Investigating the Community Solar Rebound:

The Effect of Community Solar PV Adoption on Household Electricity Consumption

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Abstract

The recent literature has noted the existence of a solar rebound effect, or increase in household electricity consumption in response to the adoption of solar PV technology. This study investigates the solar rebound for households that have adopted shares of a community solar PV farm. Using four years of electricity consumption data from a Northern Colorado electric utility, this paper employs a difference-in-differences approach to estimate the effect of community solar adoption on household electricity consumption. This paper finds that households do not exhibit a solar rebound in the community solar setting. These results are robust to numerous specifications, samples, and analyses.

JEL Classification: Q42, Q47, Q48, Q55

Keywords: rebound effect, solar rebound, solar PV, community solar, electricity consumption

1 Introduction

The electric utility industry is facing a period of tremendous change, marked in part by increased penetration of renewable energy generation technology (MIT, 2016). Declining technology costs, favorable policy, and evolving consumer preferences have proven a powerful combination, driving a general increase in the share of energy generated renewably in the United States for the last decade (EIA, 2019, p. 22; MIT, 2016). Solar photovoltaic (PV) technology, in particular, has seen a tremendous rise in deployment, with total US generation capacity reaching 62.4 gigawatts (GW) in 2019, about 75 times the solar PV generation capacity in 2008 (Wood Mackenzie & SEIA, 2019, p. 5). While solar PV still only accounted for less than 2.5% of the electricity generated in the US in 2018, this number is projected to rise to nearly 15% by 2050 (EIA, 2019, p. 22). With the increased penetration of solar PV technology has also come a tremendous expansion of solar PV business models, each with unique customer segments, services, and revenue streams (Burger & Luke, 2017; Parida, Iniyan, & Goic, 2011).

As the number of solar PV business models continues to rise, it becomes increasingly important for utilities, policymakers, and providers of solar PV technology to understand electricity consumption behavioral changes that households exhibit in response to solar PV adoption within each model. This study is concerned specifically with an electricity consumption behavioral change known as the solar rebound effect. The solar rebound effect, a term inspired by the well-studied energy efficiency rebound effect, describes an increase in electricity consumption resulting from the adoption of solar PV technology (Deng & Newton, 2017; Havas et al., 2015; Oliver et al., 2017). The existing literature has found evidence of a solar rebound effect for households that have adopted solar PV in the form of private rooftop solar PV, the predominant form of distributed solar PV wherein a household installs solar PV generation technology on its rooftop (Deng & Newton, 2017; Havas et al., 2015). The presence of a solar rebound effect for solar PV adopters necessarily alters the public and private costs and benefits associated with solar PV deployment and may therefore be important for both public and private decision-makers in the solar PV landscape. Furthermore, the probable variability of the solar rebound across specific adoption demographics and solar PV business models necessitates investigation of the solar rebound across the wide-ranging solar PV contexts.

This study contributes to the understanding of the solar rebound effect by estimating the change in household electricity consumption resulting from adoption of solar PV technology in the form of shares of community solar. This paper terms this change the community solar rebound in the case that households exhibit an increase electricity consumption. Community solar is one the several emerging models of distributed solar PV, wherein members of a community jointly own a solar array, sharing the costs and benefits associated with ownership (Burger & Luke, 2017, p. 243; Farrell, 2010, p. 2; Funkhouser et al., 2015).

To estimate the community solar rebound, this paper uses four years of monthly electricity consumption data obtained from a Northern Colorado electric utility. The basic research design is a difference-in-differences (DID) estimation approach, taking adopters of community solar as the ‘treatment’ group. The community solar rebound effect is estimated for two groups of households: a ‘standard’ group of paying community solar subscribers and a low-income-qualifying group that subscribed to shares of community solar free of charge. Because of the staggered adoption of community solar within both adoption groups, this paper is able to lend particularly compelling evidence in support of the critical common trends assumption underlying DID estimation, adding considerable statistical robustness to the model estimates. The specific common trends assumption in this setting is that in the absence of community solar adoption, the electricity consumption of households that adopted community solar in a given period *would have* followed the same trend as that of other households in the sample that did not adopt community solar in that period. To assist in identification, the models exploit panel variation in the data by including fixed-effect controls across both household and time dimensions.

This paper finds that households do not exhibit a community solar rebound on average. These results are robust across multiple specifications and across multiple samples. Additional analyses show that these results do not change for a month-by-month after adoption analysis nor depending on pre-adoption electricity consumption levels. Analysis of the effect of temperature on the solar rebound shows some evidence, however weak, that households may make small temperature-related changes to electricity consumption, despite showing no change on average. This paper concludes that households that adopt community solar within this community solar context are unlikely to exhibit a community solar rebound effect.

This research contributes to three related bodies of literature. First and primarily is the rebound effect literature. Borenstein (2015) provides a foundational theoretical analysis of the energy efficiency rebound effect, decomposing the effect into component income and substitution effects. Chan & Gillingham (2015) build upon this theoretical framework, developing the first thorough exposition of the welfare implications of the energy efficiency rebound effect. The empirical literature estimates the *direct* energy efficiency rebound effect across many types of energy services, including personal automobile (Small & Van Dender, 2007), household cooling (Davis, Fuchs, & Gertler, 2014), appliances and lighting (Chitnis et al., 2013), clothes washing (Davis, 2008), and refrigeration (Davis, Fuchs, & Gertler, 2014).[1] Both Sorrell & Dimitropoulos (2008) and Sorrell, Dimitropoulos, & Sommerville (2009) provide a thorough survey and appraisal of this literature.

While the energy efficiency rebound effect has been studied extensively in the literature, there is a considerable dearth of literature investigating the solar rebound effect. At present, studies by Deng & Newton (2017) and Havas et al. (2015) constitute the only two empirical estimations of the solar rebound effect. Deng & Newton (2017) employ a quasi-experimental econometric approach, estimating a rebound effect of 4.5% to 8% of total household electricity consumption (p. 329). While Havas et al. (2015) calculate a rebound effect of 15% through a non-econometric approach, this approach likely suffers from biases attributed to a lack of control group, a lack of adequate controls for yearly or seasonal trends in electricity consumption, and the existence of endogenous energy interventions implemented at the time of solar PV adoption. This paper builds on the solar rebound literature by contributing a second regression-based estimate of the solar rebound and by contributing a first-in-the-literature estimate of the community solar rebound. Additionally, this paper builds on the solar rebound theoretical framework developed by Oliver et al. (2017) by accommodating the framework to the community solar context. Linking the behavioral economics and environmental economics literature, this paper proposes a second mechanism for rebound: a warm glow effect.

[1] Chan & Gillingham (2015) define the *direct* rebound effect as "the additional fuel use attributable to increased energy service demand when the implicit price of the service declines as a result of an energy efficiency improvement" (p. 134). This is in contrast to the *indirect* rebound effect, which the authors describe as "the increase in energy consumption from changes in the consumption of other goods and services due to improved energy efficiency in the product of interest" (p. 134).

This paper contributes to a second literature on green consumerism and the behavioral economics of energy consumption. Both social psychological literature and economic rational choice model literature detail the motivational complexity of environmentally-conscious consumer behavior (Sunstein & Reisch, 2014; Turaga, Howarth, & Borsuk, 2010; Yatish & Rahman, 2015). The literature has long-recognized that individual consumption behavior may be inconsistent with both individual values and material incentives, illuminating the existence of 'knowledge-action' and 'value-action' gaps in consumption behavior (Frederiks, Stenner, & Hobman, 2015). These terms describe a discrepancy between an individual's knowledge or values and their subsequent actions. Recent literature has extended this area of behavioral economics research to energy consumption behavior, examining situations in which energy consumption behavior departs from neoclassical economic predictions (Abrahamse & Steg, 2011; Baddeley, 2011; Claudy, Peterson, & O'Driscoll, 2013; Flynn, Bellaby, & Ricci, 2009; Jacobsen, Kotchen, & Vandenbergh, 2012; Poortinga, Steg, & Vlek, 2004). Other relevant literature acknowledges the possibility of a warm glow for 'green' electricity, wherein "households purchase green electricity in order to mitigate disutility associated with pollution emissions generated through their own consumption of conventional electricity" (Andreoni, 1990; Jacobsen, Kotchen, & Vandenbergh, 2012, p. 947; Kotchen & Moore, 2007). The analyses contained in this paper contribute to this literature by investigating the possibility of a warm glow effect as a mechanism for the community solar rebound.

