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Impact of residential PV adoption on Retail Electricity Rates

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HIGHLIGHTS

- Households who install PV reduce their electricity consumption from the grid.
- Electricity rates must increase for utility companies to recover its fixed costs.
- However, higher electricity rates give households more incentives to adopt PV.
- We find that this feedback has significant impact on PV uptake only in later years.
- Utility companies could lose a significant fraction of high consumption customers.

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ABSTRACT

The price of electricity supplied from home rooftop photo voltaic (PV) solar cells has fallen below the retail price of grid electricity in some areas. A number of residential households have an economic incentive to install rooftop PV systems and reduce their purchases of electricity from the grid. A significant portion of the costs incurred by utility companies are fixed costs which must be recovered even as consumption falls. Electricity rates must increase in order for utility companies to recover fixed costs from shrinking sales bases. Increasing rates will, in turn, result in even more economic incentives for customers to adopt rooftop PV. In this paper, we model this feedback between PV adoption and electricity rates and study its impact on future PV penetration and net-metering costs. We find that the most important parameter that determines whether this feedback has an effect is the fraction of customers who adopt PV in any year based solely on the money saved by doing so in that year, independent of the uncertainties of future years. These uncertainties include possible changes in rate structures such as the introduction of connection charges, the possibility of PV prices dropping significantly in the future, possible changes in tax incentives, and confidence in the reliability and maintainability of PV.

1. Introduction

The number of residential households with rooftop photo voltaic (PV) panels has grown rapidly over the past few years. This growth is driven by low (and falling) PV prices and the increasing price of electricity from the power grid in many areas. Although the high sunk cost of PV is a barrier to adoption, this barrier has been partially circumvented by the expansion of third-party PV leasing offerings (Drury et al., 2012). Over the next decade, the price of electricity from the grid is projected to increase due to infrastructure capital replacements and upgrades (CERES, 2012), while the price of rooftop PV is expected to drop, and these trends are likely to lead to more residential households adopting PV.

Customers reduce their net purchases of electricity from the grid by adopting PV; however, the costs incurred by utility companies do not decrease in proportion to the decrease in energy consumed. This is because utilities pay for transmission and distribution infrastructure and these fixed costs are recovered over decades (SCE, 2012d). Electricity rates must increase as demand decreases so that utilities can recover fixed costs. And these rate increases can result in even more incentives to adopt technologies that reduce consumption from the grid. Therefore, adoption of PV leads to a positive feedback cycle via increasing electricity rates.

The adoption of PV and its subsequent effect on electricity rates are highly dependent on the tariff structure. Tariffs contain a fixed charge for connecting to the grid, typically known as a connection charge, which is independent of the amount of electricity consumed. On top of the connection charge, tariffs also contain a variable charge that increases with consumption. When residential households adopt PV, only the variable component of their

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electricity bill decreases (unless the households disconnect from the grid). A utility can recover its fixed costs via the connection charge, the variable charge, or both. We focus on a tiered tariff in which electricity price increases with the amount of electricity consumed (SCE, 2012b). Customers who consume the most electricity pay the highest prices; hence they have the greatest incentive to reduce their consumption from the grid.

Prior studies on PV adoption assume that electricity rates are externally specified (Maribu et al., 2007; Paidipati et al., 2008; Denholm et al., 2009). These studies neglect the effect of the feedback between PV adoption and grid prices, and as a consequence may forecast lower PV penetration and net-metering costs. Net-metering costs refer to the total dollar amount of subsidy from non-solar customers to solar customers (E3, 2011; Beach and McGuire, 2012; RMI, 2012; NYT, 2012; PvTech, 2012). Many residential PV owners generate more electricity than they consume during times of the day when the PV system is operating at its peak. Under the net-metering program, the utility company is required to purchase its customers' excess generation at the retail electricity rates. A portion of retail electricity rates serves to recover fixed infrastructure costs. As a result, residential customers with PV will contribute less towards infrastructure costs than the customers without PV.

In this paper, we model PV adoption for a specific investor-owned utility subject to rate-of-return regulation in the state of California. We model the rate-setting process (also known as rate case proceedings) endogenously so as to capture the effect of feedback of PV adoption on future electricity rates. Using our model and publicly available data, we investigate the significance of this positive feedback on future PV penetration levels and net-metering costs. We also study the impact of tariff structures, subsidies, and costs of PV on the impact of feedback.

Our model shows that the most important parameter in determining whether this feedback has an effect is the willingness of customers to adopt PV. The payback from PV is realized over a long term — typically over 20 years — and customers could be uncertain about factors that impact payback over such a long period. Customers are uncertain about how long they will continue to stay in their current residence, the value of PV if they sell their house before the payback period, and the possibility of electricity rates changing over the period. Changes to rate structures, such as increasing connection costs with concomitant reduction of variable costs, or flattening tier tariffs to a single tier, can significantly change payoffs from adopting PV. Moreover, customers are hesitant about adopting new technologies when existing technologies have worked well for many decades. Feedback has little impact if only a small fraction of customers, who have economic incentives to adopt PV based on prevailing prices, actually adopt PV.

We evaluate the impact of the feedback cycle by comparing the following two metrics in models with and without feedback: (i) the time for electricity generated from PV adoption to reach 15% of the total demand and (ii) the costs of net metering. The analysis in this paper shows that feedback has relatively little impact on the time for PV adoption to reach 15% of demand whereas it has substantially more impact on net-metering costs. Feedback reduces the time to get to 15% by at most four months, whereas feedback could increase net-metering costs by 5–10%.

The study is organized as follows. In Section 2, we present our model. Section 3 describes the data that is used for the study. We present our findings in Section 4. In Section 5, we discuss various assumptions that we use in our model. Section 6 highlights a few policy implications. Section 7 concludes the paper and summarizes ideas for future work.

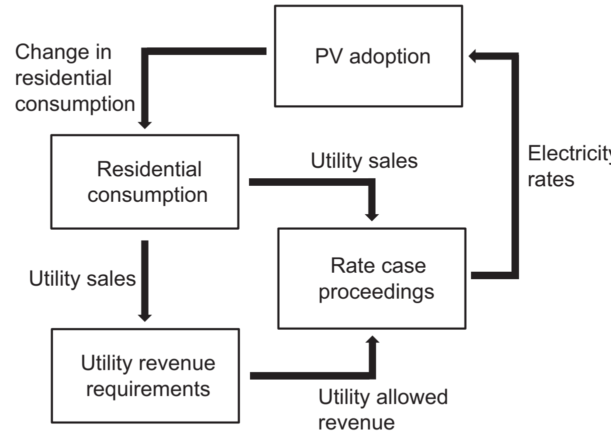

Fig. 1. Overview of model for PV adoption and its impact on electricity rates.

2. Model

In this section, we describe our model of rooftop PV adoption and its impact on the electricity rates of utility companies. For concreteness, we focus on rooftop PV adoption by residential customers in the state of California. The majority of customers in California are served by utility companies that are regulated monopolies: the prices they charge are set using a rate-of-return mechanism. Our model considers a single regulated utility. An overview of the model is given in Fig. 1. The overall model consists of four components for: (1) electricity consumption by residential customers, (2) revenue requirements of the utility company, (3) electricity rate revision by the regulatory agency and the utility (commonly known as rate case proceeding), and (4) rooftop PV adoption by residential customers. We describe each of these component models in detail in the following sections.

2.1. Residential consumption

The growth and the adoption of rooftop PV depends on the demographics of residential customers. A customer living in a house with a large roof is likely to find rooftop PV more beneficial than a customer who rents a small apartment and shares a roof with other renters. Thus, a key component of our model is the description of the residential customer base that is served by the utility company.

In our model we assume that a customer's electricity consumption in any given hour is constant—we ignore intra-hour fluctuations. Thus, a customer's energy consumption profile over a year is fully described by an hour-by-hour consumption profile. To model the heterogeneity in the customer base, we assume that each customer's yearly consumption profile is an element of the set $\mathcal{C} = \{\mathbf{c}_i : i = 1, \ldots, I\}$ where I is the number of customer categories and $\mathbf{c}_i = (c_{i,1}, c_{i,2}, \ldots, c_{i,T})$, where $c_{i,t}$ is the kWh consumption of a customer in category i at hour t. Here $T = 8760$ is the number of hours in a year. Thus, the consumption profiles take into account diurnal as well as seasonal variation in consumption.

The amount of rooftop PV capacity that a customer can install depends on the available roof space. Customers with large, unshaded roofs can install more PV panels than customers with small, shaded roofs. Furthermore, customers living in different zip codes may have different microclimates and hence may generate different amounts of electricity for the same PV installation. In this paper, we make the simplifying assumption that all PV panels in a utility's service territory generate the same power at a given point in time. We let $\mathbf{g}$ be the hour-by-hour generation profile of a representative PV panel, i.e., $\mathbf{g} = (g_1, g_2, \ldots, g_T)$, where g_t is the kWh generation of the PV panel during hour t of the year. As with the

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case of the consumption profile, we assume that the PV panel's output is constant during any given hour. The generation profile $\mathbf{g}$ takes into account daily as well as seasonal variation.

