From Production to Consumption: Residential Energy Use Increases Following Solar Installation

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ABSTRACT

California's more than 1.4 million residential solar PV projects represent over 11 GW of behind-the-meter capacity – an invaluable resource for system resiliency and sustainability (CPUC 2026). Yet a critical factor remains unclear: to what extent does PV installation impact overall home energy consumption? While early studies found no persistent consumption changes following PV installation (McAllister 2012), research on more recent adopters in California identified usage increases up to 19% (Elliot and Shelton 2022). Because the impact appears to be increasing, the need for more analysis is pressing. Moreover, understanding whether and how impacts vary by critical characteristics, such as climate zone, electric vehicle (EV) ownership, or disadvantaged community status is essential for accurate load forecasting and equitable program design. Without this granular understanding, utilities and policymakers risk overestimating grid benefits of PV, potentially jeopardizing system resiliency.

This research incorporates two residential analyses that quantify changes in electricity usage after PV installation in California. The first includes a sample of approximately 14,000 residential customers who installed PV systems between January and September 2023, focusing on how impacts differ by climate zone and EV ownership. The second examines impacts within disadvantaged communities, by studying installations made through a program that provides no-cost rooftop solar for qualifying homes.

While impacts on energy usage differ in magnitude and timing by customer segment, this research identifies ubiquitous increases in consumption after PV installation. These have broad implications for load forecasting in all solar-rich service territories.

Introduction

The growth of residential solar in California represents one of the most significant distributed energy developments in the state's grid history. With more than 11GW of behind-the-meter capacity, residential solar in California offers meaningful benefits to grid stability during periods of stress (CPUC 2026). Though recent changes in rate and incentive structures have resulted in a decreasing rate of residential solar expansion in California, there were still nearly 150,000 projects, representing over 1 GW of residential solar capacity, added in 2025 (CPUC 2026). As such, accurately forecasting the grid benefits of this resource is essential.

A major challenge to understanding and forecasting the grid benefits of residential solar is that it is unclear the extent to which solar installations lead to changes in consumer electricity consumption. This question has been a subject of much debate, often relying on anecdotal evidence regarding the motivations and behaviors of solar adopters. For example, customers who install solar due to primarily environmental considerations may show little change in electricity consumption, or may even reduce usage over time, particularly if that same mindset motivated them to pursue complimentary improvements such as improved shell sealing, smart thermostats, or upgrades to more energy efficient appliances (Gadenne et al. 2011, Qui, Kahn, and Xing 2019). On the other hand, customers who come to view their solar-generated electricity as effectively free may respond with behaviors that substantially increase electricity consumption such as the increased usage of their HVAC systems, electrification of their appliances, or even the installation of an electric vehicle charger. Recent literature refers to these post-solar consumption increases as the "Solar Rebound Effect" (SRE) (Havas et al. 2015; Deng and Newton 2017; Qui, Kahn, and Xing 2019; Boccard and Gautier 2021; Beppler, Matisoff, and Oliver 2021; Aydin, Brounen, and Ergun 2023). Both types of customers are likely to exist among the broad population of solar adopters in California, making it necessary to pursue empirical research to capture the overall grid impacts of potential consumption changes following solar installations.

While studies of early solar adopters in California found no persistent changes in consumer electricity consumption following PV installation (McCallister 2012), work focusing on more recent adopters identified pervasive increases in usage. In California, Shelton et al. (2020) found an average of 7% consumption increases for PG&E customers, and Elliot and Shelton (2022) found increases up to 19% for SDG&E customers. Outside of the United States, research in the past decade has identified solar rebounds ranging from 10 to 35% (Havas et al. 2015; Deng and Newton 2017; Boccard and Gautier 2021; Aydin, Brounen, and Ergun 2023). Because of the apparently escalating impacts, it is imperative to conduct updated research.

This paper presents the results of two analyses of electricity consumption change post-PV installation in residential households across California. The first analysis includes approximately 14,000 customers who installed PV systems between January and September 2023, with a focus on how consumption changes vary with climate zone and EV ownership. The second focuses on installations made through a program that delivers no-cost rooftop solar to qualifying homes also between January and September 2023. Overall, this work identifies consistent electricity consumption increases across customer segments ranging from 7 to 25% of counterfactual usage. Together, these analyses offer broad insights into how residential solar adoption in California affects electricity usage, which has widespread implication for load forecasting and rate planning in solar rich territories.

