).

3. Impact of Solar Installations on Distribution Networks Prices and Costs

This section assesses the impact of increases in distributed solar capacity in a utility service territory on residential distribution network prices and regulated distribution network costs using data from the three large investor-owned utilities in California—Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric. This assessment is based on a simple model of the CPUC distribution network price-setting process.

3.1.   *Economic Model of CPUC Price-Setting Process*

The CPUC process first determines the revenue requirement for the utility based on a test year output level. The revenue requirement is the utility's annual costs that the CPUC allows the utility to recover from its customers through the prices charged. The other input to the price-setting process is the test year output level, which is a forecast of the utility's annual

demand during the time period covered by the price. The utility's revenue requirement divided by this forecast of demand gives the average price utility is allowed to charge.

The utility's annual revenue requirement can and often does change several times within the year in response to regulatory decisions made by the CPUC. When this occurs, the CPUC will change the price the utility is allow to charge. Each time a price set by the CPUC is changed a new tariff sheet is issued by the CPUC giving this price and the date that it becomes effective.

I model the residential distribution network price-setting process as follows. Let F_{iy} equal the revenue requirement for utility i in year y and QRF_{iy} equal the forecast of demand for utility i and year y for the residential sector. Because prices can be revised numerous time during the year, I assume that the quarterly value of the utility's residential distribution network revenue requirement is equal to $FR_{iq} = (FR_{iy})exp(\varepsilon_{iq})$, where ε_{iq} is unobserved shock to utility i's annual revenue requirement in quarter q. I assume that the ε_{iq} are independent, identically distributed random variables with finite first and second moments for each utility.

According to this simple model, utility i's residential distribution price in quarter q, is equal to $PR_{iq} = (FR_{iy})exp(\varepsilon_{iq})/QRF_{iy}$. Taking logarithms of both sides of this equation yields:

$$ln(PR_{iq}) = ln(FR_{iy}) - ln(QRF_{iy}) + \varepsilon_{iq} \qquad (1)$$

To assess the impact of the amount distributed solar capacity in utility i's service territory on residential distribution network prices, I create the following variables. Let CI_{iq} equal the cumulative megawatts (MWs) of distributed solar installed in utility i's territory as of the start of quarter q. Define $CONC_{iq} = \sum_{z=1}^{Z(i)} \frac{CI_{zq}}{HH_z}$, where CI_{zq} is the cumulative MWs of distributed solar capacity installed in zip code z of utility i's service territory as of the start of quarter q, HH_z is the number of households in zip code z in utility i's service territory, and Z(i) is the number of zip codes in utility i's service territory. $CONC_{iq}$ is larger for given number of MWs in utility i's service territory if these MWs are concentrated in a small number of zip codes. To estimate the

impact of solar installations in the utility's service territory and the geographic concentration of these solar installations on distribution prices, I estimate the following equation:

$$\ln(PR_{iq}) = \alpha_{iy} + \beta\ln(QRF_{iy}) + \delta\ln(CI_{iq}) + \gamma\ln(CI_{iq})\ln(CONC_{iq}) + \eta_{iq}, \qquad (2)$$

where the α_{iy} are utility-year fixed effects and the η_{iq} are assumed to be independent, identically distributed mean zero and variance σ_η^2 random variables. Operationalizing this model requires an estimate of QRF_{iy}, the forecast of utility i's residential demand during year i.

For each of the utility's I estimate a univariate time series model using QR_{iy}, the annual residential demand for utility i and year y, using data from 1990 to 2016 and then use the one-step ahead forecast of Q_{iy} as the value of QF_{iy}. For each utility, the model $\ln(Q_{iy}) = \mu_i + \ln(Q_{iy-1}) + \upsilon_{iy}$ is sufficient to produce a time series model such that null hypothesis that the υ_{iy} are a white noise sequence cannot be rejected. I then compute $QRF_{iy} = (QR_{iy-1})\exp(\hat{\mu}_i + \frac{1}{2}s_\upsilon^2)$, where $\hat{\mu}_i$ is the estimate of μ_i and s_υ^2 is the estimate of the variance of υ_{iy} constructed the residuals of this regression.

This simple model for the distribution network price setting process has a number of testable restrictions and implications for the parameters of equation (2). First restricting equation (2) to satisfy the theory in equation (1), implies $\beta = -1$, $\delta = 0$, and $\gamma = 0$. In addition, $(FR_{yi})E(\exp(\varepsilon_{iq})) = \exp(\alpha_{yi})E(\exp(\eta_{iq}))$, which implies that $FR_{yi} = \exp(\alpha_{yi})E(\exp(\eta_{iq}))/E(\exp(\varepsilon_{iq}))$, so that $\exp(\alpha_{yi})$ estimates FR_{yi} up to an unknown scale factor, $E(\exp(\eta_{iq}))/E(\exp(\varepsilon_{iq}))$.

The second model I estimate relates the logarithm of the annual average revenue requirement of utility i and year y to $\ln(QF_{iy})$ and $\ln(CI_{iy})$ and $\ln(CI_{iy})\ln(CONC_{iy})$. QF_{iy}, the forecast of utility i's demand in year y, is computed from Q_{iy}, demand of utility i in year y, following the same procedure as described above to derive QRF_{iy} from QR_{iy}. To compute the annual average revenue requirement for utility i in year y, let RR_{iy} equal the annual revenue

requirement for utility i in year y. Define $AR_{iy} = RR_{iy}/QF_{iy}$ as the annual average revenue requirement for utility i in year y. I estimate

$$\ln(AR_{iy}) = \lambda_i + \tau_y + \beta\ln(QF_{iy}) + \delta\ln(CI_{iy}) + \gamma\ln(CI_{iy})\ln(CONC_{iy}) + \eta_{iq}, \qquad (3)$$

where CI_{iy} equals the cumulative megawatts (MWs) of distributed solar installed in utility i's territory as of the start of year y, λ_i is a utility fixed effect, and τ_y is a year-of-sample fixed effect. $CONC_{iy} = \sum_{z=1}^{Z(i)} \frac{CI_{zy}}{HH_z}$, where CI_{zy} is the cumulative MWs of distributed solar installed in zip code z of utility i's service territory as of the start of year y. This model assesses whether the utility i's average regulated distribution cost is responsive to changes in installed solar capacity and the distribution of this capacity in its service territory.

The final model I estimate assesses whether increases in installed solar capacity predict increases in residential distribution prices after controlling for the level of the annual average utility-level revenue requirement. I estimate the equation:

$$\ln(PR_{iq}) = \alpha_i + \varphi\ln(AR_{iy}) + \delta\ln(CI_{iq}) + \gamma\ln(CI_{iq})\ln(CONC_{iq}) + \eta_{iq}, \qquad (4)$$

where the α_i are utility fixed effects. If $\delta > 0$ and $\gamma > 0$, then residential distribution prices increase in response to more distributed solar capacity in the utility's service territory and if this solar capacity is more geographically concentrated in the zip codes in the utility's service territory even after controlling for the utility's average distribution network revenue requirement.

