Residential Solar and Changes in Consumption of Electricity

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ABSTRACT

This paper summarizes the methodology and results from analysis to assess whether residential customers with solar panels exhibit any increase in gross energy consumption in the year following installation of the photovoltaic (PV) systems. Using samples of San Diego Gas & Electric (SDG&E) customers on the NEM 2.0 rate, the analysis employed statistical models to compare pre- and post-installation consumption, controlling for weather and other effects. The analysis also identified customers on electric vehicle (EV) rates to control for the presence of EVs. The samples were segmented by climate zone, customer size, and fuels used.

The analysis found compelling evidence that total consumption increased by percentages ranging from roughly 7% to 18% depending on the customer size, fuel, and climate zone. The largest percentage increases generally were associated with smaller customers and those on electric only rates. Across all segments, the largest increases in electricity consumption were associated with high cooling load months. For electric only customers, larger increases in consumption were also observed in periods with higher heating load.

The impact of PV installation on electricity consumption found in this analysis may be associated with electrification and/or behavioral change. If behavior is driving the increased usage, grid constraints may manifest sooner and be larger than anticipated. If electrification is a cause, these results suggest that homes are jointly adopting electric appliances and PV. While these findings do not identify the cause of increased usage, they may justify additional research to better understand why it is occurring.

Introduction

The question of whether the installation of solar panels results in an increase in overall energy usage has long been a subject of conjecture and speculation. With more than a million systems and more than eight GW of behind-the-meter PV systems in California, it is more important than ever that utilities understand and account for this phenomenon in designing programs, setting incentives, and conducting system planning.

Historically, the evidence for this phenomenon has been mostly anecdotal. The hypothesized changes in usage stem from behavioral changes (e.g., some sentiment that the electricity generated by solar panels is "free") or the addition of load (e.g., an electric vehicle or air conditioning). While these potential effects seem generally logical, there has been relatively limited investigation into the topic and the available evidence has not been consistent or definitive. For example, McAlister (2012) found a small decrease in first year electricity consumption with no persistent effects. In contrast, Shelton (2020) presented evidence of a small increase in usage for residential customers.

This paper presents the findings from an analysis conducted on data for SDG&E residential customers on the NEM 2.0 rate, comparing their consumption before and after the installation of their solar systems. The objective of the analysis was to assess how total electricity consumption changes in the year following the installation of solar panels and identify the extent to which climate zone, overall customer size, and the presence of electric vehicles play a role in the observed changes.

It is important to emphasize that this analysis does not address the question of why customers might alter their consumption. It is an important matter with implications for program and rate design at a minimum, but it would require substantial investment to collect the data necessary to answer with any robustness. Instead, this research addresses how much consumption changes, when these changes occur, and what factors help to differentiate customers that exhibit changed electricity consumption. The findings in this paper provide compelling evidence for the need to conduct more intensive research into the question of why these changes occur.

Data Sources

The analysis represented in this paper relied on four data sources, which are described below. These data were used to generate a fifth source of data, which was the simulated PV generation, which is a critical component to determining the total consumption.

- **PV System Information**: The key elements from these data are the size of the system and its orientation (tilt and azimuth), which are necessary to estimate the PV generation. These data were also used to remove customers where batteries were also installed, since accounting for energy storage would have further complicated the analysis.
- **Utility Customer Information**: In addition to establishing that the customers were residential, these data helped to determine the correct climate zone and weather station. They also included information on the rate class, which was used to determine when customers were on EV rates. While imperfect, this information at least indicates the potential presence of an electric vehicle.
- **Utility Customer AMI Data**: Hourly kWh values representing the customer net consumption. For the pre-installation period, these data represent total consumption. After installation of the PV systems, these values represent the consumption net of PV generation.
- **Weather Data**: Hourly temperature and solar irradiance data as well as the latitude and longitude of the weather station. These data are used in both statistical modeling to control for the effects of weather but also were critical to the generation the simulated PV generation. For these inputs, this study relied on data extracted from the public API from the National Solar Radiation Database.[1]

PV Simulation

This study explores whether customers' total energy usage changes after the installation of PV systems. After PV installation, a household's total kWh consumption is calculated by adding the net kWh from the energy provider and the energy produced by the PV system. While the net kWh is provided by the AMI Data, the generation of individual PV system is not available for large populations, so it must be simulated.