Methodology

This analysis included a difference in differences-based approach that consisted of five primary steps, as depicted in Figure 1.

Figure 1. Analysis steps.

Data Acquisition

This analysis relied on five primary data sources, as described below.

- **Interconnection Data** – This data contained the PV system specifications (such as nameplate rating, tilt, and azimuth) as well as relevant customer information (such as Permission to Operate (PTO) date and address). These data were used to identify customers with new PV interconnections in the focal time period of January to September 2023, as well as to identify customer climate zone. The system specifications from these data were critical to our site-specific PV generation modelling.
    - This analysis focused on new PV installations between January and September 2023 because (1) the AMI data source was current only through September 2024 and (2) it was important to limit the influence on the pre-period of atypical energy usage related to COVID-19 in 2020-2021.

- **Customer AMI data** - These data included hourly net energy usage. For non-participants, and in the pre-period for participants, these data represent the total energy consumption. In the post-period for participants, these data represent total PV export (when negative) or additional grid consumption beyond generated PV (when positive). These data also included rate information and flags for participation in utility assistance programs for low-income households, which were necessary for customer model group segmentation. Specifically, flags for participation in CARE (California Alternate Rates for Energy) and FERA (Family Electric Rate Assistance) were provided. Lastly, these data were used to compute average annual customer usage in the pre-period.

- **Weather data** – These data included hourly temperature, windspeed, and solar irradiance information as well as the latitude, longitude, and elevation of the weather station. These data are necessary for PV generation simulations and were also used for weather normalization.

- **EV ownership data –** These data allowed us to identify which customers in both our participant and non-participant data set were EV owners.

- **PV Generation data –** Metered hourly PV generation data was provided for the no-cost solar program systems included in this analysis.

Customer Segmentation

Residential customer energy usage is sensitive to a variety of customer attributes. As such, to increase the reliability of our models, as well as reduce potentially confounding sources of variability, all models were run with bins separated by the following factors:

- **Climate Region –** Based on Title 24 Climate Zone, identified by customer location. Climate regions were used in lieu of climate zones due to the limited sample size in the no-cost solar installation program analysis.

- **Customer Size** – Based on the average pre-period annual consumption from an analysis of the AMI data. The groups were small (S), with less than 5,000 annual kWh, medium (M), between 5,000 to 10,000 kWh, and large (L), ranging from 10,000 to 25,000 kWh. Customers with annual consumption of more than 25,000 kWh were excluded from the analysis due to a limited number of accounts.

    - Because of limited sample size for the no-cost solar program analysis, and because of overall low variability in customer annual usage, the medium and large bins were pooled together. They were kept separate for the general population analysis.
- **EV Ownership** – As determined from the provided EV owner data. For the no-cost solar program analysis, there was insufficient sample of customers flagged as EV owners. As such, only non-EV owners were retained in that analysis.

- **Low income rate status** – As determined from Rate and CARE and FERA flags provided with the AMI data. For the general population analysis, there were few customer segments with sufficient customers on CARE or FERA rates. As such, only households on non-low-income rates were included in the general population analysis. The only results for customers on low-income rates in this work are represented in the no-cost solar program analysis.

No data was available for customer fuel type (Gas, Electric, Mixed). However, this is expected to be controlled for in the selection of matched control non-participants.

After all data cleaning steps, only segments with at least 100 remaining participants (PV adopters) were included in the analysis, leaving a total of 14,220 PV adopters for the general population analysis. For the analysis of the no-cost program-installed systems, sample size was restricted by the number of installations that occurred in the required time frame.

Table 1 shows the number of participants included in each analysis (note that for each bin the same number of matched non-participants were included in the analysis).

Table 1: Number of solar adopters included in each analysis

Analysis	Climate Region	Size Class	Num. Non-EV Owners	Num. EV Owners
General Population Analysis	Coastal	L	325	511
		M	1,240	1,022
		S	773	252
	Coastal-Inland	L	475	635
		M	1,204	844
		S	319	106
	Inland	L	1,459	756
		M	1,895	554
		S	284	-
	Desert	L	664	-
		M	477	-
	Mountain	L	197	-
		M	228	-
No Cost Solar Program Analysis	Inland	M-L	297	-

Development of the Matched Control Group

To develop a robust counterfactual estimate of participant energy usage in the post-period, it was necessary to identify a set of customers who did not install solar PV whose pre-period energy usage resembled those who did. Separate matched control groups were developed for the general population analysis and the no-cost solar program. For the general population analysis, the candidate non-participant pool was limited to households that were not on low income rates because all participant solar PV adopters retained in the analysis were on non-low-income rates. For the no-cost solar program, the non-participant pool only included customers on low-income rates because nearly all program participants were on low-income rates.

