SOLAR IMPACTS: DOES DISTRIBUTED PRODUCTION AFFECT CONSUMPTION CHOICES?

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Abstract

As the role of distributed generation grows in the electricity industry, this growth is accompanied by questions regarding its impact on the rest of the system, chiefly the impact on finances, environmental footprint and reliability. Unfortunately, analyses of these impacts assume, *a priori*, that generation from distributed resources displaces generation from "somewhere else", usually centralized resources and a 1:1 basis. We examine the behavior of customers who install solar arrays on their homes and find that these customers increase consumption by 8-14%. That is, every 100 kWh generated by residential distributed solar displaces only 86-92 kWh from other sources. This result has profound impacts on the financial compensation of these resources, their role in reducing emissions, and their impact on system reliability.

I. Introduction

The decision to consume electricity, broadly speaking, is rooted in some combination of customer cost, comfort, and convenience. Traditional consumers receive a benefit from consuming electricity, and weigh this benefit against the cost of consumption. Businesses and other institutions receive a benefit from the effect of electricity service on their ability to conduct their business. Might customers think differently about electricity when they become producers and storage providers? Might they also think differently about their impacts when they are directly involved in networked information, environmental impacts, and planning?

This question becomes even more important when we consider the financial and policy implications of this behavior. Distributed generating resources are widely seen as a tool to achieve limits on emissions such as CO_2 (U.S. EPA 2015) and the proper compensation to owners of these resources is a current challenge, with states such as Minnesota (Minnesota Department of Commerce 2014) and New York (New York Public Service Commission 2017) establishing formal proceedings. If the kWh generated from distributed resources do not displace generation from other sources on a 1 for 1 basis, then the impact of these resources on the environment or the compensation due the owners of these resources may be either over- or under-stated. Further, utility resource plans will either over- or under-state the consumption of their customers and the resources that are necessary to meet those needs, affecting the sustainability of the electricity system. Indeed the New York Public Service Commission, in its Order on Net Energy Metering Transition, Phase One of Value of Distributed Energy Resources, and Related Matters, Case 15-E-0751 and Case 15-E-0082, on March 9, 2017, stated that compensating distributed generation at the hourly zonal market price “precisely reflects the costs that utilities are avoiding based on the injected generation"[1] explicitly assuming that one kWh of distributed generation displaces one kWh of generation from other sources.

This paper addresses the question of whether consumers' behaviors regarding electricity use are affected by their changing roles. We specifically examine whether households change their consumption after they install solar photovoltaic (PV) panels on their roofs. The possibility that behavioral factors might influence consumption is documented in other areas of the economic literature, but this would be the first application to sustainable distributed energy resources, of which customer-owned solar is a part. Even though customers' roles change, the analytical work to date on such alternative models assumes that customers do not change their consumption behaviors even though their roles change. There is good reason to believe that this assumption is incorrect. Customers might view money represented in credits they receive for putting electricity onto the grid as "house money", i.e., money given as a gift and not to be managed as carefully as earned money. In their analysis of house money, Thaler and Johnson (1990) found that subjects endowed with such funds became more aggressive consumers. It is also well known that customers who adopt practices that improve their energy efficiency exhibit what has become known as the rebound effect (Khazzoom 1980), where a 10% increase in efficiency, say, leads to something less than a 10% decrease in consumption because customers alter their consumption habits. Customers may also view themselves as providers of green energy and, believing that they have alleviated possible environmental externalities from energy consumption, exert less effort in being energy conscious. As another possibility customers with solar panels may increase their consumption while the sun is shining, viewing the consumption as potentially costless. Finally, the producer role may make customers more aware of their

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energy consumption habits, leading them to be more efficient in their energy use or to undertake additional initiatives that reduce electricity consumption.

Our paper addresses this effect for households who choose to install solar panels in a net metering setting, for an electric utility in Florida between January 2011 and April 2016 (i.e., the households self-select into the treatment). Studies of demographic characteristics of early renewable energy adopters suggest that those who self-select into renewable energy programs tend to be younger, more educated, and wealthier (Labay and Kinnear 1981; Mills and Schleich 2012; OECD 2011). According to Jacobsen, Kotchen, and Vandenbergh (2012), participation in environmental programs depends on household characteristics, attitudes related to the environment, and “warm glow” motives (participation that is due to “feeling good” rather than public benefits from reduced emissions, following Andreoni 1990)).

