The Value of Distributed Energy Resources for Heterogeneous Residential Consumers

Siddharth Patel* and Ram Rajagopal†

*Department of Civil and Environmental Engineering, Stanford University
†Department of Electrical Engineering (by Courtesy), Stanford University

Abstract

The presence of behind-the-meter rooftop PV and storage in the residential sector is poised to increase significantly. Here we quantify in detail the value of these technologies to consumers and service providers. We characterize the heterogeneity in household electricity cost savings under time-varying prices due to consumption behavior differences. The top 15% of consumers benefit two to three times as much as the remaining 85%. Different pricing policies do not significantly alter how households fare with respect to one another. We define the value of information as the financial value of improved forecasting capabilities for a household. The typical value of information is 3.5 cents per hour per kWh reduction of standard deviation of forecast error. Coordination services that combine the resources available at all households can reduce costs by an additional 15% to 30% of the original total cost. Surprisingly, on the basis of coordinated action alone, service providers will not encourage adoption beyond 50% within a group. Coordinated information, however, enables the providers to generate additional value with increasing adoption.

Distributed energy resources (DERs) are an essential part of modernizing and de-carbonizing the grid [1–3] and pose challenges for the design, management, and operation of the electricity system [4–6]. Dramatic changes are expected as consumers adopt behind-the-meter DERs and become prosumers capable of responding to prices and other signals from grid operators [7,8]. Technology vendors (e.g. Solar City) and DER resource aggregators (e.g. OhmConnect) will play a significant role in the emerging ecosystem by making DERs accessible to smaller consumers and ensuring that they operate those technologies in a manner aligned with their self-interest and compatible with the needs of the grid as a system. The proliferation of DERs will create opportunities for new business models as well. The coming impact of the adoption of energy storage and rooftop photovoltaic (PV) systems by residential consumers is not well understood [9].

The impact of DERs depends on the adoption rate of technology, the operations strategy, and the financial and policy arrangements for system participants. Consumer behavior and the resulting consumption pattern heterogeneity are critical drivers of DER value and govern the interactions between these dimensions. Residential electricity consumption exhibits significantly more diversity than previously believed [10]. Yet this heterogeneity is seldom accounted for in existing studies, which use data from a small number of residential or commercial consumers to evaluate the consumer-side economics of PV [11–15], storage [16–17], or both combined [18–24].

In this paper we propose a simple and scalable methodology to estimate DER value and impact that incorporates consumption heterogeneity. We apply our methodology to provide a first of its
kind assessment of the value of these technologies to residential consumers, technology vendors, and aggregators under various business models and policy arrangements. We focus on PV and batteries because they are commercially available and gaining traction as their costs decrease [25–29]. Our study accounts for adoption rates and consumption heterogeneity in unique ways to identify tipping points for impact. We utilize a large dataset of hourly power consumption recordings for residential consumers in Northern California to capture heterogeneity. Based on this data we build various models to assess the value of storage and PV to consumers in the form of bill savings.

We estimate the value that can be delivered by entities that provide improved information to and enable resource sharing among residential consumers. Households rely on information about future consumption and generation when deciding how to operate their DERs. We model how constraints on this information impact the value of DERs to households. This analysis gives an estimate of the value of services that improve the accuracy of information available to the households. Communication technology enables aggregators to coordinate and share DERs among a group of households. We analyze the value that these coordination services can generate, which depends on the pattern of technology adoption by households and the sharing mechanism.

1 Assessing value from data

Storage devices enable households to shift their energy usage in time, and rooftop PV generates electricity that households can consume directly or sell back to the grid. Both technologies allow households to reduce their electricity costs. We estimate how much households and groups of households could save on their bills if they adopted a 5 kW rooftop PV system and a 7 kWh storage device and operated these devices to minimize their electricity costs. We take a household’s hourly smart meter data as its inflexible end-use consumption.

We provide an a-priori snapshot of potential bill savings. Thus, electricity prices are exogenous in our model. Similarly, we assume that households do not significantly alter their electricity consumption behavior when they adopt DERs or when they face differing rates. Refer to the Methods section for detailed explanations of the data sources and analyses.

2 Value of technology for households

We define absolute savings for a household, $S_{a,i}$, as how much its electricity bill decreases when it adopts PV and storage. A household’s normalized savings is $S_{n,i} = S_{a,i}/(1^T L_i)$, its absolute annual savings divided by its original total energy consumption. This gives a cents per kilowatt-hour savings estimate for each household. Relative savings is the ratio between a household’s normalized savings and that of the top household under a given policy, i.e. $S_{n,i}/(\max_i S_{n,i})$. Relative savings are always between 0 and 1, and they enable a comparison of the concentration of benefits under the different pricing policies. We compute savings under three pricing policies, incorporating time-of-use (TOU), wholesale, and dynamic rates, as listed in the table in Figure 1. We conducted five sensitivity studies with varying PV and storage device sizes. Most of the qualitative results of our study were unchanged.
Figure 1: There is considerable heterogeneity in the households in our dataset, which together consume about 0.8 GWh of electrical energy annually. Fig. (a) shows the distribution of mean electrical load for the households in our dataset (range 0.1-13.0 kW), and Fig. (b) shows the distribution of the fraction of consumption that takes place during peak hours (range 0.01-0.65). In our study, each household has a given inflexible load, $L_i$, and a 7 kWh storage device and 5 kW rooftop PV system, which are connected to the house AC bus through inverters. The table defines pricing policies used in the simulations. The retail dynamic rate exposes households directly to wholesale market price variations. Fig. (c) plots the retail TOU rate for a summer (red) and winter (blue) business day. Figure (d) does the same for the wholesale rate. The retail dynamic rate is a scaled version of the wholesale rate.
2.1 Heterogeneity in savings

Figure 2(a) illustrates the distribution of annual absolute savings under the different pricing policies. The variation in annual savings between households is the greatest under Policy 1. In this case, the sale price is much less than the purchase price, so the benefit from offsetting consumption is much greater than that from selling electricity back to the grid. Thus, heterogeneity in household consumption patterns drives greater differences in savings. In contrast, under Policies 2 and 3, in which the sale price is close to the purchase price, offsetting consumption is at most a little better than selling electricity back to the grid. Thus, the variation between household savings is reduced, given that they all have the same size PV and battery.