To develop the control groups, Euclidean distance matching on pre-period load shapes was used to select one matched control non-participant per PV adopter from the same customer segment (e.g., Climate Region, Size Class and EV Ownership Status). A suite of internal models was tested for each customer segment, with models including combinations of variables such as the average hourly usage during each season as well as each time of day. For each segment, the model that performed best by a combined Bias and Absolute error metric was used to select the final set of matched non-participants.

Importantly, the matched control group was developed using only data from 2022. Because of the significant difference in weather conditions between 2022 and 2023 across California, it was important to limit the matching period to a single, consistent time interval. Data from both 2023 and 2024 were used in subsequent impact modelling where weather conditions were controlled for.

PV Simulations

To estimate total energy consumption in the post-period, it was necessary to simulate generated PV for all participants in the post-period. PV generation was simulated with system and site-specific parameters (including location, tilt, azimuth, system size, and actual weather data) using PVLIB v 0.12.0. These simulations were calibrated to closely reflect the outputs of PVWatts and their accuracy for residential systems has been verified in previous work. Simulated PV energy production was added back to net load to arrive at the estimate of whole house consumption after adoption of solar PV. While these simulations are expected to be accurate, particularly at the daily level, one limitation of this work is that simulated generation cannot account for significant system interruptions or downtime that may occur in actual systems (e.g., shading, clouds, or down inverters).

PV Simulations were used only for the analysis of general population installations. Actual PV generation was provided for the no-cost solar program.

Difference-in-Differences Modelling

This study employed a regression-based approach by fitting a panel model to approximately one year each of pre- and post-period energy consumption. Models were run on per-customer daily usage data, with separate models being run for each customer segment in each month. The final model specification is detailed below:

$$\boldsymbol{kWh_m = \beta_{0,m} + \beta_{1,m}Post + \beta_{2,m}Part + \beta_{3,m}Post{:}Part + \beta_{4,m}Post{:}Part{:}Wx + \beta_{5,m}EV + \beta_{6,m}Wx + \varepsilon_{h,m}}$$

Where:

$\boldsymbol{kWh_m}$	The estimated typical daily kWh usage for a customer in month *m*.
$\boldsymbol{\beta_{0,m}}$	The intercept of the regression model in month *m*.
$\boldsymbol{Post}$	A dummy variable to indicate the Post-Period. Its coefficient $\boldsymbol{\beta_{1,m}}$ captures the baseline impact of being in the post-period on average daily usage for both parts and non-parts in month *m*.
$\boldsymbol{Part}$	A dummy variable to indicate the Participants. Its coefficient $\boldsymbol{\beta_{2,m}}$ captures the baseline impact of being a participant on average daily usage in month *m*.
$\boldsymbol{Post{:}Part}$	A dummy variable indicating Participants in the Post period. Its coefficient $\boldsymbol{\beta_{3,m}}$ is the core difference-in-difference impact estimate, representing the non-weather sensitive impact on usage attributable to participants in the post-period.
$\boldsymbol{Post{:}Part{:}Wx}$	A dummy variable interaction of weather and participation in the post period. Its coefficient $\boldsymbol{\beta_{4,m}}$ represents the weather-sensitive impact on usage attributable to participants in the post-period. This term is only included in the model in cases where the estimate for $\boldsymbol{\beta_{4,m}}$ is statistically significant ($p < 0.05$). When relevant, separate terms are fit for heating and cooling parameters of CDH65 and HDH55.
$\boldsymbol{EV}$	A dummy variable associated with the registration date of an electric vehicle at the site. Its coefficient $\boldsymbol{\beta_{5,m}}$ captures the impact of EV presence on daily home energy consumption.
$\boldsymbol{Wx}$	A temperature-based variable. Separate terms are fit for heating and cooling, with the cooling degree day estimate at cutoff 65°F and the heating degree day estimate at 55°F. Coefficients $\boldsymbol{\beta_{6,m}}$ account for weather sensitivity within a segment and across months.
$\boldsymbol{\varepsilon_m}$	The error term

These models were then used to estimate counterfactual consumption for the solar adopters (e.g., the estimated electricity consumption if they had not adopted solar, given post period weather conditions). To do this, $\boldsymbol{kWh_m}$ was estimated for each month for each customer segment using fitted model coefficients and actual post-period weather conditions, but with the post:part terms set to 0.

