THE REBOUND EFFECT OF SOLAR PANEL ADOPTION: EVIDENCE FROM DUTCH HOUSEHOLDS

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THE REBOUND EFFECT OF SOLAR PANEL ADOPTION: EVIDENCE FROM DUTCH HOUSEHOLDS

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ABSTRACT

THE REBOUND EFFECT OF SOLAR PANEL ADOPTION:
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Households adopt solar panels for different reasons, but always with a reduced electricity bill in mind. However, the access to solar power at near zero marginal costs may well induce rebound effects which shift households' demand curve and distort the net effects of solar PV investments. By analyzing high frequency data on electricity consumption and production of the households, we estimate the rebound effect of residential solar panel adoption. We document a rebound effect of 7.7 percent, a result that is robust to different sample and model specifications. We also find that households shift their consumption to the time periods when solar electricity production is higher. The solar PV rebound effect shows heterogeneity across time, production level and household characteristics, with higher rebound effects during seasons characterized by higher solar irradiance and among energy illiterate households with higher environmental awareness.

ÖZET

GÜNEŞ PANELİ KULLANIMININ GERİ TEPME ETKİSİ:
HOLLANDALI HANELERDEN BULGULAR

AHMET ERGÜN

EKONOMİ YÜKSEK LİSANS TEZİ, TEMMUZ 2022

Tez Danışmanı: Dr. Öğretim Üyesi ERDAL AYDIN

Anahtar Kelimeler: Geri tepme etkisi, güneş paneli, elektrik tüketimi, yenilenebilir enerji

Haneler, farklı nedenlerle güneş paneli satın alsalar da, her zaman daha düşük bir elektrik faturasını göz önünde bulundururlar. Bununla birlikte, sıfıra yakın marjinal maliyetle güneş enerjisine erişim, hane halkının talep eğrisini değiştiren ve güneş paneli yatırımlarının beklenen sonuçlarının ortaya çıkmasını engelleyen geri tepme etkilerine neden olabilir. Bu çalışmada, hanelerin elektrik tüketimi ve üretimine ilişkin yüksek frekanslı bir veri setini analiz ederek, konutlarda güneş paneli kullanımının geri tepme etkisini ölçümedik ve farklı örneklem ve model spesifikasyonlarına dayanıklı bir sonuç olan yüzde 7,7 civarı bir geri tepme etkisi olduğunu bulduk. Ayrıca hanelerin, tüketimlerini güneş enerjisi üretiminin daha yüksek olduğu zaman periyotlarına kaydırdığını da gözlemledik. Bunlara ek olarak, güneş paneli geri tepme etkisinin, daha yüksek güneş ışınımı ile karakterize edilen mevsimlerde, daha yüksek çevre bilincine sahip hanelerde veya enerji tüketim bilinci düşük hanelerde daha yüksek olduğunu ve zaman, üretim seviyesi ve hane karakteristikleri arasında heterojenlik gösterdiğini de görüyoruz.

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Sadly, we lost our friend İsmail Serhat Oğuz due to a heart disease. He was a brilliant man with hope in his eyes. He will always be in our memories and our hearts. May he rest in peace.

To my family and beloved ones...

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1. INTRODUCTION

The threat of global warming and climate change urges countries and communities to take action. Within this context, the 2021 Glasgow Agreement ratified the ambition to limit global warming to 1.5 degrees Celsius, invoking various measures to decrease greenhouse gas emissions, and requires a shift away from fossil fuel consumption towards renewable energy resources. Distributed photovoltaic energy technologies are widely considered as an important means to foster renewable energy sourcing. Thus, the widespread application of solar PVs by households is a desired outcome in that regard, while implementation of smart grids along with the sharp decline of solar panel and battery prices pave the way for solar panel adoption. To that end, many administrations have been providing incentives to promote renewable energy technologies, especially for distributed photovoltaic (PV) investments. Globally, solar PV has received the largest share (48%) of renewable power generation support, with $60.8 billion in 2017 (Gielen et al. 2019).[1]