2.2 Policy impact on savings

Policy has a fundamental impact on the absolute savings available to the households. Policies 2 and 3 are the most advantageous to them, allowing households to sell back electricity at almost the full retail rate. Switching to Policy 1, which reduces the sale price to the wholesale rate, cuts the available savings in half as compared to Policy 2. Households fare better under Policy 2 than Policy 3 because the dynamic rate is in effect a more pronounced version of the TOU, with higher peaks and lower troughs. Thus, under Policy 2 PV is worth more because higher peak hour prices coincide with peak generation hours, and the storage devices also have higher inter-hour price differentials to work upon.

2.3 Segmentation of households by normalized savings

Figure 2(b) shows that under all three pricing policies, the households are divided into three segments based on normalized savings - the top 15%, the middle 80%, and the bottom 5%. The average normalized savings among the top savers is about twice that of the rest under Policy 1, and about thrice that of the rest under Policies 2 and 3.

This concentration of benefits has a significant implication for vendors who could provide rooftop PV and storage to households. Because they stand to save more, the top savers represent a pool of greater potential surplus. The first vendor to enter into this market would reap substantial benefits by targeting them. Later entrants would have to compete over the remaining households, who have relatively similar, and lower, potential savings.

2.4 Policy impact on household savings rank

Figures 2(c) and (d) compare savings under different policies. For absolute savings, the ranking of households is very similar under the two policies in which the sale price is close to the purchase price (Policies 2 and 3) and somewhat different when the sale price is much lower than the purchase price (Policy 1). That said, the correlation in ordering is strong across all three policies. The ranking of households by normalized savings is almost identical under all three pricing policies. Thus pricing policy has a strong impact on the magnitude of savings but a weak effect on the ordering of which households do best.
Figure 2: (a) Absolute annual savings are plotted for Policy 1 (red), Policy 2 (blue), and Policy 3 (green). For each pricing policy, the households are ranked in decreasing order based on savings. About half of the available savings under Policy 2 are eliminated by switching to Policy 1. Policy 3 savings are about halfway between the other two. (b) Relative savings are plotted for the three pricing policies. The top 15% saver segment is labeled with a "T," the middle 80% with an "M," and the bottom 5% with a "B." Under Policy 1, the mean savings among the top households is 1.8 times the mean savings of the rest; that ratio is 3.1 under Policies 2 and 3. This concentration presents an opportunity for targeting. (c) Absolute annual savings under different policies are plotted against each other, with Spearman’s rank correlation coefficient $r_s$ given on each plot. The ordering of households by absolute annual savings is very similar under Policies 2 and 3, while the ordering under Policy 1 is less strongly correlated. (d) Normalized savings under different policies are plotted against each other. The household ordering is practically the same under all three policies. While not shown here, absolute annual savings are negatively correlated with normalized savings, strongly for Policy 1 and weakly for Policies 2 and 3.
3 Value of information

When deciding how to operate its storage device, a household relies on a forecast of its future consumption and rooftop PV generation. The preceding sections have assumed that households have perfect foresight of these quantities. An imperfect forecast leads a household to operate its storage suboptimally, so it saves less money than it would if its forecast were perfect. We can thus characterize the value of information for a household by evaluating how much more it pays for electricity as the forecast error level increases. This metric gives a sense of how much a household should be willing to pay a service provider for reducing forecast error through data analytics or improved algorithms.

For each household, we increase the coefficient of variation (CV) of its forecast error from 0% (perfect foresight) to 100%, and we compute how much its cost of electricity increases in absolute and normalized terms given Policy 1 pricing. The relationship between cost and CV is highly linear in this range. Thus, the slope of the best fit line between cost and CV provides a good estimate of the sensitivity of the household’s electricity cost to forecast error. This sensitivity is what we define to be the value of information for a given household.

Heterogeneous consumption behavior leads to variation in the value of information to households. Figure 3(a) shows the distribution of the value of information in absolute terms. About 50% of households have an annual value of information greater than $270 per unit of CV. In other words, assuming they adopt storage and PV, 50% of households should be willing to pay $90 annually for a service that reduces the standard deviation of their forecast errors by an amount equivalent to one third of their mean consumption.

The distribution of the value of information in normalized terms is shown in Figure 3(b). The mode is around 3.5 ¢/hour/kWh of standard deviation of forecast error. Most households should be willing to pay 3.5¢ hourly for reducing the standard deviation of their forecast errors by 1 kWh. This is not insignificant when compared to the 20-35 ¢/kWh purchase price for electricity under Policy 1, considering that most households consume on average less than 1 kWh each hour.

4 Value of coordination

We define a coordinator as an entity that collectively manages the storage and rooftop PV of a group of households. Coordinators (or aggregators) can provide services to consumers by enabling the sharing of existing assets. They can also provide services to the grid ecosystem by limiting ramping events caused by synchronized activity, shaving peak load, and regulating voltage and frequency [30,31].