Results

The primary outcome of these analyses are the estimates of actual and counterfactual hourly energy consumption for solar PV adopters in the post period, where the difference between these represents the change in consumption. Note that consumption increases are reported as differences between actual and counterfactual total consumption. This approach differs slightly from the classic rebound effect calculations where rebounds are calculated as a proportion of the energy savings attributed to the installed measure (here, total PV generation). We begin with a discussion of the general population analysis and return to the analysis of the no-cost program installed systems in the final section.

General Population Analysis

Figure 2 shows the monthly average actual post-period energy usage, partitioned by usage type, along with the estimated counterfactual, aggregated across all customer segments in the general population analysis. The difference between the counterfactual series (red line) and the top of the bars represents the estimated impact of PV installation on energy consumption. The annotation above each bar indicates the amount of consumption change (as a percentage of counterfactual electricity usage). The 90% confidence interval for the counterfactual is shown as a light red ribbon. However, it is small enough to be fully hidden by the counterfactual line.

Overall, solar adopters show a statistically significant increase in electricity consumption across all months of the year in the general population analysis. The shoulder months show the largest impact, exceeding 20% usage increases in May, June, and September. The peak summer months of July and August show the lowest consumption changes, both as a percentage and in absolute kWh change. These findings are weather normalized, and as such are not driven simply by different weather patterns in the pre and post period. These results may be indicative of increased flexibility in electricity consumption. For example, the perceived 'free' energy generated by customer's PV systems may encourage adopters to more freely utilize their HVAC systems to maintain a higher standard of comfort during shoulder months, whereas peak summer HVAC usage may have already been near its ceiling prior to solar adoption.

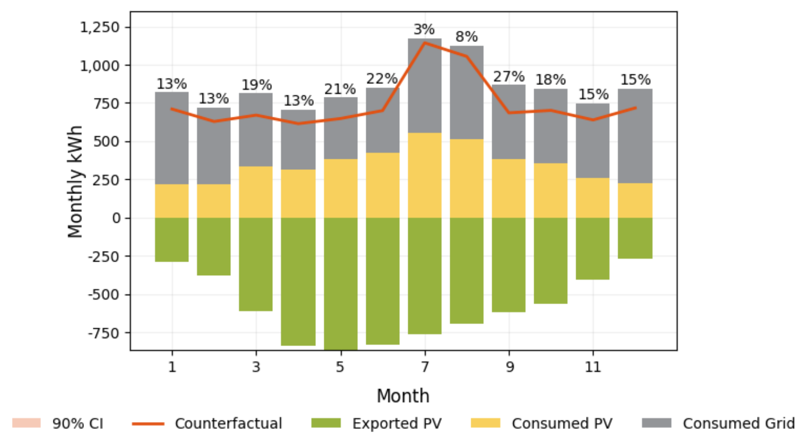

Figure 2. Monthly actual and counterfactual kWh.

Table 2 presents the annual average monthly consumption by customer segment, along with the resulting impacts for the general population analysis. All customer segments show statistically significant (at 90% confidence) increases in consumption coinciding with PV adoption, ranging from 7% to 25%. Consumption increases vary substantially by customer segment. At a high level, the Mountain climate region shows the highest consumption increase, and the Coastal-Inland and Desert climate regions show the lowest consumption increases. Additionally, while large customers show the highest consumption increase in monthly kWh, the small sized customers show the highest consumption increases as a percentage of their overall usage.

Finally, PV adopters who are also EV-owners tend to show slightly higher consumption increases than their non-EV owner counterparts. The following sections explore differences by customer segment in more detail.