Whether customers change their attitudes and behaviors towards energy consumption has implications for business model changes, pricing, grid design, and terms and conditions for how customers interconnect with the utility grid. For example, every current model of compensating distributed generation, be it net metering, net billing, feed-in tariffs, or value of solar, assumes implicitly that one kWh of distributed generation displaces on kWh of generation from “somewhere else”. If this assumption is not true, the impacts on utility finance are profound. Therefore, it is important to understand how customers change as their roles change.

This question is important both for utility companies and consumers, and for the broader picture of the impacts of electricity on the environment. Distributed rooftop solar PV, a model for renewable energy production, has gained prominence over the last ten years with decreases in the costs of solar panels and government incentives for consumers to invest in this technology. It is often cited as a perfect substitute, in terms of kWh provided, for utility scale solar and other types of centralized generation, and a component of our electricity future. But does this model affect consumers' attitudes towards consumption?

II. Literature Review

We are not aware of any studies of behavioral responses to the installation of solar PV in households using differences in the timing of adoption. The study closest to ours, Havas et al (2015) compares the electricity usage of households who participated in a program involving incentives for an energy efficiency program and solar PV system discounts as part of a government program to a control group in the same town that was not subject to these incentives in Central Australia. The control group belonged to a different electricity provider with differing tariffs, but similar weather (given the physical proximity). Like our study, this paper also looks at pre-and-post program electricity usage. Our study differs in that we only focus on solar PV adoption, and that we study only the group of users who chose to install solar panels, taking advantage of the staggered timing of the implementation. We do not have to worry about tariff differences in our study because all households in our sample belong to the same utility company. The utility studied in Havas et al. (2015) provided a Feed-in-Tariff (FIT) for solar installations. The incentives provided by the program were for solar PV panels and solar water heaters. The combination of solar panels and FIT resulted in lower electricity bills. Households that adopted solar PV were analyzed 3 years after adoption and found to have a 6% increase in electricity usage.

Studies of electricity consumption (and electric appliance holdings) typically follow Dubin and McFadden's (1984) econometric model, in which the demand for consumer durables and the derived demand for electricity are considered related decisions which need to be modeled accordingly. Researchers collect data on appliances and their saturation (e.g., space heaters, water heaters, freezers, televisions) and come up with an electricity demand equation which typically includes variables such as household income, gas availability, number of rooms, marginal price of electricity, marginal price of gas, whether the user is a homeowner, etc. obtained from consumer surveys. Our paper differs from this type of study in that we are not studying the electricity demand equation itself (or appliance use) but rather examining behavioral responses in the form of changes in consumption as a response to the installation of a solar panel in the household. An implicit assumption of our study is that appliance use doesn't change dramatically during our study period.

Jacobsen, Kotchen, and Vandenbergh (2012) use monthly billing data from Memphis Light, Gas, and Water (MLGW) utility's Green Power Switch program (GPS) between 2003 and 2008 to compare households who participated in an environmentally friendly program to those who did not. The program, GPS, provided financing for electricity generation from renewable energy sources. Participation on the GPS program allowed customers to voluntarily increase the amount of electricity that was generated by "green" sources such as solar energy, wind energy, and methane gas by paying extra for this change in the fuel mix. They still received the same type of electricity as before, but contributed to a cleaner energy mix. Participation in the program resulted in additional charges to each participating household that ranged from \$48 to \$240 per year. Households could choose how many blocks of green energy to purchase. This study seeks to answer the question "why do households engage in pro-environmental behavior?" (i.e., voluntary provision of environmental goods), but also examines the behavioral response of households who participated in the program, and is similar to our study in that it exploits differences in timing of enrollment of participants (in addition to also comparing participants to non-participants). In a manner similar to our study, the authors combine household data provided by the utility with demographic characteristics at the zip code level obtained from the Census. The authors find that GPS participation does not lead to a statistically significant change in electricity consumption. However, when they only consider participants who enroll at the minimum level (i.e., those choosing to purchase just one block) and compare them to those who purchase multiple blocks, households increase electricity consumption 2.5% after enrolling in the GPS program. This behavioral response in consumption is not enough to negate the within household environmental benefits.

Keirstead (2007), studies behavioral responses to PV systems in the United Kingdom using interview data from households that installed solar panels. Even though the initial goal of this study was to assess electricity consumption before and after solar PV panels were installed, this was not feasible due to data limitations. The author instead, administered surveys with questions regarding other forms of energy initiatives adopted by households with PV, such as installation of insulation, efficiency of appliances, type of lighting, etc. The surveys suggest that those who installed solar PV panels reported a reduction in their overall electricity use, increased energy awareness and the use of energy efficient lighting.

