Energy Economics 153 (2026) 109079

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

# Solar electricity without solar panels: Changes in consumption behavior due to community solar programs

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ARTICLE INFO

*Keywords:*
Community solar
Electricity consumption behavior
Solar electricity
Equity in renewable energy

ABSTRACT

How does electricity consumption behavior change with different energy sources? We seek to understand how consumers change their consumption behaviors when they begin to use renewable electricity via a community solar program.

Previous research has found that consumers distinguish the power sources of electricity and even change their consumption behavior. Recent studies have explored changes in consumption associated with utility-run green electricity programs and rooftop solar, finding mixed results; however, studies on community solar programs are lacking. This study explores household-level consumption behavior after adopting solar electricity without panel installation.

We use household-level monthly electricity consumption data from a large electric co-op in Georgia, U.S., ranging from 2015 to 2023, for both community solar subscribers and non-subscribers. We use staggered difference-in-differences, along with matching, to compare consumption changes before and after the subscription. Findings reveal that the consumption does not change after subscription, but subscribers' monthly bills increase by about 3–4 %, indicating they pay more to make the grid greener.

This study will broaden the understanding of electricity sources and consumer behavior by adding the analysis of prevalent but under-studied community solar electricity programs in the U.S. Southeast context. It will help utility planners understand the changing demand as a result of renewable energy adoption.

## 1. Introduction

Rapid growth in solar electricity is helping drive the clean energy transition. In 2023, cumulative solar installed capacity in the U.S. recorded a total of 177 GW (Wood Mackenzie, 2024), and solar comprised over 50 % of new electricity generation capacity added (SEIA, 2024). Solar energy is also driving economic development by providing nearly 280,000 related jobs as of 2023 in the U.S. (IREC, 2024) and stimulating private investment, while costs of solar are declining (SEIA, 2025). The significant growth in PV is rapidly changing the composition of the electricity sector with potential implications for when and how electricity is used by consumers.

Recent research suggests that *the source of electricity* consumers receive can impact their consumption patterns. Several studies suggest that the sources used to generate electricity impact consumers' preferences and willingness to pay (Bengart and Vogt, 2021; Borchers et al., 2007; Kosenius and Ollikainen, 2013). Consumers might change their consumption after they opt into green electricity programs, and behavioral responses differ by consumer characteristics and environmental preferences (Jacobsen et al., 2012; Kotchen and Moore, 2008). One stream of emerging literature specifically focuses on solar electricity and finds consumers increase their electricity consumption after installing rooftop solar panels, often referred to as the 'solar rebound' effect (e.g., Aydın et al., 2023; Beppler et al., 2023; Kim and Trevena, 2021; La Nauze, 2019; Qiu et al., 2019).

A change in consumption due to the source of electricity, and especially electricity from renewable energy sources, has important implications for consumers and grid planners. For consumers, it suggests a significant latent demand for electricity and that if presented with the opportunity to consume more renewable energy, consumers may significantly increase electricity demand (Beppler et al., 2023). For grid planners, this finding indicates that rooftop solar installations, and potentially renewable energy installations as a whole, are unlikely to displace fossil fuel electricity consumption as much as expected.

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https://doi.org/10.1016/j.eneco.2025.109079
Received 13 April 2025; Received in revised form 29 November 2025; Accepted 30 November 2025
Available online 1 December 2025

Research is needed to better understand the relationship between electricity production decisions and how those impact consumption patterns.

Understanding how electricity generation affects consumption patterns can help explain human behavior and improve forecasting of electricity demand. In this study, we explore the relationship between community solar and household-level electricity consumption behavior. We seek to understand how consumers change their consumption after subscribing to a community solar program. Do community solar customers increase their electricity consumption? If so, this may help inform the mechanisms underlying the solar rebound in rooftop solar or consumption increase in green electricity programs, such as moral licensing. Alternatively, community solar customers may change their consumption behavior in other ways. For example, community solar subscribers might reduce overall consumption by committing to a more energy-conscious lifestyle, or due to price effects of purchasing expensive solar electricity.

Community solar programs share characteristics of existing renewable electricity subscription programs. Community solar subscribers opt in to programs provided by utility companies or other third-party providers,[1] as in utility-run green electricity programs. However, in this type of program, customers know the source of renewable electricity (i.e., solar) and where it is generated (i.e., a solar project), similar to rooftop solar. The details of programs vary by utilities. For instance, some utility companies (for a cost premium) allow customers to choose the solar mix of their electricity (e.g., 50 % or 100 %). Others, including the electric cooperative in our study, allow customers to purchase "solar blocks", representing a specific solar capacity purchase, with a monthly fixed fee. Through community solar programs, aggregate purchases of solar electricity allow customers to take advantage of economies of scale and potentially reduce the costs and other barriers of purchasing solar electricity, relative to installing panels at one's home (Gai et al., 2021).

Community solar programs have rapidly expanded across the U.S., with around 1600 projects and an estimated more than 3 GW of capacity by the end of 2020 (Steele et al., 2021). These sorts of programs are also gaining popularity outside the U.S., such as in Spain. Community solar programs have been touted by researchers, advocacy organizations, and policymakers as a mechanism to increase access and alleviate equity concerns associated with access to solar electricity via panel installation (Lukanov and Krieger, 2019; Michaud, 2020). Community solar reduces infrastructure hurdles (e.g., home ownership requirements) and cost barriers that prevent lower-income customers from accessing solar (O'Shaughnessy et al., 2024).

This study uses household-level monthly electricity consumption data of 754 community solar program participants and 2726 non-participants from 2015 to 2023 from a rural electric co-op in Georgia, U.S. After matching adopters and non-adopters to account for electricity consumption differences pre-adoption, we leverage staggered timing of program subscription across households and employ the Callaway & Sant'Anna estimator (Callaway and Sant'Anna, 2021) as well as other difference-in-difference (DiD) models as robustness checks. In our analysis, we do not find a statistically significant consumption change induced by community solar participation. Our result adds empirical evidence to previous findings of small or no changes in electricity usage after voluntarily changing to green electricity sources (e.g., Jacobsen et al., 2012; Kotchen and Moore, 2008). However, our findings show an increase in monthly bills (about 3–4 %), indicating customers bear some costs to make the grid greener. Our findings also contribute to research on the solar rebound, suggesting that the solar rebound might be limited to consumer-sited rooftop solar, as opposed to grid-connected renewable energy.

In the remainder of the paper, we begin with previous literature on how adopting renewable electricity impacts consumption behavior in Section 2. Sections 3 and 4 describe our data collection and DiD methods used in this paper. Section 5 presents results estimated with additional analyses. Section 6 concludes with discussions of the results and equity concerns of community solar.

## 2. Background and literature review

### 2.1. The source of electricity generation and consumption behavior

How does the source of electricity generation impact household consumption of electricity? This question has gained attention as electricity restructuring and distributed generation have provided consumers with multiple options to source their electricity. Consumers with green preferences might be concerned with the environmental impact of electricity generation, such as greenhouse gas emissions, and change electricity providers to purchase renewable energy or alter their electricity consumption behavior (Bengart and Vogt, 2021; Byun and Lee, 2017). Even across different renewable energy sources, preferences might be heterogeneous (e.g., Borchers et al., 2007; Kosenius and Ollikainen, 2013). For instance, Bengart and Vogt (2021) found that customers in Germany are willing to pay a premium of more than €13per month for 2000 kWh of electricity sourced from renewable energy sources compared to non-renewable, and pay an additional premium if they are informed of a specific source of renewable energy. Utility companies' generation portfolio is also differentiated by customers' preference for electricity sources, generating more green electricity if customers have stronger environmental preferences (Delmas et al., 2007).

Consumers might also alter consumption patterns when adopting renewable electricity. Several studies have explored utility-run green electricity programs and consumption responses with a green-tariff mechanism (Kotchen and Moore, 2007) and found modest or no changes in consumption, with an ambiguous direction of consumption change. For instance, Jacobsen et al. (2012) found that among participants in a voluntary renewable electricity program, a subset of adopters increased electricity consumption by 2.5 %. In contrast, Kotchen and Moore (2008) found that those who do not care about the negative externalities associated with electricity generation decreased consumption after enrolling in the green electricity program with a price premium. However, the authors found that those who place greater value on environmental repercussions and community engagement do not change their consumption associated with renewably sourced electricity.

A body of recent research on the relationship between consumption behavior and electricity sources has specifically focused on solar electricity production and consumer responses to the adoption of solar energy via rooftop panel installation. The solar rebound describes a phenomenon in which households increase electricity consumption after they adopt solar electricity (Boccard and Gautier, 2021; Frondel et al., 2023; Oliver Matthew et al., 2019), undermining some of the expected benefits of adoption. The change in usage is substantial with panel installation, with estimates that up to one-third of electricity generated from panels goes to new consumption, rather than displacing grid electricity (e.g., Aydın et al., 2023; Beppler et al., 2023; Boccard and Gautier, 2021; Deng and Newton, 2017; Kim and Trevena, 2021; Qiu et al., 2019; Toroghi and Oliver, 2019). This solar rebound is remarkable in its magnitude (especially relative to green electricity purchasing programs) and its implications for electricity consumption patterns, suggesting significant latent electricity demand and potential increases in electricity demand as distributed generation and other solar generation increase.

[1] A different type of community solar program lets customers purchase solar panel(s) installed in a solar farm by paying an upfront cost similar to rooftop solar. This is referred to as a 'customer-owned model' (Michaud, 2020). In this study, we focus on the model where customers can subscribe to the program, which has been referred to as a 'rental model' (Michaud, 2020).

### 2.2. Community solar program and consumption behavior

In this study, we focus on a community solar program as a different way to adopt solar electricity to understand whether consumer behavior in this program aligns more closely with green electricity purchasing models or with the more recently identified solar rebound. In community solar programs, consumers subscribe to the program and receive a certain amount of solar electricity from utilities or other third-party organizations. In this model, solar electricity is sourced from solar farms or other off-site installations, but customers are typically told the specific solar farm or installation from which they are purchasing. Depending on program design, consumers choose a certain percentage of their total consumption (e.g., 50 %) or the amount produced by a solar block (e.g., 1 kW panel). In the latter case, which includes the one examined in this study, customers pay a fixed cost (e.g., $22) per block every month and receive the amount of electricity (kWh) generated from the assigned block(s), which is then deducted from their total consumption. Electricity generated in solar panels varies (due to weather and sunlight variability) while consumers pay a fixed price, meaning that the price of electricity (c/kWh) from community solar programs varies monthly. Programs typically provide guidance on the expected range or average of generation provided by the block. The amortized solar block price, per kWh price, represents a premium over the standard grid tariff; for instance, an average of 10.8 c/kWh (solar electricity) over an average of 7.7 c/kWh (traditional energy sources) in one electric co-op in Georgia.[2]

Community solar programs have a number of distinctive features that have the potential to influence electricity use patterns by customers. Further – given the advocacy of these programs by researchers and NGOs as an equitable solution to expand renewable energy – it is important to study the impact of community solar participation on electricity use. The consumption response following subscription to a community solar program may differ from that associated with a utility-run green electricity program. Unlike generic green electricity programs, community solar participants know the specific source of their renewable electricity and its location, and are often purchasing capacity, rather than generation. As previous studies have shown (e.g., Bengart and Vogt, 2021; Kosenius and Ollikainen, 2013), consumers distinguish among different renewable energy sources and exhibit differentiated willingness-to-pay. Accordingly, they might display distinct consumption responses if they specifically choose to receive 'solar' electricity.