3.2. Data Sources

The data used to estimate these models comes from variety of sources. The tariffs sheet for the three investor-owned utilities are the source for the quarterly value of the residential distribution price. This is the distribution price for the standard residential tariff: (1) the E-1 Tariff for Pacific Gas and Electric, (2) the Schedule D Tariff for Southern California Edison,

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and (3) the Schedule DR Tariff for San Diego Gas and Electric. These prices often change several times during the year.

For each utility and each quarter between quarter 1 of 2003 to quarter 4 to 2016, the residential distribution network tariff that was in force at the start of the quarter according to the tariff document is assigned to that quarter of the sample. For much of this sample period the residential distribution network for each utility was priced according to an increasing block price schedule. These increasing block price schedules are converted to a single weighted average residential distribution price for the quarter using the climate-region-weighted tier weights for each investor-owned utility computed in Table A2 of Borenstein (2011). For each utility residential distribution tariff, I apply the climate region weighted average weight for consumption on that tier times the value of the distribution price for that tier and sum these products over all tiers in the increasing block distribution network price schedule to arrive at quarterly residential distribution price, P_{iq}.

The annual demand in gigawatt-hours (GWh) for electricity by residential consumers of investor-owned utility i in year y, QR_{iy}, and the aggregate demand in (GWh) served by this utility in the same year, Q_{iy}, from 1990 to 2016 are available from the California Energy Consumption Database.[3] Figures 1 to 3 plot the values from Q_{iy} for Pacific Gas and Electricity, Southern California Edison, and San Diego Gas and Electric, respectively. Plots for three utilities share the several common features. First, steady load growth between 1990 and 1998, with a drop in 1998 and 1999 and a substantial uptick in 2000 consistent with a loss of customers to direct access in 1998 and 1999 and subsequent return of these customers during electricity crisis in 2000. The other feature is the significant slowdown in load growth from 2006 onward,

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[3] http://www.ecdms.energy.ca.gov/

consistent with the start of the California Solar Initiative which provided more than $2 billion in declining subsidies to households that installed rooftop solar systems between 2006 and 2016. The plots of QR_{iy} for each utility have these same patterns.

The quarterly values of cumulative MWs of distributed solar capacity installed in each zip code of each utility service territory are available from the Currently Interconnected Data Set from the *Go Solar California* web-site.[4] This data is used to construct the CI_{iq} and CI_{iy} variables. Figure 4 plots the values of CI_{iq} for each utility from quarter 1 2003 to quarter 4 of 2016. Although it is difficult determine from Figure 4, there is small amount of distributed solar capacity in each utility's service territory as of the start of the sample period. Data on the number of households in each California zip code, HH_z, is obtained from the 2010 US Census. This data is combined with the *Go Solar California* data to construct the $CONC_{iq}$ and $CONC_{iy}$ variables.

The annual total distribution network revenue requirement for utility i in year y, RR_{iy}, from 2006 to 2016 is available from Table 1.6 of the *California Electric and Gas Utility Cost Report: Public Utilities Code Section 913 Annual Report to the Governor and Legislature* available from the CPUC. Before that date, information on the annual distribution network revenue requirement for each utility is only available from CPUC Advice Letters.

3.3.   Empirical Results

The empirical results are based on quarterly data from 2003 to 2016 and annual data from 2006 to 2016. The start date for the quarterly data was chosen to coincide the start of the California's renewable energy effort. The state's renewables portfolio standard (RPS) started in 2003, and this also initiated widespread discussion of distributed solar PV capacity as a source

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of electricity for residential consumers. The start date for the annual revenue requirement data coincided with the start of the California Solar Initiative noted above. However, the primary driver of this start date was the difficulty in obtaining data before this data. I am currently attempting to compile distribution revenue requirement data back to 2000 from CPUC Advice Letters to each of the utilities.

Table 1 reports the results of estimating

$$\ln(QR_{iy}) = \mu_i + \ln(QR_{iy-1}) + \upsilon_{iy}$$

for each utility using annual data from 1990 to 2016. The ordinary least squares estimate of μ_i and the estimated standard error for this parameter estimate are reported for each utility along with the estimated value of the variance of υ_{iy}. For all three utilities, the null hypothesis that μ_i = 0 cannot be rejected. Each column of the table also reports the value of the Box-Pierce Q-statistic that tests the null hypothesis that the υ_{iy} are not autocorrelated up to lag J=11 and J=6. In all cases the P-value associated with this test statistic is substantially less than 0.05, which implies that 0.05 size test of this null hypothesis would not be rejected. Table 2 reports the results of repeating this same procedure for utility-level demand, $Q_{iy.}$

Table 3 presents the results of estimating

$$\ln(PR_{iq}) = \alpha_{iy} + \beta\ln(QF_{iy}) + \delta\ln(CI_{iq}) + \gamma\ln(CI_{iq})\ln(CONC_{iq}) + \eta_{iq}. \tag{2'}$$

A number of results are worth noting. First, a 0.05 test of the null hypothesis that β = -1 cannot be rejected. Second, the estimates of δ and γ are both positive and large relative to their standard error. This result is consistent with residential distribution prices increasing faster in utility service territories and quarters with more cumulative solar MWs and more concentrated deployment of these distributed solar MWs.

Figure 5 to 7 plot the normalized values of the annual residential distribution network cost $FP_{iy} = \exp(\alpha_{iy})/\exp(\alpha_{iy*})$ for y* = 2006 implied by our model of residential distribution

network pricing for each utility.   These values of FP_{iy} are plotted along with normalized value

of the annual distribution revenue requirement for each utility RR_{iy}/RR_{iy*} for $y* = 2006$.   The

trends in these two annual time series for each utility are remarkably similar, except for Parcific

Gas and Electric from 2011 to 2014, which provide further support for the validity of our model

of the regulatory price setting process.

Table 4 presents the results of estimating

$$\ln(AR_{iy}) = \lambda_i + \tau_y + \beta\ln(QF_{iy}) + \delta\ln(CI_{iy}) + \gamma\ln(CI_{iy})\ln(CONC_{iy}) + \eta_{iq}, \qquad (3')$$

using annual data from 2006 to 2016.   Once again estimate the estimate of β is not statistically

different from -1 and δ and γ are both positive.   The estimate of δ is significantly smaller in

magnitude than the corresponding the estimate from equation (1) and the estimate of γ is not

statistically different from zero.   Nevertheless, these results indicate that after controlling for

year-of-sample and utility fixed-effects, higher levels of cumulative solar installs are associated

with higher average utility-level distribution costs.