Table 2: Average monthly consumption change by customer segment, general population

		Non-EV Owners				EV-Owners			
		Average Monthly Usage (kWh/h)		Consumption Increase		Average Monthly Usage (kWh/h)		Consumption Increase	
Climate Region	Size Class	Actual	Counterfactual	Monthly kWh	Perc.	Actual	Counterfactual	Monthly kWh	Perc.
Coastal	L	1,113	1,019	93	9%	1,236	1,090	146	13%
	M	649	557	92	17%	740	641	98	15%
	S	373	312	62	20%	450	366	84	23%
Coastal-Inland	L	1,173	1,046	126	12%	1,243	1,095	148	13%
	M	667	594	73	12%	773	645	128	20%
	S	387	337	50	15%	458	376	81	22%
Inland	L	1,189	1,042	147	14%	1,353	1,189	164	14%
	M	700	608	92	15%	824	677	147	22%
	S	410	326	84	26%	-	-	-	-
Desert	L	1,193	1,116	77	7%	-	-	-	-
	M	687	595	92	15%	-	-	-	-
Mountain	L	1,205	969	236	24%	-	-	-	-
	M	731	587	144	25%	-	-	-	-

Consumption Changes by Climate Region

Figure 3 shows the monthly average actual post-period energy usage, partitioned by usage type, along with the estimated counterfactual, with results for each climate region shown separately. As in the previous section, the 90% confidence interval for the counterfactual is shown as a light red ribbon. However, it is often small enough to not be visible on the plot.

Similar to results shown in Table 2, both Coastal and Coastal-Inland regions tend to show lower consumption increases than those in the Inland region. The Mountain region shows the highest impacts, with electricity consumption increases exceeding 30% in the late summer months (September and October). The Desert region, on the other hand, shows the lowest increases, with insignificant consumption changes in April, May, and July.

The lower impacts observed in the Coastal and Coastal-Inland climate regions are likely associated with the milder temperature patterns, resulting in less differentiation between shoulder and winter month usage. Similarly, the high usage increases in the Mountain climate zone may be associated with the substantial cross-year variability in temperature, with consistently high usage increases potentially indicating growth in both cooling and heating load. It is unclear why the Desert region shows the lowest usage increases. It may indicate that customers in this region were already near the ceiling of their household usage in the pre-period. However, other factors such as potential differences in fuel sources (as seen in Elliot and Shelton 2022) as well as differences in post period home upgrades (such as shell improvements, electrification, etc.) likely also play a role in observed differences by climate zone.

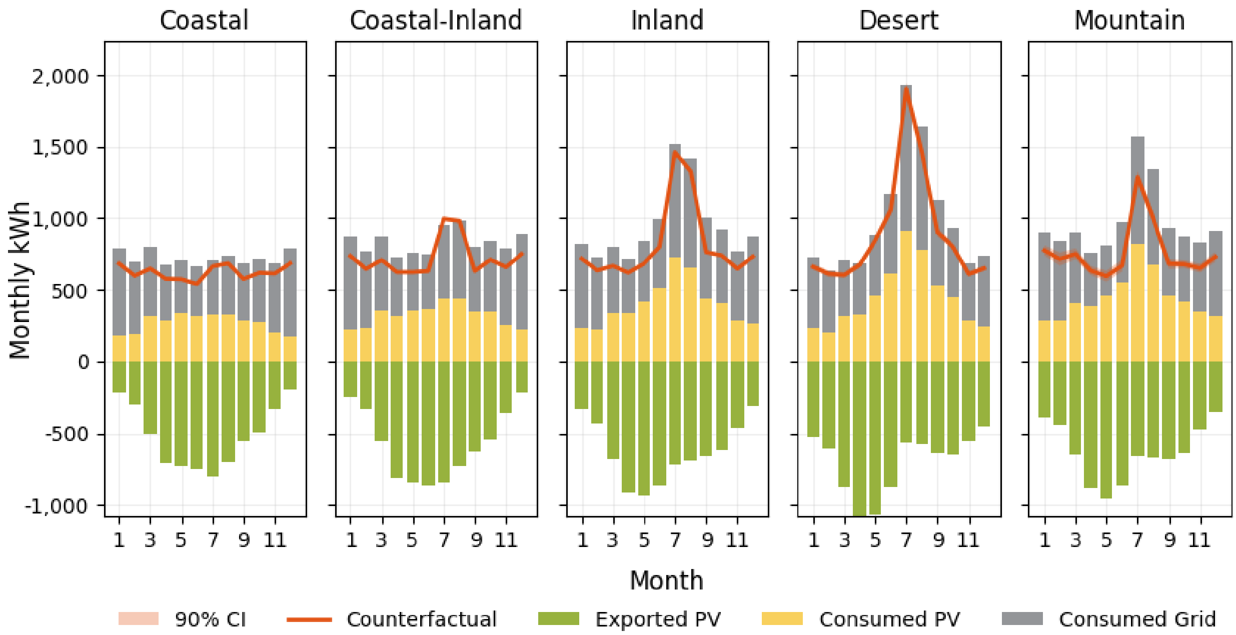

Figure 3: Consumption increases by climate region.