We focus on the additional value that coordination can bring to a group of households that includes adopters and non-adopters. We define the value of coordination as the additional savings that the coordinator can achieve for the group of households, beyond what they can achieve acting separately. These additional savings represent a fund which the coordinator can draw upon to compensate the adopters for allowing the coordinator to use their devices for the benefit of others in the group. The value of coordination is the sum of the value of coordinated action (VCA) and the value of coordinated information (VCI).

\[^2\]The coefficient of variation is defined as the standard deviation of the forecast residuals divided by the mean of the actuals.
Figure 3: The value of information is the increase in electricity costs incurred by a household due to an increase in the CV of its forecast errors. Fig. (a) shows the cumulative distribution function for the value of information in absolute terms. Fig. (b) gives the distribution of the value of information in normalized terms. The blue line is a fitted log-normal density with a log-mean of 1.497 and log-standard deviation of 0.539. These values are under Policy 1 pricing.

The value of coordination depends on the adoption rate and pattern. The pattern in which households adopt technology is subject to complex economic, behavioral, and social factors. We consider two simple adoption rules. Under forward adoption, the adopters are those who stand to save the most in absolute annual savings terms. Under reverse adoption, the adopters are those who stand to save the least. We also consider random adoption.

4.1 Value of coordinated action

The coordinator can use the capacity of a storage device in one home in order to shift energy usage in other homes. The coordinator can also ensure that electricity generated by the rooftop PV of homes in the group is used to offset consumption within the group rather than exported to the grid. In essence, the coordinator manages the group of households as one large aggregated household with a large PV system and storage device, redirecting technology capacity to the uses that decrease the group’s cost the most. We define the VCA as the additional savings that the coordinator achieves for the group of households beyond what they save when they act separately, in the perfect foresight case. The VCA can be substantial - up to 29% of the original total cost of electricity, as shown in Figure 4.

4.1.1 VCA increasing in adoption rate up to a point

For all three adoption patterns, coordination provides increasing value with increasing adoption, up to a point. Beyond 50% adoption, the value of coordination decreases. The reason for this decline is as follows. The TOU rate has an expensive peak period and an inexpensive off-peak period. When acting alone to minimize its cost of electricity, a household will use its devices to offset its consumption during the peak period first. If there is spare capacity after that, it will offset its consumption during off-peak times, and then it will sell electricity back to the grid. The coordinator, on the other hand, is minimizing the entire group’s cost of electricity. Therefore, it will use any capacity available to first offset as much of the peak period consumption across all households as possible. Thus, under coordination, more of the adopters’ home energy technology capacity goes
to offsetting peak period consumption, which means greater savings. For this reason, the VCA is much lower under Policies 2 and 3, when the sale price is very close to the purchase price.

When the level of adoption is low, there are many households who do not have the technology and who therefore need help in offsetting their peak period consumption. The coordinator provides this help. When the level of adoption is high, more households have the technology to offset their own peak period consumption. The coordinator has fewer opportunities to redirect technology capacity to offset peak period consumption, and it instead ends up offsetting off-peak period consumption or selling surplus electricity back to the grid, both of which accrue less savings. Thus, as adoption increases beyond a certain point, the coordinator is left with lower-value opportunities for redirecting capacity. In our setting, on the basis of the VCA alone, a coordinator would not encourage DER adoption beyond 50% in a group of households because doing so would reduce the value of its services. Nonetheless, even at 100% adoption, coordinated action has value because some households consume enough electricity that they can make good use of other households’ storage and PV in addition to their own.

4.1.2 Mitigating inefficient adoption

Coordination captures the value that would otherwise be lost due to inefficient adoption patterns by ensuring that the technology capacity is redirected to its most efficient application. For example, under reverse adoption, the households that stand to save the least adopt first. The coordinator does very well by redirecting their capacity to those in the group who can save more with it. Thus the VCA is higher under reverse adoption than under forward adoption. Even adopters with the highest total annual savings may not take full advantage of their DER capacity every day (e.g. when on vacation), so under forward adoption, the coordinator is still able to realize additional value by reallocating underutilized capacity. At high adoption rates, the VCA under forward adoption remains at a high fraction of its maximum because the later adopters save the least from their DERs - so redirecting their capacity elsewhere remains a very valuable service.

4.2 Value of coordinated information

When operating the aggregated storage devices of the adopters, the coordinator only needs to forecast aggregate quantities. Thus, it faces much lower forecast errors than the individual households, enabling it to achieve a more optimal outcome. We define the value of coordinated information as the additional savings beyond the VCA that the coordinator achieves in the presence of forecast error. The VCI increases with adoption level and with forecast error CV for all adoption patterns, as shown in Figure 5. The adoption pattern does not have much effect on the VCI. At higher levels of adoption, the VCI increases more for a given increase in forecast error level. This is because when adoption is higher, the coordinator is operating a greater amount of technology capacity, so its forecasting advantage yields a greater amount of additional savings. Figure 6 shows the value of coordination as the sum of the VCI and VCA for the forward and reverse adoption patterns at a forecast error level of 50%. In the case of forward adoption, at higher levels of adoption the increasing VCI more than offsets the drop in VCA, so a coordinator would encourage adoption beyond 50%. In general, the value of coordination may be increasing or decreasing in adoption rate, depending on the adoption pattern, adoption level, and forecast error level.
Figure 4: The value of coordinated action (VCA) is given here as a percentage of the baseline total cost of electricity for all households prior to any technology adoption. The purple curve is for the forward adoption pattern, the orange curve is for reverse adoption, and the gray curve is for random adoption. The VCA increases as the level of PV and storage adoption within the group increases up to about 50%, after which coordination provides less value. The VCA is greater under the reverse adoption pattern because the coordinator is able to redirect capacity and therefore overcome inefficient initial allocations of technology. The values here are computed under Policy 1 pricing.
Figure 5: These plots show the value of coordinated information (VCI) as a function of adoption level and forecast error level for the (a) forward, (b) random, and (c) reverse adoption patterns. In each graph, the lightest line corresponds to a forecast error CV of 10%, and the darkest a CV of 100%, with the intermediate colors at 10% increments. The VCI is greater when the forecast error is greater and when the adoption level is greater. The VCI is reported as a percent of the baseline total electricity cost for all households (as in Fig. 4). The values here are under Policy 1 pricing.