Table 5 reports the results of estimating

$$\ln(P_{iq}) = \alpha_i + \varphi\ln(AR_{iy}) + \delta\ln(CI_{iq}) + \gamma\ln(CI_{iq})\ln(CONC_{iq}) + \eta_{iq}, \qquad (4')$$

The estimates of δ and γ are both positive.   The estimate of δ is smaller in magnitude than the

corresponding the estimate from equation (1) and the estimate of γ is not statistically different

from zero.   Nevertheless, this result implies that even after controlling for the regulated average

cost of the distribution network, increases in solar installations implies higher distribution

network prices.

The regression results for models (2), (3) and (4) suggest the following conclusions about

the impact of distributed solar installations on both distribution network costs and residential

distribution network prices. First, the results of estimating model (2) support the conclusion that

more solar installations lead to higher residential distribution prices and even higher residential

distribution network prices for utilities where these solar installations are more geographically concentrated. Second, the model (3) results imply that the same conclusion applies to the average utility-wide regulated distribution cost, but the magnitude of these effects are smaller and they are less precisely estimated. This result could be due to the smaller annual sample of data used to estimate this regression. Third, the model (4) results support the conclusion that after controlling for the level of the average regulated distribution network cost, more solar installations and a greater geographic concentration of these installations leads to higher residential distribution prices. The above results are consistent with more solar installations increasing total distribution network costs. They are also are consistent with the view that the amount of these costs that the CPUC allocates the residential customers also increases with the amount of distributed solar capacity.

The results of estimating our model of the residential distribution network price-setting process embodied in equation (2) can be used to compute a counterfactual distribution network price path that keeps the amount of distribution solar capacity at the quarter 1 of 2003 level. This counterfactual price can be computed by multiplying each quarterly residential distribution network price by $\exp(- \delta \ln(CI_{iq}/CI_{iq^*}) - \gamma[\ln(CI_{iq})\ln(CONC_{iq}) - \ln(CI_{iq^*})\ln(CONC_{iq^*})])$ for q^* equal to quarter 1 of 2003 using the values of δ and γ obtained from estimating equation (2). For each of the three utilities, Figures 8 to 10 plot the actual average quarterly distribution network price and the counterfactual quarterly distribution network price that removes the impact of distributed solar capacity installed after quarter 1 of 2003. For each utility, roughly 2/3 of the average distribution network price increase between quarter 1 of 2003 and quarter 4 of 2016 can be attributed to the adoption of distributed solar capacity.

4. Legal Case for Utility to Recover Sunk Costs

There are a variety of reasons why a regulated utility that invests in the long-lived capital equipment necessary to provide service to consumers may not recover these sunk costs. Hempling (2015) provides seven examples of a regulated entity that was denied sunk cost recovery by the courts. Several of these legal decisions appear to be applicable to case of distributed solar investments.

All of these decisions are related to the basic legal principle in regulatory rate-making that a utility is only allowed the opportunity to recover its costs if the capital employed is "used and useful" and the "prudently operated." The utility is not guaranteed to recover these costs. The standard argument used by the utilities to justify their claims of cost recovery is the Fifth Amendment of the Constitution which states in part, "[N]or shall private property be taken for public use, without just compensation." Hempling (2015) notes that Justice Brandeis clarified what this clause meant for a regulated utility as, "The thing devoted by the investor to the public use is not specific property, tangible and intangible, but capital embarked in the enterprise. Upon the capital so invested the Federal Constitution guarantees to the utility the opportunity to earn a fair return." (p. 2)

Hempling (2015) goes on to emphasize that the courts have determined that "utility investors enjoy no constitutional guarantee of stranded cost recovery." (p. 2). Consequently, one way to justify that the utility's shareholders bearing the brunt of the revenue shortfalls relative to total costs of production is that competition from distributed solar has led to the partial obsolescence of the transmission and distribution grid, which has significantly reduced the revenues the utility is likely to earn from grid-supplied electricity. Therefore the utility's investors now own a less valuable asset in the same sense that the owners of the Market Street Railway in San Francisco that operated streetcars and buses in

the city owned a less valuable asset as a result of competition from municipal transportation companies and other modes of transportation.[5] The court upheld the Railway Commission's decision to set a lower price for Market Street Railway's services, which in turn produced a lower rate of return on its sunk costs. Hempling (2015) notes that "the Court explained that the Constitution has no sympathy for a company whose services are no longer needed."

Building on this decision, an argument for full cost recovery would be that the intermittent nature of distribution solar generation is sufficiently great that the full capacity of the existing transmission and distribution grid is necessary to serve both distributed solar and full requirements customers. Specifically, it is sometimes the case that the distributed solar systems are not producing any electricity and the transmission and distribution grid is utilized at the same rate as would be the case in the absence of any distributed solar investments. The argument that transmission and distribution networks have the same annual peak utilization rates as they did without any distributed solar investments is increasingly difficult to make as the share of distributed solar capacity increases and the diversity of distributed solar locations increases.

These opposing arguments suggest that the ultimate allocation of sunk costs of the transmission and distribution grid will involve some of these costs being recovered from utility shareholders. The above logic also suggests that the longer this regulatory decision is delayed the greater is the likelihood that more of these sunk costs will be recovered from utility shareholders, because more households are installing distributed solar systems over time. Moreover, as the results in Section 3 demonstrate, the longer utilities experiencing

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[5] Market Street Railway Co. v Railway Commission of California, 324, US 548 (1945).

significant increases in distributed solar capacity delay the resolution of this question the larger are distribution network costs at risk for under-recovery.

5. Toward More Efficient Retail Tariff Design

This section presents a simple economic model that suggests several pathways for increasing the efficiency of retail electricity pricing. I first consider the case that customers have meters that can record their consumption on an hourly basis in order to match the frequency that the marginal cost of retail electricity changes. Then I consider the case that customers only have mechanical meters.

Let $C(h)$ equal the marginal cost of retail electricity facing the customer during hour of the year h, for h=1,2,…,H, where H is the total number of hours in the year. Under all but extreme system conditions, to a first approximation, $C(h)$ is equal to the hourly wholesale price at the customer's distribution network location times one plus the marginal distribution loss factor for delivery to the customer's premises. Let the customer's hourly demand curve for electricity be $Q(h) = A(h) - P(h)/\theta(h)$, where $Q(h)$ is the customer's demand in hour h, $P(h)$ is the customer's marginal price in hour h, and $A(h)$ is the customer's willingness to pay for the first unit of consumption in hour h, or alternatively the customer's demand for electricity at $P(h)$ equal zero, and $\theta(h)$ is the slope of the customer's inverse demand curve during hour h, $\theta(h) = dP/dQ$.