The impacts of community solar on electricity demand are uncertain and may differ substantially from those of rooftop solar, even though the programs both source solar electricity. In a community solar program, the consumers contract for a share of a solar farm or its output. The location of the solar is typically identifiable and is typically, although not always, located near the electricity consumer. However, unlike rooftop solar panels, a community solar electricity project may not be easily visible to the electricity consumer. When rooftop solar panels are installed in a home, consumers can see them, and this visibility of rooftop solar panels is likely to have an important impact on their behavior (Hondo and Baba, 2010). For example, panel visibility has been cited as a driver for peer diffusion (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015). Panel visibility might also impact customers' consumption behavior as a reminder that the electricity consumed is solar or create the impression for consumers that the marginal cost of consumption is lower. When panels are located off-site, community solar consumers lack the visual cue that their electricity is solar, although they may have information about the specific location of the solar installation, making the source of electricity more salient than a renewable energy purchasing program. The only reminder that customers receive about their solar electricity usage is when they receive their monthly electricity bill.

Devices that monitor electricity generation from rooftop solar would be another source that could affect behavioral change in rooftop solar but are not present in community solar. Providing information on electricity consumption and generation, as well as the method of its delivery, is a key factor influencing changes in electricity consumption (e.g., Aydin et al., 2018; Bollinger and Hartmann, 2020; Martin and Rivers, 2018). While rooftop solar panel installation typically entails the installation of electricity consumption and/or generation monitors, community solar programs do not have these devices. Customers of community solar programs do not have as much information, except that they periodically get information about the amount of electricity generated from solar block(s) on their bills, potentially reducing their capacity to change behavior.

### 2.3. Behavior responses to community solar adoption

How does the adoption of community solar change a household's electricity consumption? Community solar programs provide varying prices for solar electricity, often different from the retail rate of electricity. In the case of a fixed monthly block price, the price of solar electricity fluctuates depending on the amount of electricity generated from the solar block. Consequently, the average price of electricity consumed may be altered. Changes in the average price of electricity can motivate shifts in consumption behavior and change electricity demand (e.g., Buchsbaum, 2022; Ito, 2014; Wichman, 2014). It is unclear whether consumers complete the complex calculations involved in calculating marginal prices (Bollinger and Hartmann, 2020), making them more likely to respond to lagged average prices (Ito, 2014).

Psychological and behavioral theories might explain potential changes in electricity demand after adopting community solar. For instance, the adoption of solar electricity might promote other pro-environmental behaviors as a positive spillover (Lacasse, 2016; Nash et al., 2017; Truelove et al., 2014); consumers might participate in other energy conservation behaviors such as reducing their electricity usage. Likewise, the adoption of solar panels or 'green' technologies might help shift consumer attitudes and behavior toward environmental-friendly behaviors and products (Hondo and Baba, 2010; Rai and McAndrews, 2012).

An alternative hypothesis suggests that because the electricity sourced from community solar programs is renewable and clean, energy usage might increase following joining a community solar program. As in the case of the solar rebound,[3] it is possible that consumers increase electricity consumption due to moral licensing or a willingness to use more electricity when electricity is produced renewably. Moral licensing, a behavioral effect associated with consumers occurs when people who have previously behaved ethically see their moral self-image heightened and become less worried about their image being seen as immoral, thus engage in 'immoral' behavior (Dütschke et al., 2018; Truelove et al., 2014). From this perspective, if consumers perceive that energy consumption is immoral due to pollution externalities after installing solar panels (a moral behavior), they then increase electricity

[2] More discussion of the prices of solar and traditional sources is in the last section.

[3] Under most net metering policies, any electricity not instantaneously consumed by the customer is credited toward future electricity production at the retail rate of electricity. In the rebound effect associated with energy efficiency, the marginal cost of consumption is lowered by adopting an energy-efficient appliance. On the contrary, under a classic net metering policy, the opportunity cost and marginal cost of consumption are held fixed at the retail rate of electricity, while the average cost decreases. Thus, under a net metering policy and in case electricity generated from solar panels does not cover all the consumption, the solar rebound is fully behavioral – perhaps due to moral licensing, perhaps due to budget anchoring, where consumers allocate a fixed amount toward their electricity bills, or perhaps due to an incorrect perception by consumers that their cost of consumption is lower when they have solar panels.

consumption. This new consumption likely represents latent energy demand. When consumers believed they were consuming electricity generated from fossil fuels, they suppressed their energy demand because they felt guilty about the negative externalities associated with it. After signing up for renewable energy sources, community solar program consumers may perceive their participation as ethically 'good' behavior and reduce concern about immoral behavior (energy consumption) after adoption.

If community solar customers do not have particularly environmental or climate-change related values, they have less incentive to reduce energy consumption (Dütschke et al., 2018). Alternatively, consumers might have a single-action bias, which refers to perceiving risk reduction after completing one action even though multiple actions are required (Weber, 1997). Consumers of community solar electricity who are motivated by climate change might become less concerned after community solar adoption and not feel the necessity to further engage in further energy conservation behavior. This might lead community solar customers to increase their electricity consumption after joining the community solar program.

## 3. Data

### 3.1. Electricity consumption data

The data in this study comes from an electric co-op in the state of Georgia, U.S., that provides service to eight counties west of metropolitan Atlanta. Despite geographical adjacency, the socio-political environments in these countries are diverse. While three counties leaned toward Democrats in the 2022 U.S. Senate election, the rest strongly aligned with support for the Republican Party (AJC, 2022). The service areas[4] of the co-op have an average median income of 78,674 USD (in 2022 inflation rate adjusted, standard deviation 19,541) and an average population of 36,833 (standard deviation of 22,514) per zipcode (U.S. Census Bureau, 2022), including rural and suburban areas that are understudied in previous literature.

As one way to provide solar electricity, the co-op offers a community solar program where consumers opt to pay a fixed cost per solar panel block in a remotely located solar farm for electricity produced by the block(s). The program charges $22 ($25 before February 2018) per block, and each block produces 160–280 kWh depending on weather and seasonal factors. The amount of electricity generated from a solar block is then deducted from monthly total electricity consumption. Customers who are willing to subscribe to the program are informed of the fixed price of each block, how much energy credit (in kWh) will be typically awarded to their account, and what they can expect on their bills, as presented in Fig. 1. Customers who subscribe to the program via phone were informed of the same acknowledgments verbally.

In the dataset received from the utility provider, 915 community solar customers subscribed to the program from 2016 to 2023.[5,6] A large share of subscriptions (more than 400) to the program happened in December 2016 when the program was launched and heavily marketed. The second wave of subscriptions happened in August 2017, when 111 consumers joined the program. During the rest of the panel, from January 2017 to October 2023, new subscribers ranged from 0 to 27.

Most of the participants live in houses (893 out of 915). This differs from recently published survey results that claimed a high proportion of renters in community solar customers (O'Shaughnessy et al., 2024) across the country, though the geographical characteristics of our sample should be considered. Customers in the co-op in our data are primarily in rural and suburban areas where multi-family housing is uncommon and where, on average, more than 80 % of households are one-unit structures (U.S. Census Bureau, 2022). More than 500 customers end up signing up for two blocks, while 394 customers choose one block. The dataset also includes about 5000 customers who have not subscribed to the program (control group), with monthly consumption and billing data ranging from May 2015 to November 2023. The dataset also includes the date that each customer subscribed to the program,[7] the number of blocks that they end up subscribing, and the electricity generated from each solar block per month. The subscribers to the community solar program are in five adjacent counties in Northern Georgia - Carroll, Cobb, Douglas, Fulton, and Paulding, as shown in Fig. 2.

From the original dataset, we exclude three community solar customers who subscribed twice (opted in, out, and in again) during the time period, nine customers who also adopted rooftop solar panels, and customers who were coded incorrectly. We also limit our sample to customers who subscribed before October 2022 to see a whole year of consumption after receiving solar electricity. Customers without county or service-type information are excluded. Also, we eliminate average usage data points from the top and bottom 1 % quantiles to remove outliers or other data entry errors.

Community solar customers consume more electricity on average than non-solar customers before opting into the community solar program. Fig. 3, panel A, shows the distributions of average annual usage of both community solar customers before subscription to the program and regular customers. For community solar customers, average annual consumption is calculated considering the differences in their subscription month and year.[8,9] Table 1 presents descriptive statistics of adopters before they subscribe to the program and non-adopters of both monthly and annual electricity consumption. A difference of means test shows that on average those who subscribe to the program consume more (121.13kWh monthly)[10] than those who do not before subscription. Panel B in Fig. 3 also shows that, on average, adopters' monthly consumption is higher than that of non-adopters pre-adoption. We also test the differences among customers regarding the number of blocks they signed up for (1 or 2) and find that customers who signed up for two blocks were those who used more electricity (on average 199 kWh monthly) than those who signed up for one block. Higher consumption observed among community solar program participants and two-block subscribers, compared to non-participants and one-block subscribers, mirrors findings from a green electricity program in a neighboring state (Jacobsen et al., 2012).

The final dataset ends up with unbalanced panel data of 754 participants and 2726 non-participants, with 55 households who opted out of the community solar program during the study period, enabling us to further explore consumption behavior transitioning from solar electricity to conventional electricity sources. We also include weather data

[4] The service areas are identified based on the zip code information provided by the Open Energy Data Initiative (Huggins, 2022).

[5] Their monthly consumption data begins in 2015, providing a pre-period before subscription.