For the PV generation used in this study, we relied on the Python "pvlib" package, which is a vetted and well-maintained library based on work of the Sandia National Laboratories to produce realistic simulations of hourly PV generation given weather data and a set of specific system characteristics.[2]

For this study, the key inputs to the PV simulation were the system size, tilt (the angle of the panels), azimuth (direction they are facing), and the geographic location (climate zone). Based on analysis of the program tracking data, simulations of a 1 kW DC system for 36 discrete bins for tilt and azimuth were generated for each climate zone to produce 108 series of hourly simulated PV generation for 2015 to 2019. These series based on 1 kW systems were merged with the individual accounts based on climate zone and the corresponding bins for tilt and azimuth and then scaled up based on the actual customer-specific system sizes.

[1] URL for API for weather data: https://nsrdb.nrel.gov/data-sets/api-instructions.html
[2] URL for documentation on "pvlib": https://pvlib-python.readthedocs.io/en/v0.2.0/

Customer Segmentation

As a means of isolating factors relevant to the research topic and minimizing sources of variability that could confound the interpretation of results, the analysis placed customers into separate bins for analysis based on the following attributes:

- **Climate Zone**: Based on the utility data, whether the customer home is in a coastal, inland, or mountain region.
- **Fuel**: Based on the utility data, whether the home is all electric or dual fuel.
- **Size**: Based on an analysis of monthly billing data for the pre-installation period, customers were allocated to groups based on annual consumption. The groups were small (S), with less than 5,000 kWh, medium (M), between 5,000 kWh to 10,000 kWh, and large (L), ranging from 10,000 kWh to 25,000 kWh. Customers with annual consumption more than 25,000 kWh were excluded from the analysis due to a limited number of accounts.

After cleaning the data, removing all account with an insufficient information in either pre or post installation periods, the final analysis data set was based on including all customers on EV rates and then random sampling for 2,000 accounts for the remaining strata. If a segment had fewer than 2,000 accounts, all accounts with sufficient cleaned data were included in the analysis. The starting and final counts are presented in Table 1.

Table 1. Accounts in Sample Frame and Final Analysis Data by Segment

Climate Zone	Fuel	Size	Accounts in Raw Data	Accounts in Model	Accounts in Model on EV Rate
Coastal	Dual Fuel	S	5,064	1,711	46
		M	15,331	2,015	254
		L	6,832	2,003	245
	Electric	M	337	121	0
		L	324	127	0
Inland	Dual Fuel	S	5,001	1,582	15
		M	19,292	1,929	156
		L	8,250	1,887	123
	Electric	M	1,118	371	0
		L	1,712	720	16
Mountain	Dual	M	368	118	0
		L	346	140	0
	Electric	L	255	97	0

METHODS

This study employed regression modeling on approximately one year of both pre- and post-installation data to assess the impact of PV installation on electricity consumption. Specifically, the approach estimated a fixed effect panel data model using ordinary least squares regression with a robust clustered error structure. In this case, the fixed effect represented the individual customers in each bin. In addition to different levels of time series aggregation (hourly, daily, or monthly), the model selection also explored using Statistically Adjusted Engineering (SAE) models with net load as the dependent variable and estimates of PV production as independent variables, as well as models of gross load with binary variables to indicate the post period. The results presented in this paper represent the findings from monthly SAE models. The final model specification is shown in Equation 1:

Equation 1: Monthly Net Consumption Model Specification

$$kWh_{it} = \alpha_i + \sum_{m=1}^{12} \left(\beta_{PV*m} \times (PV_{it} \times m)\right) + \sum_{m=1}^{12} (\beta_m \times m)$$
$$+\beta_{cdd} \times CDD_{it} + \beta_{hdd} \times HDD_{it} + \mu_{it}$$

Where:

- kWh_{it} is the net kWh for account I in month t
- α_i is the account-specific intercept associated with the fixed effect
- β_{PV*m} is the month-specific parameter estimate for PV generation
- PV_{it} is the total PV generation for account i in month t
- β_m is the parameter estimate for month m
- m is a dummy variable for the month
- β_{cdd} is the parameter estimate associated with cooling degree days (CDD)
- cdd_{it} is the monthly CDD using base 70 for account i in month t
- β_{hdd} is the parameter estimate associated with heating degree days (HDD)
- hdd_{it} is the HDD using base 60 for account i in month t
- μ_{it} is the error for account i in month t

The estimated parameters for the interaction of PV generation and month are what estimate the impact of PV generation on net consumption. Controlling for weather and calendar effects, if customers do not change their consumption following PV installation, the estimated parameters for these interactions will be -1.0, indicating the for each kWh of PV generation, net consumption decreased by one kWh. If the parameters are greater than -1.0, then each kWh of PV generation resulted in a smaller reduction to net consumption than expected. In other words, consumption increased.