Suppose that $C(h)$, $A(h)$, and $\theta(h)$ are random variables with compact support and joint density, $f(C,A,\theta)$. The support of $C(h)$ is $[C_L,C_H]$ and $[A_L,A_H]$ where $0 < C_L < C_H < \infty$, $0 < A_L < A_H < \infty$, and $A_L > C_H$. The last inequality imposes the reasonable assumption that it is socially optimal for the customer to always consume a positive quantity of electricity during every hour of the year. Assume that $\theta(h)$ also has compact support.

The economic efficiency implies that the hourly retail price of electricity should be set equal to the hourly marginal cost of grid supplied electricity, so that $P(h) = C(h)$. Using the logic of two-part tariff pricing, the maximum fixed charge that the consumer would be willing to pay for grid-supplied electricity during this hour is area below the demand curve above the hourly price, $C(h)$. This is the shaded area in Figure 11 and is equal $\frac{1}{2}\theta(h)(A(h) - C(h)/\theta(h))^2$.

Suppose before setting the fixed charge for the year or month, the regulator only knows that the $(A(h),C(h),\theta(h))'$ for all hours of the year are independent, identically distributed draws from $f(C,A,\theta)$. Figure 12 shows the value of hourly consumer surplus (CS) for the extreme case that $A(h) = A_L$ and $C(h) = P(h) = C_H$. The hourly value of consumer surplus is extremely small, which implies a small maximum hourly fixed fee. Figure 13 shows the other extreme of $A(h) = A_H$ and $C(h) = P(h) = C_L$, and the hourly value of consumer surplus is extremely large, which allows a very large hourly fixed fee.

Suppose that the consumer is risk neutral with respect to his electricity expenditures and will remain connected to the grid for the year if the expected annual fixed charge is less than the expected value of the annual consumer surplus obtained from consuming at $P(h) = C(h)$ each hour of the year. Note that $\frac{1}{2}\theta(h)(A(h) - C(h)/\theta(h))2$ can be written as $\frac{1}{2}\theta(h)*(Q(h))2$ where $Q(h)$ is the quantity demanded during hour h. Taking the expectation of $\frac{1}{2}\theta(h)*(Q(h))2$ yields

$$\text{Expected Hourly Willingness to Pay} = 1/2[\ Cov(\theta(h),Q(h)^2) + E(\theta(h))E(Q(h)^2)]. \quad (5)$$

This results implies that customers with an hourly demand that is positively correlated with the absolute value of the slope of their hourly inverse demand curve, customers with a large expected value of the slope of their hourly demand curve and customers with a large expected value of the square of their demand (or equivalently a large variance and mean of their demand)

have the largest willingness to pay to purchase their electricity each hour at a price equal to C(h).

If one assumes $\theta(h) = 1$ for hours of the year then there is an even more straightforward way to compute each customer's annual fixed charge:

Expected Hourly Willingness to Pay = ½ [E(Q(h)2] = ½[Var(Q(h)) + (E(Q(h))2.]. (6)

If FRR_{iy} is the fixed cost component of the distribution network revenue requirement, the CPUC could use historical hourly data for the past year to compute

Estimated Expected Hourly WTP for customer k = EEHWTP(k) $= \frac{1}{8760}\frac{1}{2}\sum_{h=1}^{8760} Q(h,k)^2$

where customer k's consumption in hour h of the previous year is Q(h,k). The annual fixed charge for customer k of utility i for year y is then equal to

$$F(k,i,y) = \frac{\sum_{k=1}^{K} FRR_{iy} EEHWTP_k}{\sum_{k=1}^{K} EEHWTP_k}.$$ (7)

This fixed charge could be equally divided across months of the year or tailored to the customer's monthly demand throughout the year. Each time the CPUC updates the revenue requirement, it could also update F(k,i,y) for each customer. Each year it could also update EEHWTP(k) for each customer.

This approach to assigning fixed cost recovery would not differ between distributed solar and full requirements customers, although it would clearly account for both the benefits and costs a distributed solar installation provides to the customer. Specifically, distributed solar would allow the customer to have a low value for E(Q(h)), its average hourly consumption. However, it is likely that a distributed solar customer would have a significantly larger value of Var(Q(h)) than a full requirement customer with the same value of E(Q(h)). By this logic, it is unclear if a customer would have a larger value of F(k,i,y) as a full requirements or distributed solar customer. However, because the distribution network pricing mechanism allows the

customer to withdraw electricity from the grid at hourly marginal cost, it would eliminate the incentive for inefficient bypass of the grid-supplied electricity at an unsubsidized price for a distributed solar installation. It would also provide a strong incentive for distributed solar customers to install storage devices to reduce the variance of their hourly withdraws from the grid and thereby reduce their annual fixed charge.

The expression for the EEHWTP can also be broken down according to the moments of the joint distribution of A(h) and C(h) as:

$$EEHWTP = \frac{1}{2} [Var(A(h)) - 2(Cov(A(h),C(h))) + Var(C(h))] + [E(A(h)) - E(C(h))]^2.$$

This implies that customers with a large variance in their hourly baseline (zero price) demands and a large variance in the hourly marginal cost of grid-supplied electric have a higher WTP pay to purchase grid-supplied electricity at C(h). One reason for a higher variance in the marginal cost of grid-supplied electricity is that during some hours the customer's consumption of electricity results in binding constraints in the distribution network, which produces an extremely large marginal distribution loss factor for deliveries though the distribution grid. Customers with a larger expected consumption, $E(Q(h)) = [E(A(h)) - E(C(h))]$ also have a higher expected willingness to pay. Customers with demands that are more highly correlated with the marginal cost of grid supplied electricity have a lower willingness to pay. Because higher wholesale prices tend to occur during high system demand periods, one interpretation of this result is that customers whose demands are more highly correlated with the system demand have a lower willingness to pay to consume at C(h).

For the case that the customer only has a mechanical meter, suppose the customer can only be charged a price for their consumption each hour of the year equal to the expected marginal cost of grid-supplied electricity, E(C(h)). Under these conditions, the hourly value of the consumer's willingness to pay is equal to $\frac{1}{2}(A(h) - E[C(h)])^2$. By the above logic:

$$\text{Expected Hourly WTP} = \tfrac{1}{2} E((Q(h)^2) = \tfrac{1}{2} [\text{Var}(A(h)) + [E(A(h) - E(C(h))]^2. \qquad (8)$$

However, because hourly data is not available for customers without interval meters, other methods must be employed to proxy for variables used to compute an estimate of the Expected Hourly WTP for each customer. An approach similar to load profiling can be used to compute this estimate for each customer. Specifically, for a test sample of customers with interval meters which are typically used to compute hourly load profiles, the CPUC can compute values of EEHWTP(k) for these customers and then have an algorithm for assigning values of EEHWTP(k) to each customer based on this algorithm based on observable characteristics of the customer and then this value of EEHWTP(k) can be used to compute F(k,i,y) for that customer.