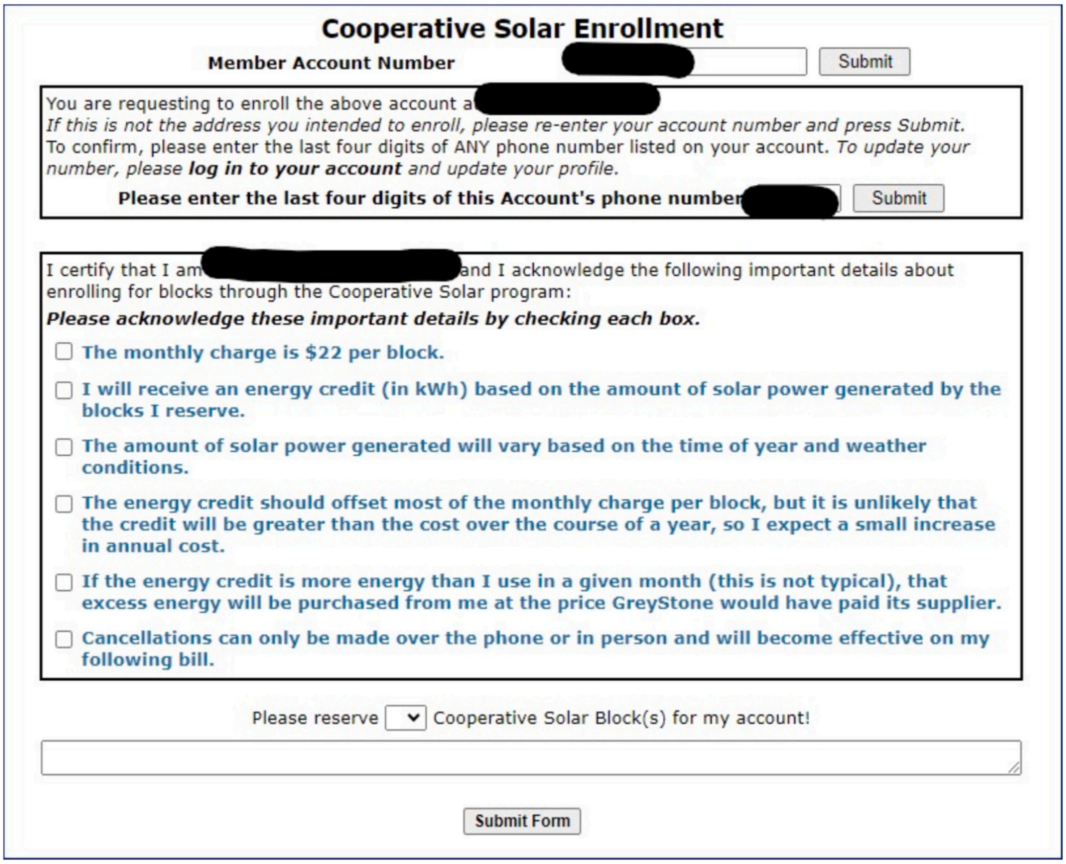
[6] During that time period, the residential rate changed once in April 2016, several months before the program launch in December 2016.

[7] For some subscribers, the first month in which they appear as "treated" (when they begin paying the solar block fee) may not align exactly with the month they enrolled in the program due to billing cycles. For example, if a household subscribed on December 25, 2016, and their billing date was January 10, 2017, they would be recorded as treated starting in January 2017. In contrast, if a household subscribed on July 3, 2019, with a billing date of July 15, 2019, their treatment would begin in July 2019.

[8] For instance, if customer A subscribed to the program in June 2019 and A's billing data is available from March 2016, the average annual consumption is calculated for the three annual cycles of June 2016–May 2017, June 2017–May 2018, and June 2018–May 2019.

[9] Because of how we calculate the average annual consumption, solar electricity adopters with less than a year-long monthly consumption data before subscription are excluded, which automatically removes someone who moves into a new house and subscribes to the program right after.

[10] Switchers excluded.



**Cooperative Solar Enrollment**

**Member Account Number** [redacted] Submit

You are requesting to enroll the above account a[redacted]
*If this is not the address you intended to enroll, please re-enter your account number and press Submit.*
To confirm, please enter the last four digits of ANY phone number listed on your account. *To update your number, please* ***log in to your account*** *and update your profile.*

**Please enter the last four digits of this Account's phone numbe**[redacted] Submit

I certify that I am[redacted]and I acknowledge the following important details about enrolling for blocks through the Cooperative Solar program:
***Please acknowledge these important details by checking each box.***

- [ ] **The monthly charge is $22 per block.**
- [ ] **I will receive an energy credit (in kWh) based on the amount of solar power generated by the blocks I reserve.**
- [ ] **The amount of solar power generated will vary based on the time of year and weather conditions.**
- [ ] **The energy credit should offset most of the monthly charge per block, but it is unlikely that the credit will be greater than the cost over the course of a year, so I expect a small increase in annual cost.**
- [ ] **If the energy credit is more energy than I use in a given month (this is not typical), that excess energy will be purchased from me at the price GreyStone would have paid its supplier.**
- [ ] **Cancellations can only be made over the phone or in person and will become effective on my following bill.**

Please reserve Cooperative Solar Block(s) for my account!

Submit Form

**Fig. 1.** The screenshot of the subscription to the community solar program.

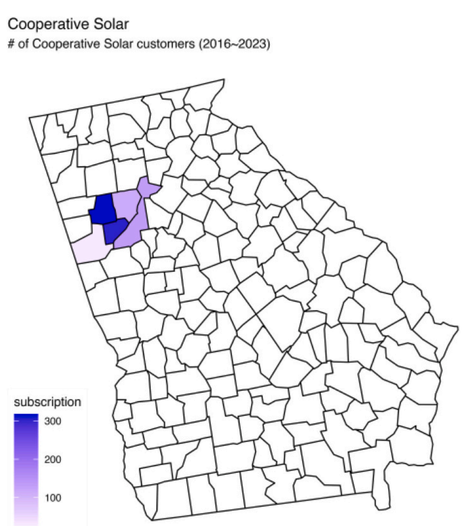



**Fig. 2.** The geographical distribution of community solar program participants.

as a control variable to account for the high dependence of monthly consumption on the weather, by adding monthly degree days above and below 18$^{\circ}C$[11] by county from the UC Davis weather data platform (Lee, 2025) which uses PRISM and other geographical data.

[11] Following the description by EIA (EIA, 2023).

### *3.2. Selection bias with solar electricity adopters*

One of the crucial parts of the analysis is the comparison between the control group (untreated, non-solar electricity consumers) and the treatment group (community solar participants). Previous studies have found that the treatment group might have different consumption patterns before the adoption of solar electricity compared to the control group, potentially resulting in biased estimates (Beppler et al., 2023). Also, research on the adoption of rooftop solar panels has identified several factors, including socio-demographics, social norms, and environmental concerns, that differentiate rooftop solar adopters from non-adopters (Lukanov and Krieger, 2019; Palm, 2018; Wolske et al., 2017). In other words, it is not reasonable to assume community solar adopters are similar to non-adopters (e.g., O'Shaughnessy et al., 2024). Thus, finding an appropriate control group for the treated group is essential to obtain unbiased results of electricity consumption behavior change of community solar electricity adopters.

Previous researchers who studied the rebound effect of rooftop solar PV customers often used matching techniques by identifying non-adopters who are most similar to adopters. They employed criteria such as seasonal load profile, annual usage, socio-demographics such as income or race, or building characteristics (Beppler et al., 2023; Qiu et al., 2019) for matching. Following previous literature, we use coarsened exact matching (CEM). In CEM, either analysts or the program selects cutpoints and bins for each covariate *ex-ante* and classifies each observation into strata, which can limit the maximum imbalance between treated and control groups (Blackwell et al., 2009; Iacus et al., 2008). Additionally, the CEM algorithm is computationally efficient and can bind the model dependence of the results (Blackwell et al., 2009; Iacus et al., 2008).

Matching has been done based on four factors: average annual consumption, county, service type, and monthly consumption pattern. Even

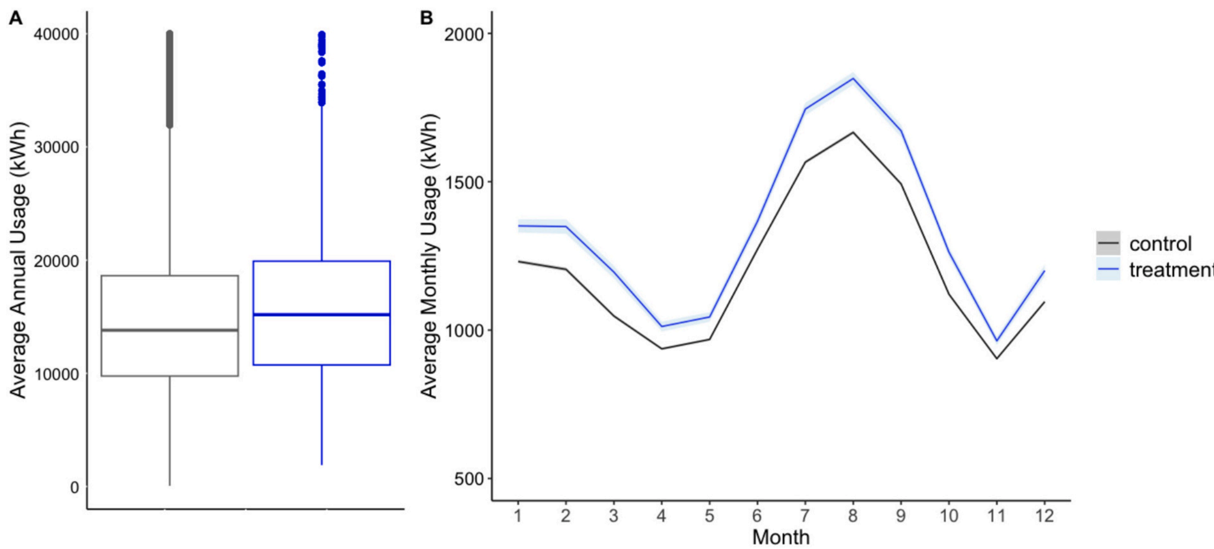



**Fig. 3.** Average annual usage (a) and average monthly usage (b) between community solar customers before subscription and control group customers.

**Table 1**
Descriptive statistics of adopters (before adoption) and non-adopters.

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| **Monthly Consumption** | | | | | |
| *Treated* | 1333.96 | 744.51 | 199 | 4093 | 14,729 |
| *Control* | 1212.83 | 706.75 | 35 | 3843 | 199,594 |
| **Annual Consumption** | | | | | |
| *Treated* | 16,319.75 | 7697.92 | 1890 | 59,848 | |
| *Control* | 15,029.50 | 7651.03 | 61 | 73,680 | |

Data include both matched and non-matched households. Switchers are excluded.

though the data collected in this study do not include household characteristics such as income or the number of family members, aggregate annual usage is correlated with household-level covariates (Bartusch et al., 2012; Nguyen-Van, 2010; Yohanis et al., 2008). The monthly consumption pattern is assigned based on clustering. Following Beppler et al. (2023), we calculate the average percentage of consumption in each month and cluster consumers based on their monthly shape, which results in four different clusters. Fig. 4 shows kernel density plots of average annual consumption of treated and control groups before (panel A) and after (panel B) matching.

## 4. Methodology

### 4.1. DiD under homogeneous treatment effect assumption[12]

We employ difference-in-differences (DiD) to measure how consumption changes after subscribing to a community solar program. This study starts with static two-way fixed effect (TWFE) DiD estimates,[13] assuming the treatment effect (i.e., the effect of opting into a community solar program) is not heterogeneous across treated consumers. The specification of TWFE DiD model is in Eq. (1).

$$usage_{i,t} = \alpha_i + \gamma_t + \beta_{DiD} Comm_i \times Sub_t + \theta W_{i,t} + u_{i,t} \tag{1}$$

where $Comm_i$ is an indicator for community solar customers and $Sub_t$ is a dummy variable turning to 1 after the month and year they subscribe to the program. $\beta_{DiD}$ accounts for the treatment effect and the interest of this study. $W_{i,t}$ represents weather including monthly heating degree days and cooling degree days in the county that a household resides in. $\alpha_i$ and $\gamma_t$ are household fixed effect and month-year indicators.