Third, this paper contributes to the literature on renewable energy and smart grid technology applications. With the emergence of new solar PV business models and distributed energy resources (DERs) has also come a collection of research exploring how these technologies can be best applied by both governments and utilities to meet specific goals, such as those related to renewable energy penetration (Wiser, 1998), climate change policy (Pollitt & Shaorshadze, 2011), demand response (Haider, See, & Elmenreich, 2016; Muratori, Schuelke-Leech, & Rizzoni, 2014), and rate design (Diaz-Rainey & Tzavara, 2012; Hobman et al., 2016). Improved understanding of household electricity consumption behavior following the adoption of solar PV technology provides numerous benefits for the development of government and utility policy related to DERs, particularly in cases where policy outcomes are found to be highly dependent on behavioral factors, such as demand response incentive programs (Eksin, Deliç, Ribeiro, 2015) and renewable energy penetration strategies (Gyamfi & Krumdieck, 2011; Gyamfi, Krumdieck, & Urmee, 2013; Pichert & Katsikopoulos, 2008).

2 Community Solar

Community-scale solar, or community solar, is one of many emerging solar PV business models in the distributed solar PV generation universe (Burger & Luke, 2017). The National Renewable Energy Laboratory (NREL) (2010) defines community solar as "a solar-electric system that, through a voluntary program, provides power and/or financial benefit to, or is owned by, multiple community members" (p. 3). For many households, community solar is a viable alternative to private rooftop solar, or installation of solar PV technology on the household's rooftop. While many community solar business models exist, the most popular is the utility-sponsored model, wherein utility customers adopt shares of a utility-commissioned solar array (NREL, 2010, p. 6). This is the community solar business model featured in this study. Popular alternatives to the utility-commissioned model include special purpose entity models and non-profit models, each with accompanying legal and financial advantages and disadvantages (NREL, 2010, p. 6).

Community solar programs feature various financial arrangements between the array host and the solar PV-adopting households. Within most utility-sponsored models, community solar adopters participate by either making an initial purchase payment or making ongoing subscription fee payments. In some cases, as is the case for the program featured in this study, payment for enrollment may feature a combination of an initial payment and an ongoing subscription fee (NREL, 2010 p. 7-8).

2.1 Coyote Ridge Community Solar

The community solar array in consideration in this study is the Coyote Ridge Community Solar Farm, a 1.95 megawatt (MW) capacity single-axis tracking array located southwest of Fort Collins, CO. The site was commissioned in September 2017 by Poudre Valley Rural Electric Association (PVREA), with intermittent household adoption occurring thereafter. Of the 36,414 households serviced by PVREA that are included in the sample of this study, 226 households adopted community solar.

The 226 households that adopted community solar at Coyote Ridge belong to two groups. Group 1 consists of 95 households that participated in the *myLocal Solar* program. Subscribers to the *myLocal Solar* program pay a one-time initial payment of $48 per 0.32 kW share and a recurring monthly subscription fee of $3.46 per share. Households are subsequently credited on their monthly bill for the electricity generation corresponding to the generation capacity of the household's subscription. The maximum generation capacity a *myLocal Solar* household can adopt is limited to the lower of 120% of the household's annual energy usage or 25 kW.[2] There is a minimum adoption size of three panels, or 0.96 kW.[3,4]

Group 2 consists of 131 households that participated in the *PV For All* program. The *PV For All* program, facilitated in partnership with the non-profit GRID Alternatives and the Colorado Energy Office, provides qualifying low-income households with no-cost subscriptions to the Coyote Ridge Community Solar Farm. That is, qualifying households that subscribe are not required to pay the one-time initial payment nor the ongoing monthly fee. A household qualifies if its annual gross income is below a critical income threshold, specified based on the number of household residents and the county to which the household belongs. Specific annual gross income qualification criteria are included in Appendix 1. There are no other criteria by which households are assessed and all households meeting the income criterion are accepted. The maximum generation capacity a *PV For All* household can adopt is limited to the lower of 100% of the household's annual energy consumption or 6.08 kW. This maximum adoption level is much lower compared to that of the *myLocal Solar* group. Like households participating in the *myLocal Solar* program, *PV For All* subscribers are credited on their monthly bill for the electricity generation corresponding to the generation capacity of the household's subscription.[5]

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[2] Generation is projected based on an assumed panel generation of 465 kWh/panel/year.
[3] Examination of kW capacity adoption data shows there is, in fact, one household that adopted only one panel (0.32 kW), below the stated 0.96 kW minimum.
[4] Additional information can be found in PVREA's guidebook to *myLocal Solar*: https://www.pvrea.com/mylocalsolar.
[5] Additional information can be found on PVREA's *PV For All* web page: https://www.pvrea.com/pvforall.

3 Mechanisms for Community Solar Rebound

3.1 Conceptual Framework

Building on the conceptual framework for the solar rebound developed by Oliver et al. (2017), this section illuminates two general mechanisms for the community solar rebound. The section first constructs a demand function for a household's electricity consumption subject to the household's budget constraint *before* adopting community solar. Then, modifications are imposed to reflect a household's demand for electricity *after* that household adopts community solar. In taking the difference, the community solar rebound attributed to an income effect is shown, as well as the specific conditions under which a solar rebound will occur. A second mechanism for the community solar rebound is identified: the warm glow effect. The framework developed is consistent with the community solar program featured in this study, but is readily adaptable to alternative programs with appropriate modifications.

The basic conceptual framework is as follows. Take household with the two-good Cobb-Douglas utility function U with inputs of grid electricity, e_g, and of composite normal good (numeraire), x, which captures all goods and services consumed by a household besides grid electricity. Grid electricity (e_g) simply reflects household electricity consumption, but is indexed as 'grid' (g) to differentiate it from the electricity generated by a household's share of community solar, e_{cs}. The utility function is given by:

$$U(e_g, x) = e_g^{\alpha} x^{\beta} . \tag{3.1.1}$$

Assuming a household's spending cannot exceed its total household budget, it is imposed that the sum of α and β is equal to one. Consequently, α and β are equal to the optimal household budget shares spent on grid electricity (e_g) and the composite normal good (x), respectively.

Before community solar adoption, the budget constraint of the household with permanent income M spent on grid electricity (e_g) and the composite normal good (x) is given by:

$$M = p_e e_g + p_x x, \tag{3.1.2}$$

where p_e is the household retail rate of electricity set by the utility and p_x is the price of composite normal good x.

From the household's Cobb-Douglas utility function (3.1.1), it is possible to derive the household's demand curve subject to the budget constraint equation (3.1.2). Solving the Lagrangian

$$\max \mathcal{L}(e_g, x, \lambda) = e_g^{\alpha} x^{\beta} + \lambda(M - p_e e_g - p_x x) \tag{3.1.3}$$

provides the following household demand function for grid electricity (e_g) before a household adopts community solar:

$$e_g = \left(\frac{\alpha}{\alpha + \beta}\right)\left(\frac{M}{p_e}\right). \tag{3.1.4}$$

Following from the assumption that α and β sum to one, equation (3.1.4) is simplified to:

$$e_g = (\alpha)\left(\frac{M}{p_e}\right). \tag{3.1.5}$$

Now, examine the household demand for grid electricity *after* community solar adoption. Upon adopting community solar, the household's permanent income changes to

$$M^* = M - C - mn + p_{e,cs} e_{cs}, \tag{3.1.6}$$

where new permanent income M^* is equal to original permanent income M less the up-front fixed cost C of community solar adoption, less the monthly community solar subscription fee m times the number of months subscribed n, plus the credit to the household for its share of generation at the facility. Recall from section 2, households that adopt community solar in this study are credited for their share of community solar generation (e_{cs}) at the prevailing retail rate of electricity p_e. Despite this, this framework specifies the compensation rate for community-solar-generated electricity more flexibly as $p_{e,cs}$, allowing the compensation rate to vary from the retail rate of electricity (p_e). Components of this new budget constraint equation may vary based on the specific terms of a given community solar program.