This model also helps illustrates the inefficiency of pricing mechanisms such as a monthly demand charge that assesses on \$/KW charge on a customer's peak demand during the month. Unless the hour the demand charge is assessed coincides with the hour when the marginal cost of grid-supplied electricity is highest, there is no economic efficiency reason for charging a customer a higher price during the hour in the month that its demand is highest. Depending on a customer's pattern of demand throughout the month, the customer could incur a demand charge which significantly increases the marginal price of electricity when the marginal cost of grid-supplied electricity is extremely low. Consequently, there is no economic efficiency rationale for a demand charge, if the customer's hourly demands are uncorrelated with the hourly marginal cost of grid-supplied electricity. There is, however, a limited efficiency argument for demand charges if customer's hourly demands are positively correlated with the marginal cost of grid-supplied electricity, but this argument can be easily refuted if the hourly marginal price of electricity is set equal to marginal cost of grid-supplied electricity.

6. Concluding Comments

If current technological and social trends continue, the share of United States electricity consumption provided by distributed solar generation capacity is likely to continue to increase. According to our distribution network pricing model parameter estimates this will lead to increasing distribution network costs and prices to residential customers. If current residential distribution network tariffs remain in place, utilities will find it increasingly difficult to recover the costs of their distribution networks, even if the revenues they receive from supplying distributed solar and full-requirements customers exceeds the incremental cost to both customers. Moreover, the legal precedents for the recovery of sunk investments by regulated entities imply that electric utilities would be well-served to seek a resolution to the cost recovery issue as soon as possible because further delay will increase these distribution network costs (as more customers install distribution solar systems) and increase the likelihood that a greater share of these sunk costs must be recovered utility shareholders.

For customers with interval meters, which is the vast majority of customers in regions with significant solar resources such as California and Arizona, there is a straightforward approach to increasing the economic efficiency of retail electricity pricing and reducing the incentive for inefficient bypass of grid-supplied electricity. The hourly retail price should be set equal to the hourly marginal cost of grid-supplied electricity and the remainder of the utility's costs that can be recovered can be obtained through customer-specific monthly fixed charges that depend on the expected value of the square of the household's hourly consumption. Setting default retail electricity prices in this manner will also provide strong incentives for customers to install on-site storage devices and other mechanisms for shifting their consumption away from high-priced hours.

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Table 1: Regression Results for Forecasting Annual Utility-Level
Residential Demand in GWh

	PG&E	SCE	SDG&E
μ_i	0.00337	0.00632	0.0123
	(0.00845)	(0.0109)	(0.0110)
s_i^2	0.001231	0.00283	0.0284
Box-Pierce statistic (lag=11)	6.9430	12.9303	10.9349
Prob > chi2(11)	0.8039	0.2979	0.4487
Box-Pierce statistic (lag=6)	5.2154	9.0647	7.2321
Prob > chi2(6)	0.5171	0.1699	0.2999
Number of Obs.	26	26	26

Standard errors in parentheses below coefficient estimate

Table 2: Regression Results for Forecasting Annual Total Utility-Level Demand in GWh

	PG&E	SCE	SDG&E
μ_i	0.00672	0.00712	0.0110
	(0.00773)	(0.0109)	(0.0110)
s_i^2	0.0014924	0.0029975	0.0030489
Box-Pierce statistic (lag=11)	8.4430	14.4959	12.8822
Prob > chi2(11)	0.6732	0.2068	0.3011
Box-Pierce statistic (lag=6)	7.4304	10.0387	8.2416
Prob > chi2(6)	0.2829	0.1230	0.2209
Number of Obs.	26	26	26

Standard errors in parentheses below coefficient estimate

Table 3: Model (2) Estimates--Residential Distribution Network Price-Setting Process

Dependent Variable = Logarithm of Quarterly Average Residential Distribution Network Price		
Regressor		
ln(QFR)	-0.751 (1.032)	-0.671 (1.085)
ln(CI)	0.058 (0.023)	0.068 (0.023)
ln(CI)*ln(CONC)	0.003 (0.001)	
	Utility*Year Fixed Effects	Utility*Year Fixed Effects
Number of Observations	168	168

Table 4: Model (3) Estimates--Average Distribution Network Cost

Dependent Variable = Logarithm of Annual Average Distribution Network Cost		
Regressor		
ln(QF)	-1.252 (1.342)	-1.671 (1.851)
ln(CI)	0.028 (0.013)	0.039 (0.018)
ln(CI)*ln(CONC)	0.002 (0.002)	
	Utility and Year Fixed Effects	Utility and Year Fixed Effects
Number of Observations	33	33

Table 5: Model (4) Estimates—Residential Distribution Network Price Controlling for Average Distribution Network Costs

Dependent Variable = Logarithm of Quarterly Average Residential Distribution Network Price		
Regressor		
ln(RR/QF)	1.020 (0.906)	1.671 (1.851)
ln(CI)	0.026 (0.013)	0.035 (0.015)
ln(CI)*ln(CONC)	0.001 (0.001)	
	Utility*Year Fixed Effects	Utility*Year Fixed Effects
Number of Observations	132	132

Figure 1: Plots of Annual Demand in GWh for Pacific Gas & Electric
(Red Line) and Forecast Demand (Black Line)

Figure 2: Plots of Annual Demand in GWh for Southern California Edison
(Red Line) and Forecast Demand (Black Line)

Figure 3: Plots of Annual Demand in GWh for San Diego Gas and Electric
(Red Line) and Forecast Demand (Black Line)

Figure 4: Cumulative Installed Distributed Solar Generation Capacity by Quarter and
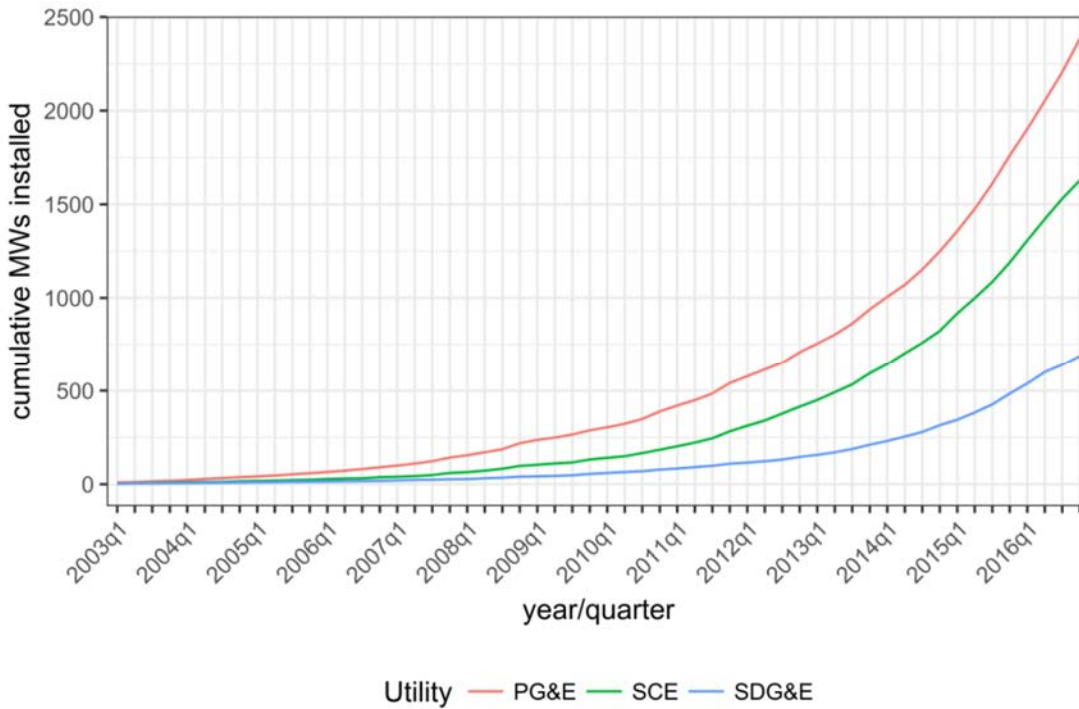Utility in Megawatts (MWs)