However, the actual impact of solar PV systems in decreasing carbon emissions is still unclear. Although the impact of solar PV investments on households' grid-based electricity consumption can be easily predicted based on engineering models, these predictions might be wrong because of the potential behavioral changes associated to solar PV use. It is clear that solar electricity generation would decrease households' electricity consumption from the grid and consequently their utility bill. Still, the consumption from the grid may not decrease as much as the electricity generated by solar panels. Generating solar power at near zero marginal cost decreases the effective average price of electricity for the household, invoking a demand shift upwards as a result of price elasticity. This phenomenon is referred to as the "re-

[1] In order to encourage solar PV investments, countries generally use investment subsidies that refunds part of the installation cost and/or feed-in tariffs/net metering mechanism in which producer is paid under a multiyear contract at a guaranteed rate . For instance, the Japanese government ran a successful subsidy program from 1994 to 2003, and reached to an installed PV capacity with over 1.1 GW in 2004. In 2004, the German government introduced the first large-scale feed-in tariff system, which resulted in huge growth of PV installations. In October 2008, Spain, Italy, Greece and France introduced feed-in tariffs. In 2006 California approved the 'California Solar Initiative', offering a choice of investment subsidies or FIT for small and medium systems and a FIT for large systems. In 2006, the Ontario Power Authority (Canada) began its Standard Offer Program, the first in North America for small renewable projects, guaranteeing a fixed price of Canadian $0.42 per kWh for PV over a period of twenty years.

bound effect", which needs to be taken into account while assessing the effectiveness of solar PV incentives. This paper aims to provide evidence on the size of rebound effect associated to solar PV use and its potential heterogeneity.

The rebound or "*takeback*" effect, is described as the loss in expected gains from an efficiency-increasing technological change that is caused by a behavioral change (Berkhout, Muskens, and W. Velthuijsen 2000). Rebound effect has been mostly studied in the energy efficiency literature. Research has shown that technological improvements may lead to lower energy savings than expected as a result of the associated changes in consumer behavior (Jevons 1906; Khazzoom 1987; Wirl 1997). The mechanism underlying this behavioral change relates to neoclassical economic theory: when the energy efficiency of a particular energy service is improved, households realize a reduction in the effective price of that service. Consequently, improved energy efficiency leads to an increase in the demand of energy service. This implicit price mechanism generates a so-called rebound effect, as it partially offsets the initial efficiency gains.

Although the existence of the rebound effect is widely acknowledged, the real debate lies in the identification and the size of the effect (Gillingham et al. 2013; Greening, Greene, and Difiglio 2000*b*). The discussion on the extent of the rebound effect has led to different views on the role of energy efficiency policies in addressing climate change (Borenstein 2015). Thus far, due to the uncertainty regarding its actual size, the rebound effect has been disregarded in ex-ante impact assessments of energy conservation measures (e.g. building regulations and energy efficiency subsidy programs), leading to perhaps misguided expectations about the role of these measures in saving energy (Fowlie, Greenstone, and Wolfram 2018; Jacobsen and Kotchen 2013). This is of importance, as realized savings ultimately determine the success of energy policies in reducing energy consumption and carbon emissions. Incorporating the rebound effect into policy evaluations can thus help to develop cost-effective energy conservation policies.[2]

In the literature, the transport sector and the residential sector are the two main areas where improvements in energy efficiency have previously been studied, as energy consumption levels are high in both sectors, and there is significant potential for technological innovations.[3] However, due to limited availability of data, the

[2]It is important to note that, as the rebound effect is a re-optimization as a response to implicit price changes, it can be regarded as welfare improving according to neoclassical economic theory. On the other hand, its extent has important implications on the outcomes of energy conservation policies.

[3]See, for example, Aydin, Kok, and Brounen (2017) for the case of residential heating, Wheaton (1982) and Small and Van Dender (2007) for the case of vehicle fuel economy, Hausman (1979) for the case of air conditioners, Davis, Fuchs, and Gertler (2014) for the case of refrigerators, and Davis (2008) for the case of clothes washers.

empirical evidence on the rebound effect resulting from the use of solar PVs is relatively scarce. To our knowledge, so far, there are only three studies that estimate the rebound effect for the households using solar PV. Analyzing billing data for a sample of households in Sydney, Deng and Newton (2017) document a rebound effect of around 21 percent for the households who have solar PV installation. In another study, using household level high frequency electricity consumption and production data from a sample of houses in Arizona, Qiu, Kahn, and Xing (2019) found that when solar electricity generation increases by 1 kWh, solar PV homes increase their total electricity consumption by 0.18 kWh. Finally, in a recent study, using monthly billing data before and after solar panel adoption from eastern US, Beppler, Matisoff, and Oliver (2021) document a rebound effect of 28.5 percent.[4] Although these studies are valuable as they provide the first empirical evidence on the solar rebound effect, we aim to contribute to this literature by dealing with some methodological concerns related to the correct identification of the rebound effect and by analyzing the heterogeneity in the size of this effect.