### 4.2. DiD under heterogeneous treatment effect assumption

Recent literature has found that TWFE DiD may not be appropriate in staggered treatment timing with heterogeneous treatment effects. In our dataset, customers opt into the program in different months and years, and the treatment effect may vary among them. For instance, as the diffusion of innovation theory (Rogers, 2003) reveals, early adopters could have different features compared to late adopters. Additionally, customers who decided to use solar electricity in the summer might be different from those who did so in the winter. When the treatment effect varies across groups and time, static or dynamic TWFE can result in a biased aggregate treatment effect estimate because of the negative weight problem and the characteristics of TWFE estimation that it is affected by each group size, the number of periods overall, and the timing of treatments (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021).

As an alternative approach for staggered treatment timing, Callaway and Sant'Anna (2021)) introduced cohort and time-varying average treatment effect on treated, $ATT(g,t)$. When we alleviate conditional parallel assumption by assuming parallel trend is unconditional to pre-treatment covariate, $ATT(g,t)$ becomes.

$$ATT(g,t) = E\left[Y_t - Y_{g-1} | G_g = 1\right] = E\left[Y_t - Y_{g-1} | C = 1\right] \tag{2}$$

Here, we assume there are no anticipation effects, and treated group is compared to the 'never treated' group.[14] In Eq. (3), $g$ is for each cohort (i.e., consumers who opted in the same month and year), and $G_g$ is an indicator for each group. $C$ is an indicator for the control group and $Y_t$ is the outcome at time t. The aggregation across cohort time is estimated with weight $w(g,t)$ by.

[12] In this section, we follow terms used in Roth et al. (2023).

[13] Figure A1 shows a parallel trend before the adoption between the treated group (first and second adopters) and the matched control group.

[14] The CSDiD estimate provides options to choose a comparison group, either 'never treated' or 'not yet treated'. In the study, since the data has a sizable group of non-participants who did not use solar electricity the whole time period and who are matched to participants, we use 'never treated' as a control group. As a robustness check, we also try 'not yet treated' as a comparison group excluding non-participants.

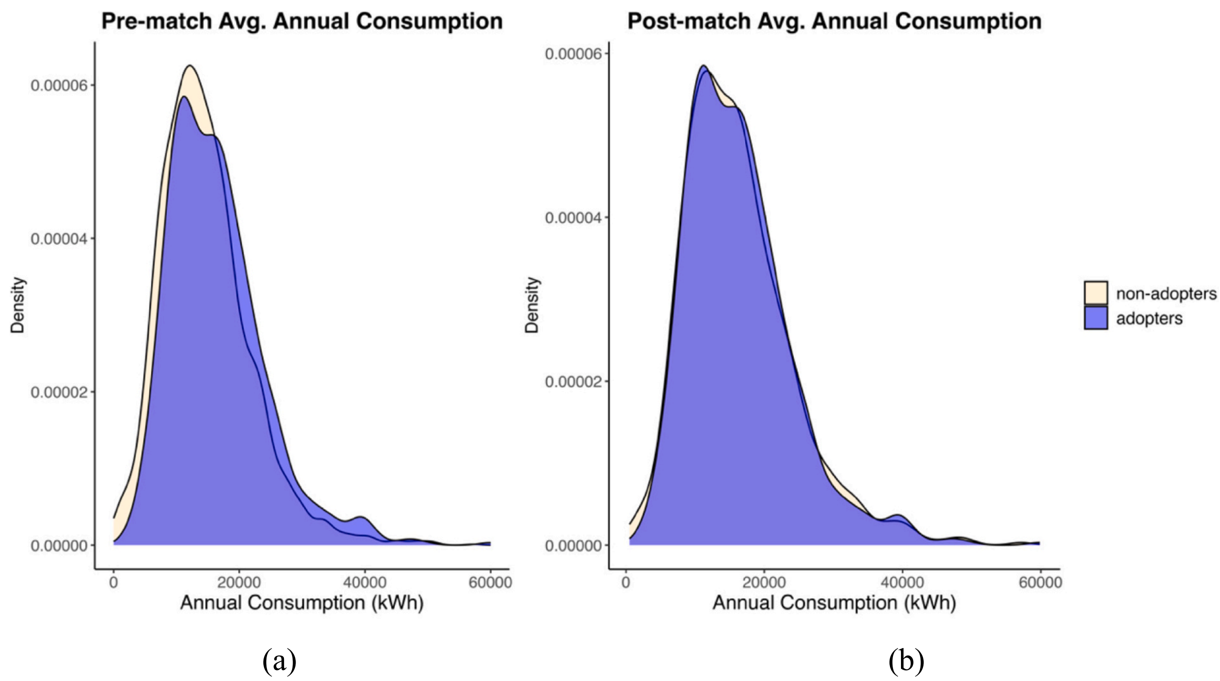



**Fig. 4.** (a) Average annual consumption before matching (b) Average annual consumption after matching.

$$\theta = \sum_{g \in G} \sum_{t=2}^{T} w(g,t) \times ATT(g,t) \tag{3}$$

We limit the panel to individuals without any missing value from January 2016 to December 2022[15] for Callaway and Sant'Anna (2021) estimate (hereafter, *CSDiD*). In addition, the estimate assumes 'irreversible treatment', i.e., once treated treatment remains, so we exclude those who opt out of the program in the middle of the period (i.e., 'switchers') in our primary analysis.

As a robustness check, we also implement Stacked DiD (Wing et al., 2024), another way to account for heterogeneous treatment timing. In Stacked DiD, we decide the size of the event window $\kappa$[16] and create sub-experiments containing the adoption cohort (i.e., customers who adopted at time *T*) and clean controls. Clean controls can include both never-treated individuals and treated individuals who have not yet been exposed to the treatment during the time window ($T$-$\kappa$ to $T$+$\kappa$) (Wing et al., 2024). After creating a stacked set of sub-experiments, we use a weighted regression approach similar to the TWFE model.

The alternative staggered DiD estimation method, including CSDiD estimate, has two main benefits compared to the traditional TWFE estimate, according to Roth et al. (2023). First, even in cases when treatment effects are arbitrarily heterogeneous, it offers reasonable estimands since weights are specified by the researcher. Second, a comparison group is clearly indicated. For instance, in CSDiD estimate, either non-participants ('never treated') or later adopters who haven't been treated yet at the time ('not yet treated') can be chosen to be a comparison group. Likewise, in Stacked DiD (Wing et al., 2024), a combination of both 'never treated' and 'not yet treated' becomes comparison group. However, in TWFE DiD, the comparison group for each treatment cohort is not clear.

[15] Our data includes pre- and post-COVID years. Time indicator in our analysis covers yearly variation, but we also check similar consumption patterns in these periods among the control group, as in Figure A3.

[16] Length of windows can differ before and after the adoption. For instance, one can choose four years pre-treatment and three years post-treatment.

## 5. Estimation and results

### 5.1. Consumption behavior after the adoption

Our findings show that total monthly consumption does not change after subscription, suggesting the absence of a rebound effect. However, the amount that consumers pay monthly increases by about 3.3–4 % on average, which is equivalent to an additional 1c/kWh in the average price. Traditional economic theory of price and demand predicts that demand would decrease once price increases, but this pattern does not apply to community solar customers.[17] The finding could be a result of customers willing to pay a premium for their green consumption, a lack of information on higher electricity costs, or 'stickiness' of consumption habits. We cannot test these mechanisms with this dataset.

On average, using our preferred Callaway & Sant'Anna estimates, we find that average consumption, post-adoption of community solar program, decreases by less than 4 kWh/month (Table 2), which is less than 1 % change in usage (considering the average monthly consumption of 1318 kWh among participants in our dataset).[18] These results are statistically not discernible from zero at the 95 % confidence level, indicating the actual change would be negligible.

To estimate short-term effects of community solar subscription, we use a series of pooled samples that include data from 12 months before adoption up to 1 month after, then 2 months after, 3 months, 4 months, and so on. For each time window, we estimate the ATT separately. The results in Fig. 5 show a small but statistically significant increase in consumption shortly after subscription when employing the CSDiD estimator, around 45 kWh in the first one to two months post subscription ($p < 0.1$). Estimates including TWFE DiD do not reveal

[17] The sign of average treatment effect on the treated (ATT) in Table 2 is negative across different estimation methods, which aligns with downward-sloping demand, although it is not statistically significant.

[18] We also tested sample weights that are disproportionate to the number of participants in each subscription month, noting that half of the subscriptions occurred in December 2016; however, the long-term results remained consistent, with Callaway & Sant'Anna estimate of ATT of −77.04 (95 % confident interval: −161.29, 7.21).

**Table 2**
Estimates of the treatment effect using different DiD methods.

| | (1) TWFE DiD | (2) CSDiD | (3) CSDiD2 | (4) Stacked DiD |
|---|---|---|---|---|
| ATT | −16.01 [−39.99, 7.96] | −3.86 [−42.41, 34.69] | −3.13 [−39.14, 32.88] | −18.11 [−41.14, 4.93] |
| N | 99,721 | 53,256 | 53,256 | 63,499 |
| Control | Y | Y | Y | Y |
| Matched | Y | Y | Y | Y |
| Balanced | N | Y | Y | Y |

Column (3): 'not yet treated' as control. Column (4): 12 months of event window.
Standard errors are clustered at the household level. 95 % confidence intervals are in brackets.
The results show no significant consumption change post-adoption across different estimations.

**Table 3**
Estimates of the treatment effect on monthly bill and average price using different DiD methods.

| | *Monthly Bill ($)* | | *Average Price ($/kWh)* | |
|---|---|---|---|---|
| | (1) TWFE DiD | (2) CSDiD | (3) TWFE DiD | (4) CSDiD |
| ATT | 4.58*** (1.15) | 4.60* (2.06) | 0.01*** (0.00) | 0.01*** (0.00) |
| N | 99,721 | 53,256 | 99,721 | 53,256 |
| Control | Y | Y | Y | Y |
| Matched | Y | Y | Y | Y |
| Balanced | N | Y | N | Y |

Columns (2) and (4): 'never treated' as control.
Standard errors are clustered at the household level and in parentheses.
The results show consumers pay about $4.6 more post-adoption.
*p < 0.05, **p < 0.01, ***p < 0.001.