Figure 5: Normalized Annual Distribution Cost and Normalized Proxy Annual Residential
Distribution Cost from Model 1 Estimates for Pacific Gas and Electric
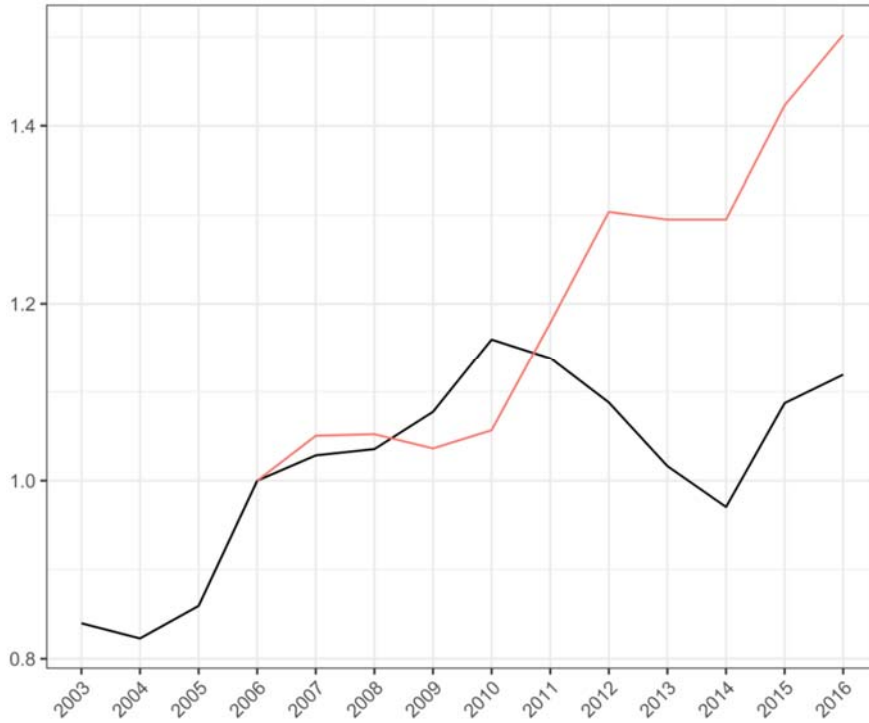
Figure 6: Normalized Annual Distribution Cost and Normalized Proxy Annual Residential
Distribution Cost from Model 1 Estimates for Southern California Edison
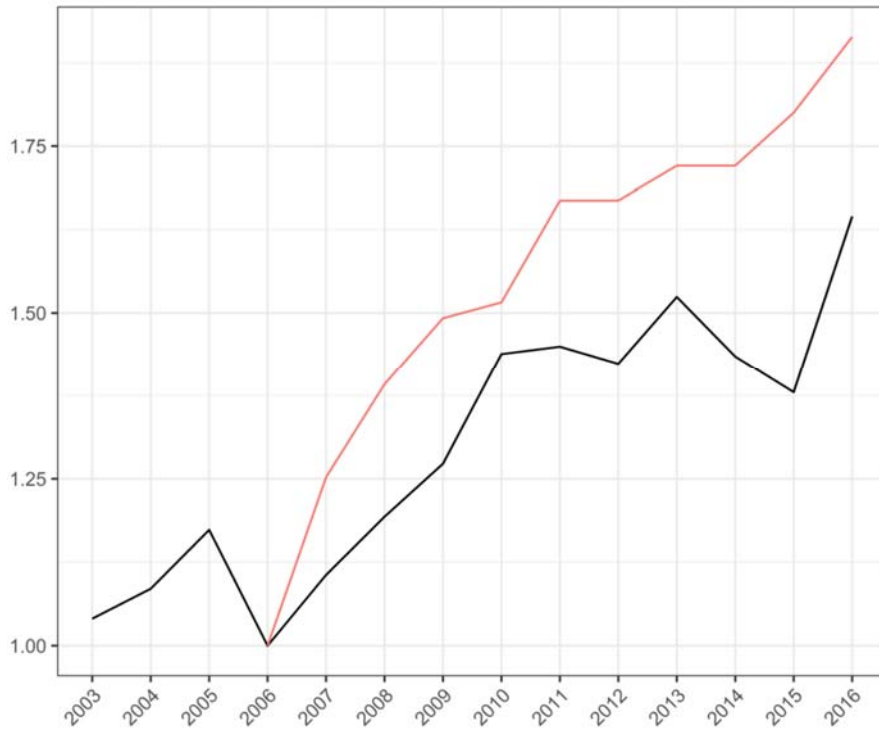
Figure 7: Normalized Annual Distribution Cost and Normalized Proxy Annual Residential
Distribution Cost from Model 1 Estimates for San Diego Gas and Electric
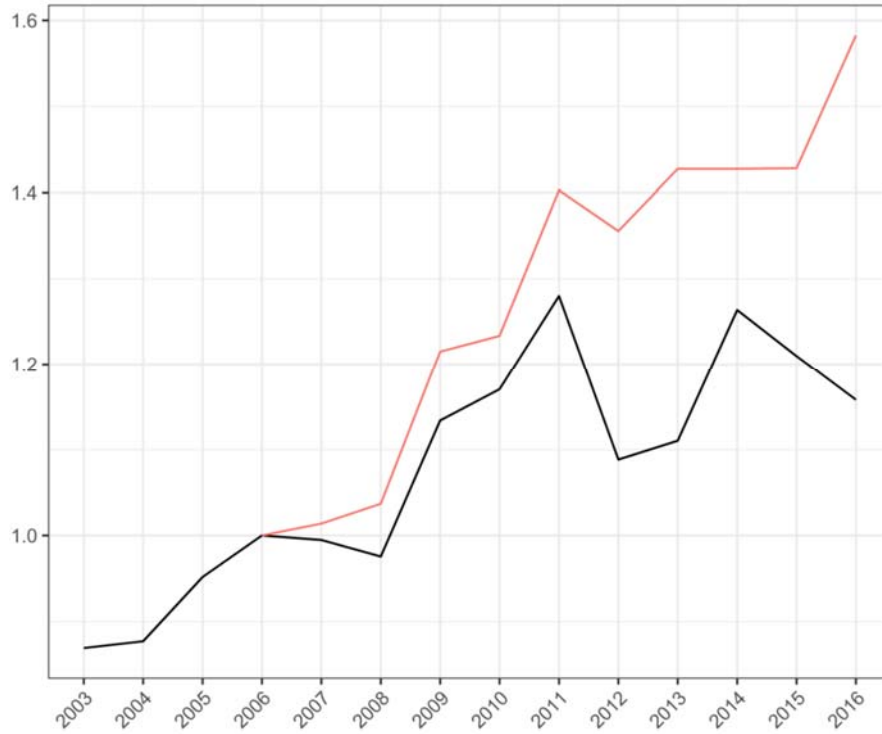
Figure 8: Actual and Counterfactual (No Post-2003 Distributed Solar Installations)
Quarterly Residential Distribution Price for Pacific Gas and Electric
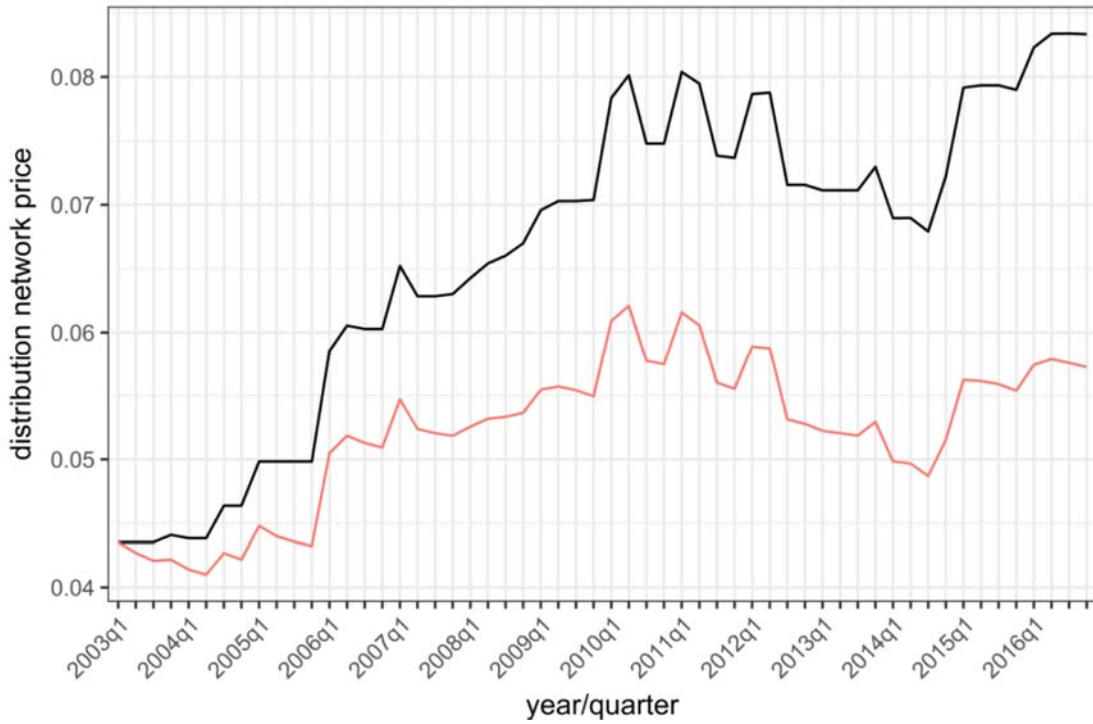
Figure 9: Actual and Counterfactual (No Post-2003 Distributed Solar Installations)
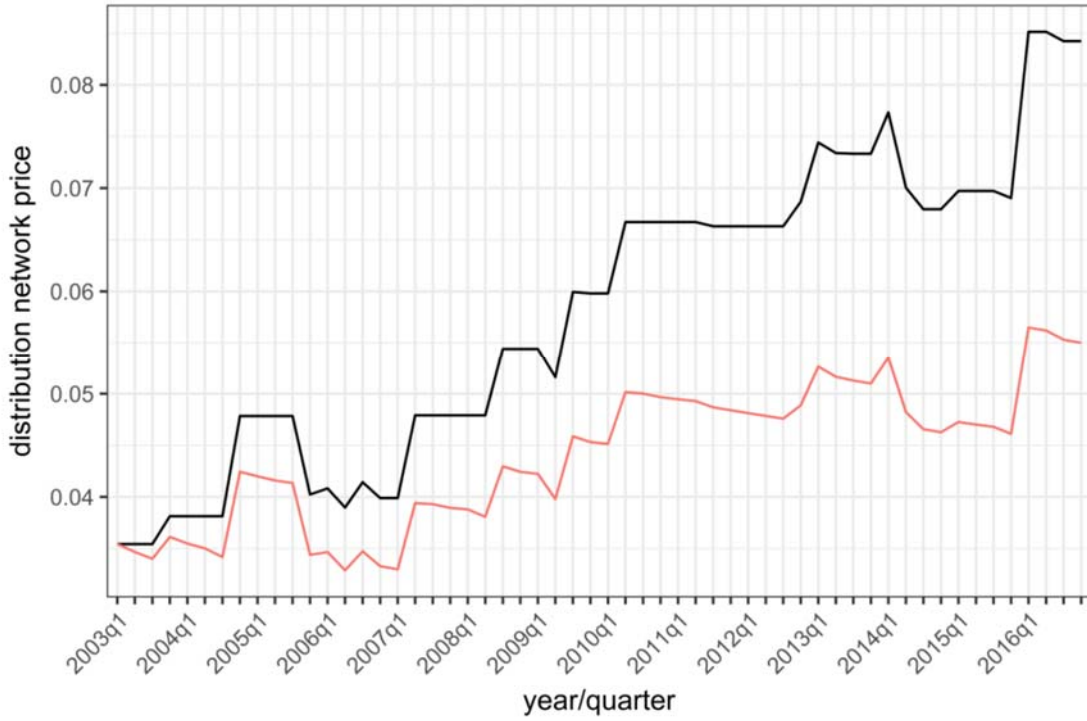Quarterly Residential Distribution Price for Southern California Edison