We assume that the output of the rooftop PV system scales linearly with the number of the panels. Hence, a household with r panels has a generation profile given by $r\mathbf{g}$. A customer without rooftop PV has $r=0$. Let $\underline{r}$ be the minimum (nonzero) number of PV panels that can be installed by customers; we set this parameter to the smallest number of panels in working rooftop PV systems. Let $\overline{r}$ be the maximum number of PV panels that can be installed by a customer; we set this parameter to the number of panels that can be installed in the largest homes in the utility's service territory.

Let $x_{i,r}[k]$ be the number of customers with consumption profile $\mathbf{c}_i$ and with r rooftop PV panels in year k. Since customers have either no panels or at least $\underline{r}$ panels, $x_{i,r}[k]=0$ for $0<r<\underline{r}$. Each customer has a net demand profile given by the vector $\mathbf{c}_i - r\mathbf{g}$ which specifies the amount of electricity consumed for each hour over the entire year. Here $\mathbf{c}_i - r\mathbf{g}$ is the pointwise difference between the consumption profile $\mathbf{c}_i$ and the generation profile $r\mathbf{g}$. If the local generation for the t-th hour (given by rg_t) exceeds the consumption $c_{i,t}$ during that hour, then the customer is a net supplier of electricity in that hour.

The net residential electricity consumption served by the utility over the entire year is then given by

$$\text{consumption}(\mathbf{x}[k]) = \sum_{r=0}^{\overline{r}} \sum_{i=1}^{I} \sum_{t=1}^{T} x_{i,r}[k](c_{i,t} - rg_t). \tag{1}$$

2.2. Utility revenue requirements

The rates of a regulated investor-owned utility company are set by a regulatory agency. For example, in California, utility rates are set by an independent commission called the California Public Utilities Commission (CPUC). Typically, the regulatory agency sets rates so that the utility can recover its expenses as well as make a specified *rate-of-return* on its capital investments. The revenue which the utility company is allowed to receive from its customers is determined by the regulatory agency and is termed the *revenue requirement*.

The revenue requirement is typically split into two major components—generation and delivery. The generation component is largely proportional to the total amount of energy delivered by the utility. In contrast, the delivery component is independent of the amount of energy that the utility delivers. The generation revenue requirement is used to recover the utility's generation costs, which includes energy procurement costs, capacity procurement costs, and also self-generation costs. The delivery revenue requirement is used to recover the utility's transmission and distribution costs and other miscellaneous costs and includes the allowed return on the utility's capital investments.

We assume that the regulatory agency allows the utility company a generation revenue of $v[k]$ dollars for each net kWh of electricity it supplies to its residential customers in year k.[1] We assume that the regulatory agency uses the net consumption from year $k-1$ as the estimate of net consumption in year k. Hence a utility's generation revenue in year k is estimated to be $v[k] \cdot \text{consumption}(\mathbf{x}[k-1])$, the product of the generation rate $v[k]$ dollars per kWh in year k and the volume $\text{consumption}(\mathbf{x}[k-1])$ kWh of net consumption in year $k-1$.

We assume that the regulatory agency allows the utility company a delivery revenue of $d[k]$ dollars for year k which is independent of the level of consumption. Thus, the total revenue requirement for year k is given by

$$\text{revenue}[k] = v[k] \cdot \text{consumption}(\mathbf{x}[k-1]) + d[k]. \tag{2}$$

2.3. Rate case proceeding

Customers are more likely to adopt rooftop PV if doing so results in substantial savings. These savings are a function of the electricity rates which are revised periodically by the regulatory agency in a process called the *rate case proceeding*. We assume that there is no delay in implementing new rates.

The procedure for electricity rate revision depends on the tariff structure used by the utility company. In California, most residential customers of regulated privately owned utilities pay block-inclining rates for their electricity (CPUC, 2010). This means that energy usage is divided into tiers and higher tiers are charged higher rates. For concreteness, we will focus on the rate structure used by a particular utility in California (SCE, 2012b).

The results presented in this paper assume that the *rate structure* is given exogenously. For example, the number of tiers, the price differential between tiers, and the monthly charge, are given exogenously. Given the rate structure, the electricity rates are endogenous—the model calculates the electricity rates based on the principle that the utility's estimated revenues equal its total revenue requirement. Models in which rate structures are changed endogenously are indeed important. We do not, however, consider such models in this paper because the processes by which agents — utilities, regulatory commissions, consumer advocates — determine rate structures are complex. There are many inter-related factors that must be considered including subsidies for low-income customers, mandates for percentages of renewable energy, the relative percentages of bulk versus distributed energy generation, and the difficulty of maintaining power quality with increased uncertainty of moment-to-moment power from PV.

We first assume that the current rate structure applies for the lifetimes of our models. Under the current rate structure, customers pay a connection charge which is independent of their energy consumption and a variable charge which depends on their energy consumption. To calculate the variable charge, monthly energy consumption is divided into five tiers as shown in Table 1. This tier structure is designed based on a certain minimum consumption called the *baseline allowance*. The baseline refers to a specific amount of electricity that is allocated to a customer and is charged at the lowest price (Conkling, 2011). A customer's baselines are set by CPUC based on the average electricity consumption in the customer's geographic area. Currently the baseline is 55% of the average aggregate consumption (SCE, 2012a). Baselines are revised during each rate case proceeding.

Different baselines may be set for different seasons. We do not differentiate customers based on their geographic location; hence all customers are assumed to have the same baseline which is computed from the total electricity consumption over the entire

Table 1
An example of tiers and rates for a California utility.

Rate tiers	Allocation	Delivery rate ($/kWh)	Generation rate ($/kWh)
Tier 1	0–100% of baseline	0.04985	0.08205
Tier 2	101–130% of baseline	0.07899	0.08205
Tier 3	131–200% of baseline	0.16189	0.08205
Tier 4	201–300% of baseline	0.19689	0.08205
Tier 5	Over 300% of baseline	0.23189	0.08205

[1] In practice, a utility's generation costs are likely to depend on the particular day and hour. For instance in California, demand is typically highest during summer afternoons. During those hours, the utility's generation costs would be significantly higher due to the usage of peaker plants and additional standby capacity. We will discuss the impact of this on our results in Section 5.

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service territory of the utility. The model does, however, have different baselines for summer and winter months.[2] We assume that baselines are revised at the beginning of each rate case proceeding based on the electricity consumption in the past year. That is, the baselines for year $k+1$ are set at 55% of average aggregate residential consumption in year k.

Residential customers with PV systems may generate more electricity than they consume during certain hours of the year. The excess generation is sold back to the utility company and customers are compensated for supplying power to the grid under the net-metering program. A customer is billed annually for the net charges accrued on her account over the past 12 months. The customer is charged for net consumption or credited for net generation on a monthly basis. The bill (debit or credit) for each month is summed over the 12 months, and if the net bill over the year is a debit then the customer pays that total amount.

If, however, the net bill over the year is a credit, the dollar credit which the customer receives from the utility will depend on whether he has a net kWh generation over the year. If the customer consumes more kWh over the entire year than she generates, then the customer gets paid nothing regardless of her net dollar credit. If (in the extremely rare case that) the customer consumes fewer kWh than he generates over the year, then the customer will be credited for his excess generation over the year at a relatively low rate called the net surplus compensation rate (NSCR). The NSCR is derived from hourly day-ahead wholesale market prices and changes every month. Since the NSCR changes very little over each year, we assume that the NSCR is constant within each year. We let $p_0[k]$ denote the NSCR in year k.

To model the rate case proceedings, we first look at the prices set in historical rate case proceedings of SCE (SCE, 2012b). Over the past ten years, connection charges fluctuated between \$0.50 and \$1.50 per month. The retail energy rates are shown in Fig. 2. Tier 1 and 2 rates barely increased over the last ten years due to various policy decisions (such as California State Assembly Bill 1X and California Senate Bill 695) that protect low-income customers who typically consume within the first two tiers. Most of the increase in the utility's costs have been borne by higher tier customers.

Based on the observations of historical electricity rates, we assume that the annual percentage increases in the monthly charge are fixed and exogenously specified. We also assume that the annual percentage increases in tiers 1 and 2 rates are fixed and exogenously specified. Furthermore, we assume that the differences in rates between higher tiers, i.e., between tiers 3 and 4 and between tiers 4 and 5, are fixed and exogenously specified. This assumption is based on the observation that the differences between the rates for tiers 3–5 have not changed much over the last few years.