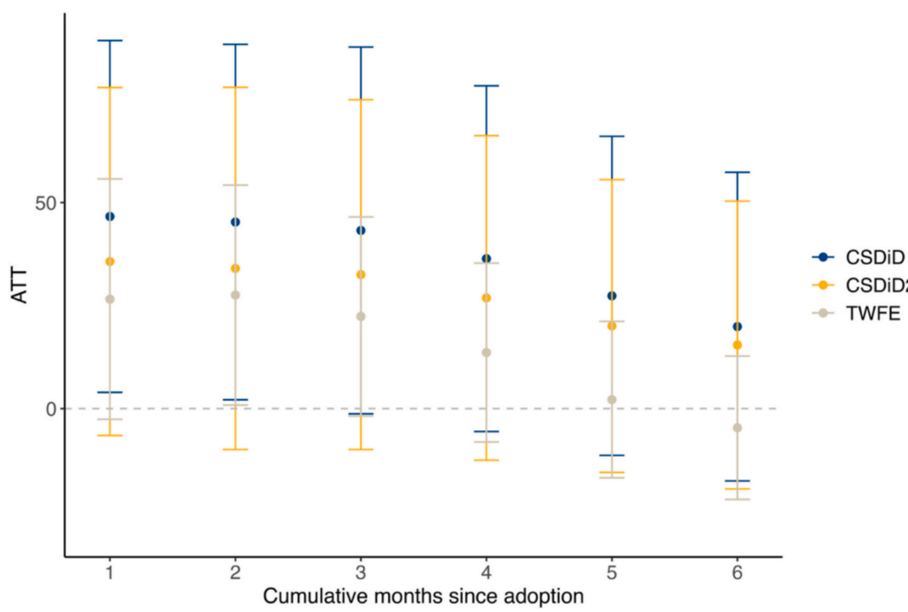



**Fig. 5.** Estimated ATT by cumulative months since adoption of community solar programs.
(Note: 90 % confidence intervals are presented. CSDiD: 'never treated' as control group. CSDiD2: 'not yet treated' as control group).

statistically significant increases across any of the pooled samples. In addition, even the CSDiD estimate diminishes quickly, becoming statistically insignificant once at least three months are pooled. The short-term increase in consumption following adoption may be driven by psychological factors discussed in Section 2, such as moral licensing or the excitement of signing up for a clean energy program, calling for further investigation into the underlying mechanisms driving consumption change. We also present DiD event studies in Fig. A2. These reveal positive deviation immediately after subscription, consistent with the pattern observed in Fig. 5, but the estimates are not statistically significant.

Although consumers have not significantly changed their consumption patterns, findings show they are paying an average of $4.60 more per month (approximately 3.3 %, based on an average monthly bill of $138) after subscribing to the program, as shown in Table 3.[19] This equates to an increase of 1 c/ kWh average price, which is calculated as a total bill divided by total usage.[20] Even when excluding all fixed and time-varying fees, such as Service Charges, results stay consistent, as shown in Table A4, with monthly bills increasing by 4.1 %. Consequently, consumers are paying marginally more to adopt solar electricity.

In terms of the average electricity price that consumers are paying, solar electricity is found to be more expensive, explaining community solar adopters' higher bills. In our case, the price paid by community solar customers was about 10.8 c/kWh, with the lowest amount being 7.6 c/kWh (June 2022) and the highest being 17.2 c/kWh (January 2022), as in Fig. 6. The average price of solar electricity from the program is higher than the price of traditional energy sources such as coal or natural gas (the average cost of electricity is about 7.7 c/kWh for 1300 kWh in the electric co-op in this study).

[19] The co-op has not changed its marginal electricity price or service charges during the analyzed period, and the other fees remained largely unchanged as well.

[20] This value does not represent the exact average price of electricity; the average price shown in Table A4 provides a more accurate reflection of electricity cost, which also shows a 1c/kWh increase. As a comparison, the average price of control group is 10.8 c/kWh, and tier 3 pricing is 6.45 c/kWh in winter and 10.58 c/kWh in summer.

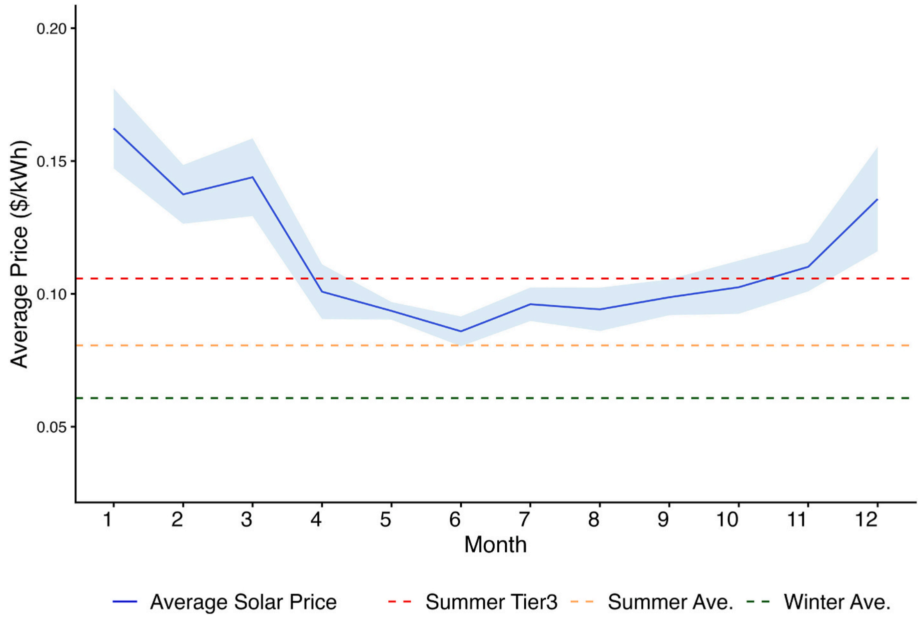



**Fig. 6.** Comparison between average monthly price of solar electricity ($/kWh) and electricity from traditional sources.
(Note: Summer and Winter average rates are an average of the three tiers' rates. In other words, it is the average price of electricity for those who consume 1500 kWh.)

### 5.2. Consumption responses during summer

We shift our attention to customers near the upper thresholds of the highest electricity tier particularly during the summer when solar electricity becomes cheaper. In these months, with abundant solar radiation, customers could anticipate that electricity generated from solar blocks would be higher than usual.

Fig. 7 shows that the co-op in our study offers a three-tier, increasing block price rate schedule for residential customers, with different prices for tiers 2 (consumption range of 500 kWh – 1000 kWh) and 3 (over 1000 kWh) for winter and summer. For those typically consuming just above tier 3 (10.58 cents/kWh in summer) at around 1000 kWh, ample solar generation during the summer can lower customers' marginal cost of traditional electricity to tier 2 (9 cents/kWh) by deducting the solar generation so that electricity consumption is below the 1000 kWh threshold. As a result, they might be encouraged to increase their overall electricity consumption during the summer. To explore this behavioral response, we focus specifically on the summer months, limiting the analysis to adopters whose average monthly consumption was between 950 and 1250 kWh prior to subscription, alongside a control group within the same range. Given the smaller sample size and unbalanced panel data, we employ the TWFE DiD model with household and year indicators for this subset analysis.

As expected, during the summer months, consumers who slightly exceeded the tier 3 threshold increased their total consumption by 47 to 74 kWh (Table 4).[21] With solar generation during these months averaging around 200 kWh, customers are still likely able to lower their overall usage enough to qualify for tier 2 rates and achieve savings even with a slight increase in total consumption. However, consumers may adjust their behavior in response to fluctuations in solar generation and changes in marginal electricity prices.

[21] We also estimated the overall treatment effect for different threshold cohorts. The estimation results shows that the overall effect is not discernible from zero, which adds evidence for the summer effect, not the general tier-3 effect.

### 5.3. Heterogeneity analysis and switchers

We also examine whether treated individuals with different features respond heterogeneously to the adoption. We test different numbers of solar blocks and counties, which are included as a dummy variable $R_i$ in Eq. (4). The results in Table A5 indicate that consumption does not vary across customers with different numbers of blocks. This contrasts with the findings of Jacobsen et al. (2012) that observed slightly varying behavioral responses among participants with minimum threshold levels (one block) and those who purchase more green electricity (two or more blocks). Additionally, the results show no meaningful variation in responses among different neighborhoods.

$$usage_{i,t} = \alpha_i + \gamma_t + \beta_{DiD} Comm_i \times Sub_t \times R_i + \theta \mathrm{W}_{\mathrm{i,t}} + u_{i,t} \tag{4}$$

We explore the consumption behavior of switchers (those who opt in and then out of the community program) separately, limiting the dataset to only switchers and a matched control group[22] with static TWFE DiD. Table 5 shows that this subset of community solar customers did not alter their electricity consumption patterns when joining the community solar program; however, they experienced an increase in electricity consumption after opting out of the program. Different consumption responses between opt-in and opt-out are noticeable. Switchers might have different characteristics from non-switchers; for instance, they are more price-sensitive. They might realize the premium they are paying for solar electricity and decide to switch back to cheaper energy sources, which triggers their increased consumption after opting out.

### 5.4. Price change of solar block

In February 2018, the co-op reduced the price of one block of solar

[22] The control group here is matched to switchers, therefore, it is a subset of the control group used in the previous analyses.

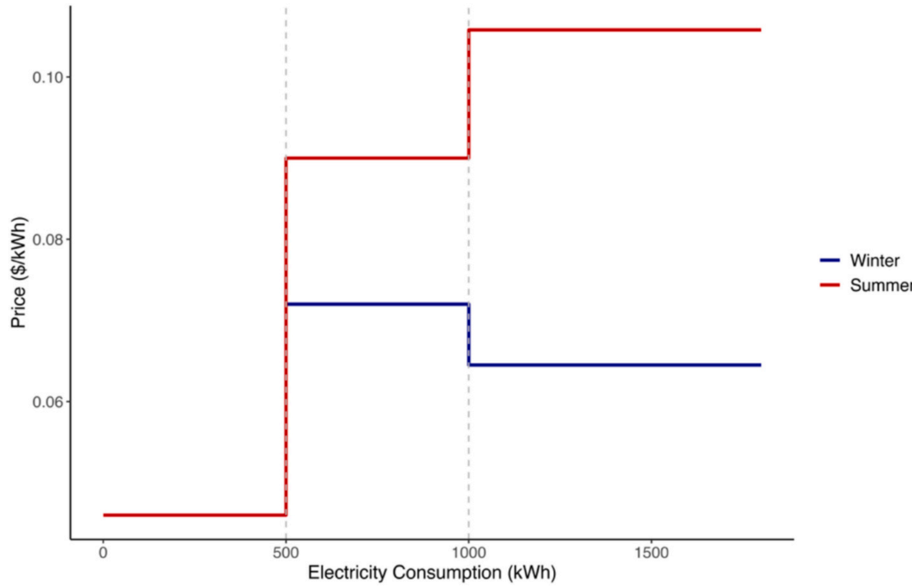



**Fig. 7.** Rate schedule for residential customers in the co-op.

**Table 4**
Estimates of the treatment effect on consumption in summer months among consumers in the tier 3 threshold.

| | (1) June | (2) July | (3) August | (4) September | (5) October |
|---|---|---|---|---|---|
| ATT | 47.0$^{+}$ | 73.8$^{+}$ | 67.7$^{+}$ | 55.0 | 22.9 |
| | (26.1) | (39.6) | (40.0) | (34.8) | (25.3) |
| N | 1755 | 702 | 1022 | 1388 | 1854 |
| FE | Y | Y | Y | Y | Y |
| Control | Y | Y | Y | Y | Y |

Standard errors are clustered at the household level and in parentheses.
Consumption behavior changes during summer times for those who consumed near the tier-3 price threshold.
$^{+}$ $p < 0.1$.