Figure 6: (a) This diagram illustrates the definitions of VCA and VCI. TC_S is the total cost of electricity paid by the group of households when they optimize separately. TC_C is the total cost they pay under coordination. The light gray bars are costs under perfect foresight, and the dark gray bars are the additional costs due to forecast error. VCA is the reduction in cost under perfect foresight. VCI is the additional reduction in cost in the presence of forecast errors. The sum of VCA and VCI is the value of coordination. The value of coordination when the forecast error CV is 50% is plotted for the (b) forward and (c) reverse adoption patterns. The lighter color is VCA, and the darker color is VCI. As in Fig. 4, the values are reported as a percent of the baseline total cost of electricity without technology, and Policy 1 prices apply.
5 Discussion

Our methodology and results are useful to stakeholders developing their plans of action with respect to behind-the-meter DERs. We provide a tool for policy makers to understand the high-level impact of different pricing policies on household incentives and ordering. Pricing policy is a useful lever to adjust the amount of savings available to households and hence their economic incentives to adopt DERs. It does not, however, significantly alter which households fare the best when adopting DERs. For that purpose other policy tools, such as targeted subsidies, would be required.

Enabling sharing arrangements that allow for coordination is another way that policy makers can ensure that as many households as possible can benefit from DER adoption. With coordination, even if the households who consume the most electricity are the ones who adopt DERs, other households can share in their capacity and reduce their costs as well. In the end, all households are better off with coordination, and the technology capacity is deployed to its most efficient applications.

Our study reveals key insights for emerging business models that serve households who adopt DERs. The magnitude and distribution of household savings give a sense of the market size and structure for vendors of DER equipment. These vendors will do best when households have the largest potential savings - so they would do well to support pricing policies that are the most generous to households, like Policies 2 and 3. These two policies also result in more even benefits across all households, which would make targeting less of a priority if the vendors’ sales and operations take place on an absolute dollar basis. On the other hand, under Policy 1, targeting is important because absolute savings are rather unevenly distributed.

By contrast, vendors who operate on a normalized ($ per kWh) basis must prioritize targeting no matter what because the market is segmented similarly under all pricing policies. Normalized savings are negatively correlated with absolute savings, meaning that the top market segment is composed of households who don’t save a large amount in total but whose consumption behavior is aligned very well with the incentives created by the pricing policies. This finding underscores the importance of devising arrangements and business models for coordinating DER capacity among groups of households, many of whom would not adopt on their own but who could collectively benefit a great deal from a shared resource.

The value of information analysis gives clear guidance to information service providers about potential price points for algorithms and analytics that help households manage their DERs. Similarly, the value of coordination analysis gives aggregators a sense of the revenue possibilities for sharing DERs among households. We also identify a tipping point for these aggregators. When the adoption rate within a group of households exceeds a certain level, the VCA declines. In the presence of uncertainty, however, the aggregator can deliver a VCI that increases in adoption rate. The combined value of coordination may increase or decrease with increasing adoption, depending on the adoption pattern, adoption level, and uncertainty level. It may be the case that the aggregator delivers maximum value when it assembles households into groups that include adopters and non-adopters in a particular mix.

Finally, we note a tension between the business models of the equipment vendor and the coordination service provider. An equipment vendor interested in selling PV and storage systems to households does best by targeting those with the highest potential savings because they can pay the most for the equipment. It will be inclined to proceed along the forward adoption pattern so that it can charge higher prices and get more customers. On the other hand, a coordination service provider would want to encourage the reverse adoption pattern because that makes its services more valuable. However, the coordination service provider will not encourage adoption beyond the
point at which the value of its services is maximized (e.g., 50% adoption in Figure 4). The tension between these two business models could manifest in support for competing policies dealing with pricing, equipment subsidies, and sharing mechanisms.

6 Methods

Our study incorporates actual smart meter data, pricing data, solar irradiance data, and specifications for currently available home energy technologies. We assume that households and groups of households operate the technologies to minimize their cost of electricity. Here, we describe in detail the data sources we use and the analyses we perform.

6.1 Data sources

6.1.1 Household consumption

The household electricity consumption data comes from over 100,000 residential smart meters over a one year period spanning from August 2010 to July 2011. The households are all customers of Pacific Gas and Electric Company (PG&E) in California. These meters include single family homes and apartments. Meters with very low consumption (<0.1 kW annual mean) are excluded, as are meters with a high amount of zero readings (>50% of all readings).

We treat the smart meter data that we have for a household as its inflexible load $L_i$. This move rests on two assumptions. The first is that consumption behavior does not change due to rate changes. Thus, even though almost all of these households were on an inclining block rate for the period of time of the meter data, their electricity consumption behavior does not change when exposed to the pricing policies in our study. Note that retail rate design typically aims for revenue neutrality, which means that between different rates, the marginal price faced by consumers varies much more than the average price. Both [33] and [34] find that household electricity consumption responds most strongly to the average price of electricity, lending support to using the meter data as the inflexible load.

The second assumption is that consumption behavior does not change due to DER adoption. For the sizes of PV systems we study, [35] suggests that most households would increase their overall electricity consumption. Computing bill savings based on greater consumption would result in larger savings than what we report, so our study is conservative in that sense.