We now specify how the rates for all tiers are calculated in our model. Let $F[k]$ be the monthly connection charge for year k; this is a charge that each customer pays each month, independent of the amount of electricity consumed. Thus the total yearly revenue from the connection charge in year $k+1$ is

$$\text{TotalFixedRevenue}[k+1] = 12 \cdot F[k+1] \cdot \text{NumberOfCustomers}$$

Here, we assume that the number of customers is constant over all years. Let $p_l[k]$ be the electricity rate for tier l in year k and let $\mathbf{p}[k] = (p_l[k] : l = 1, \ldots, 5)$ be the vector of electricity prices in year k. We assume that the regulatory agency uses the consumption in year k as the estimate of the consumption in year $k+1$. We use $\text{consumption}_l(\mathbf{x}[k])$ to denote the amount of consumption charged in tier l during year k. Assuming that consumption patterns for year $k+1$ are the same as that for year k, at the end of year k, the utility's estimated income in year $k+1$ from consumption in tier l is $p_l[k+1] \cdot \text{consumption}_l(\mathbf{x}[k])$. Hence at the end of year k, the estimated total variable revenue for year $k+1$ is

$$\text{TotalVariableRevenue}[k+1] = \sum_l p_l[k+1] \cdot \text{consumption}_l(\mathbf{x}[k])$$

Since $p_1[k+1]$ and $p_2[k+1]$ are given exogenously, the unknowns in the sum on the right-hand side of this equation are $p_3[k+1]$, $p_4[k+1]$, and $p_5[k+1]$; however, since $p_4[k+1]$ and $p_5[k+1]$ are functions of $p_3[k+1]$, the estimated total variable revenue in year k is a function of $p_3[k+1]$ only.

Let $\text{purchase}(\mathbf{x}[k])$ be the total kWh which the utility has to compensate its customers at the NSCR rate in year k. At the end of year k, we estimate that this value will be the same in year $k+1$ as in year k. Hence the estimated NSCR compensation in year $k+1$ is

$$\text{NSCR\_compensation}[k+1] = p_0[k+1] \cdot \text{purchase}(\mathbf{x}[k])$$

We assume that the NSCR rate $p_0[k]$ for all k is given exogenously. So, the estimated NSCR compensation for year $k+1$ is known.

At the end of year k the utility's estimated revenue for year $k+1$ is the sum of its estimated fixed and variable revenues minus the estimated NSCR compensation it pays

$$\begin{aligned}\text{revenue}[k+1] = {} & \text{TotalFixedRevenue}[k+1] \\ & + \text{TotalVariableRevenue}[k+1] \\ & - \text{NSCR\_compensation}[k+1] \end{aligned} \tag{3}$$

The only unknown in the above equation is $p_3[k+1]$. The value of this unknown is calculated by equating the revenue that is estimated will be obtained from customers in year $k+1$ to the revenue allowed by the regulatory commission, i.e., from Eqs. (2) and (3).

The amount of grid power consumed by customers in year $k+1$ will be less than the estimate because the estimate for year $k+1$ is the same as the consumption in year k, and some customers will reduce grid consumption in year $k+1$ by installing PV panels during the year. Thus, in this model, the utility's actual revenue will be less than its anticipated revenue, in every year.

To correct for deviations between revenue requirements and actual collected revenues, certain regulatory commissions adopt a policy known as *revenue decoupling* (ELCON, 2007). Under revenue decoupling, electricity rates are revised outside of regular rate case proceedings. The rates are increased (or decreased) to account for any accumulated shortfall (or excess) in collected revenues under (or over) the allowed revenue requirement. Revenue decoupling rate adjustments are typically more frequent than rate case proceedings (e.g., while rate case proceedings might be held every three years, revenue decoupling rate adjustments might be held

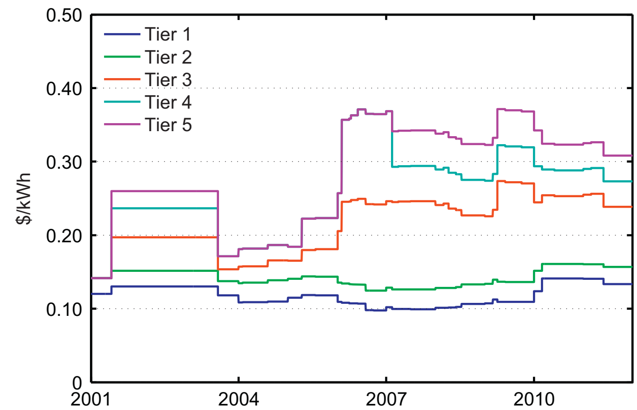

Fig. 2. SCE's domestic service energy rates from 2001 to 2011.

[2] Summer refers to the months from June to September (inclusive). All other months are winter.

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yearly). The results of our study are, however, not significantly impacted by revenue decoupling. This is because the deviations between revenue requirements and actual collected revenues are too small to have a significant impact on PV adoption.

2.4. PV adoption

The model of how customers adopt PV is crucial in determining whether the feedback cycle has a significant effect. We assume that the likelihood that a customer will consider installing PV increases with the amount of reduction in the customer's electricity bills by installing PV. Even people who can save money by installing PV in any given year may not install PV that year—waiting may allow them to get PV at lower prices later, or electricity grid rate structures may change and thus change the cost-benefit ratios of solar in later years, and customers may expect to move houses before the PV payback period. We assume that a customer who is considering installing PV because of potential cost savings are more likely to actually install PV in any given year if many other customers have already installed PV. In summary, in our model we assume that whether a customer adopts PV in a given year depends on only two factors: (a) the savings in that year by adopting PV and (b) the prevalence of residential PV in that year.

Our model for PV adoption takes into account the heterogeneity in the types of homes in which customers live. For example, customers (independent of their consumption profile) who live in apartments are likely to be unable to install rooftop PV panels. To account for such customers, we let y_i be the number of customers in consumption category i who are unable to use rooftop PV.

For the rest of the $x_{i,0}[k]-y_i$ customers who can benefit from rooftop PV and who have not purchased any PV yet at the end of year k, the decisions that these customers make in year $k+1$ depend on the prices of solar and electricity from the grid in that year; customers are not influenced by scenarios for future prices. In reality customers do make decisions based on possible future scenarios including scenarios with radical changes in rate structures, subsidies and costs of PV. We make the assumption that, despite these uncertainties, the greater the savings that a customer gets in a given year from adopting PV, based on that year's prices, the greater is the likelihood that the customer will adopt PV in that year. We assume that customers use the levelized cost of electricity from PV when calculating their savings from adopting PV. We also assume that customers are more likely to adopt technologies that are already in widespread use. Next, we discuss how these two factors — savings and prevalence — impact the numbers of customers who adopt solar in our model.

Even when PV is leased rather than purchased outright, customers incur a transaction cost including the hassle of selecting contractors and having people working on the roof. A high-income customer may decide that \$30 of monthly savings obtained by installing solar is not worth the hassle, while a low-income customer could come to the opposite conclusion. We model this effect by assuming that the parameter that influences a customer's decision in year k is the savings from adopting the technology in year k as a percentage of the customer's (initial) bill in year 0. For example, if year 0 is 2012, then the influence of monthly savings of \$20 (from adopting PV) in year 2015 on a customer with a monthly bill of \$200 in year 2012, is the same as the influence of monthly savings of \$10 on a customer with a monthly bill of \$100 in year 2012.

In our model, the likelihood of a customer installing PV in any year is a function of savings and prevalence and the form of the function plays a key role in the results. There seems to be no universally accepted form for this function in the literature. We begin by considering a product form: the likelihood of a customer adopting a technology in a given year is a product of a function of the savings by adopting the technology in that year and a function of the prevalence of the technology in that year (Maribu et al., 2007). A rationale for the product form is that customers make decisions in two steps. First they decide whether to consider installing PV based on the potential savings; customers are more likely to evaluate PV further if they make more savings. Then they determine if they are confident enough about PV technology to install PV, and their confidence increases with the prevalence of the technology. A product form is, however, simplistic because savings and prevalence may interact in more complex ways. Our analysis suggests that perturbations to the simple product form do not change the results significantly.

A customer's savings from installing PV depends on the number of panels that the customer installs. We assume that the only choice that a customer has is to either not install any panels or to install the optimum number of panels. Furthermore, once a customer installs PV panels, the customer will not add more panels or remove panels during the time horizon of the model. For a given customer in consumption category i who does not have PV, let $\mathsf{savings}_i[k+1]$ be the savings (based on prices in year $k+1$) from installing the optimum number $r_i^*[k+1]$ of panels and let $\mathsf{prevalence}[k]$ be the fraction of the total population that has adopted PV as of the previous year k (note that savings could be 0.) We assume that the likelihood that the customer will adopt PV is the product $g(\mathsf{savings}_i[k+1]) \times h(\mathsf{prevalence}[k])$, where functions g and h are described next.