Now, substituting M^* for M in the original household demand function, equation (3.1.5), yields the new demand function for e_g^*, household electricity after a household has adopted community solar:

$$e_g^* = (\alpha)\left(\frac{M - C - mn + p_{e,cs}e_{cs}}{p_e}\right). \tag{3.1.7}$$

Finally, by subtracting the original demand for grid electricity (e_g) from the grid electricity consumption after community solar adoption (e_g^*), the change in grid electricity demand resulting from community solar adoption is given by:

$$e_g^* - e_g = (\alpha)\left(\frac{M - C - mn + p_{e,cs}e_{cs}}{p_e}\right) - (\alpha)\left(\frac{M}{p_e}\right). \tag{3.1.8}$$

Simplifying and rearranging gives the following equation for the change in demand for grid electricity following community solar adoption:

$$\Delta e_g = \alpha\left(\frac{p_{e,cs}e_{cs} - C - mn}{p_e}\right). \tag{3.1.9}$$

The change expressed by equation (3.1.9) is considered a community solar rebound effect in the case that Δe_g is positive. Put differently, a rebound effect will occur when a household's compensation for its share of community solar generation exceeds the subscription costs of community solar to the household. This is expressed as the following inequality:

$$p_{e,cs} e_{cs} > C + mn \quad (3.1.10)$$

Equation (3.1.10) shows that the community solar rebound effect is driven exclusively by an income effect. This analysis of the income effect is consistent with the conceptual framework provided by Oliver et al. (2017), who suggest that the magnitude of solar rebound in the *private rooftop solar PV* setting depends on the solar panel purchase price and solar PV generation compensation structure. That the literature has identified the solar rebound as being entirely comprised of an income effect marks a critical critical difference from the energy efficiency rebound effect, which is comprised of *both* income and substitution effects (Borenstein, 2015; Chan & Gillingham, 2015). This difference is a consequence of the fact that energy efficiency improvements decrease the marginal cost of energy, whereas community solar adoption has no effect on the marginal cost of electricity for a household.

Building on the literature at the intersection of behavioral and environmental economics, this paper proposes a second mechanism for rebound: a warm glow effect. Numerous studies have suggested that individuals may experience a 'warm glow' in the 'green power' setting. Jacobsen, Kotchen, & Vandenbergh (2012) explain that the warm glow effect may occur when voluntary provision of a public good provides individuals with utility by "[minimizing] disutility from knowing their conventional electricity consumption generates emissions" (p. 949).[6] The

[6] In the case of electricity consumption, the public 'good' can be considered cleaner air from reduced pollutant concentrations or an atmosphere with reduced greenhouse gas concentrations.

warm glow effect from enrollment in green power programs has been shown to manifest itself through increases in household electricity consumption (Jacobsen, Kotchen, & Vandenbergh, 2012). This paper proposes that the warm glow may function similarly in this setting: adoption of community solar may lead a household to consume more electricity because adoption of community solar mitigates some of the household's disutility associated with its 'conventional' electricity consumption. Ma & Burton (2016) specifically describe the two types of warm glow effects identified in the literature: "a buy-in warm glow irrespective of commitment level and a contribution warm glow that depends on the commitment level" (p. 107). Both Jacobsen, Kotchen, & Vandenbergh (2012) and Ma & Burton (2016) find that the buy-in warm glow dominates in the green power setting. In the case of community solar, it is impossible to empirically distinguish the contribution warm glow effect from an income effect, as both increase as a function of kW generation capacity adopted. However, in the case that a rebound is observed, it may be possible to identify if the solar rebound is driven by a buy-in warm glow effect, as this effect would occur irrespective of kW generation capacity adopted.

3.2 Income Effect Calculation and Hypothesis

Using Coyote Ridge Community Solar Farm electricity generation data, county-level median income statistics, and income elasticities of demand for electricity estimates, this subsection conducts a back-of-the-envelope calculation of the anticipated rebound effect attributed to an income effect alone. This section abstracts away from the initial purchase payment for community solar adoption.

Based on 2017-2018 generation data, the 1.95 MW Coyote Ridge Community Solar Farm array generates an average of 7954.24 kWh/day, equivalent to 4.08 kWh/day per 1 kW of generation capacity.[7] Based on PVREA's flat rate tariff of $0.09396/kWh and a 31-day month, households receive an average of monthly payment of $11.88 per kW of community solar adopted. For the *myLocal Solar* group, this translates to a monthly payment of $1.07 per kW once net of the monthly community solar fee.[8] Taken at the average generation capacity adoption level of *myLocal Solar* adopters, 9.25 kW, this translates to an average payment of $9.90/month to *myLocal Solar* households. By contrast, due to the lack of a monthly fee, *PV For All* households receive a much larger average monthly payment of $60.11 when considered at the average generation capacity adoption level of 5.06 kW.

For *myLocal Solar* adopters, this paper translates payments from the utility to a percentage change in income using county-level median income data from the 2017 Census (U.S. Census Bureau, 2017). By taking a linear average of median income from Larimer, Weld, and Boulder counties, the median income for the PVREA service territory is estimated to be $76,273.34, or $6,356.11 monthly. Based on this income, the $9.90/month payment from PVREA translates to a 0.1557% increase in monthly income for *myLocal Solar Adopters*.

For *PV For All* adopters, this paper translates payments from the utility to a percentage change in income using the *PV For All* annual gross income eligibility guidelines. Based on a census-reported annual household size of 2.57 across Larimer, Weld, and Boulder counties from 2013-2017, the average household income for *PV For All* adopters is estimated to be $53,333.33,

[7] This empirical calculation is roughly consistent with PVREA's projection of 465 kWh per 0.32 kW panel per year, which translates to 3.98 kWh/day per 1 kW of generation capacity.
[8] Recall that the monthly fee for *myLocal Solar* adopters is $3.46 per 0.32 kW share, or $10.81/kW.

or $4,444.44/month (U.S. Census Bureau, 2017).[9] Based on this income, the $60.11/month payment from PVREA translates to a 1.35% increase in monthly income, nearly ten times that of the *myLocal Solar* group.

Based on a residential income elasticity of demand of 0.2, this paper hypothesizes that the income effect will induce increases in electricity consumption of 0.031% and 0.26% for *myLocal Solar* adopters and *PV For All* adopters, respectively.[10] These hypothesized increases in electricity consumption are very small and may be difficult to statistically differentiate from zero in empirical estimates. This is particularly true for the case of the *myLocal Solar* group, for which the percentage change in income and demand for electricity are likely to be overestimated due to abstraction from the initial purchase fee. Consequently, in the case that households increase electricity consumption notably in excess of these hypothesized changes, this may be evidence to suggest the existence of a warm glow effect as a mechanism for rebound.

4 Data

4.1 Data Description

This study uses an unbalanced panel of daily household electricity consumption data provided by Poudre Valley Rural Electric Association (PVREA), an electricity distribution cooperative that services over 42,000 entities in Larimer, Weld, and Boulder counties in

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[9] This is constructed by taking an average of the annual gross income requirements for households with two and three individuals, within each county. Then, these figures are averaged across counties. This is likely to be a slight overprojection of average household income, as households that qualify for *PV For All* are necessarily earning less than the annual gross income eligibility requirement.

[10] A wide range of income elasticities of demand are estimated in the literature, with most between between 0.15 and 0.311 (Branch, 1993; Espey & Espey, 2004; Sun, 2015). This paper uses an income elasticity of demand for electricity of 0.2 as an approximation of the true value.

Northern Colorado. After sample trimming, data cleaning, and collapsing observations to the monthly level, the final data consists of monthly household electricity consumption data reported in kilowatt-hours (kWh) for 36,414 households from January 1, 2015, through December 31, 2018.[11] The households span 45 unique zip codes across PVREA's over 2,000 square mile service territory. Data on each adopting household's date of adoption and generation capacity of adoption was also provided by PVREA.

Households are defined broadly in accordance with PVREA's 'household rate' designation. Households are "single residential unit farm, single-unit home consumers, small schools, and churches for all uses up to and including loads of 25 kW" (PVREA, p. 2). Due to data constraints, it is impossible to differentiate between types of consumer units within the group defined broadly as households. Households are identified by zip code. No other household attribute information is available.

Temperature measures are included as a control in the models employed by this paper. County-level average daily temperature data are obtained from the publicly available PRISM Climate Data service provided by the PRISM Climate Group of Oregon State University (PRISM Climate Group, 2019). The daily average temperature is constructed as a linear average of the daily high and low temperatures observed in each county. Cooling degree days (CDD) and heating degree days (HDD) are constructed for each county by taking the degrees daily average temperature is above or below, respectively, 65° Fahrenheit. Consistent with the electricity consumption data, CDD and HDD are constructed on the monthly level.