Model Fit

It is important to know that the panel data models exhibited good fit before delving into the more relevant results. Using the overall model R^2 as the metric, the models all had values between roughly 0.62 to 0.73, which is a good range for the types of data used in this analysis. An interpretation of the R^2 is that it represents the percentage of variability in the dependent variable explained by models, so given the typical volatility of residential consumption, that the worst model explained more than 60% of the variation in monthly load should lend confidence to the overall reliability of the models.

Parameter Estimates

The far more relevant results from the modeling are the parameter estimates for the independent variables. For this report, the focus will be on those associated with weather (CDD & HDD), the PV generation, and the interaction of electric vehicle rates with month.

While not relevant to the main areas of interest, the parameters for CDD and HDD are important to assess the validity of the model specification. As shown in Table 2, all the parameter estimates are positive, which is important because a model that suggested a decrease in consumption with extreme temperatures would have questionable validity. Furthermore, the magnitude of the parameter estimates follows intuitive patterns with respect to customer size and fuel. For example, the parameter estimates for homes with larger consumption are larger than medium and medium is larger than small. Likewise, the HDD estimates for electric homes are markedly larger than the dual fuel homes, which will almost always have gas for the majority of heating load. All parameter estimates are statistically significant at the p <.001 level.

Table 2. Cooling (CDD) And Heating Degree Day (HDD) Parameter Estimates

Parameter	Coastal					Inland					Mountain		
	Dual Fuel			Electric		Dual Fuel			Electric		Dual Fuel		Electric
	S	M	L	M	L	S	M	L	M	L	M	L	L
CDD	0.772	1.390	2.315	1.252	2.101	0.533	1.009	1.697	0.855	1.295	1.023	1.133	1.487
HDD	0.117	0.234	0.267	0.538	1.042	0.092	0.143	0.196	0.435	0.891	0.212	0.603	1.214

The parameter estimates central to this paper are the interactions between month and PV generation, which are shown in Table 3. As explained previously, in the SAE approach, if household consumption does not change after PV installation – after accounting for weather and other effects - the net kWh should fall in proportion to amount of PV generation, which will result in a parameter estimate of -1.00. If the parameter estimates are greater than -1.0, then the model suggests that customer net consumption fell less than PV production and total customer consumption increased. All the parameter estimates are statistically significant at the p.<.001 level.

For all but three of the parameter estimates, the models suggest that the PV generation led to a smaller decrease in net consumption than expected, which means that total consumption increased. Additionally, there are some consistent patterns to where the parameter estimates are markedly greater than -1.0, primarily in the main heating and cooling months, with shoulder months in the spring generally much closer -1.0.[3] The interpretation of the parameters, however, is complicated by the variability in PV generation. As a result, a more meaningful discussion will come later in this paper where these parameters are translated into kWh impacts.

Table 3. PV Generation Monthly Interaction Parameter Estimates

Month	Coastal					Inland					Mountain		
	Dual Fuel			Electric		Dual Fuel			Electric		Dual Fuel		Electric
	S	M	L	M	L	S	M	L	M	L	M	L	L
Jan	-0.77	-0.82	-0.86	-0.68	-0.72	-0.83	-0.92	-0.95	-0.85	-0.85	-0.92	-0.88	-0.83
Feb	-0.81	-0.89	-0.92	-0.82	-0.79	-0.85	-0.93	-0.95	-0.83	-0.84	-0.79	-0.79	-0.74
Mar	-0.91	-0.94	-0.96	-0.93	-0.90	-0.92	-0.97	-0.99	-0.91	-0.93	-0.89	-0.88	-0.87
Apr	-0.95	-0.96	-0.97	-0.97	-0.94	-0.97	-1.00	-1.01	-0.98	-0.99	-0.97	-0.97	-0.97
May	-0.93	-0.95	-0.97	-0.91	-0.94	-0.90	-0.94	-0.96	-0.91	-0.95	-0.84	-0.85	-0.86
Jun	-0.99	-1.00	-1.01	-0.95	-1.00	-0.85	-0.89	-0.93	-0.89	-0.93	-0.94	-0.94	-0.99
Jul	-0.93	-0.94	-0.96	-0.90	-0.94	-0.82	-0.87	-0.92	-0.84	-0.88	-0.87	-0.86	-0.93
Aug	-0.83	-0.85	-0.87	-0.82	-0.84	-0.73	-0.79	-0.83	-0.79	-0.84	-0.86	-0.84	-0.92
Sep	-0.84	-0.85	-0.89	-0.81	-0.88	-0.82	-0.86	-0.88	-0.82	-0.87	-0.82	-0.83	-0.86
Oct	-0.83	-0.84	-0.87	-0.79	-0.85	-0.82	-0.86	-0.88	-0.81	-0.85	-0.86	-0.85	-0.84
Nov	-0.79	-0.81	-0.85	-0.73	-0.85	-0.80	-0.84	-0.86	-0.78	-0.79	-0.82	-0.82	-0.78
Dec	-0.74	-0.78	-0.81	-0.67	-0.71	-0.76	-0.83	-0.84	-0.76	-0.74	-0.82	-0.83	-0.68