6.1.2 Prices

Retail TOU Utilities are moving towards time-varying rates, which create incentives for consumers to shift their electricity purchases to periods when the rate is lower [36]. PG&E’s E-TOU Option B serves as the retail TOU rate for this study [37]. Table 1 contains the relevant elements of the tariff. We exclude fixed charges in the tariff when computing household electricity bills.

Discounted TOU In a recent survey, industry professionals were asked what households should receive for electricity they sell back to the grid. A plurality of them favored the full retail rate minus the costs of using the physical infrastructure of the grid [38]. These costs are estimated as 20% of the retail rate, so households would be compensated at 80% of the retail rate - what we call the discounted TOU.
| June - September | Off peak hours | $0.25511 / kWh | Peak hours (4pm-9pm) | $0.35817 / kWh |
|------------------|----------------|----------------|----------------------|----------------|
| October - May    | $0.20191 / kWh | $0.22071 / kWh |

Table 1: The retail TOU rate for this study comes from PG&E’s E-TOU. Peak hour rates apply only on non-holiday weekdays. On holidays and weekends, all hours are charged at the off peak rate.

**Wholesale** Locational marginal prices (LMPs) serve as the wholesale price. They come from a wholesale energy market administered by the California Independent System Operator (CAISO). We use the day ahead LMPs published by CAISO for the dates corresponding to the household consumption data, but we set any negative prices to zero.

The wholesale rate varies by location. We use a rough mapping from a household’s zip code to the nearest CAISO pricing node by latitude and longitude, and we use the LMP from that node as the wholesale price for the household. Thus all households in a given zip code face the same wholesale price.

**Retail dynamic** The retail dynamic rate is a scaled version of the wholesale rate. The scaling is designed to maintain day-by-day revenue neutrality with the retail TOU. For each day, across all zip codes, the total cost of all of the households’ inflexible load at the retail TOU rate and the wholesale rate is computed. The LMPs for each zip code are then scaled up by the ratio of the retail TOU revenue to the wholesale revenue. The retail dynamic rate exposes households more directly to the fluctuations of the wholesale market.

**Discounted dynamic** The discounted dynamic rate is 80% of the dynamic rate.

### 6.1.3 Home technologies

We assume that households can install DERs behind the meter without interference from their electricity provider, and that households living in apartments can adopt DERs by participating in a building or neighborhood sharing arrangement [39].

**Rooftop PV** We size the rooftop PV system for an output of 5 kW under the PVUSA Test Condition (PTC) of 140 W/m². This equates to an array area of about 35.7 m². According to the Solar Energy Industries Association, 5 kW was the average size of installed residential systems in the United States a few years ago [40].

**Storage device** The storage device specifications are based on the first generation of the 7 kWh Tesla Powerwall. The capacity is 7 kWh. The maximum sustained charging rate is 2 kW, which is also the maximum sustained discharging rate. The round trip efficiency is 0.92. We take the square root of that, 0.959, to split it into a charging and discharging efficiency. We assume no self-discharge.

**Interconnection** We assume that the rooftop PV is connected to the house AC bus through an inverter with 92% efficiency. The storage device is connected in the same way. Thus, all energy
flows to and from the storage device, and from the PV, incur 8% loss through the inverters. We assume that there is no limit on the power that a household can draw from or provide to the grid.

6.1.4 Solar irradiance

There are 67 Class 1 and 2 (CRN1 and CRN2) weather stations with solar irradiance data in California \cite{41,43}. For each station, we fit a beta distribution for global horizontal irradiance (GHI) based on statistics for 2010 published by the National Solar Radiation Data Base (NSDRB). The only geographic information we have for the households is their zip code. For the weather stations we have latitude and longitude. We use a rough mapping to match a zip code to the nearest weather station. We sample from the beta distribution for that station to generate a solar irradiance for the households in the zip code, i.e. all households in the same zip code get the same irradiance sample.

6.2 Pricing scenarios

We analyze three different pricing policies, as listed in the table in Figure 1 of the main text. Under Policy 1, households purchase electricity at the retail TOU rate, and they sell any surplus back to the grid at the wholesale rate. Investor-owned utilities in California have proposed this price structure in recent discussions with regulators. This is generally considered the least generous compensation scheme that households are likely to encounter. Under Policy 2, households purchase at the retail dynamic rate and sell surplus back at the discounted dynamic rate. Under Policy 3, households purchase electricity at the retail TOU, and they sell it back to the grid at the discounted retail TOU. The retail TOU or discounted retail TOU rate is the same for all households. Thus, all households face the same prices under Policy 3.

In all three scenarios, electricity prices are exogenous\footnote{Conventional residential retail rates do not change rapidly, so for all intents and purposes the retail TOU rate in our study would be fixed as households begin the uptake of DERs.}. There is no dynamic market clearing in our study. In other words, households are price takers; their actions do not influence the prices they face.

6.3 Operation of storage device

We consider rooftop PV an uncontrollable system - it will produce however much power is dictated by the solar irradiance. The storage device, however, is controllable, and households have to determine how to operate it. In our study, households solve a linear program on a daily basis to choose an optimal schedule for charging and discharging the battery. Here we describe that linear program.

\( L_i \) is the \( i \)th household’s hourly smart meter data for a year, and \( l_i^{(j)} \) is the data for the \( j \)th day, so that \( L_i = [l_i^{(1)} \cdots l_i^{(365)}] \). We take \( l_i^{(j)} \) as the household’s inflexible electrical energy consumption for the day.