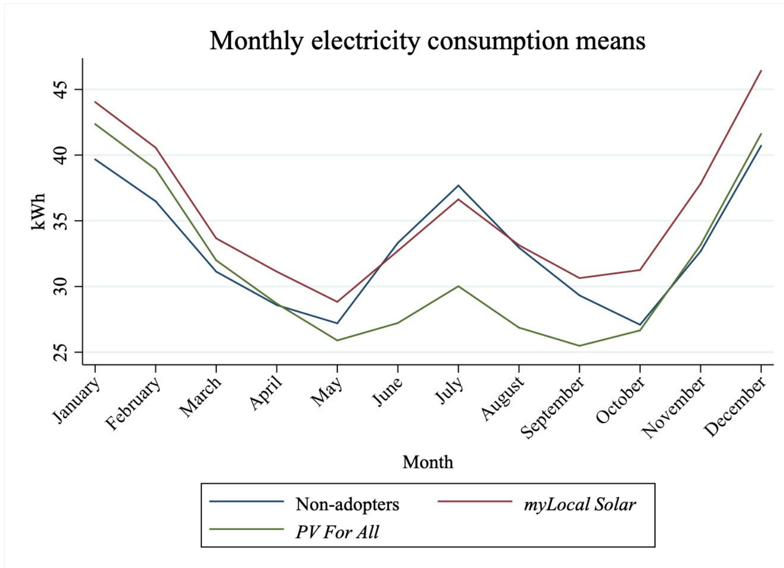
[11] Data, data cleaning, and results replication information are detailed in Appendix 2.

4.2 Summary Statistics

This section summarizes household electricity consumption data and community solar data. This is useful for developing a familiarity with the consumption patterns of households included in this sample, for helping to contextualize the character and magnitude of estimated effects, and for informing the extent to which the estimated effects are externally generalizable to other groups with contrasting electricity consumption and community solar adoption profiles.

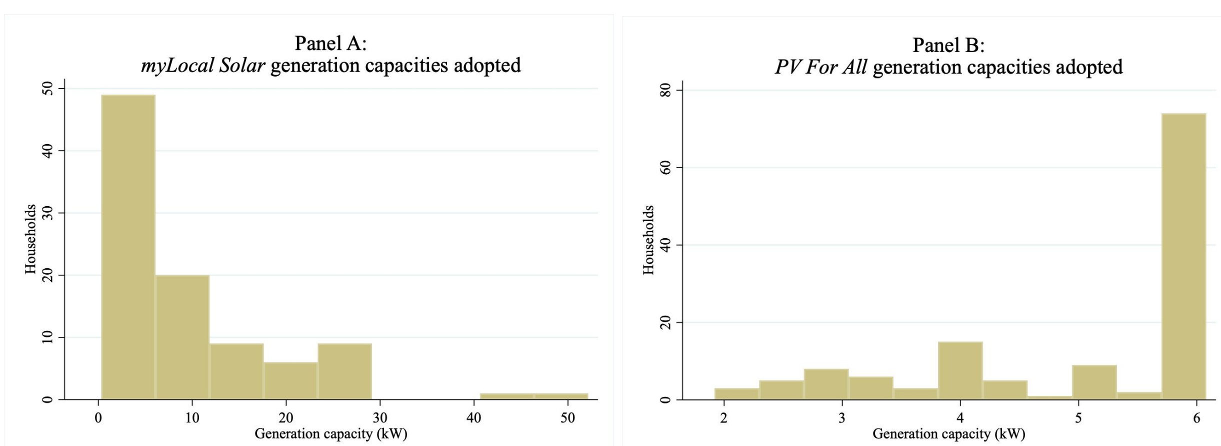
Figure 1 plots monthly trends in household electricity consumption for each group. Note that means for each community solar group are not calculated separately for pre- and post-adoption periods. The patterns depicted in Figure 1 illustrate the seasonality of electricity consumption for each group, with peaks during the winter and summer months as households increase the use of electricity-intensive household climate control devices to satisfy comfort needs. The lower electricity consumption peak during warm weather months (May - September) for *PV For All* adopters suggests that low-income households use less energy in warmer months than do households in the two other groups. This is likely due to the fact that the low-income households included in the *PV For All* group are either less likely to have in-home air conditioning appliances or use these appliances less heavily than do households in the other two groups.

Figure 1. Monthly electricity consumption trends



During the sample period, 131 households adopted community solar through the *myLocal Solar* program and 95 households adopted community solar through the *PV For All* program. Panels A and B in Figure 2 present the frequency distribution of the generation capacities adopted within each group. The distributions show that *myLocal Solar* households generally adopt larger generation capacities and have more variation in generation capacity adopted than do *PV For All* households.

Figure 2. Distributions of generation capacity adopted



5 Empirical Methods

5.1 Critical Considerations

The intention of this study is to estimate the change in household electricity consumption resulting from community solar adoption. There are three main potential challenges related to experimental design and identification. The first and major challenge is omitted variable bias. If adoption of community solar is correlated with some other unobserved variable also affecting household electricity consumption, the respective effects would be impossible to statistically disentangle. Consequently, estimation of the effect of community solar adoption on household electricity consumption would be biased in the same direction that the correlated event affects electricity consumption.

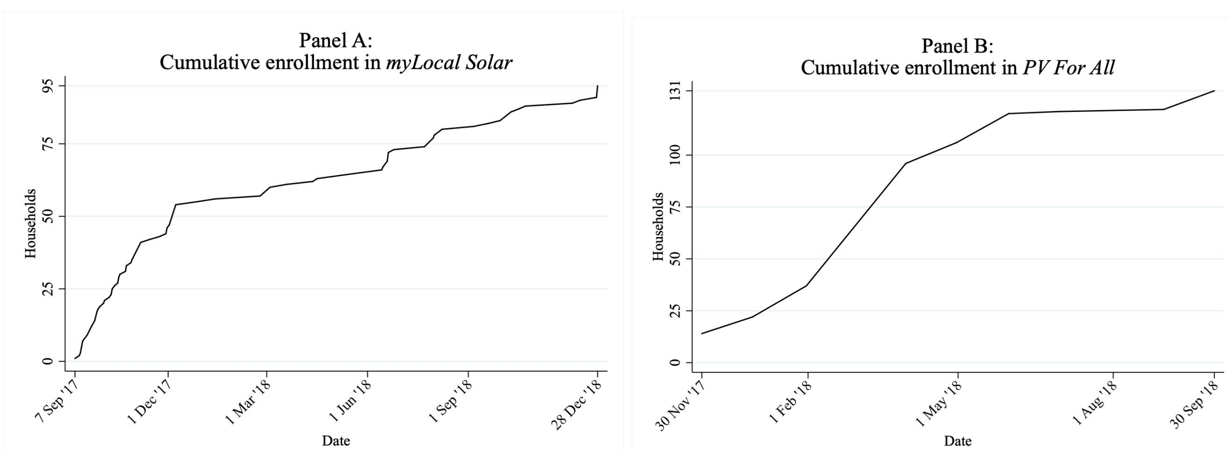
The principal source of possible omitted variable bias stems from treatment selection bias. On purely theoretical grounds, that community solar adoption occurred on a voluntary, non-random basis raises concerns about the endogeneity of adoption. The extent to which this is likely to bias estimation depends on the extent to which households in the 'treated' and 'control' groups follow similar electricity consumption trends in post-adoption periods. This issue of common trends is addressed in great detail in section 5.3. In the case that the common trends assumption is valid, the estimates of the community solar rebound will still reflect effects for a unique group of households: those that voluntarily chose to adopt community solar. This paper finds this limitedly problematic, as perfectly exogenous variation in community solar adoption is generally not representative of real-world community solar. That is, in practice, households are not randomly assigned community solar adoption, but essentially always adopt community solar on a voluntary basis. Consequently, the results estimated in this setting with imperfect experimental design may, in fact, be more informative for decision-makers in the community solar landscape than would be results estimated in a setting with perfectly randomized assignment of adoption.

This paper also takes measures to overcome differences in the treatment and control group arising from treatment selection bias. This is accomplished by exploiting the staggered nature of community solar adoption to estimate models with a restricted sample that excludes non-adopting households. This sample restriction has the effect of comparing community solar adopters in each period to other community solar adopters in the same group that did not adopt community solar in the same period. This approach minimizes differences between the treatment and 'control' groups and serves as a check on the robustness of the main estimates.