A related strand of literature examines the relationship between energy and behavioral responses in the energy efficiency sector that is known as the "rebound effect". Whenever there is a rebound effect, expected gains from efficiency savings are not one-to-one because consumers alter their behavior. A consumer can, for example, drive more when owning an energy efficient automobile. This literature is summarized in Greening, Greene and Difiglio (2000), and has been studied for washers, vehicles, and other durable goods. For example Davis (2008) proposes a model where energy efficient washers cost less to operate, resulting in higher household use. His article addresses endogeneity by studying a field trial in which washers were replaced by the trial rather than purchased by the household, removing the self-selection bias that would exist if users purchased the washers themselves. The rebound effect is expected to occur through both an income and a substitution effect.

III. Solar PV System Adoption for an Investor Owned Utility in the State of Florida

In order to obtain and operate a household solar PV system consumers of investor owned utility companies in the state of Florida have to first complete a certified installation of the system. The utility company then interconnects the user's system to the grid and installs a bi-directional net meter. This net meter measures excess kilowatt-hours produced by the consumer's system. Excess electricity (electricity that is produced and not consumed by the household) is then delivered to the utility company's grid. Customers receive a credit for that electricity, based on their current retail electricity rate. More information about the rules and regulations pertaining to net metering in the state of Florida are available in Florida Public Service Commission's Rule 25-6 065[2] and at each utility's website.

In order to become connected, users must first self-select into the program. They must submit an application to the utility company, complete an interconnection agreement (interconnection agreements and requirements vary based on array size) and agree to an inspection of their system by the utility company. Once a user completes all these steps, the utility company replaces the household's traditional meter with a net meter. The utility company provides a list of certified solar contractors in good standing for the state of Florida.

IV. Data

[2] These rules are available in the FPS Commissions website: https://www.flrules.org/gateway/readFile.asp?sid=0&tid=5455200&type=1&File=25-6.065.doc

Our dataset was created by merging data from four sources. Our electricity data comes from an electric utility firm in Florida spanning several counties, this dataset was merged with National Oceanic and Atmospheric Administration (NOAA) weather data, NREL data, and demographic data from the U.S. Census.

The utility firm's dataset includes monthly consumption data for all customers who installed panels who were in the system during the period covered (145 households) that had pre- and post-solar panel installation electricity usage, for a total of 8,652 observations. The period covered spans from January 2011 to April 2016. The data provided by the utility includes: the size of the solar panel, the date the household became interconnected, the total installation costs, the type of inverter, the inverter manufacturer, and the household's zip code.

Total electricity consumption is given in kWh for the pre-solar panel period. For the post-solar panel installation period, the dataset contains information on kWh received (what the household "sold" to the utility firm), and kWh purchased (what the household purchased from the utility firm). The amount of electricity that was produced and used by the household is unknown. We create a proxy for this variable by using information provided by the utility on the size of the installation (in kW) and data from NREL's PV Watts Calculator[3] of the estimated monthly output per kW of installation for the area where the utility is located (which is available on a monthly basis)[4]. NREL's data is provided at the MSA level. We first calculate an estimate of total solar output by multiplying NREL's monthly output per kW of installation in our utility's city by the size of the installation (kW). Once we have the estimated total solar output, we know that:

[3] NREL's PV Watts Calculator is available at http://pvwatts.nrel.gov/

[4] While it is possible that NREL's numbers could be systematically overestimating solar panel output, we expect this to be unlikely since for some households we calculate negative electricity consumption (i.e., it works in other direction).

Estimate of total solar output = Electricity produced for self-use + Electricity produced and sold to the grid.

Since we already know how much electricity is produced and sold to the grid, we then just calculate:

Estimate of electricity produced for self-use = Estimate of total solar output – Electricity produced and sold to the grid[5].

We then supplement our dataset with demographic data that was obtained at the zip code level from the US Census ACS database[6]. These variables include average household size for owner occupied housing, median age, and median income. Our data span 983 zip codes[7]. It is important to note that while our consumption data is at the household level, our demographic data is at the zip code level.

We used the provided zip code to find weather data for Cooling Degree Days (CDD) and Heating Degree Days (HDD) for each year and month combination between January 2011 and April 2016 from the NOAA[8]. HDD and CDD are functions of average daily temperature often used to explain demand for electricity (Papalexopoulos and Hesterberg, 1990). They are the aggregate of the average daily temperatures either above (cooling) or below (heating) 65 degrees Fahrenheit. For example, if the average daily temperature is 70 degrees, then that day is said to have 5 cooling degrees. Data from the NOAA are provided on a zonal basis. Our data span two NOAA zones.