**Table 5**
The DiD estimates of switchers who opted in and out.

| | (1) Total | (2) Opting in | (3) Opting out |
|---|---|---|---|
| ATT | 74.82** | −15.78 | 141.8*** |
| | (26.63) | (35.01) | (33.17) |
| N | 7887 | 6284 | 6937 |
| FE | Y | Y | Y |
| Control | Y | Y | Y |

Standard errors are clustered at the household level and in parentheses.
While no consumption change is observed when they sign in to the community solar program, switchers increase consumption when they opt out of the program.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

panels from \$25 (on average 12.3 c/kWh) to \$22 (on average 10.8 c/kWh),[23] with an announcement to customers via email and letter. For the treatment group, we test whether the price reduction of solar electricity led to a change in consumption as in Eq. (5).

$$\text{usage}_{i,t} = \alpha_i + summer_t + \theta \mathrm{W}_{i,t} + \beta_{\text{block}} PD_t + u_{i,t} \tag{5}$$

In the model in Eq. (5), $\alpha_i$ represents the household fixed effect and $PD_t$ is an indicator for months after the price changed, starting from February 2018. We also include weather variable $W_{i,t}$, and an indicator for summer $summer_t$ (June to October, where summer rates apply) to account for high monthly variation and seasonality in consumption. We limit the sample to the treated group, those who subscribed at least seven months (one month before the six-month window) prior to the price changed, i.e., those who subscribed to the program before August 2017.[24]

As expected, we find a slight increase in consumption after the price drop. Demonstrated in Table 6, for the six months after the price drop, consumers increased their consumption by about 24 kWh per month (less than 2 % given average monthly consumption of 1318 kWh).

**Table 6**
The result of regression discontinuity in time considering a block price change.

| | (1) |
|---|---|
| $PD_t$ | 23.68$^{+}$ |
| | (12.25) |
| N | 3888 |
| FE | Y |
| Control | Y |

Standard errors are clustered at the household level and in parentheses.
Consumers respond to price changes in solar blocks and increase consumption when block prices drop.
$^{+}$ $p < 0.1$.

[23] Average monthly electricity generation per block was 203kWh in 2018–2023.

[24] Data limited to a balanced panel, i.e., adopters who subscribed to the program prior to August 2017 and have monthly consumption dataset for August 2017 – July 2018.

## 6. Discussion and conclusion

Consumption response to different electricity sources is a crucial but understudied area in the penetration of electricity generated from renewable energy sources such as solar or wind. This study investigates electricity consumption following participation in the community solar program, an alternative way to adopt solar electricity. We observe that customers do not change their consumption patterns after subscribing to the community solar program. In contrast to other research that shows a strong rebound effect when solar panels are installed, we do not observe this effect when solar energy is procured through a community solar program or green purchasing program. The finding suggests that this type of community solar program is not associated with an increase in demand for electricity. Further research should continue to explore the relationship between consumption behaviors and the design of pricing models to deliver renewable electricity.

Another avenue for future research is the relationship between consumption behavior and the share of electricity coming from renewable energy sources. Compared to the average size of rooftop solar (e.g., 6.6 kW in Qiu et al., 2019), the sizes of solar blocks in community solar are typically smaller (e.g., 1 kW per block in our study), resulting in a lower share of renewable electricity. By contrast, in certain community solar or green electricity programs, consumers can receive up to 100 % of their electricity from renewable energy sources. Previous studies have found varying behavioral responses with respect to the amount of renewable electricity generated. For instance, Aydın et al. (2023) observe that households with higher solar production tend to exhibit a stronger rebound effect. Investigating how the proportion of renewable energy in total electricity consumption influences consumer behavior could provide valuable insights into the link between energy sources and consumption patterns.

We also find consumers pay about 3–4 % of their monthly bill on average, equivalent to a 1 c/kWh increase in the average price, suggesting the need to reconsider the argument that community solar projects are an equitable alternative to rooftop solar. Because of its accessibility and lower financial barriers (e.g., no cost to install panels), community solar has been considered a solution for equitable access to solar by reducing hurdles such as housing and cost barriers in rooftop solar panel installation (Michaud, 2020; O'Shaughnessy et al., 2024). However, our analysis shows, for this program, solar adopters bear the cost of adoption through their bills. In addition, the price of solar electricity in community solar programs may cast doubt on its ability to serve as an equitable solution. As explained in Fig. 6, the average price of solar electricity is more expensive than the retail price of electricity from traditional energy sources in this co-op. This cost disparity could deter participation among those who might already be unable to install solar panels and access solar electricity due to financial and other barriers. It remains unclear whether other community solar programs have similar price premia associated with participation and this is an area for future investigation.

Considering the higher costs of solar electricity for community solar programs found in our analysis, the role of regulation and policy should be re-examined, especially among low-income households who have a high energy burden. A few states have taken steps to encourage their participation by implementing policies specifically targeting low and middle-income households. For instance, Maryland included 125 MW of carveout for low and middle-income households when the state introduced a community solar pilot program in 2017 (Fekete, 2020). Financial subsidies might be necessary to bridge the gap between solar electricity prices from community solar programs and those of other energy sources. Colorado has been awarded $156 million of funding and announced the Colorado Solar for All (COS4A) to support low-income residents with all varieties of solar electricity, from rooftop solar to community solar (Colorado Energy Office, 2024). Also, various pricing structures for solar electricity, such as flat rate or varying rates, could be considered.

This study bears several limitations, mostly due to data constraints. The most crucial drawback of analyzing solar electricity adoption and consumption data is selection bias. There might be several unobserved factors affecting both the decision to adopt and consumption behavior post-adoption, such as environmental awareness or customers' predetermined plan to increase their electricity consumption (Beppler et al., 2023; Qiu et al., 2019). This study uses matching to find customers in the control group who show similar consumption behavior to the treatment group pre-adoption, on the assumption that consumption behavior post-adoption is correlated with pre-adoption patterns, though this approach cannot address anticipatory effects if adopters were already planning to increase electricity consumption.

Second, it is difficult to empirically test the underlying mechanism driving the behavioral change post-adoption. Even though several non-monetary drivers can potentially explain the behavioral change, proving their influence on actual consumers is impossible given data limitations. Additional data such as household-level characteristics or interviews with adopters, on top of appliance-level consumption data, might reveal mechanisms driving behavioral change.

Lastly, the external generalizability of the findings is unclear, as it focuses on one community solar program of an electric co-op in the Southeastern U.S., which may not be similar to the designs of other community solar programs. While we believe that this community solar program is a common type of community solar program in the U.S., consumption behaviors may differ depending on the design of community solar programs (e.g., fixed monthly block price or c/kWh price premium for solar electricity), the residential rate structure (e.g., increasing block pricing or dynamic pricing), regional factors (e.g., places with abundant solar radiation or not), and electricity regulations (e.g. places that allow third-party contracting for community solar). Further research on different community solar programs will enhance our understanding of consumption behavior with solar electricity.

Despite limitations, this study broadens the understanding of consumer behavior by analyzing prevalent but under-studied community solar electricity programs in the context of the Southeastern United States. This study contributes to an emerging literature on the relationship between consumer behavior and different electricity sources, providing evidence that consumer response might differ even for the same solar electricity compared to rooftop solar. This research will help utility planners understand the changing demand due to renewable energy adoption. Also, this study provides implications for equity concerns in household solar adoptions, highlighting the rate structure of community solar programs that have been considered an equitable alternative to rooftop solar.

## CRediT authorship contribution statement

**Min-kyeong (Min) Cha:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Daniel Matisoff:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization.

## Acknowledgment

This paper is a revised version of one chapter of Min-kyeong Cha's thesis at Georgia Institute of Technology. The authors gratefully acknowledge support from the Brook Byers Institute for Sustainable Systems for the fellowship. We appreciate invaluable help from Brad Henderson, Drew Hook, and Caitlyn Ownbey. Several individuals provided valuable feedback on the manuscript, including Dylan Brewer, Gaurav Doshi, Casey Wichman, and John Kim. We are also grateful for the invaluable comments and feedback from the reviewers and the editor.

## Appendix A. Appendix

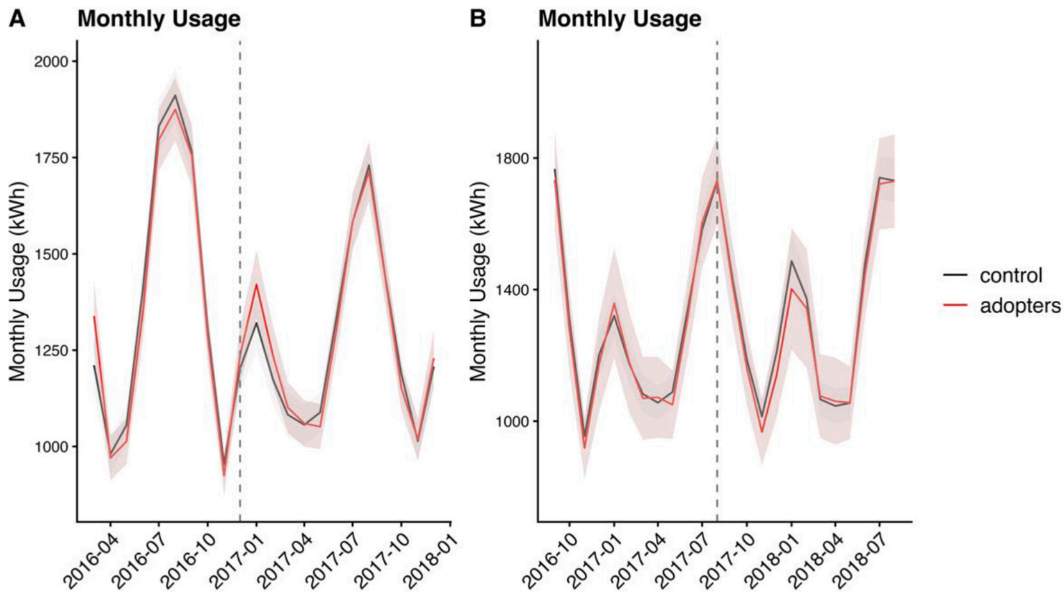



**Fig. A1.** Monthly consumption of the matched control group and treated group before and after the subscription. Panel A: first adopter (subscription in December 2016), Panel B: second-wave adopter (subscription in August 2017).

**Table A1**
Descriptive statistics.

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| **Monthly Consumption** | | | | | |
| *Treated (excluding switchers)* | 1318.10 | 741.67 | 198 | 4100 | 58,612 |
| *Treated (switchers only)* | 1329.27 | 706.89 | 199 | 4095 | 4666 |
| *Control - total* | 1212.84 | 706.76 | 35 | 3843 | 199,594 |
| *Control - matched* | 1324.31 | 736.02 | 35 | 3841 | 52,437 |
| **Monthly Bill** | | | | | |
| *Treated (excluding switchers)* | 138.74 | 72.58 | 24.82 | 522.48 | 58,612 |
| *Control - matched* | 137.36 | 77.17 | 15.2 | 493.92 | 52,437 |
| **Cooling Degree Days** | 104.58 | 98.50 | 0.1 | 305.15 | |
| **Heating Degree Days** | 126.87 | 129.96 | 0.00 | 478.85 | |

**Table A2**
Estimation of treatment effect using static TWFE DID.

| | (1) without matching | (2) with matching |
|---|---|---|
| ATT | −15.78<br>[−37.24, 5.68] | −16.03<br>[−40.00, 7.95] |
| N | 231,018 | 99,721 |
| Control | Y | Y |
| FE | Y | Y |

Standard errors are clustered at the household level.
95 % confidence intervals are in brackets.