[3] The hottest months in San Diego or the summer cooling months, are typically July, August, September, and October with the warming occurring earlier inland than coastal.

The final parameters of interest are the interactions of EV rate and month shown in Table 4. These parameters represent the increase in kWh in each month associated with accounts that are on an EV rate. Except for one parameter estimate, all the results show an increase in monthly consumption. There is some variation throughout the year, including a consistent decline in July relative to the other summer months. Unlike the previous parameter estimates, not all these results were statistically significant, which is indicated by an asterisk next the parameter estimate. Note, however, that the number of customers on EV rates in some of these segments with insignificant results is very small.

Table 4. EV Rate Flag Parameter Estimates

Month	Coastal			Inland			
	Dual Fuel			Dual Fuel		Electric	
	S	M	L	S	M	L	L
Jan	167.41	203.40	279.72	144.39	219.13	232.37	62.43*
Feb	143.52	210.35	286.26	121.32*	224.09	207.97	6.02*
Mar	164.13	213.69	282.15	139.27	237.62	246.60	73.63*
Apr	165.09	205.20	254.62	89.37	207.40	234.44	175.19*
May	179.22	206.31	264.63	105.21	227.58	273.69	175.18*
Jun	144.34	168.67	232.12	60.16*	165.30	201.06	206.31*
Jul	93.71	122.46	162.61	44.59*	75.37	104.64*	130.40*
Aug	104.48	143.71	200.59	14.30*	94.10	129.07*	89.56*
Sep	111.64	160.85	240.10	83.28*	128.25	165.19	20.48*
Oct	159.44	182.59	264.28	86.20	182.50	203.22	91.90*
Nov	172.72	196.15	266.00	99.03	200.35	217.44	82.33*
Dec	172.01	177.39	227.25	151.41	205.88	215.78	-13.83*

Interpretation of Observed and Counterfactuals

The results for the parameter estimates shown in Table 3 are ample evidence that homes increased their consumption after installing PV. However, it is more illustrative to quantify these impacts in terms of kWh impacts, which are calculated by using the model results to calculate estimates of gross consumption based on two scenarios. The first is “Actual,” where the estimated values are based on the actual data, and the second is “Counterfactual,” where the PV generation is set to zero. A third scenario where the EV rate flags were set to zero was also calculated to explore the impacts of EVs.

Based on these scenarios, Table 5 shows different estimates of average household consumption and the calculated impacts for each of the climate zone, size, and fuel bins for all accounts as well as by EV rate. Focusing on the results for all customers (where “EV Rate” = “All”), the increase in estimated gross consumption following PV installation ranges from ~6% to ~19%. The largest increases as a percentage are associated with smaller homes, although larger homes have greater absolute increases in energy consumption. The causes for this are largely speculative, but one explanation is that smaller homes simply have more potential ways to increase consumption, such as the addition of air conditioning. Homes with higher consumption largely already have most of the end uses.