Functions g and h are monotone increasing, and $g(0)=h(0)=0$ and $g(1)=h(1)=1$. We use a sigmoid function for g (Maribu et al., 2007), and we assume a linear function for h

$$h(\mathsf{prevalence}[k]) = \alpha + (1-\alpha)\cdot \mathsf{prevalence}[k]$$

where α is a constant parameter. We can think of α as the fraction of early adopters, as it is the fraction of potential users of a new technology that adopt the technology in a year when the technology has not been used previously. In this model, $(1-\alpha)\cdot \mathsf{prevalence}[k]$ represents the fraction of customers who adopt PV despite uncertainties about the future, because of the confidence gained by seeing the fraction of customers prevalence[k] who had already adopted PV. For example, if $\alpha=0.02$, then h (prevalence[k]) depends almost entirely on prevalence[k], i.e. the rate of new customer adoption depends primarily on the fraction of customers who have already adopted.[3] In most of the calculations we assume that the savings function reaches 0.95 for a savings of 30% and we assume that α is 2%; so that the likelihood of a customer with a savings of 30% or more adopting PV is almost a linear function of prevalence.

The number of adopters in year $k+1$ from consumption category i is given by

$$\mathsf{adopters}_i[k+1] = (x_{i,0}[k]-y_i)\cdot h(\mathsf{prevalence}[k])\cdot g(\mathsf{savings}_i[k+1]) \tag{4}$$

The number of adopters in any year depends on the electricity prices in that year (via $g(\mathsf{savings}_i[k+1])$) and the total number of customers who have adopted earlier (via $h(\mathsf{prevalence}[k])$). Then, in year $k+1$, the total number of customers in consumption category i and who do not have PV is given by

$$x_{i,0}[k+1] = x_{i,0}[k] - \mathsf{adopters}_i[k+1] \tag{5}$$

and the number of customers in consumption category i and r PV panels is given by

$$x_{i,r}[k+1] = \begin{cases} x_{i,r}[k] + \mathsf{adopters}_i[k+1], & r = r_i^*[k+1] \\ x_{i,r}[k], & r \neq r_i^*[k+1] \quad \text{and} \quad r \neq 0. \end{cases} \tag{6}$$

[3] Our results show that α is the single most important factor affecting the impact of feedback.

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Table 2
Summary of model parameters.

Parameter	Description
I	Number of customer categories
$\underline{r}$	Minimum number of PV panels of a PV system
$\overline{r}$	Maximum number of PV panels of a PV system
$\mathbf{c}_i$	Hour-by-hour consumption profile of each consumption class i
$\mathbf{g}$	Hour-by-hour generation profile of a representative 1 kW PV panel
$v[k]$	Generation revenue requirement in each year k in dollars per kWh
$d[k]$	Delivery revenue requirement in each year k in dollars
$F[k]$	Monthly charge in each year k in dollars
$p_0[k]$	Net surplus compensation rate in each year k
$p_1[k], p_2[k]$	Electricity rates for tiers 1 and 2 in each year k
$\Delta_4[k]$	Rate difference between tiers 3 and 4 in each year k
$\Delta_5[k]$	Rate difference between tiers 4 and 5 in each year k
$s[k]$	Levelized cost of solar energy based on the price of PV in year k
y_i	Number of customers in each consumption class i that are unable to use rooftop PV
g	Savings function, that is, the probability that a customer adopts PV as a function of her annual savings
α	Coefficient of external influence in prevalence model

2.5. Dynamics

We now describe the dynamics of PV adoption along with rate change. Let us assume that rate case proceedings take place every year. Given a customer profile $\mathbf{x}[k]$, we can compute the baselines and the electricity rates $\mathbf{p}[k+1]$ (using Eq. (3)) that would be in effect for the year $k+1$. Given the electricity rates, customers who have not installed PV determine if they want to install PV systems based on their potential savings for year $k+1$ and current prevalence of PV. The prevalence of PV for the following year is increased to reflect the number of customers who adopt PV in the previous year. Taking into account the current prevalence of PV, we determine the number of customers who adopt rooftop PV (c.f. Eq. (4)). Then, the distribution of the customers in the year $k+1$ is given by Eqs. (5) and (6). If this new customer distribution is different from the previous distribution, the cycle repeats until no more customers adopt PV. We summarize the parameters of the model in Table 2.

3. Model data

In this section, we describe the data that we used in our model. We focus our attention on the adoption of PV by residential customers of SCE.

3.1. Data for residential customers

We obtained usage data of SCE's residential customers from proceedings in the 2012 general rate case (SCE, 2012a). Currently, SCE serves about 4 million residential customers, whose average monthly consumption typically falls within the range of 0–2000 kWh. This range of consumption was divided into 20 different classes; hence, for the purposes of this simulation, we will use $I=20$ customer categories. To obtain the consumption profile of each consumption class i, we first obtain SCE's average residential load profile in 2011 (SCE, 2011), and then we scale the average profile by an appropriate factor. The scaling factor was chosen such that the consumption profile $\mathbf{c}_i$ would match the average monthly consumption of class i.

Next, we obtained data on the PV systems installed within SCE's territory in 2011 from the California Solar Initiative (CSI) database (CSI, 2011). The nameplate DC capacities of new residential PV systems installed in 2011 ranged from 1 kW to 33 kW, with the 5th percentile at 2.24 kW and the 95th percentile at 10.18 kW. Furthermore, the average conversion factor between the nameplate DC capacity and the CSI AC capacity was 0.83. To model the range of PV system capacities that a household can install, we assume that a PV panel has a capacity of 0.2 kW, the minimum number of panels in a PV system is $\underline{r}=10$ (i.e., corresponding to a capacity of 2 kW), and the maximum number of panels in a PV system is $\overline{r}=50$ panels (i.e., corresponding to a capacity of 10 kW). We derive the hourly generation profile of each PV panel from solar radiation data[4] obtained from the national solar radiation database (NREL, 2005) under the assumption that the DC-to-AC conversion efficiency is 0.83. Hence, a 1 kW PV system would generate 1514 kWh annually.

Table 3
Energy rates for SCE's domestic service as of March 2012. The monthly kWh allocations in this table are for a thirty-day month. In practice, the kWh allocation for a particular month would depend on the number of days in that month.

Summer consumption (kWh/month)	Winter consumption (kWh/month)	Delivery ($/kWh)	Generation ($/kWh)
0–386	0–318	0.04985	0.08205
387–501	318–413	0.07899	0.08205
502–771	414–636	0.16189	0.08205
772–1157	637–954	0.19689	0.08205
Over 1158	Over 955	0.23189	0.08205

The initial customer distribution was chosen based on the usage distribution obtained from the rate case proceedings. The usage distribution includes customers with and without PV systems. It was estimated that residential PV added after 2007 comprises 79% of California's total residential PV capacity (SEIA, 2010). Since there were only 23,000 new residential PV systems in SCE's territory between 2007 and 2011 (CSI, 2011), we estimate that about 30,000 of SCE's customers have PV systems, which is less than 1% of SCE's total customer population of about 4 million. Hence, we assume the initial customer distribution to have no PV systems. To initialize the simulation, we set $x_{i,r}[0]=0$ for all $r>0$, and we set $x_{i,0}[0]$ to equal the number of customers in consumption class i. The values for $x_{i,0}[0]$ are listed in Table 4.

3.2. Data for revenue requirements

We estimated SCE's generation revenue requirement using SCE's residential generation rates. Table 3 shows the generation rates for SCE's residential service as of April 2012 (SCE, 2012b).

[4] In practice, the output of a PV panel would vary with the location of the household. However, our model does not take into account households' geographic locations. Hence, we used the solar radiation data recorded at Los Angeles.

From the table, we see that SCE charges a uniform generation rate of $0.08205/kWh. Therefore, we assume that for each year k, SCE's generation revenue requirement is $v[k] = 0.08205/\text{kWh}$.[5]

We estimated SCE's residential delivery revenue requirement using usage data as well as SCE's current residential delivery rates. First, we calculate SCE's total residential delivery revenue from the usage data and the current residential delivery rates, which amounted to 2.58 billion. This value is close to SCE's proposed residential delivery revenue requirement for 2012 of $2.547 billion (SCE, 2012c). Therefore, we assume that SCE's initial residential delivery revenue requirement is $d[1] = 2.58$ billion. To estimate SCE's future residential delivery revenue requirement, we first obtain SCE's historical distribution revenue requirement (SCE, 2012). From 2003 to 2011, SCE's distribution revenue requirement increased by an average of about 2.5% per year after adjusting for inflation. Furthermore, distribution revenue requirement currently comprises around 80% of the total delivery revenue requirements (SCE, 2012c). Unfortunately, there is limited public information on how the remaining 20% of the delivery revenue requirements has varied over the years. Hence, we will consider two scenarios for future residential delivery revenue requirements—a 1% annual increase and a 3% annual increase. In both scenarios, the increase is irrespective of the net residential consumption.

3.3. Data for rate case proceedings

We assume that rate case proceedings are held every year.[6] We also assume that there is no regulatory delay in setting rates.