We multiply the day’s solar irradiance for the household by the panel power rating to get the energy generated by the household’s PV system, \( e_i^{(j)} \). (If the household doesn’t have a PV system, then \( e_i^{(j)} = 0 \).) Finally, we get the household’s net load for the day, \( n = l_i^{(j)} - \eta_I e_i^{(j)} \), where \( \eta_I \) is

\footnote{The San Francisco International Airport (SFO) weather station has a particularly low irradiance when compared to nearby areas. Therefore, we manually assigned zip codes near SFO to weather stations in the area using the average GHI as reported by the NSRDB Data Viewer as a guide \cite{44}.}
the inverter efficiency. In this section we assume that households have perfect foresight of $l_i^{(j)}$ and $e_i^{(j)}$ for the coming 24 hours.

Let $Q_i$ and $R_i$ be the year-long vectors of hourly prices at which the household buys and sells electricity, respectively, under the given pricing policy. Let $q_i^{(j)}$ and $r_i^{(j)}$ denote the prices on the $j$th day.

Each day, the household must select $u^{(j)}$, a sequence of hourly actions for the storage device. Let $u_h^{(j)}$ denote the action during hour $h$ of the day. When $u_h^{(j)}$ is positive, the device is charging in hour $h$; when it is negative, the device is discharging. Similarly, $x$ denotes the state of charge of the device, and $x_h$ the state of charge at the end of hour $h$. Let $\eta_C$ and $\eta_D$ be the charging and discharging efficiencies, respectively. Finally, $g$ denotes the hourly net exchange with the grid. When $g_h$ is positive, the household is drawing power from the grid during hour $h$; when it is negative, the household is supplying power to the grid.

The household seeks to minimize what it pays for electricity this day. It solves the following linear program.

$$\begin{align*}
\text{minimize} \quad & u^{(j)}_i, x_i, g_i \in \mathbb{R}^{24} & \\
\text{subject to} \quad & g_i = n + \frac{1}{\eta_C \eta_D} [u^{(j)}_i]^+ + (\eta_D \eta_I) [u^{(j)}_i]^-, \\ & -u \leq u^{(j)}_i \leq u, \\ & 0 \leq x \leq x, \\ & x_0 = x_0, \\ & x_h = x_{h-1} + u_h^{(j)}, \forall h \in \{1, \ldots, 24\},
\end{align*}$$

where $u$ and $u$ are respectively the maximum charge and discharge rates for the storage device, $x$ is the maximum capacity of the storage device, and $x_0$ is the state of charge of the device at the end of the prior day. The $[\cdot]^+$ and $[\cdot]^-$ operators represent element-wise application of $\max(\cdot, 0)$ and $\min(\cdot, 0)$, respectively.

Let the optimal schedule be denoted $u^{(j)*}_i$. The household operates the battery per $u^{(j)*}_i$, so the minimized objective is what it pays for electricity this day. Denote the minimized objective value as $c_i^{(j)}$.

### 6.4 Household savings analysis

For a given pricing policy, we first compute the baseline annual bill for the household in the absence of the home energy technologies: $b_{BL,i} = L_i^T Q_i$. Next, we compute the household’s new bill in the presence of the technologies for the given pricing policy: $b_{N,i} = \sum_{j=1}^{365} c_i^{(j)}$. The absolute annual savings $S_{a,i} = b_{BL,i} - b_{N,i}$. The distribution of absolute annual savings under the different pricing policies is plotted in Figure 2(a).

The normalized savings $S_{n,i} = \frac{100}{L_i} S_{a,i}$. We convert normalized savings to relative savings by dividing by the maximum value over all households under a given policy, i.e. $S_{n,i} / (\max_i S_{n,i})$. Figure 2(b) plots the distribution of relative savings under different pricing policies.
We compute error bars for the absolute annual savings and normalized savings by bootstrap resampling from the 365 days of the year for each household. The error bars are very small, so we omit them in the graphs.

### 6.5 Value of information analysis

We estimate the value of information as the additional cost incurred by a household due to an increase in forecasting errors.

For a given day, instead of having perfect foresight of its inflexible consumption $l^{(j)}$ and generation $e^{(j)}$, the household must generate forecasts $\hat{l}^{(j)}$ and $\hat{e}^{(j)}$. Note that the household will know all relevant prices without uncertainty because the retail TOU does not change on a daily basis, and the day ahead LMPs are published prior to the start of the day on which they apply.

We introduce forecast error based on the coefficient of variation $[32]$. Let $\hat{l}^{(j)}_{i,h} = l^{(j)}_{i,h} + \epsilon^{(j)}_{h,i}$, and $\hat{e}^{(j)}_{i,h} = [\epsilon^{(j)}_{i,h} + \gamma^{(j)}_{h}]_+$ where $\epsilon^{(j)}_{h,i}$ and $\gamma^{(j)}_{h}$ are independently and identically distributed across $j$ and $h$. For the forecast error CV of $P$, $\epsilon^{(j)}_{h,i}$ is normally distributed with $\mu = 0$ and $\sigma = PL$ $i$, where $L_i$ is the mean hourly inflexible load of the $i$th household. Similarly, $\gamma^{(j)}_{h}$ is normally distributed with $\mu = 0$ and $\sigma = PL\overline{E}_i$, where $\overline{E}_i$ is the mean hourly solar generation for household $i$.

The household uses these forecasts to schedule the operation of its storage device. Let $\hat{n} = \hat{l}^{(j)}_{i,h} - \eta r^{(j)}_{i,h}$. The household solves the same linear program as before, except that $\hat{n}$ replaces $n$ in constraint (1b). The optimal schedule $u^{(j)\dagger}$ from this solution is what the household uses to operate its storage device.

The household’s cost of electricity in this case is not the objective from the linear program because the true consumption and solar generation are different from the forecasts. Let $g^{(j)} = n + \frac{1}{\eta} \left[ \left[ u^{(j)\dagger} \right]_+ + (\eta P) n \right] [\left[ u^{(j)\dagger} \right]_+]_-$, where $n$ is the true net load, i.e. $n = l^{(j)}_{i,h} - \eta r^{(j)}_{i,h}$. Then the household’s cost of electricity for this day is $c^{(j)}_{i,h} = [g^{(j)}]_+ T q^{(j)}_{i} + [g^{(j)}]^- T r^{(j)}_{i}$.