The design of the community solar programs allows this paper to rule out two other potential sources of omitted variable bias. First, PVREA did not facilitate home energy audits or other energy interventions at the time of community solar adoption. This consideration is neither trivial nor unlikely in studies of this type. In previous studies estimating changes in household electricity consumption from solar photovoltaic (PV) adoption, adoption of solar PV technology was accompanied by a energy efficiency improvements, threatening to bias estimation downward (Havas et al., 2015). It *is* possible, however, that community solar households pursued energy consumption modifications without the assistance of PVREA. Though there is no intuitive reason why energy efficiency improvements would be strongly temporally correlated with community solar adoption, the presence of such endogenous energy consumption modifications, which would likely reduce total household electricity consumption, may cause models estimated in this study to underestimate the true effect of community solar adoption.

Second, the staggered nature of community solar adoption within each program contributes to the validity of each program as a valid quasi-experimental setting and allows this paper to rule out an additional source of omitted variable bias. Panels A and B in Figure 3 plot cumulative adoption counts for each group from the group's earliest to latest date of adoption.[12] In a perfect experimental setting, each household's date of adoption would be random (Athey & Imbens, 2018). While this assumption is very strong and does not hold in this setting, adoption of community solar within each group appears to be highly staggered throughout the period of adoption, thereby reducing the likelihood that adoption is rendered endogenous by some singular unobserved correlated event also affecting household electricity consumption.

Figure 3. Cumulative enrollment in *myLocal Solar* and *PV For All*



[12] The smoother trend in enrollment in the *PV For All* program is attributed to the fact that there are fewer discrete dates of adoption due to PVREA's batch-processing of *PV For All* applications.

A second potential concern is the possibility of reverse-causality (Strumpf, Harper, & Kaufman, 2017, p. 355). That is, might anticipation of increased (or decreased) future electricity consumption cause a household to adopt community solar and not vice versa? While this may be a considerable concern in the energy efficiency rebound effect setting (Sorrell et al., 2009), this is less likely to be a concern in the solar rebound effect setting. In the community solar subscription model featured in this study, adopting community solar shares in anticipation of higher future consumption would shift a large share of a household's energy costs forward in time to the date of community solar enrollment, thereby increasing the implicit cost of electricity. Consequently, a rational consumer is unlikely to purchase solar panels anticipatorily. A Granger test of causality was employed to estimate leading effects of community solar adoption and found statistically insignificant effects for the six months leading up to enrollment, providing empirical evidence against the existence of reverse-causality (Angrist & Pischke, 2009, p. 177; Granger, 1969). The Granger test results are reported in section 5.3.

A third and related concern is the possibility of anticipatory effects. The presence of statistically significant changes in electricity consumption in the periods preceding community solar adoption would indicate that households changed their electricity consumption behavior anticipatorily, resulting in improper identification of the effect of community solar adoption. Much like the case of reverse-causality, the insignificant Granger test results indicate a lack of anticipatory effects.

5.2 Difference-in-differences Estimation

To identify changes in household electricity consumption following community solar adoption, this study employs a two-way fixed effects difference-in-differences (DID) estimator, estimated by ordinary least squares (OLS) (Angrist & Pishke, 2009; Athey & Imbens, 2008; Meyer, 1995). The DID specification exploits panel variation in the data to control for unobservable variables and is therefore deemed less susceptible to omitted variable bias than alternative settings that exploit only cross-sectional variation in the data (Greenstone & Gayer, 2009, p. 23-24). This paper utilizes two key estimation specifications: (1) a binary treatment DID model and (2) a non-binary treatment DID model that estimates the change in household electricity consumption per kW capacity of community solar adopted. From these two specifications, modifications are made to provide additional analyses.

The binary treatment DID model is as follows. Let E_{imy} be the log of electricity consumption of household i in month m of year y. At some time during the sample period, a household adopts community solar. ADOPT_{imy} is a binary treatment indicator equal to one for household i in each period my after that household adopts community solar.[13] The binary treatment DID model is provided by:

$$\mathrm{E}_{imy} = \beta + \pi \mathrm{ADOPT}_{imy} + \delta_1 \mathrm{HDD}_{imy} + \delta_2 \mathrm{CDD}_{imy} + \alpha_i + \mu_{my} + \epsilon_{imy}, \quad (5.2.1)$$

where HDD_{imy} and CDD_{imy} are heating degree days and cooling degree days, respectively.[14] Household fixed effects are indicated by α_i, which control for time-invariant household-specific

[13] ADOPT is equal to one beginning the first month of community solar adoption. For example, if a household adopts community solar on November 15, 2017, ADOPT will be equal to one for that household starting in November 2017 and for all months thereafter.
[14] HDD and CDD are scaled to terms of hundreds of heating and cooling degree days.

attributes affecting electricity consumption. Month-of-sample fixed effects are captured by μ_{my}, which control for month-to-month trends in electricity consumption exhibited by all households. As a check on specification robustness, this paper also estimates an alternative specification that includes zip code-month fixed effect in addition to month-of-sample fixed effects in order to more precisely control for the strongly seasonal trends in household electricity consumption. This model is estimated for the *myLocal Solar* and the *PV For All* adoption groups individually.

The primary modification made to this model allows for non-binary treatment of solar adoption by modifying the binary treatment specification to be sensitive to the generation capacity a household adopts. This specification is given by:

$$\begin{aligned} \mathrm{E}_{imy} = \beta + \pi_{KW}\mathrm{ADOPT}_{imy} \times \mathrm{KW}_i + \delta_1\mathrm{HDD}_{imy} \\ +\delta_2\mathrm{CDD}_{imy} + \alpha_i + \mu_{my} + \epsilon_{imy}, \end{aligned} \tag{5.2.2}$$

where KW_i is the kW generation capacity of community solar adopted by household i. For this specification, π_{KW} indicates the average change in household electricity consumption attributed to the adoption of community solar *per kW* of generation capacity adopted.

Comparison of the coefficient π from the binary treatment specification to π_{KW} from the non-binary treatment specification may assist in uncovering the dominant mechanism for rebound. If π is significant or large in the binary treatment specification, for example, but π_{KW} is insignificant or small in magnitude in the non-binary treatment specification, this shows that households are consuming more electricity irrespective of generation capacity adopted. This would suggest the existence of a buy-in warm glow as a mechanism for rebound. Alternatively, if π_{KW} is significant or large in the non-binary treatment specification, but π is insignificant or small in magnitude in the binary treatment specification, the mechanism for rebound is ambiguous: an income effect and/or a contribution warm glow effect may be mechanisms for rebound.

5.3 Common Trends

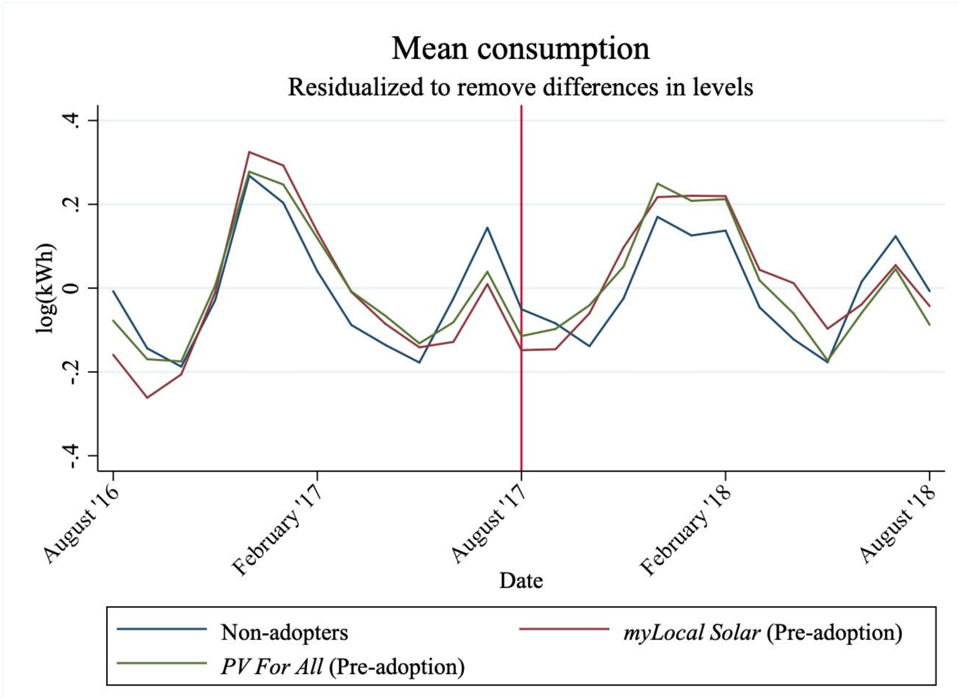
Unbiased identification in the DID setting hinges on the validity of the common trends assumption. Greenstone and Gayer (2009) describe the critical common trends assumption: "the [DID] estimator will only produce a valid estimate of the treatment effect under the assumption that in the absence of the treatment the outcomes in the [treatment and control groups] would have changed identically … between periods 1 and 2" (p. 28). In the context of this study, the specific common trends assumption is that in the absence of community solar adoption, the electricity consumption of households that adopted community solar in a given period *would have* followed the same trend as that of other households in the sample that did not adopt community solar in that period.