In this paper, we exploit high-frequency data which enables us to control for a variety of unobservable confounders, including time-variant and individual unobservables. Measuring the solar rebound effect with high-frequency data has its merits, but other factors should also be taken into consideration, such as consumption-shifting behavior. Consumption-shifting occurs when an individual moves a planned consumption, such as laundry, to a period with more electricity generation. While this shifting behavior does not change the overall consumption of the household, it would cause a bias on the estimated impact of electricity generation on the consumption of the household. Thus, ignoring the shifts in consumption with high frequency data may lead to an overestimation of the solar rebound effect. In this paper, we explicitly control for the consumption-shifting behavior by including lagged effects of electricity generation in a two-way fixed-effects model.[5]

Compared to the previous work on the solar rebound effect, the sample that we

[4]Rebound effect resulting from solar PV use might also be associated with the rebound effect resulting from the increasing efficiency of the electricity using household services. The literature estimates a rebound effect of 5-12 percent for lighting (Greening, Greene, and Difiglio 2000*a*), 6 percent for clothes washing (Davis 2008), and around 8 percent for cooling (Mizobuchi and Takeuchi 2019).

[5]Another factor that needs to be considered when evaluating the efficiency of distributed PVs is the change in grid load. Inability to satisfy electricity demand at peak hours might cause blackouts that lead to substantial financial and welfare losses (de Nooij, Lieshout, and Koopmans 2009; Vasconcelos and Carpio 2015). On the other hand, investing in electricity infrastructure constitutes a major expenditure for the distribution and transmission firms, and increasing capacity to meet peak electricity demand that will stay idle during off-peak hours is financially wasteful. Moreover, inefficiencies in distribution and transmission infrastructure lead to energy waste, which increases proportionally to the distance between production and consumption locations (Bouffard and Kirschen 2008; Bradley, Leach, and Torriti 2013; Joskow 2012; Pepermans et al. 2005). By decreasing the net electricity consumption from the grid, distributed PV systems mitigate the losses associated with transmission and distribution, increasing economic and environmental efficiency. Therefore, observing the shifts in net electricity consumption over time is of importance for peak shaving purposes, and including lagged-independent variables allows us to measure the decrease in load caused by PV electricity generation.

exploit differs in various ways. Around 17.4% of the households in our sample are yearly net producers, and the Dutch energy companies make a payment for the excess production of households on a yearly basis. That is to say, PV electricity generation constitutes an actual source of income for net producer households, thus, the governing mechanisms for rebound effect for net producer households may be different. As we can expect an increasing trend in share of net producers among solar households in the future, our results can provide an important input for future policy discussions.[6] Furthermore, the Netherlands experiences four seasons which would suggest a greater variance in weather conditions and, in particular, solar irradiance compared to the state of Arizona. Consequently, we can observe the heterogeneity in rebound effect for different production levels, resulting from the variation in solar irradiation. Finally, benefiting from a detailed household survey data, we are able to check the potential heterogeneity in the rebound effect that might result from differing household characteristics.

In the analysis, we first estimate the average size of the rebound effect on residential PV electricity generation. We exploit a household level electricity consumption and electricity generation data-set that includes 317 Dutch homes for the period 2014 to 2015, and we apply a two-way fixed effects model with lagged independent variables to control for unobservable confounders. Our results suggest that 1 kWh increase in PV electricity generation results in an increase of 0.07 kWh in total electricity consumption, implying a rebound effect around 7 percent. The results are robust to the use of different estimation approaches and sample specifications. We also examine how the generated electricity influence net electricity consumption from the grid in terms of timing and magnitude. We document that increased electricity generation causes a significant amount of consumption shifting. We also document that the size of the rebound effect increases by the increasing electricity generation. Assessing household related heterogeneity, we observe a higher rebound effect for the households with higher environmental awareness, lower energy literacy and lower saving tendency. However, these differences are not statistically significant.