Table 5. Comparison of Annual Actual and Counterfactual Consumption

Climate Zone	Fuel	Size	EV Rate	Gross kWh Estimated	Net kWh Observed	Gross kWh No PV	Gross kWh No EV	PV kWh Impact	PV Percent Impact	EV kWh Impact	EV Percent Impact
Coastal	Dual Fuel	S	All	4,826	-190	4,184	4,788	642	15.3%	38	0.8%
			No	4,785	-206	4,146	4,785	639	15.4%	-	0.0%
			Yes	6,699	539	5,918	4,921	781	13.2%	1,778	36.1%
		M	All	8,260	251	7,436	8,042	824	11.1%	218	2.7%
			No	8,031	157	7,217	8,031	814	11.3%	-	0.0%
			Yes	10,325	1,095	9,414	8,134	911	9.7%	2,191	26.9%
		L	All	14,693	1,562	13,656	14,394	1,036	7.6%	299	2.1%
			No	14,394	1,360	13,359	14,394	1,035	7.7%	-	0.0%
			Yes	17,353	3,363	16,305	14,393	1,048	6.4%	2,960	20.6%
	Electric	M	All	8,927	818	7,703	8,927	1,225	15.9%	-	0.0%
		L	All	15,994	1,850	14,264	15,994	1,730	12.1%	-	0.0%
Inland	Dual Fuel	S	All	5,070	-92	4,264	5,061	807	18.9%	9	0.2%
			No	5,060	-94	4,254	5,060	806	18.9%		0.0%
			Yes	6,298	102	5,378	5,159	919	17.1%	1,139	22.1%
		M	All	8,466	178	7,566	8,328	900	11.9%	138	1.7%
			No	8,324	102	7,428	8,324	896	12.1%	-	0.0%
			Yes	10,550	1,306	9,595	8,382	955	10.0%	2,168	25.9%
		L	All	14,504	980	13,403	14,374	1,102	8.2%	131	0.9%
			No	14,372	886	13,273	14,372	1,099	8.3%	-	0.0%
			Yes	16,824	2,652	15,685	14,392	1,139	7.3%	2,431	16.9%
	Electric	M	All	9,172	114	7,850	9,172	1,322	16.8%	-	0.0%
		L	All	16,054	1,467	14,318	16,031	1,736	12.1%	24	0.1%
			No	16,032	1,443	14,295	16,032	1,737	12.2%	-	0.0%
			Yes	17,076	2,566	15,391	15,976	1,685	10.9%	1,100	6.9%
Mountain	Dual Fuel	M	All	9,253	-516	7,998	9,253	1,255	15.7%	-	0.0%
		L	All	15,935	633	13,889	15,935	2,047	14.7%	-	0.0%
	Electric	L	All	15,857	674	13,887	15,857	1,970	14.2%	-	0.0%

Another observation related to home size is that three segments with a negative net kWh are comprised of the two small home segments and one medium. Despite this, these segments do show an increase in gross consumption, which means that the net kWh without an increase in post-installation consumption would have been even lower, which means that the PV systems for these segments were markedly oversized. Irrespective of home size, there is anecdotal evidence that installers encourage the upsizing of systems based on anticipated new end uses. This approach could be a more persuasive with these smaller homes, which might have more potential load to add than larger homes. An alternate and not mutually exclusive explanation is that there is an informal lower limit to the size of installed systems, so even if a smaller system might be adequate for a home's consumption, contractors will view smaller jobs as not worth the effort and this results in more oversized systems for these segments. These, again, are the kind of issues that merit additional research.

Although a secondary interest, the results in Table 5 also provide estimates of how much EVs increase household consumption. Based on the analysis, customers on an EV rate increase consumption from 1,100 kWh to 2,960 kWh depending on the segment, as shown in the rows where "EV Rate" is equal to "Yes." The variability in these numbers is not surprising given the uncertainty and volatility associated with electric vehicle usage in general. This is exacerbated in some cases by the small numbers of EV rate customers in each segment. Estimates of annual EV consumption vary, but some examples range from 3,400[4] to 3,600 kWh[5] to 4,000 kWh[6]. The estimates of EV consumption from the analysis fall short of all these estimates by varying amounts, but there are several mitigating factors. First, not all charging happens at home, so this would not be captured in the AMI data. Second, while most homes on an EV rate likely have an EV, there are many homes not on EV rates that also have EVs, which means there is surely some EV charging present in the baseline. Finally, EV rates also apply to plug-in hybrids, which have lower levels of charging. Given these considerations, the relative consistency of these results shows that the inclusion of the EV rate interactions in the model is at least having the intended effect.

As a final note on EVs, one recurring hypothesis has been that the acquisition of an EV is associated with the installation of PV because consumers install solar panels with the specific intent to charge an electric vehicle. While these data cannot establish a causal relationship, it is certainly true that EV rates were far more prevalent in the period after system installation. For those customers that were on an EV rate at any point, in the pre-installation period those customers were on an EV rate for around 48% of the time. In the post-installation period, this value increases to more than 80% of the time.