Consumption Changes by Size Group

Figure 4 shows the monthly average actual post-period energy usage along with the estimated counterfactual, with results broken out by customer pre-period size. Consistent with the annual results, large customers show the highest usage increases in absolute kWh, but small customers show the highest usage increases as a percentage of baseline consumption. Usage increases for small customers exceed 20% in eight months of the year, as compared to only two for large customers. Customers of all sizes show similar monthly patterns in usage changes, with the highest impacts occurring in shoulder months.

One potential explanation for this trend is that PV systems are more oversized for customers in the small usage group than those in the large group. Over the year, small usage customer exports equal ~100% of gross consumption, while large customers export ~60% of their gross consumption. Having an oversized system may reinforce the sentiment that energy is ‘free’ and, as such, contribute to increased flexibility in electricity consumption among smaller consumption households. Additionally, the systems may have been purposely oversized in anticipation of adding new end uses or increasing cooling load. A similar trend in usage increases by customer size class was also noted in an analysis of consumption change by PV adopters in SDG&E territory (Elliot and Shelton 2022).

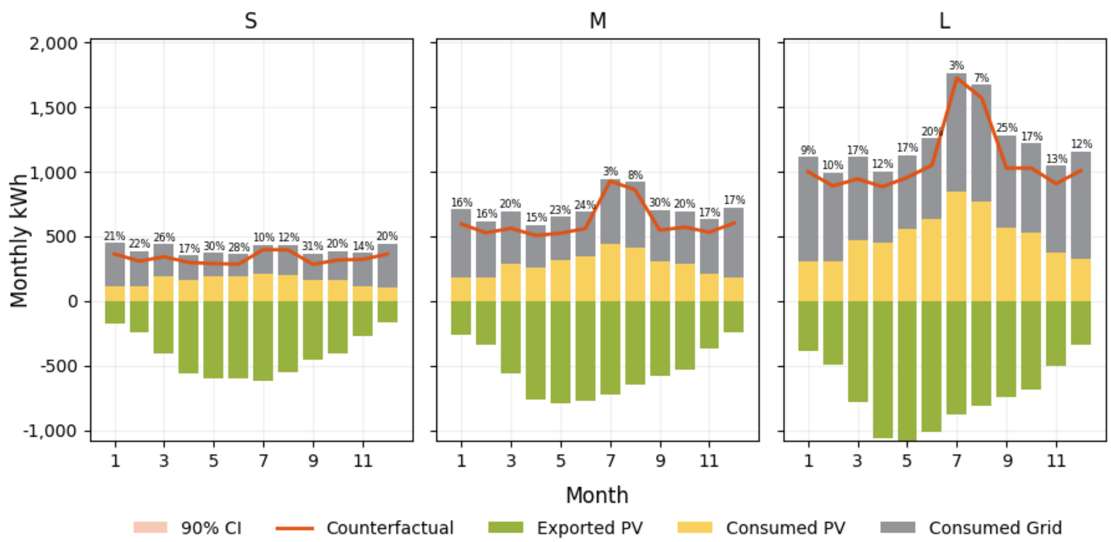

Figure 4: Consumption increases by customer size class.

Consumption Changes by EV Ownership

For the final comparison of the general population analysis, Figure 5 shows the monthly average actual post-period energy usage, partitioned by usage type, along with the estimated counterfactual, with results for each customer size group shown separately. Because there was insufficient sample of EV owner solar adopters in the Mountain and Desert climate regions, only data from the Coastal, Coastal-Inland, and Inland climate regions is included for this comparison.

EV owners tend to increase electricity consumption more than non-EV owners. However, the overall differences are small, at a maximum of four percentage points in September. In terms of absolute kWh consumption changes, EV owners show increases between 15 and 54 kWh per month higher than non-EV owners, which is largely attributable to their higher average overall consumption.