The remainder of the paper will first describe the data and discuss the summary statistics. In section 3, we present a simplified theoretical model and our estimation methodology. Section 4 discusses our results, including robustness checks and heterogeneity analysis. The paper ends with a short concluding section in which we discuss policy implications.

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[6] While Deng and Newton estimate a rebound effect for gross-metered households, Qiu, Kahn, and Xing estimate for net-metered households and argue that these households have different causal mechanisms for solar rebound effects, claiming net-metered households see generated energy as ”free” and perceive electricity generation as a decrease in electricity prices.

2. DATA

In this study, we examine the electricity consumption behaviour of households on the Dutch island of Texel.[1] Conforming with its aim of becoming energy-neutral by 2020, the island has been subject to many sustainability related policies and projects. In one of these projects, household-level electricity consumption and electricity production data was collected by Liander, one of the largest energy grid managers in Netherlands. The data was collected during a field experiment and the project was designed to reduce energy consumption by providing consumption feedback.[2]

The data covers a sample of 317 households for the period between March 2014 and March 2015. In this sample, 187 households have a solar panel and 126 households do not. The data on electricity production of these households is available with 15 minute intervals, however, electricity consumption data is available on a daily basis until September 2014 and with 15 minute intervals onwards. As part of the project, several surveys were conducted among the households, which reveal their motivations in terms of energy consumption, their attitudes towards the interventions and the changes they experienced during the project. 165 households in our sample responded to survey that covers 373 different questions, which can be used to characterize participants in more detail.

[1] Texel is an island located in North Holland, Netherlands, inhabited by more than 13,000 people. The island enjoys 1650 sun hours a year, the highest number in the Netherlands, and it experiences a relatively mild climate. These circumstances make Texel an interesting case for solar energy research.

[2] Through the installed in-house displays (IHDs) called "KIEK", the households received feedback and insights about their consumption. Another goal of the project was to initiate and foster the usage of smart grids. The experiment started on March 15th 2014 and it consists of three phases. In the first phase, which lasted until May 15th 2014, participants were observing their consumption levels through the installed IHDs. In the second phase of the experiment, the participants were supplied with smart plugs, which allowed them to acquire a deeper understanding about their individual home appliances. Furthermore, participants received information about how they compare to their neighbors, and they were exposed to suggestions and insights for saving energy. The third phase began in September 2014, which introduced price incentives to the experiment, varying between €0,1522/kWh and €0,3071/kWh within the day. Although it is not the main research question of this paper, we also check whether these treatments had any influence on the size of the estimated rebound effect.

2.1 Descriptive statistics

First, as a descriptive analysis, we present the summary statistics for solar and non-solar houses separately (see Table 2.1). The statistics suggest that, on average, the households with solar panels consume around 7.5 kWh more electricity on a daily basis compared to the households without solar panel. This difference might be related to potential differences in household characteristics that affect energy consumption and/or potential rebound effects arising from solar panel electricity production. We also compare these households based on characteristics that might affect their energy consumption. For this purpose, we measure their environmentalism, energy saving and energy literacy scores based on the survey answers of a sub-sample of households.[3] Survey statistics show that, on average, both types of households are similar in these characteristics, except for age. The solar houses in our sample are inhabited by slighlty older households. Overall, we observe that households that adopt solar panels show similarities to non-adopting households in observable characteristics such as cost-saving behavior and environmental awareness. However, since there might still exist unobservable differences between these households, as a robustness check, we take these potential variations into account and limit our sample to only solar panel homes in our analysis.

[3]These scores are calculated as follows: Questions that are related for the respective characteristics are identified. Then, the answers for these questions are normalized between 0 and 1. Finally, the average of these normalized answers is taken to calculate respective final scores.