Monthly and Annual Impacts by Overall, Climate Zone, Fuel, and Size

To show how the individual segment results translate into overall impacts, Table 6 shows the actual and counterfactual estimated gross consumption by month and annually along with the resulting impacts. These series are based on averages of the results from the individual segments weighted by the number of accounts in the population. Overall, the analysis indicates that the NEM 2.0 customers increased their consumption by nearly 11% annually, with the largest increases in August and September, where cooling load is typically high. In contrast, the shoulder month of April has the lowest absolute and percent impacts.

[4] https://www.virta.global/blog/ev-charging-101-how-much-electricity-does-an-electric-car-use

[5] https://www.energy.gov/sites/prod/files/2019/12/f69/GITT%20ISATT%20EVs%20at%20Scale%20Grid%20Summary%20Report%20FINAL%20Nov2019.pdf

[6] https://news.energysage.com/how-many-panels-do-you-need-for-your-ev/

Table 6. Overall Monthly Impacts Summary

Month	Actual Gross kWh	PV Generation kWh	Counterfactual Gross kWh	PV kWh Impact	kWh Percent Increase	EV kWh Impact	EV Percent Increase
Jan	763.3	526.8	698.5	64.8	9.3%	14.0	1.9%
Feb	682.1	589.6	625.6	56.5	9.0%	14.0	2.1%
Mar	669.8	796.3	636.4	33.5	5.3%	14.9	2.3%
Apr	613.5	906.2	599.4	14.1	2.4%	13.7	2.3%
May	671.8	856.4	625.5	46.3	7.4%	14.4	2.2%
Jun	719.3	928.8	663.4	55.9	8.4%	11.5	1.6%
Jul	1,054.2	954.8	967.5	86.7	9.0%	7.3	0.7%
Aug	1,126.2	931.5	962.9	163.3	17.0%	8.7	0.8%
Sep	926.5	793.0	817.0	109.5	13.4%	10.3	1.1%
Oct	818.0	744.5	710.3	107.7	15.2%	12.3	1.5%
Nov	739.1	578.2	641.3	97.7	15.2%	13.2	1.8%
Dec	848.5	539.2	742.1	106.4	14.3%	12.4	1.5%
Total	9,632.3	9,145.6	8,689.8	942.5	10.8%	146.5	1.5%

As a visualization of the overall impacts, Figure 1 presents the data in Table 6 in terms of the estimated actual consumption broken out in stacked bars of exported excess PV generation, PV generation consumed by the household, and energy delivered by grid. The counterfactual consumption is presented as a red line. The difference between the top of the stacked bars and the counterfactual line represents the increase in consumption after PV system installation.

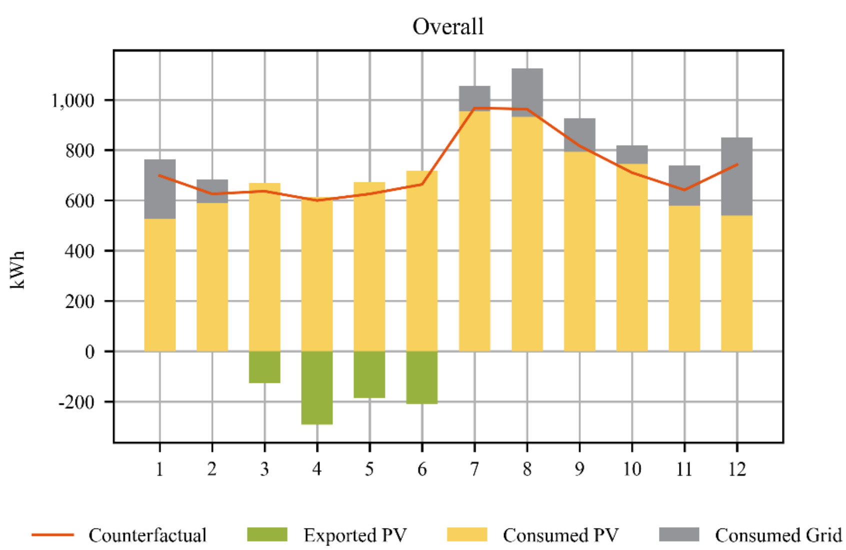

Figure 1. Overall Plot of Monthly Disaggregated Modeled kWh and Counterfactual

To show the effects associated with the different segmentation dimensions, Figure 2 through Figure 4 show the disaggregated estimates of actual load along with the counterfactual for aggregations by climate zone, fuel, and customer size, respectively. The main observation when comparing climate zones in Figure 4 is that coastal customers have smaller impacts, both absolute and as a percentage. The annual impacts in Table 5 corroborate this observation, but these figures show that this is associated with a far less pronounced summer peak, indicative of the milder climate. This is also true of the winter months, though the effect is less marked and surely diluted by those dual fuel homes. A secondary observation is that the mountain climate zone has larger absolute impacts, which is related in large part to its higher proportion of larger customers.