Figure 10: Actual and Counterfactual (No Post-2003 Distributed Solar Installations)
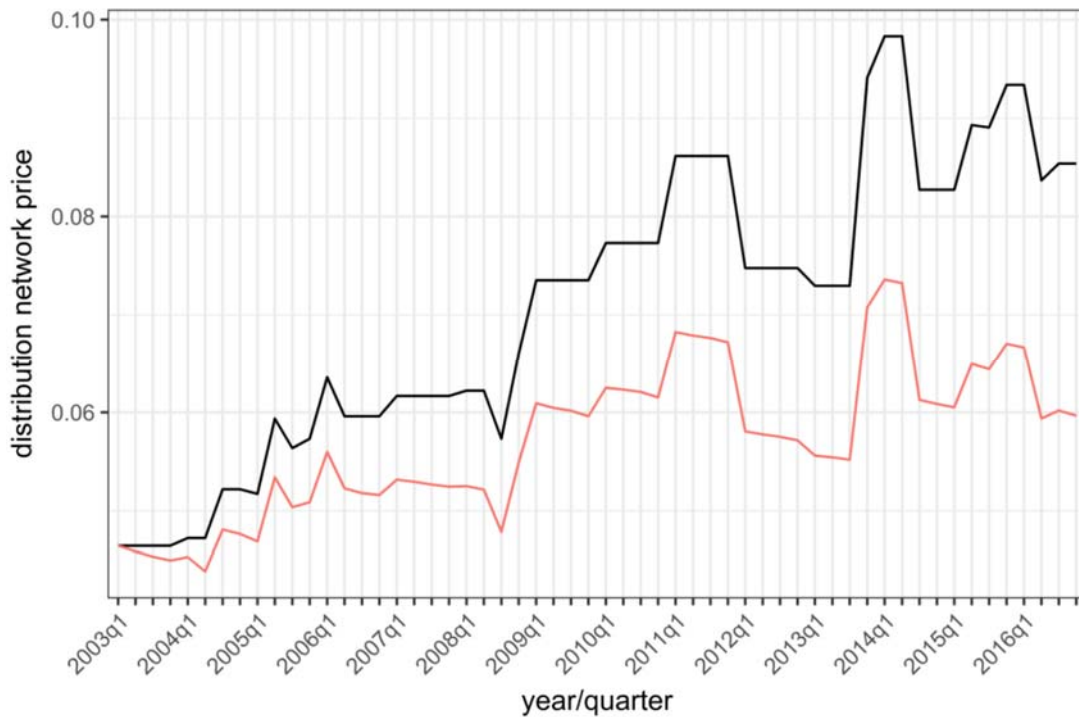Quarterly Residential Distribution Price for San Diego Gas and Electric