The common trends assumption cannot be tested empirically, as the counterfactual trend in the outcome variable for the treated group is unobservable. As is common practice in the literature employing DID estimation, this subsection examines pre-treatment, or pre-adoption, trends in household electricity consumption to provide evidence to support the common trends assumption (Angrist & Pischke, 2009, p. 178; Roth, 2018, p. 2). Of course, "the presence of parallel trends in the pre-period does not guarantee these trends would have continued in the absence of treatment" (Kahn-Lang & Lang, 2018, p. 4-5). However, given the staggered adoption of community-solar during the sample period in this study, examination of pre-adoption trends lends much stronger evidence in support for the common trends assumption than would similar analysis in a simpler two-period sample (Strumpf, Harper, & Kaufman, 2017, p. 354). An additional important consideration with respect to analysis of pre-adoption trends is that "if there is a common trend in logs, there will not be one in levels, and vice versa" (Angrist & Pischke, 2009, p. 171). Consequently, this subsection investigates trends in logs of consumption, the functional form of electricity consumption employed in this study.

This paper lends support to the common trends assumption using three forms of evidence: (1) visual inspection of graphical pre-treatment and during-treatment trends, (2) the often-employed Granger causality test (Angrist & Pischke, 2009, p. 177; Granger, 1969), and, in a similar spirit to the Granger causality test, (3) an event-study analysis reported in the following results section.

First, Figure 4 shows plotted means of log of monthly electricity consumption from January 2016 to December 2018 for each of the three groups: *myLocal Solar* adopters*, PV For All* adopters, and non-adopters. The vertical line indicates August 2017, the final month in which no household in the sample had adopted community solar. To the left of the line, the similarity in consumption trends between each group is obvious, lending strong evidence in support of the common trends assumption. The maintenance of common trends to the right of the line reflects persistent common trends throughout the period of intermittent community solar adoption.

Figure 4. Pre- and during-adoption trends in electricity consumption



Second, the Granger test is used to ensure that a treatment of interest caused a particular outcome (Angrist & Pischke, 2009, p. 177). This is assessed by estimating an equation that regresses the outcome variable on six months of community solar adoption leads.[15] Results for this estimation are reported in Table 1. All leads are found to be statistically insignificant for each group of community solar adopters, confirming the absence of differential pre-treatment trends between non-adopters and each adoption group. The similar event study analysis reported in the subsequent section serves to confirms these findings.

[15] For this specification, the ADOPT variable is replaced with a 'start of adoption' indicator variable equal to one in the first month that a household adopts community solar and zero in all other months.

Table 1. Granger test of causality results

Dependent variable:	Monthly household electricity consumption (log kilowatt-hours)	
Adoption group:	*myLocal Solar*	*PV For All*
	(1)	(2)
Leads of $\mathrm{ADOPT}_{start,imy}$:		
6 month lead	0.00248	0.00724
	(0.0413)	(0.0312)
5 month lead	-0.0189	0.0465
	(0.0452)	(0.0332)
4 month lead	-0.0264	0.0218
	(0.0427)	(0.0346)
3 month lead	-0.0186	0.0466
	(0.0501)	(0.0396)
2 month lead	-0.0459	0.0523
	(0.0432)	(0.0408)
1 month lead	-0.0172	0.0532
	(0.0436)	(0.0405)
$\mathrm{ADOPT}_{start,imy}$	0.0258	0.0290
	(0.0428)	(0.0344)
HDD	0.00674	0.00642
	(0.00344)	(0.00344)
CDD	0.111***	0.112***
	(0.00633)	(0.00633)
Constant	3.180***	3.181***
	(0.0190)	(0.0190)
Total households	36,283	36,319
Adopting households	95	131
R^2	0.838	0.837

Note: All models include month-of-sample, zip code-month, and household fixed effects. CDD and HDD are in hundreds of degree days. Consistent with the literature on Granger tests of causality, models estimated also control for six months of adoption lags. Standard errors in parentheses are clustered at the household level. Estimates significant at * $p < 0.05$, ** $p < 0.01$, or *** $p < 0.001$.

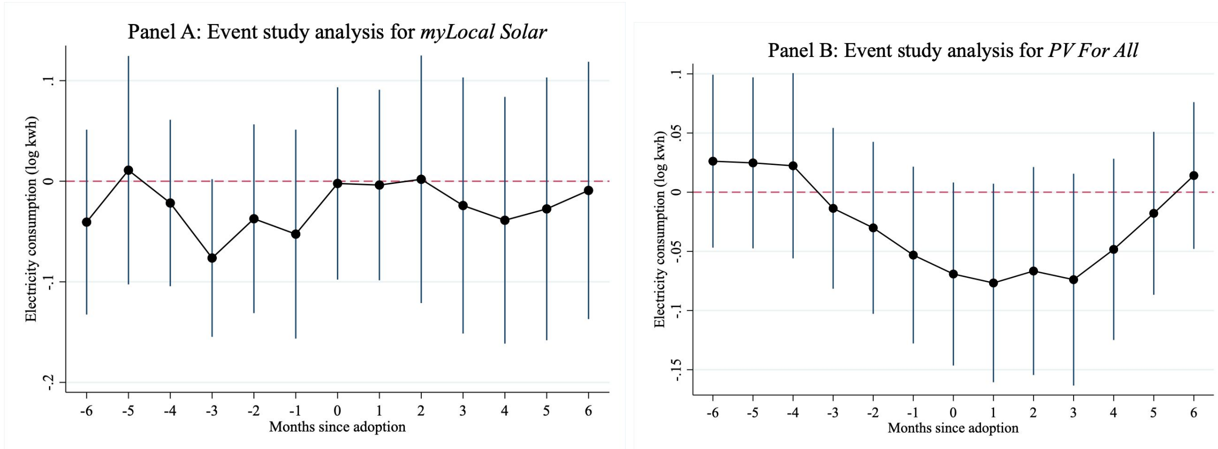
6 Results

6.1 Main Results

This section begins with the results estimated from an event study version of equation (5.2.1), providing a visual representation of the effect of community solar adoption. The period-by-period coefficients plotted in Figure 5 are estimated by regressing log electricity consumption on a vector of event month indicators specified as the month-of-sample minus the first full month of community solar adoption.[16] As was noted in the analysis of Granger causality results, the statistically insignificant coefficients estimated for periods prior to RHR enrollment show a lack of differential pre-adoption trends in electricity consumption, supporting the validity of the common trends assumption. The coefficients estimated in the periods after community solar adoption show that community solar adoption did not have a statistically significant effect on household electricity consumption in each of the six periods following enrollment. The following tables of regression estimates summarize this effect on average and investigate possible sources of heterogeneity in effects across two additional dimensions: temperature and pre-adoption consumption levels.

[16] Unlike the Granger causality test model, the event study model is estimated for only households that adopt community solar within each group, excluding non-adopting households. While estimated coefficients in each analysis are not statistically different from zero, the difference in control group between the two analyses may explain the differences in specific coefficient estimates between the Granger test and event study analysis.

Figure 5. Plot of event study coefficient estimates



Note: Coefficients are estimated from an event study-modified version equation (5.2.1) which regresses log electricity consumption on a vector of event month indicators specified as the month-of-sample minus the first full month of community solar adoption. The model is estimated for the restricted sample of households. Vertical lines indicate 95% confidence intervals.