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[5] Using this method, 21 out of 4,577 observations end up with a negative amount of electricity produced for self-use (0.0046% of all observations). The negative values vary from -111 to -7 kWh. We change these values to 0 since negative electricity production can't occur. For two households, this number was negative and large. We dropped these two households from our sample, because their numbers imply that a small panel is producing much more than it would be expected to produce, even in the best weather and location conditions.

[6] The ACS did not have data for 2016 available, so our observations from January to April 2016, use demographic data from 2015. The ACS has an income category of 250,000+. We coded these incomes as 250,000.

[7] The ACS data has missing observations for some variables in a few zip codes.

[8] The NOAA data are available here: https://www.ncdc.noaa.gov/cag/time-series/us/8/4/cdd/1/1/2011-2016?base_prd=true&firstbaseyear=1901&lastbaseyear=2000

We created a dummy variable, "treated with solar", which takes a value of 1 if the household has a solar panel installed, and 0 otherwise. Data for household consumption before treatment ("pre solar monthly consumption") are available and used for dates before the solar panels were installed. Data for household consumption after treatment ("post solar monthly consumption") are calculated by adding up the variable "kWh delivered" (consisting of kWhs billed to customers) to our estimate of the portion of solar output that was produced for self-use (i.e, the solar output that was consumed by the household rather than sold to the grid). We estimate the model with and without fixed effects. Summary statistics are provided in Table 1.

Table 1: Summary Statistics

Variable	N	Mean	Standard Deviation	Min	Max
Size (kW)	8,541	8.37	2.79	1.02	20.5
Pre Solar (kWh)	3,964	1,724.13	1,018.40	34	9,114
Solar output sold to grid (kWh received)	4,577	429.47	268.30	0	1,650
Solar output for self-use (kWh)	4,577	607.42	319.93	0	2,537.25
Electricity billed to customer after solar panel installed (kWh delivered)	4,577	1,180.75	701.17	0	6,196
Post Solar (kWh)	4,577	1,788.17	934.63	40	7,542.90
Average household size (persons)	8,477	2.76	0.26	1.75	3.34
Median age of habitants (years)	8,477	37.6	5.31	29	73.6
Median income ($)	8,477	62,310.97	19,926.92	25,341	101,119
Cooling degree days (Df)	8,477	296	172.46	30	577
Heating degree days (Df)	8,477	45.94	69.31	0	344

V. Model

We use a differences strategy, taking advantage of how solar panels were installed on a staggered basis over time, providing rollover timing differences[9]. For example, in our dataset

[9] These differences are not shocks, since consumers self-select into the program.

person A installed the panels in March 2013, person B in January 2014, person C in April 2014, etc, as opposed to all customers installing their panels on the same date. This roll-out nature allows us to identify effects of the installation on behavior better than if everyone installed the panels at the same time (by allowing us to compare the customers to themselves and to customers who have yet to install solar panels without worrying about "something else" happening at the same time of our measurement of the treatment). Every household in our sample installed a solar panel at some point during the study period. For this reason, we expect our results to only apply to consumers who choose to install solar panels in their homes. A potential source of bias is that the timing of solar panel adoption could be endogenous. Using an example similar to one proposed by Jacobsen, Kotchen, and Vandenbergh (2012), suppose that a household experiences a change in personal ideology and decides to conserve electricity. This household would simultaneously install a solar panel and change their behavior to reduce its electricity consumption. This endogeneity would cause a negative bias to our estimate of behavioral changes.

We control for household characteristics by linking zip codes to Census data. We can also control for time-invariant differences between households via individual fixed effects. The control group is users before adoption of panels, taking advantage of differences in timing of installation of solar panels.

The empirical model can be represented by the following equation:

$$Y_{ht} = \beta_0 + \beta_1 \vec{X}_{zt} + \beta_2 S_{ht} + \beta_3 \overrightarrow{W}_{rt} + \beta_4 interaction + \tau year + \theta month + \varphi zip + \varepsilon$$

Where Y_{ht} is the log of the household's monthly kWh electricity consumption, $\vec{X}_{zt}$ is a vector of yearly time varying zip code-level demographic characteristics such as median income, S_{ht} is a binary variable indicating the presence of a solar panel in the household on a monthly basis. A household is considered as "treated" when a solar panel is installed and in all months thereafter. $\vec{W}_{rt}$ is a vector of variables representing Cooling and Heating degree days measured on a monthly basis by NOAA region. The model also includes month and zip code fixed effects (we also include year fixed effects in some specifications). We also tested interactions between HDD and treatment and CDD and treatment. Errors are clustered at the household level, so that standard errors are robust to serial correlation of residential electricity consumption.