The household’s annual cost of electricity at this level of forecast error CV is $b^{\dagger}_{N,i}(P) = \sum_{j=1}^{365} c^{(j)}_{i}$. We compute $b^{\dagger}_{N,i}(P)$ for $P = 10, 20, \ldots, 100$, and $b^{\dagger}_{N,i}(0) = b_{N,i}$. We then perform a linear regression of $b^{\dagger}_{N,i}(P)$ on $P$. The value of information for household $i$ in absolute terms is the slope coefficient from this regression, which has units of $$/year/CV. The cumulative distribution of this metric under Policy 1 prices is given in Figure 3(a).

To get the value of information for household $i$ in normalized terms, we linearly regress $b^{\dagger}_{N,i}(P)$ on $P$. This is the same as multiplying the value of information in absolute terms by $\frac{100}{P_{L}}$, which will then have units of $$/hour/kWh of standard deviation of forecast error. The distribution of this metric under Policy 1 pricing is given in Figure 3(b).

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*Multiplying the total annual cost ($$/year) by 100 $$/ gives total annual cost in $$/year. Dividing that figure by total annual load (kWh/year) yields cost per unit load ($$/kWh). The coefficient of variation is defined as the standard deviation of the forecast errors divided by the mean of the actual signal. For the hourly load, the CV has units of kWh standard deviation over hourly kWh load. Dividing the $$/kWh load standard deviation yields units of $$/hour/kWh standard deviation of forecast error. For the hourly solar generation, the units still work out to $$/hour/kWh, but the CV has units of $$/kWh solar/hour, so the cancellations aren’t as clean as in the case of load. We choose to report the metric as $$/hour/kWh standard deviation of forecast error because the CV for solar generation scales directly with the CV for load in our method.
6.6 Value of coordination analysis

For a given scenario, we compute the value of coordination as the additional savings that the entire group of about 100,000 households could obtain if they acted collectively instead of as individuals. We break the value of coordination into two components: the value of coordinated action (VCA) and the value of coordinated information (VCI).

6.6.1 Total costs without coordination

Index all households by $i = 1, \ldots, N$, where $N$ is the total number of households. Under a given pricing policy, let $f(i)$ be the ordering position of household $i$ when the households are sorted in decreasing order of $S_{a,i}$. Let $r(i)$ be the ordering position of household $i$ when the households are sorted in increasing order of $S_{a,i}$. Finally, let $s(i)$ be the ordering position of household $i$ in a random permutation. Thus, if household $m$ saved the most under this policy, then $f(m) = 1$, $r(m) = N$, and $s(m)$ is wherever $m$ is in the random permutation.

Consider a given adoption rate, $t\%$. Define $A_{fwd}(t) = \{i : f(i) \leq N \cdot t\%\}$, $A_{rev}(t) = \{i : r(i) \leq N \cdot t\%\}$, and $A_{rdm}(t) = \{i : s(i) \leq N \cdot t\%\}$. Define $B_{fwd}(t) = \{1, \ldots, N\} \setminus A_{fwd}(t)$, and define $B_{rev}(t)$ and $B_{rdm}(t)$ analogously.

Define the total cost under forward adoption as $T_{fwd}(t) = \sum_{i \in A_{fwd}(t)} b_{N,i} + \sum_{i \in B_{fwd}(t)} b_{BL,i}$. In other words, add up the new bills (i.e., with technology) for the adopters and the baseline bills (i.e., without technology) for the non-adopters. The total costs under reverse adoption and random adoption are defined analogously. Next, define the baseline total cost without technology as $T_{BL} = \sum_{i=1}^{N} b_{BL,i}$. Figure 7 plots $T_{fwd}(t)$, $T_{rev}(t)$, and $T_{rdm}(t)$ as a percent of $T_{BL}$, under Policy 1 pricing.

6.6.2 Value of Coordinated Action

The group minimizes its electricity costs on a daily basis. For a given day, we set up the optimization as follows. Note that the VCA is under perfect foresight.

We take the mean of prices across all households to be the prices the coordinator faces. That is, $q_G^{(j)} = \frac{1}{N} \sum_{i=1}^{N} q_i^{(j)}$, and $r_G^{(j)} = \frac{1}{N} \sum_{i=1}^{N} r_i^{(j)}$.

Take a given level of adoption, $t\%$, and assume the forward adoption pattern. The solar energy generated by the group, $e_G^{(j)}$, is that generated by the PV systems of the adopters: $e_G^{(j)} = \sum_{i \in A_{fwd}(t)} e_i^{(j)}$. The group’s inflexible load is the total across all households: $l_G^{(j)} = \sum_{i=1}^{N} l_i^{(j)}$. The group’s net load $n_G = l_G^{(j)} - \eta e_G^{(j)}$.

We obtain the group’s storage device capacity and charging and discharging rates by scaling up the parameters of the household storage device by the number of adopters $n = N \cdot t\%$.

The coordinator solves the following optimization problem to schedule the operation of the collective storage.
Figure 7: The total annual cost of electricity without coordination for all households, as a percent of the baseline total cost without technology ($T_{BL}$), is plotted against the percent of households that have adopted storage and PV. This analysis is under Policy 1 prices. The purple curve is for the forward adoption pattern, the orange curve is for reverse adoption, and the gray curve is for random adoption. $T_{BL}$ is about $182$ million, and it serves as the baseline cost used for Figs. 4 through 6.
The coordinator then controls the adopters’ storage devices to execute the optimal schedule \( u^{(j)}_G \) at the aggregate level. There are generally many ways to distribute \( u^{(j)}_G \) over the adopters’ devices.