Note that Panel B shows some evidence of persistent seasonality even after the inclusion of numerous seasonal controls. This is likely reflective of the large uptick in adoption of *PV For All* in April 2018 as shown in Panel B of Figure 3. To partially mitigate this issue, this paper estimates all main models with both a complete sample and a restricted sample of only households within a given adoption group, thereby minimizing the likelihood that differential seasonal trends between community solar adopters and non-adopters induces a Type I error. All additional analyses to explore heterogeneity in effects are estimated with the more reliable restricted sample. Though the sample size is much smaller, this is the more conservative approach.

The main estimation results for the binary treatment specification (equation 5.2.1) and non-binary treatment specification (equation 5.2.2) are presented for the *myLocal Solar* group in Table 2 and for the *PV For All* group in Table 3. The binary treatment specification estimates are reported in column (1) through column (4) of each table. The non-binary treatment specification estimates are reported in column (5) through column (8) of each table. The results in every column suggest that, on average, community solar adoption has no effect on household electricity consumption. While income level is not the only factor that differentiates the *myLocal Solar* group from the *PV For All* group, these results lend some evidence to suggest that income level is not a sufficiently large determinant of the solar rebound to show a difference in effects between the two groups.

Table 2. Main difference-in-differences results for *myLocal Solar*

Dependent variable:	Monthly household electricity consumption (log kilowatt-hours)							
Adoption group:	*myLocal Solar*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ADOPT	0.0359	0.0404	-0.000465	0.0251	0.00884	0.0158	-0.0290	0.00293
	(0.0264)	(0.0259)	(0.0470)	(0.0471)	(0.0345)	(0.0334)	(0.0538)	(0.0528)
× *KW*					0.00365	0.00332	0.00392	0.00306
					(0.00235)	(0.00221)	(0.00237)	(0.00243)
HDD	-0.0179***	0.0116***	-0.0316	0.0851	-0.0179***	0.0116***	-0.0298	0.0876
	(0.00232)	(0.00278)	(0.0633)	(0.101)	(0.00232)	(0.00278)	(0.0635)	(0.102)
CDD	0.259***	0.126***	0.433*	-0.295	0.259***	0.126***	0.432*	-0.297
	(0.00594)	(0.00635)	(0.166)	(0.165)	(0.00594)	(0.00635)	(0.166)	(0.165)
Constant	3.246***	3.112***	3.291***	2.735***	3.246***	3.112***	3.280***	2.720***
	(0.0121)	(0.0151)	(0.345)	(0.572)	(0.0121)	(0.0151)	(0.346)	(0.574)
Fixed effects:								
Month-of-sample	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip code-month	No	Yes	No	Yes	No	Yes	No	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample:	Complete	Complete	Restricted	Restricted	Complete	Complete	Restricted	Restricted
Total households	36,283	36,283	95	95	36,283	36,283	95	95
Adopting households	95	95	95	95	95	95	95	95
R^2	0.803	0.818	0.850	0.880	0.803	0.818	0.850	0.880

Note: Standard errors in parentheses are clustered at the household level. CDD and HDD are in hundreds of degree days. Estimates significant at * $p < 0.05$, ** $p < 0.01$, or *** $p < 0.001$.

Table 3. Main difference-in-differences results for *PV For All*

Dependent variable:	Monthly household electricity consumption (log kilowatt-hours)							
Adoption group:	*PV For All*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ADOPT	-0.0245	-0.0235	-0.0352	-0.0422	0.0659	0.0619	0.0410	0.0251
	(0.0237)	(0.0234)	(0.0452)	(0.0461)	(0.115)	(0.114)	(0.113)	(0.119)
× *KW*					-0.0178	-0.0168	-0.0156	-0.0137
					(0.0207)	(0.0205)	(0.0209)	(0.0216)
HDD	-0.0181***	0.0113***	-0.0690	-0.0356	-0.0181***	0.0113***	-0.0698	-0.0368
	(0.00232)	(0.00278)	(0.0376)	(0.0464)	(0.00232)	(0.00278)	(0.0377)	(0.0466)
CDD	0.258***	0.126***	0.190*	0.0524	0.258***	0.126***	0.191*	0.0553
	(0.00593)	(0.00634)	(0.0944)	(0.103)	(0.00593)	(0.00634)	(0.0943)	(0.102)
Constant	3.247***	3.113***	3.572***	3.410***	3.247***	3.113***	3.577***	3.417***
	(0.0121)	(0.0151)	(0.202)	(0.260)	(0.0121)	(0.0151)	(0.203)	(0.261)
Fixed effects:								
Month-of-sample	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip code-month	No	Yes	No	Yes	No	Yes	No	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample:	Complete	Complete	Restricted	Restricted	Complete	Complete	Restricted	Restricted
Total households	36,319	36,149	131	131	36,319	36,319	131	131
Adopting households	131	131	131	131	131	131	131	131
R^2	0.803	0.818	0.749	0.784	0.803	0.818	0.749	0.784

Note: Standard errors in parentheses are clustered at the household level. CDD and HDD are in hundreds of degree days. Estimates significant at * $p < 0.05$, ** $p < 0.01$, or *** $p < 0.001$.

The finding of no changes to electricity consumption resulting from the adoption of community solar suggests that the mechanisms for the community solar rebound were sufficiently weak to provide a statistically significant change electricity consumption. With respect to the income effect, these results are consistent with the hypothesis presented in section 4.2, that the income from electricity generation is likely too low to induce an identifiable rebound effect. That the estimated effects are not statistically different from zero also suggests that the warm glow effect does not play a sufficiently large role in the community solar context to induce an identifiable rebound effect. It is worth recalling that in the case that adoption is correlated with other endogenous energy efficiency improvements, these effects may also be underestimating the true effect of community solar adoption.

This paper's estimate of no community solar rebound differs from the literature that finds a significant solar rebound effect for private rooftop solar adopters (Deng & Newton, 2017). There are several possible explanations for this difference. First and most generally, the households that adopt community solar are likely to be different than those that adopt private rooftop solar. The many observable and unobservable differences between these households may contribute to differences in behavior following community solar adoption. Second, monthly electricity bills for private rooftop solar adopters may serve as a more salient reminder of electricity generation-related income than do monthly electricity bills for community solar adopters. This is due to differences in the financing structures common to each of the two solar PV business models. Because community solar adopters in this study pay for solar PV adoption partially through monthly subscription payments, the electricity generation compensation payments made to community solar adopters are practically quite small once the monthly fee is subtracted. This was discussed briefly in section 3.2. By comparison, private rooftop solar adopters generally pay for their entire purchase of solar PV in one upfront payment. Consequently, the monthly on-bill payments to private rooftop solar adopters tend to be much larger than those made to community solar adopters, providing a more salient reminder of solar-related ‘income’ that may belie the true income solar-related income of those households, but may induce a larger ‘income’ effect nonetheless. Third, solar panels on a household’s rooftop, rather than part of a more distant community solar array, may serve as more frequent visual reminder to members of a household that the household is voluntarily providing a public good, thereby inducing a larger warm glow effect.

While the event study analyses reported in Figure 5 rule out the possibility of dynamic heterogeneity in effects, the remaining model estimates employ additional analyses to explore two other possible sources of heterogeneity in effects. The subsequent models are estimated for the restricted sample to reduce the possibility of bias induced by slight differentials in seasonal trends between adopting and non-adopting households.

6.2 Temperature Analysis

While the dynamic specification results explore trends in effects in months following adoption, these results tell nothing of the effect of temperature on changes in electricity consumption resulting from community solar adoption. It is possible that changes in electricity consumption from community solar adoption may vary across seasons or depending on temperature levels. For example, when temperatures increase during summer months, a household that has adopted community solar may choose to more heavily use electricity-intensive climate control devices, such as air conditioning or fans. Additionally, households may choose to heat their home to a warmer temperature during winter months, increasing electricity consumption for households with electricity-powered heat. To explore this possibility, this paper employs a specifications that interact heating degree days and cooling degree days with the adoption indicator. Zip code-month fixed effects are excluded in these models to minimize suppression of variation in electricity consumption that would otherwise be explained by heating and cooling degree days. The results for estimates of this specification are reported in Table 6.