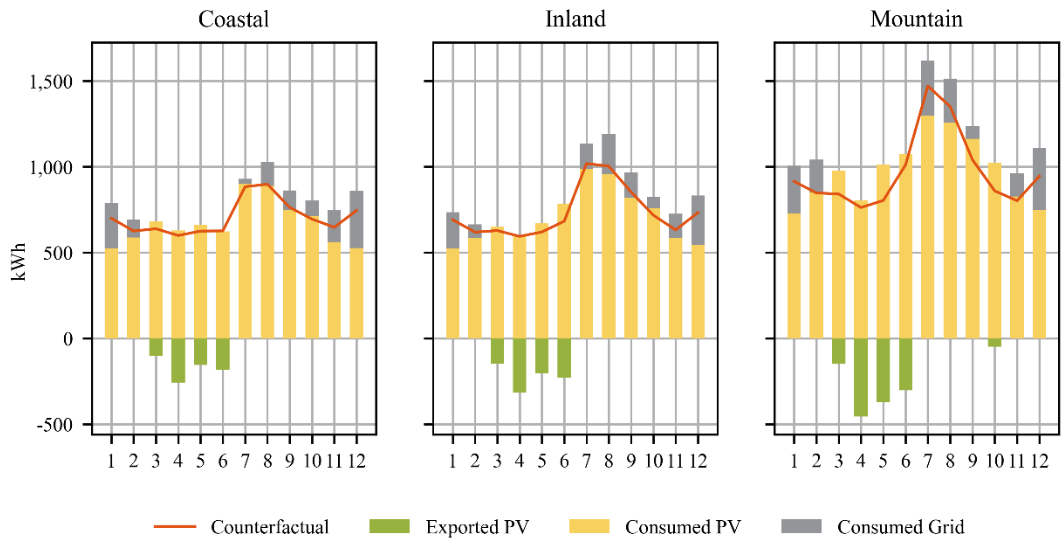

Figure 2. Plot of Monthly Disaggregated Modeled kWh and Counterfactual by Climate Zone

For the comparison of monthly profiles by fuel in Figure 3, the most salient observation is that not only is there more consumption in months with heating load, but the estimated increase in usage is also markedly higher for all electric homes. These results are logical, given that homes with dual fuels do not use electricity for primary heating, but are also likely to use gas for water heating and cooking. This further suggests that much of the increase in consumption in driven by cooling and, for electric-only customers, heating load.

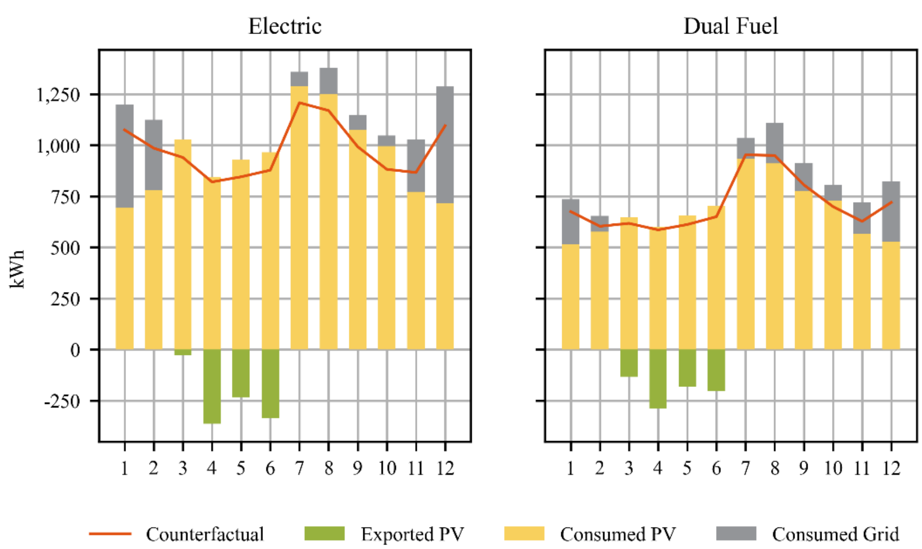

Figure 3. Plot of Monthly Disaggregated Modeled kWh And Counterfactual by Fuel

For the different customer sizes, Figure 4 shows that the absolute increase in energy consumption increases with customer size, although the underlying numbers show that the percentage increases have the reverse relationship. For August, which is when the largest increases in consumption occur, the small customers show a 25.5% increase, compared to 18.4% for medium and 13.9% for large. If the increases are related exclusively to behavioral effects, one would think that consumption would increase by similar percentages. The addition of more end uses – again, air conditioning the most likely culprit – would explain these findings, but the available data simply cannot tell us why increase in consumption are occurring.