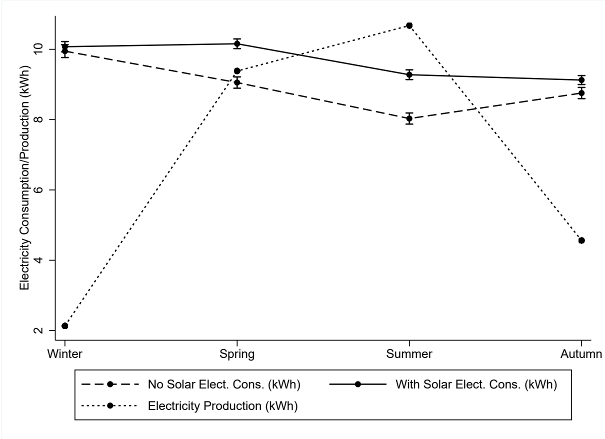
Table 2.1 Descriptive Statistics

	(1) All	(2) No Solar	(3) With Solar	(4) t-Test
Daily Electricity Consumption (kWh)	9.32	8.88	9.63	-0.75***
	(5.63)	(5.48)	(5.72)	(-17.89)
Daily Electricity Production (kWh)			6.72	
			(6.0)	
Observations	75,097	30,896	44,201	
Number of Households	317	126	187	
Environmentalism Score	0.439	0.439	0.439	-0.000
	(0.142)	(0.138)	(0.146)	(-0.0110)
Savings Score	0.609	0.597	0.618	-0.022
	(0.144)	(0.140)	(0.149)	(-0.939)
Energy Literacy Score	0.506	0.485	0.520	-0.035
	(0.142)	(0.126)	(0.151)	(-1.565)
Age	54.307	51.627	55.915	-4.288**
	(10.66)	(12.09)	(9.045)	(-2.574)
Education				
Higher than Bachelor's	13.77%	10.29%	16.49%	
Bachelor's or Equivalent	30.54%	36.76%	25.77%	
Some College	20.69%	23.53%	18.56%	
Secondary Education	28.14%	23.53%	31.96%	
Other	6.59%	5.88%	7.22%	
Number of Survey Participants	165	68	97	

Notes: Column (1) reports statistics for the whole sample. Column (2) reports the statistics for non-solar households and column (3) reports the statistics for solar households. Column (4) presents the t-statistics comparing solar and non-solar houses. Survey scores are calculated as follows: Questions that are related for the respective characteristics are identified. Then, the answers for these questions are normalized between 0 and 1. Finally, average of those normalized answers is taken to calculate respective final score. Std. deviations (t-statistics for the t-test) are given in the parentheses. For the t-test; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, we compare households electricity consumption across the four seasons of the year. First of all, we observe in Figure 2.1 that average electricity consumption is higher during winter compared to summer for both household types (e.g. with and without solar PV). This time variation is a likely result from the energy needs arising from weather conditions, as more lighting is needed during the darker months of the year. When we focus on the differences between groups, we notice a consumption gap that widens during spring and summer and reduces to near zero during the autumn and winter. During these dark autumn and winter months solar electricity production is low (see Figure 2.1), hence this seasonality in gap can be interpreted as a first indication of a potential rebound effect arising from solar electricity production. Solar house owners might be relatively generous in their energy use, at times when they know their solar generation levels are high, and vice versa.

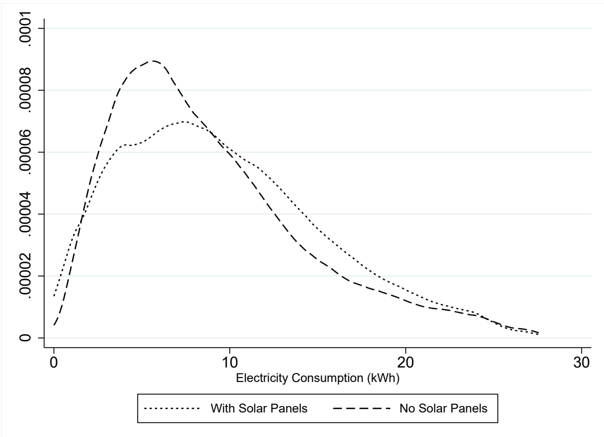
Figure 2.1 Electricity Consumption and Production Based on Seasons



Notes: The graph reports the seasonal average electricity consumption and production for solar and non-solar households. Values on the left axis report the average electricity consumption/production of solar households. Consumption means are given with 99% confidence intervals.