Historically the monthly connection charge ranged from $0.50 to $1.50 which is insignificant relative to a consumer's total electricity bill. Hence, we assume for the purposes of this study that the monthly connection charge $F[k] = 0$ for all years k. As mentioned in the model section, rate case proceedings are governed by various regulatory policies. We assume that rate changes made by utility companies would abide by California Senate Bill 695 which mandates that the annual rate increases for tiers 1 and 2 cannot exceed 1% above inflation. For the purposes of our simulation, we assume that over the horizon being considered, the inflation rate is zero, and that the rate increases for tiers 1 and 2 are equal to the maximum of 1% allowed every year. The initial rates for tiers 1 and 2 are equal to the current residential electricity rates charged by SCE. Thus, we have that $p_1[0] = 0.13190$ and $p_2[0] = 0.16104$ and these rates increase by 1% at every subsequent rate change.

We model the rates for tiers 3–5 based on CPUC's decision in the 2010 rate case proceedings. In that year, the CPUC decided that the rate differentials between tiers 3 and 4 and between tiers 4 and 5 would be set at $0.035/\text{kWh}$ (CPUC, 2011). We assume that these rate differentials remain constant. We model this by using $\Delta_4[k] = \Delta_5[k] = 0.035$ for all years k.

We model the NSCR by obtaining data on SCE's NSCR over 2011 (SCE, 2012b). The NSCR ranged between $0.035 and $0.040 per kWh and the average value was $0.037 per kWh. We assume that, for each year k, $p_0[k] = 0.037/\text{kWh}$, that is, the initial NSCR is equal to SCE's average NSCR in 2011 and that this is constant.

3.4. Data for adoption

We consider the heterogeneity in the types of homes to model the rate of adoption of rooftop PV. For this study, we classify a residential home according to whether the home is an *apartment* or *single-family* home, and whether the home is rented or owned.

Typically, customers who live in apartments and rental homes would not have exclusive rights to the roof; hence we assume that these customers are unable to adopt PV systems. To estimate the number of customers that live in apartments, we assume that the fraction of people (that are served by SCE) living in apartments is equal to the fraction of people that live in apartments in the entire state of California. According to data from the Energy Information Administration (EIA), approximately 31% of California's households live in apartments. Hence, we have that approximately 1.2 million customers of SCE live in apartments (EIA, 2005). Unfortunately, there is limited public information on how these customers are distributed across the consumption classes. However, it is known that the average electricity consumption of single-family homes in the entire US is approximately twice that of apartments (EIA, 2005). Motivated by this aggregate statistic, we make the following assumption on the percentages of each consumption class that live in apartments—100% of 100 kWh customers, 75% of 200 kWh customers, 50% of 300 kWh customers, 25% of 400 kWh customers, and 10% of each class above 500 kWh. The actual numbers are shown in Table 4.

Next, to estimate the number of customers that live in rented single-family homes, we assume that the fraction of rented single-family homes is equal to the fraction of rented single-family homes in the entire state of California. According to data from EIA, approximately 19% of California's single-family homes are rented (EIA, 2005). We apply this percentage uniformly to all consumption classes to obtain the number of rented single-family homes in each consumption class. By subtracting the number of apartments and the number of rented single-family homes in each consumption class, we obtain the number of owner-occupied single-family homes in each consumption class. These calculations are illustrated in Table 4.

Residential customers who own their single-family homes will also not able to use rooftop PV if their roofs are shaded from the sun. We assume that, in each consumption class, 35% of the single-family homes are not able to use PV due to shading (Denholm et al., 2009).[7] The number of such customers in each consumption class is listed in Table 4. Hence, for each consumption class, the total number of customers who are unable to use PV is the sum of the number of customers who live in apartments, the number of customers who rent single-family homes, and the number of customers who own single-family homes but have shaded roofs. These numbers are given in the right-most column of Table 4. In summary, there are approximately 2.5 million customers who are unable to use PV.

To calculate the levelized cost of solar energy for each year, we first obtained data on the residential PV systems installed within SCE's territory over 2007–2011 from the California Solar Initiative database (CSI, 2011). We performed a linear regression on the

[5] Clearly, the generation cost could change over time and hence the assumption of constant per-unit generation revenue requirement seems unrealistic. However, there is limited public information on SCE's generation cost since a significant portion of generation is procured in long-term contracts. It is also not possible to rely on historical generation rates. This is because, prior to 2011, generation rates were different for different tiers. It was only in 2011 that a uniform generation rate was assigned to all tiers and different delivery rates were assigned to the different tiers. Given limited information on generation costs and the fact that the focus of this study is on the recovery of fixed delivery costs, it is prudent to assume that the per-unit generation revenue requirement is constant.

[6] In practice, rate case proceedings are held every three years. However, SCE is subject to revenue decoupling, so its rates are revised as frequently as every few months. We assume in the model that rate case proceedings are held yearly in order to better capture the more frequent rate revisions with revenue decoupling.

[7] In Denholm et al. (2009), it was assumed that 35% of the total roof area in the United States is shaded. However, many customers would have partially shaded roofs, hence the actual number of customers who have shaded roofs would likely be greater. Since we do not model partially shaded roofs and there is limited public information on the number of partially shaded roofs, we assume that the 35% factor applies to the fraction of homes that have shaded roofs.

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Table 4
Distribution of average monthly consumption for different household characteristics.

i	Average consumption (kWh/month)	Total number of customers, $x_{i,0}[0]$	Apartments	Rented single-family homes	Owner-occupied single-family homes with shaded roofs	Number of customers not able to use PV, y_i
1	100	152,825	152,825	0	0	152,825
2	200	514,066	385,550	24,418	36,434	446,402
3	300	599,871	299,936	56,988	85,031	441,955
4	400	650,102	162,526	92,639	138,228	393,393
5	500	538,394	53,839	92,065	137,372	283,276
6	600	413,408	41,341	70,693	105,481	217,515
7	700	346,548	34,655	59,260	88,422	182,337
8	800	194,827	19,483	33,315	49,710	102,508
9	900	170,615	17,062	29,175	43,532	89,769
10	1000	88,875	8888	15,198	22,676	46,761
11	1100	117,678	5884	21,241	31,694	58,819
12	1200	55,506	2775	10,019	14,949	27,743
13	1300	49,652	2483	8962	13,372	24,817
14	1400	52,475	2624	9472	14,133	26,229
15	1500	29,767	1488	5373	8017	14,878
16	1600	8743	437	1578	2355	4370
17	1700	10,383	519	1874	2797	5190
18	1800	8649	432	1561	2330	4323
19	1900	14,959	748	2700	4029	7477
20	2000	8630	432	1558	2324	4314
		4,025,973	1,193,927	538,089	802,886	2,534,902

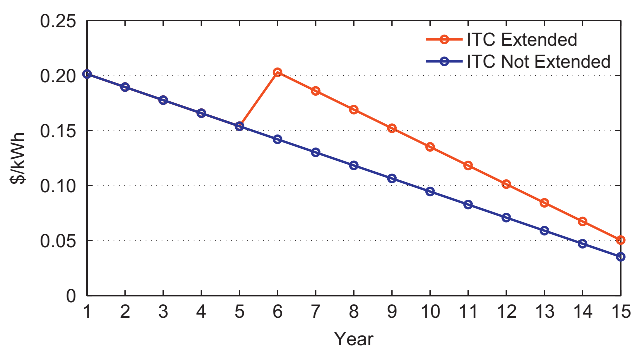

Fig. 3. Levelized cost of solar energy $s[k]$.

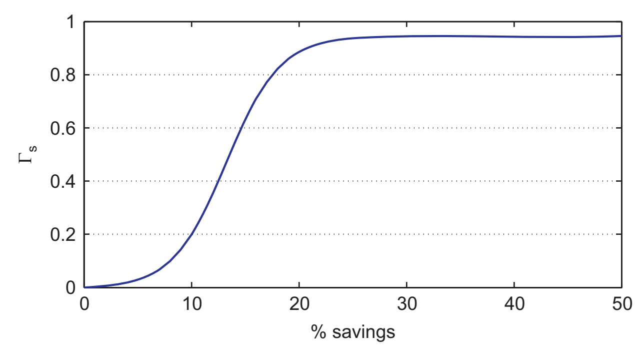

Fig. 4. Savings function.

average price of PV from 2007 to 2011 and found that prices decreased at a rate of $0.42/Watt per year over 2007–2011. In our model, we assume that the initial price of PV is equal to the average price in 2011, which was $7.13/Watt. We also assume that the price of PV decreases by $0.42/Watt each year throughout the time horizon of the model which we chose to be 15 yr. Hence, the price of PV would decrease to approximately $5/Watt in year 5 and $3/Watt in year 10 which are close to the targets in Department of Energy's SunShot Initiative (RMI, 2012).