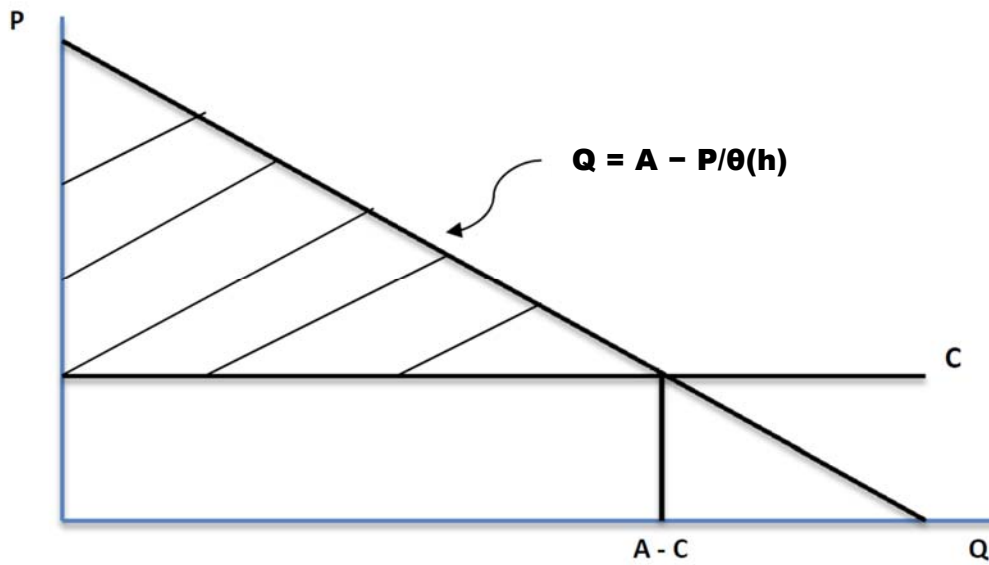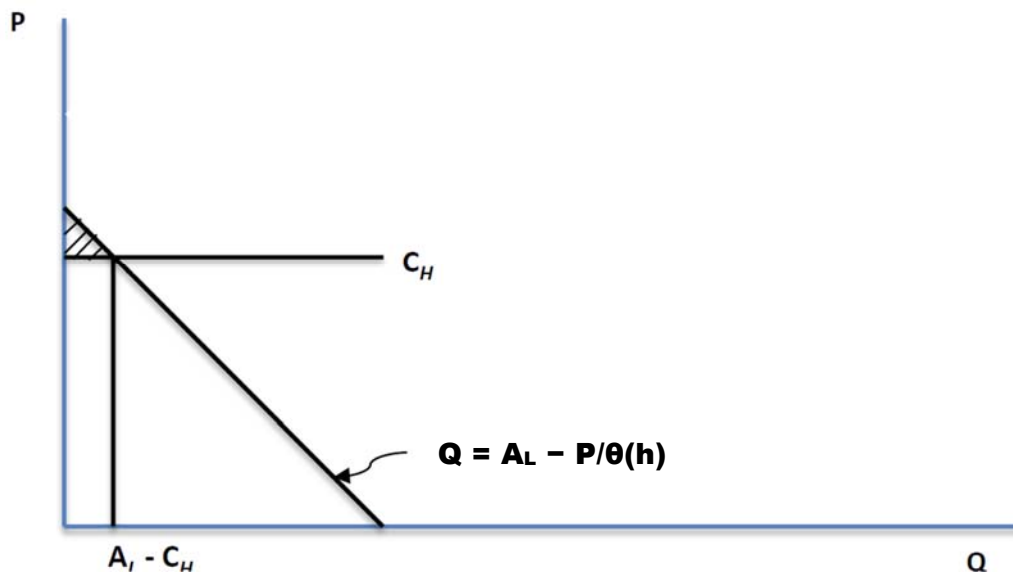Figure 11: Efficient Two-Part Tariff Pricing

Figure 12: Worst-Case Hourly Willingness to Pay

Figure 12:   Best-Case Hourly Willingness to Pay

$$Q = A_H - P/\theta(h)$$

C_L

$A_H - C_L$

P

Q