VI. Results

Table 2: The impacts of solar panel installation of household electricity consumption

Variable	(1)	(2)	(3)
Treated with solar	0.0873***	0.1483***	0.1455***
	(3.75)	(3.81)	(3.76)
Average household size	-0.0073	-0.0064	No
	(-0.04)	(-0.03)	
Median age	0.0144	0.0144	No
	(1.43)	(1.44)	
Median income	$-1.18\text{x}10^{-6}$	$-1.18\text{x}10^{-6}$	No
	(-0.34)	(-0.34)	
Cooling degree days	0.0013***	0.0013***	0.0013***
	(9.99)	(10.15)	(10.32)
Heating degree days	0.0013***	0.0013***	0.0013***
	(6.11)	(5.87)	(6.02)
CDD*Solar installed	No	-0.00018**	-0.00018**
		(-2.47)	(-2.49)
HDD*Solar installed	No	-0.00017	-0.00017
		(-0.95)	(-0.97)
Monthly FE	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Dependent variable in logs	Yes	Yes	Yes

Note: The dependent variable is the log of the household's kWh monthly electricity use. *, **, and *** indicate significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the household level. Year is relative to 2011 and month is relative to January. N = 8,477 for models (1) and (2) and N= 8,541 for model (3) (given missing observations in the American Community Service data from the Census).

Our results suggest that, for the group of users who choose to install solar panels at their homes during the study period, households use 8-14% more electricity after the solar panels are installed. This result is consistent with Havas et al.'s (2015) study of solar PV and energy efficiency management's rebound effect. Variables important in determining monthly household electricity use include HDD and CDD, as expected, with higher or lower temperatures associated with greater electricity consumption. Another noteworthy result is the significance of the interaction term between solar installations and the consumer's response to CDD (higher temperatures). The coefficient is negative, suggesting that customers with solar panels consume less electricity on hotter days than those without. This empirical result mirrors the experimental results in Dominguez et al. (2011) which explored the effects of solar panels on roof heat transfer and concluded that the panels exhibited an insulating effect.

The policy implications of the main result are profound. Electricity demand in the United States is projected to be nearly flat through 2050, while solar generation is expected to grow rapidly (United States Energy Information Administration 2017). This growth in solar generation may spur unexpected growth in electricity consumption, affecting the planning processes used to ensure the sustainability of the system. Policymakers examining the role that distributed generation plays in allowing utilities to avoid investments in generation, transmission, and distribution capacity should be aware of any changes in consumer's behavior, as distributed generation may displace fewer resources than previously assumed from centralized sources.

Perhaps even more insidious is the degree to which this increased consumption may be opaque to the utility. If increased consumption as a result of the installation of solar panels is independent of whether those panels are actually producing electricity (a study that would require far more granular metering data than currently available), any interruption in the production capability of these solar PV systems (such as sudden cloud cover or system failure) would instantaneously impose the burden of that increased demand on the electricity grid. This heretofore hidden demand may not have been anticipated by the utilities and planning authorities, and may not have been accounted for in their resource planning decisions, potentially affecting the reliability of the system.

Finally, consumers make long term investment decisions in distributed generation with an expectation of when that investment will be repaid. Under net metering policies tied to prevailing retail rates, the revenue (or defrayed cost) stream is already uncertain, subject to the regulated rates of service. Unanticipated changes in their behavior potentially introduces additional uncertainty into the payback period for this investment, and if they do not recoup their costs within the expected time frame, it may inhibit future investment in this sector.

This analysis would be improved by utilizing metering data on distributed solar PV production, instead of the estimates that we have employed here. However, production metering of solar PV systems requires additional expense, and is not required by net metering, the most prevalent system of compensating distributed generation; therefore, its use is not widespread. As other compensation schemes for distributed generation are implemented that require production metering of distributed solar systems, the assumptions we've made here may be relaxed.

VII. Conclusion

In a manner similar to the rebound effect in the energy efficiency literature, households who self-select into solar panel home installations use 8-14% more electricity once the panels are installed. A possible explanation for this finding is that users feel that the electricity is costless when the sun is shining. Consumers may also view themselves as providers of green energy and, believing they have alleviated possible environmental externalities from energy consumption, exert less effort into being energy conscious (this is formally referred to in the literature as "moral licensing"). While we cannot make conclusions for the general population, we can, at the very least, argue that it is time to stop assuming that there is no change in behavior.

This result has a wide range of applications within the electricity sector. This result can be utilized to inform more robust compensation schemes for the owners of distributed generation. It is also critical to discussions of system planning and resource adequacy, to ensure the reliability of the electricity system, as well as the planning and future expansion of any home solar PV panel programs.

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