Residential customers who purchase PV from now till 2016 benefit from a federal incentive tax credit (ITC) amounting to 30% of the cost of the system. We consider both the scenarios where this tax credit does not get renewed after 2016 and where it gets renewed for at least another 10 yr. To model the former scenario, we assume a 30% discount on PV purchased during years 1–5, and no discount during years 6–20. To model the latter scenario, we assume a 30% discount throughout all years.

To calculate the levelized cost of solar energy from the price of PV, we use the financing assumptions in Drury et al. (2012). That is, we assume that a residential customer finances his PV system with a 20% down payment and a 20-year loan at an interest rate of 5%; the PV system has a lifetime of 30 years; and that the residential customer has a discount rate of 5%. The levelized cost of solar energy for each year is shown in Fig. 3.

The remaining components of the adoption model in Eq. (4) that must be specified are the savings function g and the coefficient of external influence α in the diffusion function h. We assume that $\alpha = 0.02$; this value was used in a previous study on adoption of distributed gas generation among commercial customers (Maribu et al., 2007). We assume that the savings function g takes the following form:

$$g(\text{savings}_i[k+1]) = \frac{0.95}{1+200\cdot\exp(-0.4\cdot\text{savings}_i[k+1])} - \frac{0.95}{1+200}.$$

This function, plotted in Fig. 4, resembles the savings function that was used in the adoption of distributed gas generation among commercial customers (Maribu et al., 2007). We assume that most of the potential adopters would need to have savings of between 10% and 20% in order to be willing to adopt PV. Hence, the savings function increases very gradually for savings below 10%, rises sharply as savings increase from 10% to 20%, and begins to flatten off as savings exceed 20%. We assume that some fraction (in this case 5%) of the potential adopters will not be willing to adopt PV regardless of the financial incentives; hence, the savings function flattens at 0.95.

4. Results

We evaluate the impact of the feedback cycle on two predictions: (i) the number of years it takes for total PV capacity to reach 15% and 30% of initial peak demand[8] and (ii) the annual cost of net-metering at

[8] The time taken for PV capacity to reach 15% of peak demand is a quantity of significant interest due to the following reasons. Grid-connected rooftop PV

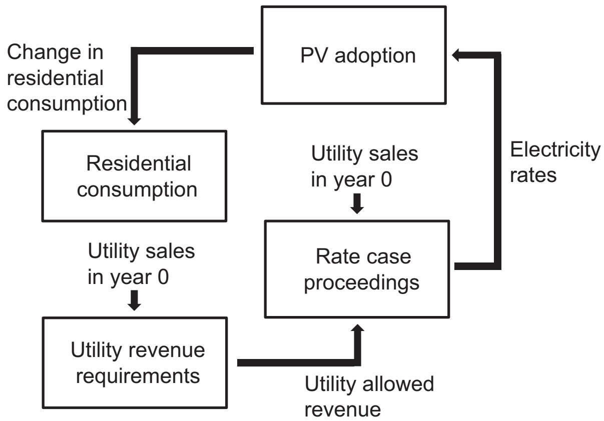

Fig. 5. Overview of model for PV adoption without the feedback cycle.

those instances. Annual net-metering costs are given by the utility's lost revenues (due to reduced consumption by solar customers) less the utility's avoided costs (due to serving less consumption). Lost revenues are calculated at prevailing electricity rates. Hence, net-metering costs represent the amount of delivery revenues that must be recovered by increasing retail electricity rates due to PV adoption. PV penetration levels and net-metering costs in between years are obtained by interpolating linearly between consecutive years.

To evaluate the impact of the feedback cycle, we compare the predictions of the model with and without the feedback loop. An overview of the model without the feedback loop is given in Fig. 5. In this model, we use the initial consumption patterns to solve Eq. (3) for the electricity rates for every year. The rest of the assumptions regarding electricity rates, generation revenue requirements, delivery revenue requirements, and PV adoption, are the same as in the original feedback model. In other words, in the non-feedback model, the electricity rates throughout the model are calculated without taking into account the feedback of future PV adoption on consumption. Since PV adoption reduces consumption which would have increased electricity rates, we expect the non-feedback model to have lower electricity rates, and therefore lower PV uptake and lower net-metering costs.

4.1. *Impact of feedback cycle*

Table 5 shows the differences between the feedback and non-feedback models on the time taken to reach the 15% mark and the annual net-metering cost at that instant. Feedback has negligible impact on adoption rates—decreasing the time taken to reach the 15% level by less than 2 months (or 1.3%). The feedback cycle has more impact on net-metering costs—increasing that by up to 25 million (or 9.3%). The reasons for this phenomena are two-fold. Net-metering cost is a function of both PV uptake levels and electricity rates. The feedback cycle increases both PV uptake levels and electricity rates; hence, it will have more impact on net-metering costs. In addition, higher electricity rates do not always lead to significantly more households adopting PV. Consumers might not be convinced that PV is a reliable technology. The payback from PV is realized over a long term and consumers might be uncertain about factors which impact the payback over the long term.

Table 5 shows that, in both the feedback and non-feedback models, extending the tax credit always reduces net-metering costs. Extending the tax credit causes solar adopters to comprise more of lower tier customers than higher tier customers. This is due to the fact that the after-incentive cost of solar will fall below the tier 1 rate after 2016. Since lower tier customers pay lower electricity rates, these customers have less impact on electricity rates when they reduce their consumption. Hence, net-metering costs will be smaller. It is true that extending the tax credit also gives higher tier customers more savings when they adopt PV which exerts an upward pressure on net-metering costs. However, the results show that the increase in adoption by these higher-tier customers is relatively less significant than the increase in adoption by the lower-tier customers. This could be due to the fact that the population of higher-tier customers is relatively small compared to that of lower-tier customers.

Table 6 shows the differences between the feedback and non-feedback models on the time taken to reach the 30% mark and the annual net-metering cost at that instant. The previous observations continue to hold—the feedback cycle has negligible impact on PV uptake, it has more impact on net-metering costs than PV uptake, and extending the tax credit always reduces net-metering costs.

4.2. *Increased consumer confidence in PV*

We have observed that, although the feedback cycle increases electricity rates and gives consumers more incentive to adopt PV, its impact on adoption rates could still be limited if consumers are not convinced that PV is a reliable technology. However, consumer confidence in PV could be boosted by government-sponsored outreach policies or advertisements by solar companies. We study the potential impact of such policies by increasing the coefficient of external influence α.

Tables 7 and 8 show the impact of the feedback cycle for $\alpha = 0.20$. The higher value of α reduces the time taken for total PV capacity to exceed 15% of initial peak demand to less than 4 years. In addition, annual net-metering costs increase by about 70 million. This increase is due to a shift in the demographic of PV adopters towards higher tier consumers (i.e., those with higher consumption). With more confidence in PV, consumers who have an economic incentive to adopt PV are willing to do so at an earlier time. Consumers in higher tiers pay higher electricity rates and generally have more incentive to adopt PV than consumers in lower tiers. Therefore, the PV adopters will comprise more consumers in higher tiers and less consumers in lower tiers. Consumers in higher tiers pay higher electricity rates. Hence, when these consumers reduce their consumption from the grid, they have a greater impact on electricity rates than lower tier consumers. Therefore, electricity rates increase more rapidly and net-metering costs are higher.

Tables 7 and 8 also show a significantly larger disparity between the feedback and non-feedback models than for the case of $\alpha = 0.02$. When consumers are more willing to adopt PV, electricity rates increase more rapidly and the feedback cycle has more impact.

Tables 7 and 8 show that similar patterns continue to hold for $\alpha = 0.20$. Specifically, the feedback cycle has more impact on net-metering costs than on adoption rates, and that in both the

(*footnote continued*)
systems could disrupt the operating stability of the grid if they deliver too much power into the grid. Hence, customers who would like to connect their PV systems to the grid have to obtain approval from their utility company. In California, the utility company's review process is regulated by CPUC. Currently, the utility is obligated to approve a PV connection request as long as the total generating capacity on the distribution feeder does not exceed 15% of the peak demand on the feeder. Connection requests which do not satisfy this initial rule will be subject to supplemental reviews which could incur significant costs and delays. Hence, the time taken for PV capacity to reach 15% of peak demand is a quantity of significant interest. Since our model does not differentiate customers by geographical location, it is not possible to measure PV capacity as a percentage of peak demand on a particular distribution feeder. Thus, we measure PV capacity as a percentage of initial system peak demand.

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Table 5
Comparison of feedback and non-feedback models for the case where $\alpha = 0.02$ and delivery costs increase by 1% each year.

Comparison metric	Scenario	No feedback	With feedback	Difference
Time for PV capacity to reach 15% of initial peak demand (in years)	ITC not extended	11.16	11.04	−0.12 (−1.3%)
	ITC extended	8.99	8.95	−0.04 (−0.4%)
Net-metering costs when PV capacity reaches 15% of initial peak demand (in million $ per year)	ITC not extended	265	290	+25 (+9.3%)
	ITC extended	243	263	+20 (+8.2%)

Table 6
Comparison of feedback and non-feedback models for the case where $\alpha = 0.02$ and delivery costs increase by 1% each year.