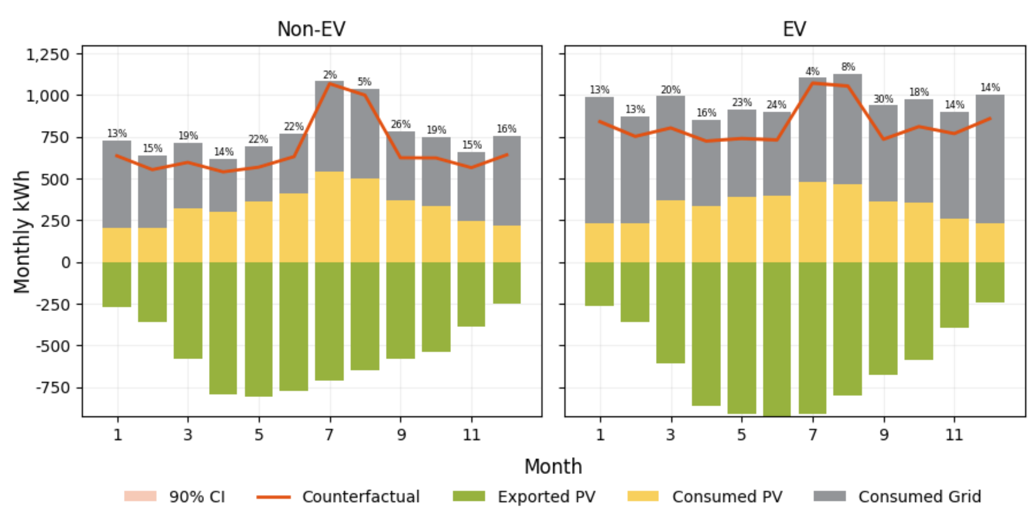

Figure 5: Consumption increases by EV-ownership.

Analysis of customers in the no-cost solar program

Figure 6 shows the monthly average actual post-period energy usage, partitioned by usage type, along with the estimated counterfactual, aggregated across all customers in the no-cost solar program analysis. As in the general population analysis, these customers show significant electricity consumption increases in most months of the year. However, consumption increases were not statistically significant in August or September. The monthly trend in usage increases is also similar to those in the general population, with the lowest increases in peak summer months and the highest increases in shoulder months, though the increases in this analysis are most prevalent in April through June.

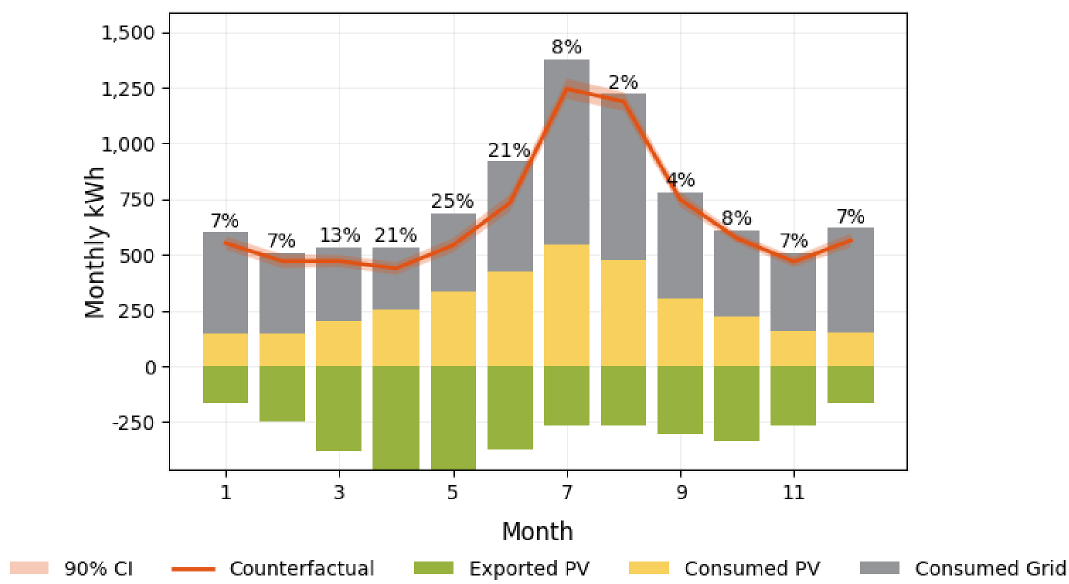

Figure 6: Consumption Increases for no-cost solar program participants.