Another interesting finding associated with customer size is the amount of exported surplus PV production. While the absolute quantity of exported energy increases with customer size, as a percentage of the total gross consumption the relationship is again reversed. Looking at April, which is the month with the most exported PV generation for all the customer sizes, the exported PV as a percentage of gross consumption declines from 59.6% to 52.4% to 40.1% for small, medium, and large customers, respectively. This might be associated with a higher prevalence of oversized systems for smaller homes, which was posited earlier as one explanation for smaller homes showing annual net export. This might seem contradictory to the idea that additional end uses are driving larger increases in the smaller homes. However, given that these exports are occurring in April, when cooling load is likely negligible, it is possible that smaller homes are being oversized, possibly in anticipation of added cooling, which leads to both observed phenomena.

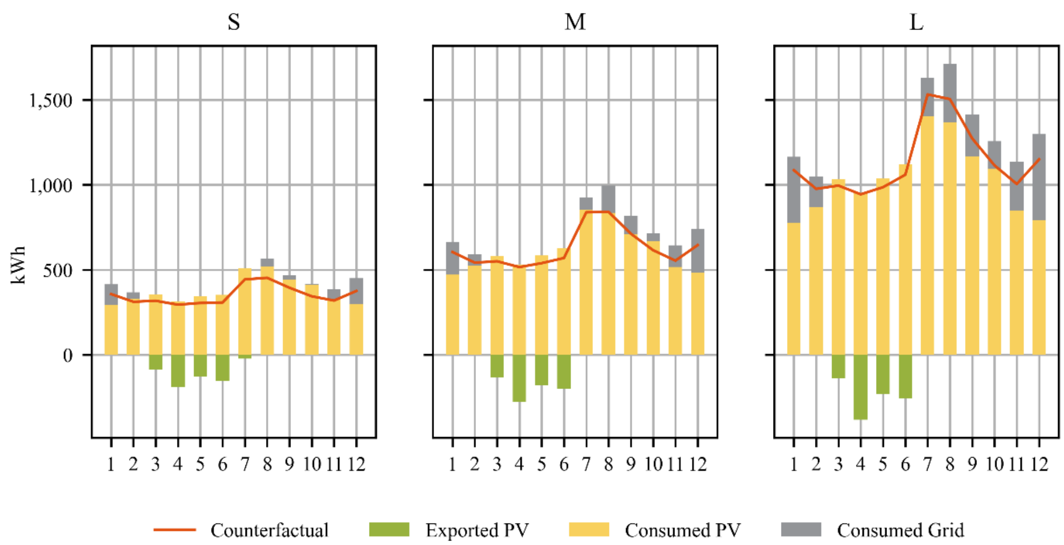

Figure 4. Plot of Monthly Disaggregated Modeled kWh And Counterfactual by Customer Size

Conclusion

The findings from the analysis suggest that for NEM 2.0 participants, who represent a broader and more representative population relative to early adopters of photovoltaics, there is strong evidence that usage of electricity increases substantially after installation. From a set of intuitive results with robust statistical properties, the overall increase in consumption is approximately 10% and is likely associated in large part with increased cooling and heating load.

If there is a major caveat to these findings, it is their reliance on simulated PV generation. Nevertheless, the available research on simulated PV generation is that while there are issues with precision at the hourly level, it is unbiased at the monthly level, so the aggregated monthly values used in this analysis should be sufficiently accurate representations of reality. Had they been available, actual metered generation would have bolstered the defensibility of the methodology and allowed for a more meaningful analysis of hourly data. It is unlikely, however, that using metered PV generation would alter substantively the conclusions presented in this paper.

While the analysis and results do not help explain why customers increase their consumption after installing solar panels, they are sufficient evidence to justify investment in additional research that would provide more useful information for utilities to account for this phenomenon in their rate and program design activities.

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