Comparison metric	Scenario	No feedback	With feedback	Difference
Time for PV capacity to reach 30% of initial peak demand (in years)	ITC not extended	13.74	13.61	−0.13 (−0.9%)
	ITC extended	11.53	11.49	−0.04 (−0.3%)
Net-metering costs when PV capacity reaches 30% of initial peak demand (in million $ per year)	ITC not extended	500	589	+89 (+17.8%)
	ITC extended	476	555	+79 (+16.6%)

Table 7
Comparison of feedback and non-feedback models for the case where $\alpha = 0.20$ and delivery costs increase by 1% each year.

Comparison metric	Scenario	No feedback	With feedback	Difference
Time for total PV capacity to reach 15% of initial peak demand (in years)	ITC not extended	3.75	3.47	−0.28 (−7.5%)
	ITC extended	3.75	3.47	−0.28 (−7.5%)
Net-metering costs when PV capacity reaches 15% of initial peak demand (in million $ per year)	ITC not extended	334	367	+33 (+9.9%)
	ITC extended	334	367	+33 (+9.9%)

Table 8
Comparison of feedback and non-feedback models for the case where $\alpha = 0.20$ and delivery costs increase by 1% each year.

Comparison metric	Scenario	No feedback	With feedback	Difference
Time for total PV capacity to reach 30% of initial peak demand (in years)	ITC not extended	7.63	6.14	−1.49 (−19.5%)
	ITC extended	5.78	5.47	−0.31 (−5.4%)
Net-metering costs when PV capacity reaches 30% of initial peak demand (in million $ per year)	ITC not extended	654	786	+132 (+20.2%)
	ITC extended	608	745	+137 (+22.5%)

Table 9
Comparison of feedback and non-feedback models for the case where $\alpha = 0.02$ and delivery costs increase by 3% each year.

Comparison metric	Scenario	No feedback	With feedback	Difference
Time for total PV capacity to reach 15% of initial peak demand (in years)	ITC not extended	10.40	10.30	−0.10 (−1.0%)
	ITC extended	8.70	8.67	−0.03 (−0.3%)
Net-metering costs when PV capacity reaches 15% of initial peak demand (in million $ per year)	ITC not extended	355	384	+29 (+8.2%)
	ITC extended	301	324	+23 (+7.6%)

feedback and non-feedback models, extending the tax credit always reduces the net-metering costs.

4.3. Increased delivery revenue requirements

Next, we explore the impact of higher delivery revenue requirements on the feedback cycle. Tables 9 and 10 show the impact of the feedback cycle for the cases where $\alpha = 0.02$ and $\alpha = 0.20$ respectively and where delivery revenue requirements increase by 3% per year in both cases. Increasing the delivery revenue requirements reduces slightly the time taken for total PV capacity to exceed 15% of peak demand. However, annual net-metering costs increase significantly by up to 94 million dollars. There are two reasons for this phenomena. First, there is a shift in the demographic of PV adopters towards higher tier consumers. When delivery revenue requirements increase more rapidly, rates for higher tiers increase more rapidly while rates for tiers 1 and 2 are not affected (since these tiers are protected). Higher tier consumers will have more incentives to adopt PV and therefore the PV adopters will comprise more higher-tier consumers than

Table 10
Comparison of feedback and non-feedback models for the case where $\alpha = 0.20$ and delivery costs increase by 3% each year.

Comparison metric	Scenario	No feedback	With feedback	Difference
Time for total PV capacity to reach 15% of initial peak demand (in years)	ITC not extended	3.46	3.31	−0.15 (−4.3%)
	ITC extended	3.46	3.31	−0.15 (−4.3%)
Net-metering costs when PV capacity reaches 15% of initial peak demand (in million $ per year)	ITC not extended	362	399	+37 (+10.2%)
	ITC extended	362	399	+37 (+10.2%)

Table 11
Energy rates of a new tariff where the connection charge is $10 and the delivery rates for tier 1 is reduced to $0.01985/kWh. The rate for tier 2 is unchanged (from the original tariff), and the rates for tiers 3, 4, and 5 are calculated from Eq. (3). The monthly kWh allocations in this table are for a thirty-day month.

Summer consumption (kWh/month)	Winter consumption (kWh/month)	Delivery ($/kWh)	Generation ($/kWh)
0–386	0–318	0.01985	0.08205
387–501	318–413	0.07899	0.08205
502–771	414–636	0.15405	0.08205
772–1157	637–954	0.18905	0.08205
Over 1158	Over 955	0.22405	0.08205

lower-tier consumers. Second, net-metering costs are calculated based on rates for the highest tiers. Since these rates are higher (due to higher delivery revenue requirements), the perceived net-metering cost is also higher.

Tables 9 and 10 show that for both the cases where $\alpha = 0.02$ and $\alpha = 0.20$, the disparity between the feedback and non-feedback models do not appear to change significantly when delivery revenue requirements are increased. This indicates that the impact of the feedback cycle is more heavily determined by the willingness of consumers to adopt PV (represented by the parameter α) than by the utility's delivery revenue requirements.

4.4. Impact of higher connection charges

Next, we explore the impact of higher connection charges on the feedback cycle. There are many degrees of freedom to adjust connection charges and variable charges. We consider here one particular scenario in which the connection charge in year 0 is $10 per month and the variable delivery rate for tier 1 is reduced to $0.01985/kWh. The rate for tier 2 is unchanged (from the original tariff), and the rates for tiers 3–5 are calculated from Eq. (3). Table 11 shows the energy rates of the new tariff.

Fig. 6 shows the initial annual utility bill for different consumers under the old and new tariffs and Fig. 7 shows the percentage change in their bill. With higher connection charges, consumers who consume more than 400 kWh per month experience a marginal 2% reduction in their annual utility bill while consumers who consume less than 400 kWh per month experience an increase of up to 35%. This asymmetry is a consequence of the steeply inclining energy rates.

The rest of the assumptions for the rate case remain the same as before, i.e., the rates for tiers 1 and 2 increase by 1% every year, and the rate differential between tiers 3 and 4 and between tiers 4 and 5 is $0.035/kWh respectively. In addition, we assume that the connection charge increases by 1% each year. Hence, the annual utility bill of tiers 1 and 2 customers would increase by 1% each year.

There are multiple reasons for considering this particular tariff. The escalating net-metering subsidy has generated significant interest in tariffs that can recover the utility's infrastructure costs from residential PV owners even while these customers reduce

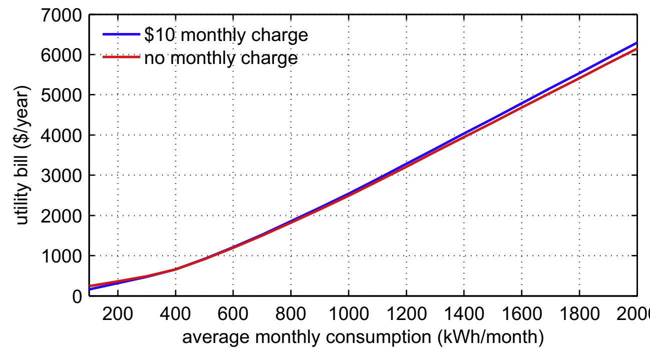

Fig. 6. Comparison of annual utility bill of each customer in year 0 under the original tariff (with no connection charge) and the new tariff ($10 connection charge).

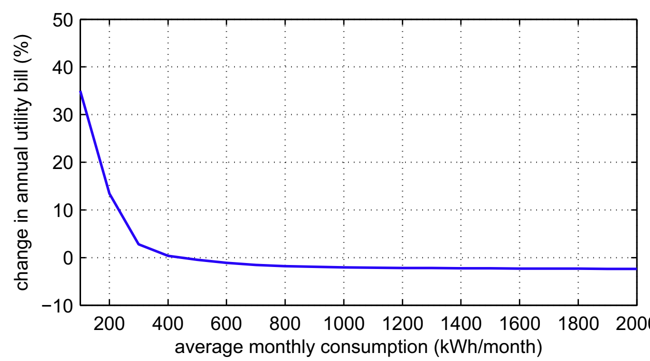

Fig. 7. Percentage change in annual utility bill of each customer in year 0 due to the new tariff ($10 connection charge).

their net consumption of electricity from the grid (NYT, 2012). The connection charge recovers the portion of the utility's costs that are incurred independent of consumption. Hence, to ensure that residential PV owners continue to contribute an appropriate share of the infrastructure costs, one might consider raising the connection charges and lowering the variable charges. On the other hand, it is also reasonable to expect any modification to existing tariffs to not cause an abrupt increase in the electricity costs of any particular customer. The described tariff seems reasonable as it achieves higher connection charges while limiting the impact on the burden of lower tier customers to at most 35% annually.