Table A2 compares estimates with and without matching using the basic TWFE model. The table shows consistent results with and without limiting the dataset to matched samples via the CEM algorithm.

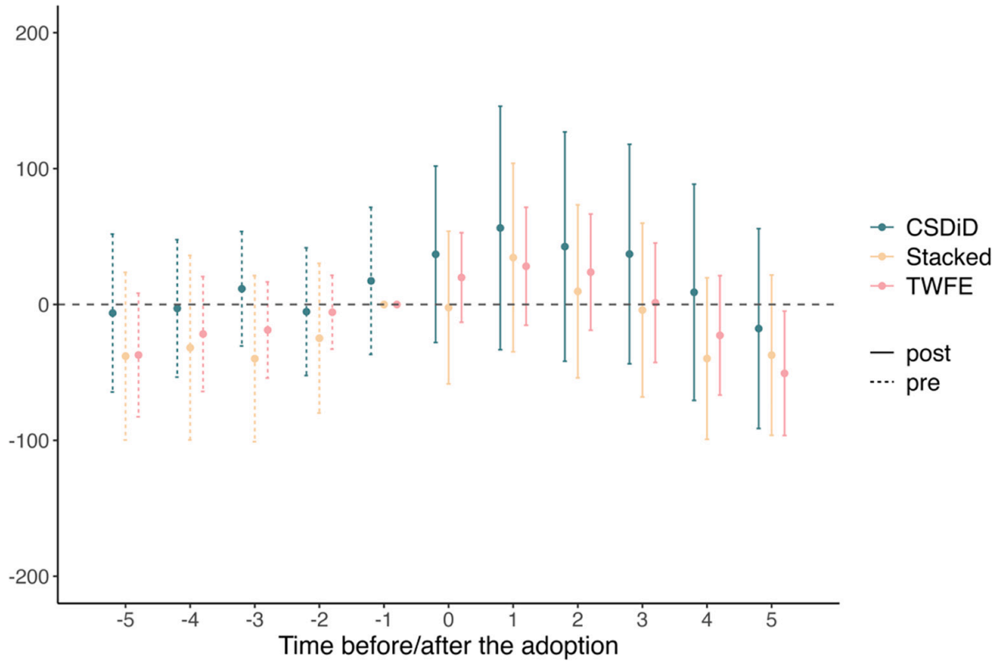



**Fig. A2.** Event studies result of different DiD estimates. (Note: 95 % confidence intervals are presented).

**Table A3**
Regression results of event studies using different DID estimates. The results correspond to Fig. A2.

| time before/after the adoption | (1) CSDiD | (2) Stacked DiD | (3) TWFE DiD |
|---|---|---|---|
| −6 | −13.94 (16.60) | −49.72 (28.16) | −47.77 (23.71) |
| −5 | −6.30 (20.80) | −38.03 (31.46) | −37.16 (23.19) |
| −4 | −2.89 (18.09) | −31.80 (34.62) | −21.70 (21.55) |
| −3 | 11.60 (15.08) | −39.86 (31.15) | −18.77 (18.02) |
| −2 | −5.29 (16.81) | −24.83 (28.08) | −5.70 (13.85) |
| −1 | 17.36 (19.37) | . | . |
| 0 | 36.94 (23.24) | −2.27 (28.64) | 19.86 (16.79) |
| 1 | 56.30 (32.06) | 34.53 (35.36) | 28.12 (22.11) |
| 2 | 42.59 (30.19) | 9.65 (32.44) | 23.80 (21.80) |
| 3 | 37.11 (28.91) | −4.11 (32.62) | 1.29 (22.41) |
| 4 | 8.99 (28.47) | −39.79 (30.31) | −22.73 (22.39) |
| 5 | −17.73 (26.32) | −37.29 (30.07) | −50.66* (23.33) |
| N | 53,256 | 55,297 | 55,103 |
| FE | Y | Y | Y |
| Control | Y | Y | Y |

Column (2): 6 months of event window.
Standard errors are clustered at the household level and are in parentheses.
* $p < 0.05$.

**Table A4**
Estimates of the treatment effect on monthly bill and average electricity price excluding fixed charges.

| | *Monthly Bill ($)* | *Average Price ($/kWh)* |
|---|---|---|
| ATT | 5.74*** | 0.01*** |
| | (0.88) | (0.00) |
| N | 92,192 | 92,192 |
| Control | Y | Y |
| Matched | Y | Y |

Standard errors are clustered at the household level and in parentheses.
*p < 0.05, ***p* < 0.01, ****p* < 0.001.

The monthly bill for general customers of the co-op consists of four components: (1) an Energy Charge based on usage at a rate of cents per kWh, (2) a fixed Service Charge of $25 per month, (3) a Wholesale Power Cost Adjustment (WPCA) charge of cents per kWh to account for the difference between actual and projected electricity costs, and (4) a Wallet Watch Credit (WWC) of cents per kWh credited to customers. Table A4 presents monthly payments that exclude the Service Charge, WPCA, and WWC, only including the Energy Charge.

**Table A5**
The treatment effect among customers with different numbers of blocks subscribed (column 1) and with counties (column 2).

| | (1) Num. of blocks | (2) County |
|---|---|---|
| One Block | −14.21 | |
| | (14.30) | |
| Two Blocks | −17.57 | |
| | (16.92) | |
| County 1 | | −31.59 |
| | | (54.33) |
| County 2 | | −9.16 |
| | | (21.49) |
| County 3 | | −10.00 |
| | | (19.50) |
| County 4 | | −54.59 |
| | | (32.32) |
| County 5 | | −5.29 |
| | | (18.01) |
| N | 99,721 | 99,721 |
| FE | Y | Y |
| Control | Y | Y |

Standard errors are clustered at the household level and in parentheses.

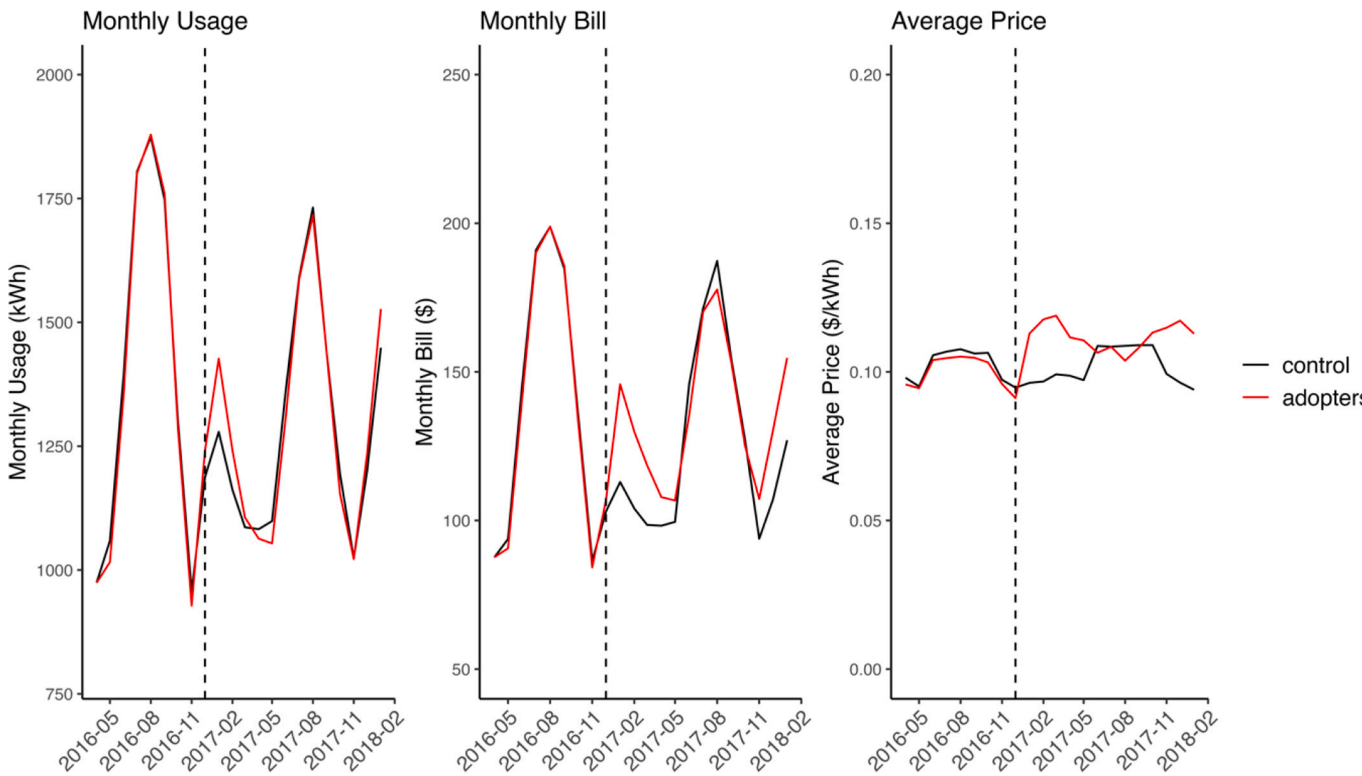



**Fig. A3.** Monthly usage, bill, and average price before and after the adoption (first adopters only).

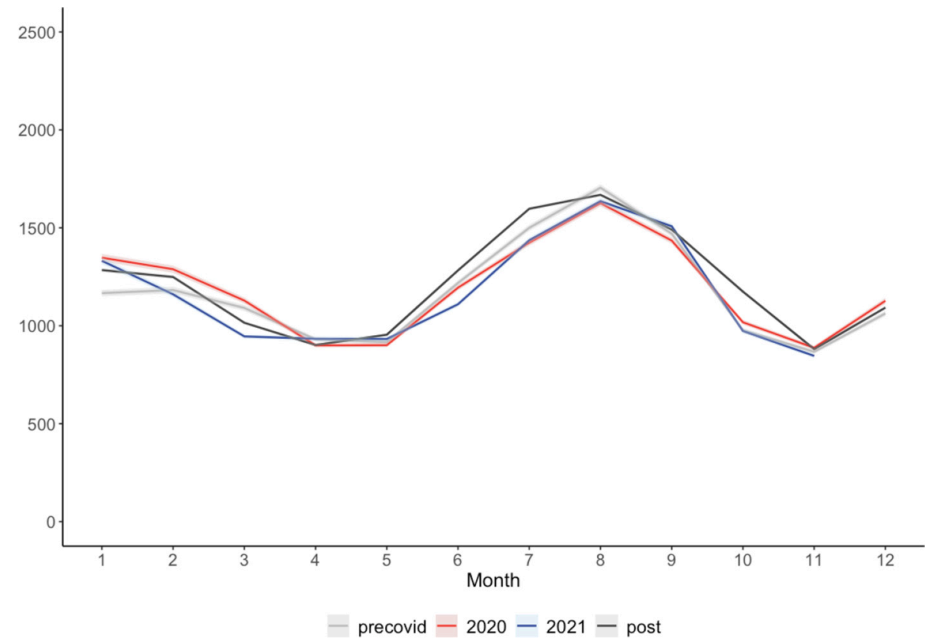



**Fig. A4.** Average monthly consumption before and after COVID among control group.

## Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2025.109079.