An implicit assumption of this model of coordination is that the group of households has free use of the wires between the homes and that there are no losses in sharing energy this way. Energy supplied to the grid by one home in the group, whether by its rooftop PV or its storage device, can be used to offset the consumption of a separate home in the group with no loss and no fees, other than the losses induced by the first home’s inverter and storage device inefficiencies. In effect, this model of coordination treats the group of homes as one big household, combining their consumption, rooftop PV generation, and storage devices.

The cost of electricity for the group of households for this day will be the optimal value of the objective; call it \( c^{(j)}_G \). Define \( C_{fwd}(t) = \sum_{j=1}^{365} c^{(j)}_G \). The VCA for the forward adoption pattern at adoption level \( t\% \) is then \( VCA_{fwd}(t) = T_{fwd}(t) - C_{fwd}(t) \). The VCA for the reverse and random adoption patterns are defined analogously. Figure 4 plots the VCA for different adoption patterns and levels.

### 6.6.3 Value of Coordinated Information

The VCI is defined as the additional savings achieved by coordination on top of the VCA in the presence of forecast errors.

For a given day, the coordinator must generate forecasts \( \hat{l}^{(j)}_G \) and \( \hat{e}^{(j)}_G \). Let \( \hat{l}^{(j)}_G = [l^{(j)}_G, e^{(j)}_G]_+ \), and \( \hat{e}^{(j)}_G = [e^{(j)}_G, e^{(j)}_G]_+ \) where \( e^{(j)}_G \) and \( e^{(j)}_G \) are independently and identically distributed across \( h \) and \( j \). The coordinator is forecasting aggregate quantities, so its error is lower than that of the individual household. \( e^{(j)}_G \) is normally distributed with \( \mu = 0 \) and \( \sigma = w(\bar{L}_G)\bar{L}_G \), where \( \bar{L}_G = \sum_{i=1}^{N} \bar{L}_i \), and \( w(\cdot) \) is the fit for the CV scaling law for forecasting model \( M_3 \) from [32]. \( \gamma^{(j)}_{G,h} \) is normally distributed with \( \mu = 0 \) and \( \sigma = w(\bar{E}_G)\bar{E}_G \), where \( \bar{E}_G = \sum_{i=1}^{N} \bar{E}_i \).

Let \( \hat{n}_G = \hat{l}^{(j)}_G - \eta I \hat{e}^{(j)}_G \). The coordinator solves the same linear program as before, except that \( \hat{n}_G \) replaces \( n_G \) in constraint (2b). The optimal schedule \( u^{(j)}_G \) from this solution is the coordinator’s schedule of charging and discharging for the collective storage.

Let \( g^+_G = n_G + \frac{1}{\eta D}\cdot[|u^+_G|]_+ + (\eta D \eta I)[|u^-_G|]_- \), where \( n_G \) is the true net load, i.e. \( n_G = l^{(j)}_G - \eta I e^{(j)}_G \). The group’s cost of electricity for this day is \( c^{(j)}_G = [g^+_G]^T q^+_G + [g^-_G]^T r^-_G \). Let \( C^{(j)}_{fwd}(t) = \sum_{j=1}^{365} c^{(j)}_G(t) \). Let \( C^{(j)}_{fwd}(t) = \sum_{i \in A_{fwd}(t)} b^{(j)}_N, (P) + \)
Table 2: Five sensitivity study cases were evaluated. Net 0 means that household $i$’s PV system is sized so that over the course of the year, it generates as much energy as the household’s inflexible load ($1^T L_i$). This leads to variation in the size of the panels among households, with the shape of the distribution basically in line with that of the mean load given in Fig. 1(a). The maximum charging and discharging rates for the 2 kWh storage device are scaled from the 5 kWh device parameters. The maximum charging and discharging rates for the 13.5 kWh device are both 5 kW, based on the second generation Tesla Powerwall.

$$\sum_{i \in B_{\text{fwd}}(t)} b_{BL,i} - C^i_{\text{fwd}}(t) - VCA_{\text{fwd}}(t).$$

The VCI for the reverse and random adoption patterns are defined analogously. Figure 5 plots the VCI for different adoption patterns, forecast error CV levels, and adoption levels.

6.7 Sensitivity studies

We conducted five sensitivity studies on a subset of 12,000 households as listed in Table 2. All of the qualitative results are preserved in cases 1 and 2. In case 3, the only major difference is that the VCA under forward adoption is monotonically increasing - there is no maximum before 100% adoption. Because the capacities are relatively small in this case, the storage and PV of even the last adopter can be redirected to high value applications for other households (i.e., offsetting peak period energy consumption). In cases 4 and 5, households with larger inflexible loads have larger PV systems. Thus, the absolute annual savings distribution is very uneven, with the largest energy consumers saving much more compared to other households. On the other hand, normalized savings, which are scaled to household consumption, are more even across the population, to the point of being almost the same for all households under Policy 3. Relatedly, the ordering of households by normalized savings under Policy 2 is weakly correlated with the orderings under Policies 1 and 3. Thus, pricing policy does have a significant impact on which households do best by the normalized savings metric.

6.8 Data availability

The pricing and solar irradiance data are publicly available. The smart meter data is the property of PG&E and was obtained by the authors under a non-disclosure agreement. To preserve privacy, resampled versions of the data underlying Figures 1, 2, and 3 were made available to the editors and reviewers. The data underlying Figures 4, 5, and 6 were made available in original form. The analysis code was made available to the editors and reviewers. In addition, reviewers were able to modify the simulation parameters and evaluate the altered results.
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