Table 3 presents the annual average monthly consumption by customer segment, along with the resulting impacts. The customers in the no-cost solar program show a statistically significant (at 90% confidence) increase in consumption coinciding with PV adoption of 10%. This increase is quite similar to, though marginally lower (by approximately four percent points), than similar customers in the general population analysis. This difference is within error bounds for this estimate.

Table 3: Average monthly consumption change by customer segment, no-cost solar program participants

		Average Monthly Usage (kWh/h)		Consumption Increase	
Climate Region	**Size Class**	**Actual**	**Counterfactual**	**Monthly kWh**	**Percent**
Inland	M-L	733	667	66	10%

We can gain some insight into these consumption changes from a survey of 146 participants in the no-cost solar program. Many of these participants reported making energy related changes to their home after their solar panels were installed. For example, 10% of the customers reported installing EV chargers at their home. EV charging adds substantial additional electricity consumption to households, so this may drive a sizable portion of the observed usage increases. Additionally, six customers reported installing electrification measures (e.g., replacing a gas baseline with an electric appliance) that would also result in increased household electricity consumption (including water heaters, kitchen stoves, and laundry appliances). Participant responses also indicate that solar installation changed how they felt about their ability to use energy at home. For example, 65% of respondents indicated that they were less stressed about using their appliances after program participation and 67% indicated that they were less stressed about their energy usage overall. In the open-end response section, multiple participants highlighted that they specifically felt more comfortable with utilizing their air conditioning systems as a result of their program participation.

On the other hand, responses also showed substantial uptake of energy efficient upgrades including 19% of respondents indicating they had made shell upgrades to their home and 17% of respondents reporting an upgrade to a smart thermostat. These efficiency upgrades may mitigate some of the increased consumption from EV chargers, electrification, and additional behavioral changes (such as increased HVAC usage or altering responses to TOU rate structures). More research is necessary to understand the relative contributions of each of these changes to the overall observed consumption increases. Additionally, conducting similar research with general population solar adopters would be an exciting future avenue to better understand how the drivers of consumption change after solar installation may be similar or different to those seen for the no-cost solar program.

Conclusion

We identified widespread increases in electricity consumption following installation of solar. The overall general population analysis shows electricity consumption increases of approximately 15%, though the magnitude of these increases depends on a range of factors, including climate region, average pre-period usage, and electric vehicle ownership. The analysis of customers participating in a no-cost solar installation program showed consumption increases of 10%, though this only included medium to large sized Inland customers. These increases represent meaningful reductions in the expected grid-benefits of residential solar, suggesting that post-installation consumption increases may erode the benefits of more than 1 in 10 residential solar PV systems installed in California.

One limitation to the general population analysis is its reliance on simulated generation data. However, we have tested our PV simulations against actual metered data and find it to be accurate at the daily level. Additionally, the consistency of the general population analysis findings and the findings from the analysis of the no-cost solar program (which relied on actual metered data) suggest that the results of the general population are indeed robust.

While these analyses add to the growing body of evidence that solar adopters increase their usage after installation, they cannot explain why these consumption changes occur. The survey of customers who participated in the no-cost solar program shed some light on this question, demonstrating that many customers make meaningful energy-related changes to their households after solar installation, ranging from shell upgrades to installations of EV chargers.

More research that pairs analyses of consumption change with systematic monitoring of energy related household changes would be valuable to expanding understanding of these results.

Another important avenue for future research concerns the policy implications of these findings, particularly regarding residential versus utility scale solar. Recent evidence suggests that utility scale solar avoids the solar rebound effect (Oliver 2023), meaning that same installed PV capacity would offer greater grid benefits when deployed at the utility rather than the residential scale. On the other hand, residential scale solar offers additional advantages beyond direct grid benefits that should be considered in policy decisions. For example, residential solar offers a significant avenue for reductions in household energy burden, especially for low-to-moderate income adopters (Forrester et al. 2024).

Finally, research suggests that the primary driver of the SRE under net billing structures is the perception of access to "free" energy (Qui, Kahn, and Xing 2019). With the introduction of the Net Billing Tariff (NBT) in California – which reduces financial return on solar exports, it is possible these results will change substantially for newer solar installations. Conducting similar analyses on more recent solar installations will be of great interest to updating load forecasting efforts, considering potential future rate designs, and informing policy decisions in solar rich territories.

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