Table 4. Temperature difference-in-differences results

Dependent variable:	Monthly household electricity consumption (log kilowatt-hours)			
Adoption group:	*myLocal Solar*		*PV For All*	
	(1)	(2)	(3)	(4)
ADOPT	0.0903	0.122	-0.0312	0.371
	(0.0990)	(0.110)	(0.121)	(0.202)
× *HDD*	-0.0123	-0.0201	0.000132	-0.0656**
	(0.0144)	(0.0162)	(0.0137)	(0.0238)
× *CDD*	-0.107	-0.173	-0.0485	0.174
	(0.0838)	(0.0889)	(0.0946)	(0.166)
× *KW*		-0.00565		-0.0834*
		(0.00512)		(0.0334)
ADOPT×HDD×KW		0.00124		0.0137**
		(0.000659)		(0.00414)
ADOPT×CDD×KW		0.0115		-0.0345
		(0.00863)		(0.0282)
HDD	-0.0286	-0.0227	-0.0693	-0.0711
	(0.0636)	(0.0641)	(0.0378)	(0.0382)
CDD	0.462**	0.461**	0.203*	0.203*
	(0.167)	(0.169)	(0.0931)	(0.0928)
Constant	3.269***	3.235***	3.573***	3.581***
	(0.348)	(0.350)	(0.203)	(0.205)
Total households	95	95	131	131
Adopting households	95	95	131	131
R^2	0.850	0.850	0.749	0.753

Note: All models include month-of-sample, zip code-month, and household fixed effects. CDD and HDD are in hundreds of degree days. Standard errors in parentheses are clustered at the household level. Estimates significant at * $p < 0.05$, ** $p < 0.01$, or *** $p < 0.001$.

The coefficients estimated for the binary treatment specification shows insignificant effects for all coefficients of interest for both groups, suggesting that heating and cooling degree days have no effect on the community solar rebound. By contrast, some coefficients estimated in column (2) and column (4) are statistically significant. These results suggest that community solar adoption induces changes in electricity consumption that are highly localized to particular aspects of electricity consumption. The coefficient estimated on the

$\text{ADOPT}_{imy} \times \text{HDD}_{imy} \times \text{KW}_i$ interaction for the *PV For All* group, for example, suggests that *PV For All* households exhibit a slight rebound effect in the aspect of electricity consumption attributed to both cold days and generation capacity adopted. While some effects are found to be statistically significant, one possible concern with employing a specification so rich with fixed effects and interaction terms is that coefficients are estimated based on little remaining variation in the outcome variable, possibly increasing the chance of falsely finding statistically significant coefficients. For this reason, this paper considers these results less reliable than the model estimates presented in Table 2 and Table 3 which jointly present 14 model estimates conclusively showing no average effects.

Despite the shortcomings of this abundantly rich model, the differential results between *myLocal Solar* and *PV For All* adopters highlights differences between the two groups. A first possible explanation for the differences in effects between the two groups may be that the groups use different sources of fuel for heating their homes. If *myLocal Solar* households are more likely to have electricity-powered heat than *PV For All* households, then the estimated results will pick up a larger increase in household heating-related consumption for the *myLocal Solar* group than the results will for the *PV For All* group, possibly explaining the significant coefficient on $\text{ADOPT}_{imy} \times \text{HDD}_{imy} \times \text{KW}_i$ for the *PV For All* group. A second source of difference between the two groups is the starkly different levels of solar generation-related income each group receives, with *PV For All* adopters receiving much greater community solar income. This also helps to explain the positive coefficient on $\text{ADOPT}_{imy} \times \text{HDD}_{imy} \times \text{KW}_i$, which may reflect a slight income effect attributed to generation capacity adopted. A third possible difference between the two groups may be that the groups have different motivations for community solar adoption. Because *myLocal Solar* adopters do not receive community solar shares for free, this group of adopters may be more environmentally motivated than financially motivated to adopt community solar compared to the *PV For All* group. While this line of reasoning may suggest that *myLocal Solar* adopters would exhibit a larger rebound effect than would *PV For All* adopters, this outcome is not reflected in the estimated results. Consequently, this source of difference between the two groups appears to not to hold in this setting.

6.3 Consumption Level Analysis

Electricity consumption levels are an additional dimension across which there may be heterogeneity in effects. It is possible, for example, that households with low levels of electricity consumption are more likely to exhibit a rebound than households with high levels of electricity consumption. This may be because low-consumption households are not yet at an electricity consumption 'satiation point' and are more likely to dedicate additional income to the consumption of additional electricity.[17] This paper explores this possibility by estimating the binary and non-binary treatment specifications for two samples: households with pre-adoption mean monthly electricity consumption levels above and below the median level of household electricity consumption in the sample. The zip code-month fixed effects specification is employed for these additional analyses, as this specification better controls for variation in seasonal trends across zip codes than do month-of-sample fixed effects alone. Estimated results are reported in Table 5. The results show insignificant estimates across both binary and non-binary treatment specifications for both groups, lending additional evidence to support the

[17] In other words, these households may have a higher income elasticity of demand for electricity.

overarching conclusion of no effect of community solar adoption on households electricity consumption.

Table 5. Consumption level difference-in-differences results

Dependent variable:	Monthly household electricity consumption (log kilowatt-hours)							
Adoption group:	*myLocal Solar*				*PV For All*			
Consumption level:	Lowest 50th percentile		Highest 50th percentile		Lowest 50th percentile		Highest 50th percentile	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ADOPT	0.0142	0.0327	0.0254	-0.0115	0.0142	0.0327	0.0254	-0.0115
	(0.0705)	(0.0752)	(0.0703)	(0.0812)	(0.0705)	(0.0752)	(0.0703)	(0.0812)
× *KW*		-0.00418		0.00382		-0.00418		0.00382
		(0.00467)		(0.00279)		(0.00467)		(0.00279)
HDD	0.0604	0.0601	0.194	0.205	0.0604	0.0601	0.194	0.205
	(0.184)	(0.183)	(0.130)	(0.128)	(0.184)	(0.183)	(0.130)	(0.128)
CDD	-0.418	-0.414	-0.193	-0.191	-0.418	-0.414	-0.193	-0.191
	(0.236)	(0.236)	(0.254)	(0.253)	(0.236)	(0.236)	(0.254)	(0.253)
Constant	2.216*	2.218*	2.741***	2.678***	2.216*	2.218*	2.741***	2.678***
	(1.050)	(1.044)	(0.716)	(0.704)	(1.050)	(1.044)	(0.716)	(0.704)
Total households	44	44	51	51	64	64	67	67
Adopting households	44	44	51	51	64	64	67	67
R^2	0.824	0.824	0.703	0.703	0.824	0.824	0.703	0.703

Note: All models include month-of-sample, zip code-month, and household fixed effects. CDD and HDD are in hundreds of degree days. Standard errors in parentheses are clustered at the household level. Estimates significant at * $p < 0.05$, ** $p < 0.01$, or *** $p < 0.001$.

7 Conclusion

This paper finds strong evidence to suggest that households that adopt community solar as a part of the Coyote Ridge Community Solar Farm do not exhibit a community solar rebound effect on average. When analyzed month-by-month for the six months following adoption, results still show no changes in electricity consumption in each month. Additionally, pre-adoption consumption levels are found to have no influence over a household's rebound effect. Despite not showing a rebound effect on average, it may be possible that households exhibit changes in specific temperature-related aspects of electricity consumption, though these estimated effects differ between the two groups of community solar adopters examined in this study. In the case that community solar adoption is correlated with other energy efficiency interventions, models estimated in this paper may understate the true effect of community solar adoption.

These results have implications for utilities, policymakers, and economists. For utilities, these effects suggest that household electricity demand is unlikely to increase in any appreciable way from the adoption of community solar. Consequently, utilities should not avoid deployment of community solar solely on the basis of curtailing total load or in an effort to defer investment in grid infrastructure to accommodate increased electricity demand. For policymakers, these results suggest that changes in electricity consumption are unlikely to erode the environmental benefits of community solar associated with the displacement of fossil fuel-generated electricity. Consequently, policies that are favorable to community solar may provide environmental benefits in excess of those realized by alternative energy saving measures for which a large rebound effect exists. Lastly, for economists, these results show that while a warm glow effect may play a role in determining electricity consumption behavior in other green power settings, it likely plays a limited role in the community solar context.

Considered in light of the literature that estimates a significant, positive solar rebound effect for private rooftop solar PV adopters, these results serve to emphasize the fact that the solar rebound is likely to vary considerably across solar PV adoption business models and contexts. Consequently, despite the limited evidence of a solar rebound found within the community solar business model context, the subject of the solar rebound effect remains a highly understudied area of environmental economics ripe for continued investigation.

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