Tables 12 and 13 show the impact of the feedback cycle under the new tariff. With higher connection charges, the time taken for total PV capacity to exceed 15% of initial peak demand increases by about 2 years. This is not surprising since higher tier customers have lower utility bills; hence, they have less incentive to adopt PV. Higher connection charges also decreases the net metering cost. This decrease can be attributed to a shift in the demographic of PV adopters towards lower tier consumers. Higher tier consumers are now adopting less PV than before since their electricity rates have decreased.

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Table 12
Comparison of feedback and non-feedback models for the case where $\alpha = 0.02$ and delivery costs increase by 1% each year. The connection charge is $10 per month in year 0 and increases by 1% each year. The initially delivery rate for tier 1 was $0.01985/kWh.

Comparison metric	Scenario	No feedback	With feedback	Difference
Time for total PV capacity to reach 15% of initial peak demand (in years)	ITC not extended	12.27	12.17	−0.10 (−0.8%)
	ITC extended	10.12	10.06	−0.06 (−0.6%)
Net-metering costs when PV capacity reaches 15% of initial peak demand (in million $ per year)	ITC not extended	250	272	+22 (+8.8%)
	ITC extended	233	250	+17 (+7.3%)

Table 13
Comparison of feedback and non-feedback models for the case where $\alpha = 0.20$ and delivery costs increase by 1% each year. The connection charge is $10 per month in year 0 and increases by 1% each year. The initially delivery rate for tier 1 was $0.01985/kWh.

Comparison metric	Scenario	No feedback	With feedback	Difference
Time for total PV capacity to reach 15% of initial peak demand (in years)	ITC not extended	4.25	4.01	−0.24 (−5.6%)
	ITC extended	4.25	4.01	−0.24 (−5.6%)
Net-metering costs when PV capacity reaches 15% of initial peak demand (in million $ per year)	ITC not extended	328	359	+31 (+9.5%)
	ITC extended	328	359	+31 (+9.5%)

The disparity between the feedback and non-feedback models do not appear to change significantly under higher connection charges. This is because the electricity costs of higher tier consumers did not change significantly (as shown in Fig. 7).

5. Discussion

A major assumption is that PV adoption decisions are based only on adoption savings. Furthermore, these savings are calculated assuming prevailing PV prices and constant electricity prices. In practice, customers might have expectations of future prices. Furthermore, purchasing a PV system typically involves a huge capital outlay. Even if one were to lease the PV system (hence avoiding the capital outlay), a leasing contract is still a long-term commitment. Hence, a customer's decision is likely to be influenced by other factors, e.g., his level of income, how long he intends to live in his existing home, his geographic location, etc. The existing model can be extended to incorporate such heterogeneity among customers by creating more refined customer categories. However, it is challenging to model customer behavior in such great detail. Most importantly, the main objective of this work is to study the impact of adoption feedback on electricity rates. We believe that the existing model, while simplistic, captures the aggregate behavior of consumers sufficiently well to provide insights on adoption feedback.

Another major assumption is that generation costs are constant. Many studies have pointed out that rooftop PV provides energy during the peak hours when the grid needs it the most. Hence, solar energy replaces energy which would have been generated by expensive peaker plants (E3, 2011; ABCS, 2012). Therefore, the utility's avoided cost of using energy generated from rooftop PV is likely to be above the average generation cost. Hence, adoption feedback would have less impact than that observed in our results. To account for the above-average value of PV, we could have assigned different generation costs to different hours of the day. However, we chose constant generation costs for two reasons. First, there is significant variation in the avoided cost assigned by different studies (E3, 2011; ABCS, 2012). Second, there is limited public data on actual generation and capacity costs since a significant portion of these costs are incurred in long-term power purchase contracts.

Another major assumption is that the consumption patterns of residential customers are constant over time. In practice, consumptions could change because old houses are demolished and new houses are built, and also because of improvements in energy efficiency. Due to lack of data on such trends, we used constant consumption patterns. Nevertheless, it is worth pointing out that an EIA study considered a reference case with 1% annual growth in the number of households and 1% annual decrease in the energy use per capita (EIA, 2010). We experimented with these aggregate statistics and found no significant change in our results. This is because the increase in the number of households was approximately offset by improvements in energy efficiency.

6. Policy implications

Our study shows that adoption feedback cycle is unlikely to have a significant impact on future PV uptake rates in the next 10 years. Hence, existing forecasts of PV adoption, although they do not model feedback cycle, should still be fairly accurate. However, our study also shows that consumer confidence in PV is a major factor which could cause the feedback cycle to have a more significant impact. Hence, regulatory agencies and utility companies should take into account current and future level of consumer confidence in PV when assessing the impact of the feedback cycle on their forecasts.

Since there are many forecasts of PV penetration levels but limited forecasts of net-metering costs, regulatory agencies and utility companies might be tempted to use forecasts for the rate-of-growth of PV as estimates for the rate-of-growth of net-metering costs. However, our study shows that this is not always a wise decision. One reason is that net-metering costs always increase when electricity rates increase. However, electricity rate increases do not always lead to significantly more adoption PV—PV adoption could be stifled by a lack of consumer confidence in the technology. Therefore, net-metering costs could grow at a faster rate than PV penetration. Another reason is that net-metering costs depend on the consumption demographics of the adopters.

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Having more higher-tier adopters relative to lower tier adopters lead to higher net-metering costs.

Our study also shows that, under the current net-metering scheme, PV adoption will definitely lead to a rapid increase in net-metering costs and also the fraction of distribution costs that are borne by lower tier customers. Regulated utility companies could lose a significant fraction of their high income customers in the near future. This shift in customer base towards low income customers also presents business risks for utility companies because low income customers are more sensitive to electricity rate increases than high income customers. To this end, utilities in California have been proposing to merge tiers 4 and 5 in order to lower tier 5 rates and reduce the attractiveness of PV to tier 5 customers. However, our experiments with merging some/all of tiers 3–5 did not reveal any significant differences in future net-metering costs. Therefore, there is an urgent need to depart from existing volumetric tariffs that primarily charge customers based on amount of energy consumed. Moreover, volumetric tariffs with net-metering do not account for the fact that solar customers utilize distribution infrastructure when they sell their excess generation to the grid. There is a need for further research into the true value of rooftop solar generation (E3, 2011; ABCS, 2012) and alternative tariff schemes that differentiate between consumption and generation. An example is a recent scheme implemented by Austin Energy that records consumption and generation separately; all residential solar generation is compensated at a single rate that accounts for the multiple benefits of solar including its energy value, generation value, and environment value, etc. (GTM, 2012).

7. Conclusion

Due to falling PV prices and rising electricity rates, it is becoming increasingly attractive for residential consumers to install rooftop PV systems and reduce their electricity purchases from the grid. On the other hand, capital investments in transmission and distribution infrastructure are unlikely to fall in proportion with grid consumption. In order for utility companies to recover their infrastructure costs from a smaller consumption base, they will have to increase electricity rates. However, higher electricity rates make it more attractive for consumers to adopt PV and cause utility companies to lose more sales. Concerns have been raised regarding the impact of this feedback cycle on non-solar customers.

We developed a model to study the impact of this feedback cycle for a specific utility company in Southern California. We evaluated the impact of the feedback cycle on the number of years it takes to reach 15% of peak demand and the annual cost of net-metering when that occurs. The model shows that the feedback cycle reduces the time it takes for PV capacity to reach 15% of peak demand by up to 4 months. Moreover, the feedback cycle has a greater impact in later years. Hence, existing forecasts of PV adoption, although they do not model adoption feedback, should still be fairly accurate in the short-run. However, the model also shows that feedback has substantially more impact on net-metering costs and could increase annual net-metering costs by up to 10%. This is due to the fact that feedback increases electricity rates which, in turn, increase net-metering costs. These conclusions hold even if the incentive tax credit is extended beyond 2016. Hence, regulated utility companies could lose a significant fraction of their high income customers in the near future. This shift in customer base towards low income customers presents business risks for utility companies because low income customers are more sensitive to increases in electricity rates.

Our model shows that the most important parameter in determining whether the feedback cycle has a significant impact is the willingness of consumers to adopt PV. The payback from PV is realized over a long term and consumers could be uncertain about many factors that impact payback over such a long period. Feedback has little impact if only a small fraction of consumers, who have an economic incentive to adopt PV based on prevailing prices, actually adopt PV.

Our results depend fairly critically on the value of the parameter α in the model. We are currently working on a website where users can run our model using their own data and parameters (Caltech, 2013). While this study is limited to a specific investor-owned utility company in Southern California, the proposed model is applicable to other utility companies in other states. Possible future work include—modeling other non-financial factors that could affect a customer's decision on whether to adopt PV, e.g., income, geographical location, etc., modeling the utility's avoided generation and delivery costs in greater detail so as to capture the benefits of distributed PV more accurately, and studying other rate structures, e.g., time-of-use rates, real-time rates, etc.

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