## Data availability

The data used in this study is confidential, though the authors are willing to share the code used in the analysis.

## References


AJC, 2022. Live election map: Georgia county results. Atl. J.-Const. Retrieved from: https://www.ajc.com/politics/election/live-election-map-georgia-county-results/CTQLZGI4FVECPOET6NN47OWNWI/.

Aydin, E., Brounen, D., Kok, N., 2018. Information provision and energy consumption: evidence from a field experiment. Energy Econ. 71, 403–410.

Aydın, E., Brounen, D., Ergün, A., 2023. The rebound effect of solar panel adoption: evidence from Dutch households. Energy Econ. 120, 106645.

Bartusch, C., Odlare, M., Wallin, F., Wester, L., 2012. Exploring variance in residential electricity consumption: household features and building properties. Appl. Energy 92, 637–643.

Bengart, P., Vogt, B., 2021. Fuel mix disclosure in Germany—the effect of more transparent information on consumer preferences for renewable energy. Energy Policy 150, 112120.

Beppler, R.C., Matisoff, D.C., Oliver, M.E., 2023. Electricity consumption changes following solar adoption: testing for a solar rebound. Econ. Inq. 61 (1), 58–81.

Blackwell, M., Iacus, S., King, G., Porro, G., 2009. CEM: coarsened exact matching in Stata. Stata J. 9 (4), 524–546.

Boccard, N., Gautier, A., 2021. Solar rebound: the unintended consequences of subsidies. Energy Econ. 100, 105334.

Bollinger, B., Gillingham, K., 2012. Peer effects in the diffusion of solar photovoltaic panels. Mark. Sci. 31 (6), 900–912.

Bollinger, B.K., Hartmann, W.R., 2020. Information vs. automation and implications for dynamic pricing. Manag. Sci. 66 (1), 290–314.

Borchers, A.M., Duke, J.M., Parsons, G.R., 2007. Does willingness to pay for green energy differ by source? Energy Policy 35 (6), 3327–3334.

Buchsbaum, J., 2022. Long-run price elasticities and mechanisms: empirical evidence from residential electricity consumers. In: Energy Institute Working Paper, 331.

Byun, H., Lee, C.Y., 2017. Analyzing Korean consumers' latent preferences for electricity generation sources with a hierarchical Bayesian logit model in a discrete choice experiment. Energy Policy 105, 294–302.

Callaway, B., Sant'Anna, P.H., 2021. Difference-in-differences with multiple time periods. J. Econ. 225 (2), 200–230.

Colorado Energy Office, 2024. Colorado Solar for all. Retrieved from: https://energyoffice.colorado.gov/cos4a.

Delmas, M., Russo, M.V., Montes-Sancho, M.J., 2007. Deregulation and environmental differentiation in the electric utility industry. Strateg. Manag. J. 28 (2), 189–209.

Deng, G., Newton, P., 2017. Assessing the impact of solar PV on domestic electricity consumption: exploring the prospect of rebound effects. Energy Policy 110, 313–324.

Dütschke, E., Frondel, M., Schleich, J., Vance, C., 2018. Moral licensing—another source of rebound? Front. Energy Res. 6, 38.

EIA, 2023. Units and Calculators Explained – Degree Days. U.S Energy Information Administration. Retrieved from. https://www.eia.gov/energyexplained/units-and-calculators/degree-days.php.

Fekete, E., 2020. States with Community Solar Policy Updates and Capacity Growth Potential [PowerPoint] (No. NREL/PR-6A20-78174). National Renewable Energy Lab. (NREL), Golden, CO (United States).

Frondel, M., Kaestner, K., Sommer, S., Vance, C., 2023. Photovoltaics and the solar rebound: evidence from Germany. Land Econ. 99 (2), 265–282.

Gai, D.H.B., Shittu, E., Attanasio, D., Weigelt, C., LeBlanc, S., Dehghanian, P., Sklar, S., 2021. Examining community solar programs to understand accessibility and investment: evidence from the US. Energy Policy 159, 112600.

Goodman-Bacon, A., 2021. Difference-in-differences with variation in treatment timing. J. Econ. 225 (2), 254–277.

Graziano, M., Gillingham, K., 2015. Spatial patterns of solar photovoltaic system adoption: the influence of neighbors and the built environment. J. Econ. Geogr. 15 (4), 815–839.

Hondo, H., Baba, K., 2010. Socio-psychological impacts of the introduction of energy technologies: change in environmental behavior of households with photovoltaic systems. Appl. Energy 87 (1), 229–235.

Huggins, J., 2022. U.S. electric utility companies and rates: Look-up by zipcode (2021). In: Open Energy Data Initiative. Retrieved from: https://data.openei.org/submissions/5806.

Iacus, S.M., King, G., Porro, G., 2008. Matching for Causal Inference without Balance Checking. Available at SSRN 1152391.

IREC, 2024. Census Solar Job Trends. Interstate Renewable Energy Council (IREC). https://irecusa.org/census-solar-job-trends/.

Ito, K., 2014. Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing. Am. Econ. Rev. 104 (2), 537–563.

Jacobsen, G.D., Kotchen, M.J., Vandenbergh, M.P., 2012. The behavioral response to voluntary provision of an environmental public good: evidence from residential electricity demand. Eur. Econ. Rev. 56 (5), 946–960.

Kim, J.D., Trevena, W., 2021. Measuring the rebound effect: a case study of residential photovoltaic systems in San Diego. Util. Policy 69, 101163.

Kosenius, A.K., Ollikainen, M., 2013. Valuation of environmental and societal trade-offs of renewable energy sources. Energy Policy 62, 1148–1156.

Kotchen, M.J., Moore, M.R., 2007. Private provision of environmental public goods: household participation in green-electricity programs. J. Environ. Econ. Manag. 53 (1), 1–16.

Kotchen, M.J., Moore, M.R., 2008. Conservation: from voluntary restraint to a voluntary price premium. Environ. Resour. Econ. 40, 195–215.

La Nauze, A., 2019. Power from the people: rooftop solar and a downward-sloping supply of electricity. J. Assoc. Environ. Resour. Econ. 6 (6), 1135–1168.

Lacasse, K., 2016. Don't be satisfied, identify! Strengthening positive spillover by connecting pro-environmental behaviors to an "environmentalist" label. J. Environ. Psychol. 48, 149–158.

Lee, S., 2025. PRISM weather data by zipcode, county, or state. In: Download US Weather Data. Retrieved from. https://asmith.ucdavis.edu/data/prism-weather.

Lukanov, B.R., Krieger, E.M., 2019. Distributed solar and environmental justice: exploring the demographic and socio-economic trends of residential PV adoption in California. Energy Policy 134, 110935.

Martin, S., Rivers, N., 2018. Information provision, market incentives, and household electricity consumption: evidence from a large-scale field deployment. J. Assoc. Environ. Resour. Econ. 5 (1), 207–231.

Michaud, G., 2020. Perspectives on community solar policy adoption across the United States. Renewable Energy Focus. 33, 1–15.

Nash, N., Whitmarsh, L., Capstick, S., Hargreaves, T., Poortinga, W., Thomas, G., Sautkina, E., Xenias, D., 2017. Climate-relevant behavioral spillover and the potential contribution of social practice theory. Wiley Interdiscip. Rev. Clim. Chang. 8 (6), e481.

Nguyen-Van, P., 2010. Energy consumption and income: a semiparametric panel data analysis. Energy Econ. 32 (3), 557–563.

Oliver, M., Moreno-Cruz, J., Beppler, R., . Microeconomics of the Rebound Effect for Residential Solar Photovoltaic Systems. CESifo Working Paper No. 7635, Available at SSRN https://ssrn.com/abstract=3387671. or. https://doi.org/10.2139/ssrn.3387671.

O'Shaughnessy, E., Barbose, G., Kannan, S., Sumner, J., 2024. Evaluating community solar as a measure to promote equitable clean energy access. Nat. Energy 1–9.

Palm, J., 2018. Household installation of solar panels–motives and barriers in a 10-year perspective. Energy Policy 113, 1–8.

Qiu, Y., Kahn, M.E., Xing, B., 2019. Quantifying the rebound effects of residential solar panel adoption. J. Environ. Econ. Manag. 96, 310–341.

Rai, V., McAndrews, K., 2012. Decision-making and behavior change in residential adopters of solar PV. In: Proceedings of the World Renewable Energy Forum, pp. 1–6.

Rogers, E.M., 2003. Diffusion of Innovations, 5th edition. Simon and Schuster.

Roth, J., Sant'Anna, P.H., Bilinski, A., Poe, J., 2023. What's trending in difference-indifferences? A synthesis of the recent econometrics literature. J. Econ. 235 (2), 2218–2244.

SEIA, 2024. The Solar Century: Landmark Moments in the History of Solar Energy. SEIA. Retrieved from. https://seia.org/blog/solar-century-landmark-moments-history-solarenergy/.

SEIA, 2025. Solar Industry Research Data. SEIA. Retrieved from. https://seia.org/research-resources/solarindustry-research-data/.

Steele, N., Heeter, J., Xu, K., Chan, G., 2021. Sharing the Sun: Community Solar Deployment, Subscription Savings, and Energy Burden Reduction. NREL. Retrieved from. https://www.energy.gov/sites/default/files/2021-11/Sharing%20the%20Sun_FY21_Final.pdf.

Toroghi, S.H., Oliver, M.E., 2019. Framework for estimation of the direct rebound effect for residential photovoltaic systems. Appl. Energy 251, 113391.

Truelove, H.B., Carrico, A.R., Weber, E.U., Raimi, K.T., Vandenbergh, M.P., 2014. Positive and negative spillover of pro-environmental behavior: an integrative review and theoretical framework. Glob. Environ. Chang. 29, 127–138.

U.S. Census Bureau, 2022. American Community Survey (ACS) 5-Year Estimates. US Census. Retrieved from. https://data.census.gov/table.

Weber, E.U., 1997. Perception and expectation of climate change: precondition for economic and technological adaptation. In: Environment, Ethics, and Behavior: The Psychology of Environmental Valuation and Degradation. Lexington Books, pp. 314–341.

Wichman, C.J., 2014. Perceived price in residential water demand: evidence from a natural experiment. J. Econ. Behav. Organ. 107, 308–323.

Wing, C., Freedman, S.M., Hollingsworth, A., 2024. Stacked Difference-in-Differences (tech. rep.).. National Bureau of Economic Research.

Wolske, K.S., Stern, P.C., Dietz, T., 2017. Explaining interest in adopting residential solar photovoltaic systems in the United States: toward an integration of behavioral theories. Energy Res. Soc. Sci. 25, 134–151.

Wood Mackenzie, 2024. Solar Installations Skyrocket in 2023 in Record-setting First Full Year of the Inflation Reduction Act. Wood Mackenzie. https://www.woodmac.com/press-releases/2024-press-releases/solar-installations-skyrocket-in-2023/.

Yohanis, Y.G., Mondol, J.D., Wright, A., Norton, B., 2008. Real-life energy use in the UK: how occupancy and dwelling characteristics affect domestic electricity use. Energ. Buildings 40 (6), 1053–1059.