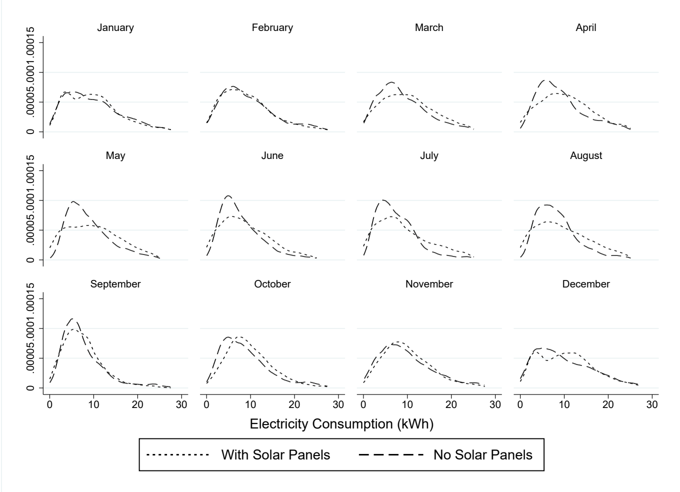
Next, we examine the distribution of electricity consumption for solar and non-solar households. Figure 2 presents the distribution of average daily electricity consumption of households for solar and non-solar homes, separately. While both distributions are skewed to the right, we also find that electricity consumption of households without solar panels is distributed more narrowly. This difference is most pronounced during high radiation months, indicating again that electricity consumption of solar house owners then shifts outward (see Figure 3). Between September and February consumption curves are very similar across both groups.

Figure 2.2 Distribution of Daily Electricity Consumption



Notes: Figure shows the kernel density of daily electricity consumption by solar panel adoption for the whole year. Dashed lines show the values for households without solar panels. Dotted lines indicate density for the solar households.

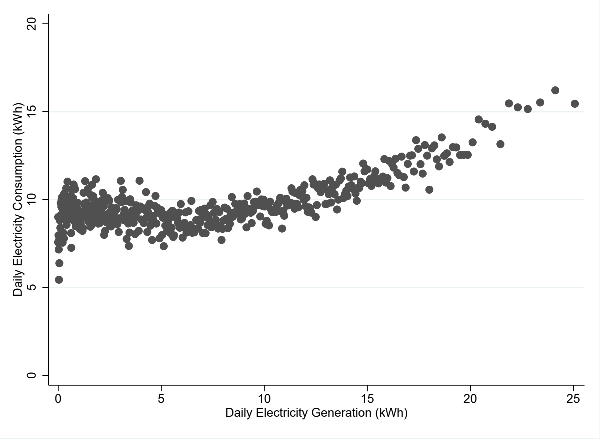
Figure 2.3 Distribution of Average Daily Consumption by Months



Notes: Figure shows the kernel density of daily electricity consumption by solar panel adoption for each month. Dashed lines show the values for households without solar panels. Dotted lines indicate density for the solar households.

Finally, we plot the relationship between solar electricity generation and electricity consumption for the homes that have solar panel. Figure 2.4 indicates a positive relationship between the two variables. Electricity consumption spikes during the days (or for households) that electricity generation is highest. This figure supports the existence of a potential rebound effect in residential PV electricity generation. Moreover, the magnitude of the correlation between electricity consumption and generated electricity seems to increase as generated electricity increases. However, this descriptive analysis neglects the fact that households might switch some part of their required electricity consumption to the time periods when there is more electricity generation. In that case, this observed positive relationship might appear because of a change in timing of consumption instead of a change in the amount of total consumption. Therefore, in the subsequent analysis, we formally take this potential switching behavior into account.

Figure 2.4 Daily Electricity Consumption and Solar Electricity Generation



Notes: Daily Electricity Consumption (kWh) is reported on the y-axis. Daily Electricity Generation (kWh) of houses with solar panels is reported on the x-axis. Data points are scattered into 500 consecutive bins according to their daily electricity generation levels.

3. METHODOLOGY

3.1 Theoretical Framework

Given that we analyze the electricity consumption of households, the rebound effect that we estimate will be on the micro-economic level. In order to better grasp the underlying economic mechanisms, we describe a theoretical framework similar to Qiu, Kahn, and Xing (2019), where it is assumed that households respond to average electricity prices instead of marginal electricity prices, as it is shown by Ito (2014). In this framework, the average electricity price from the grid is denoted as p_0, and the effective average price, denoted by p_{eff}, is determined as follows:

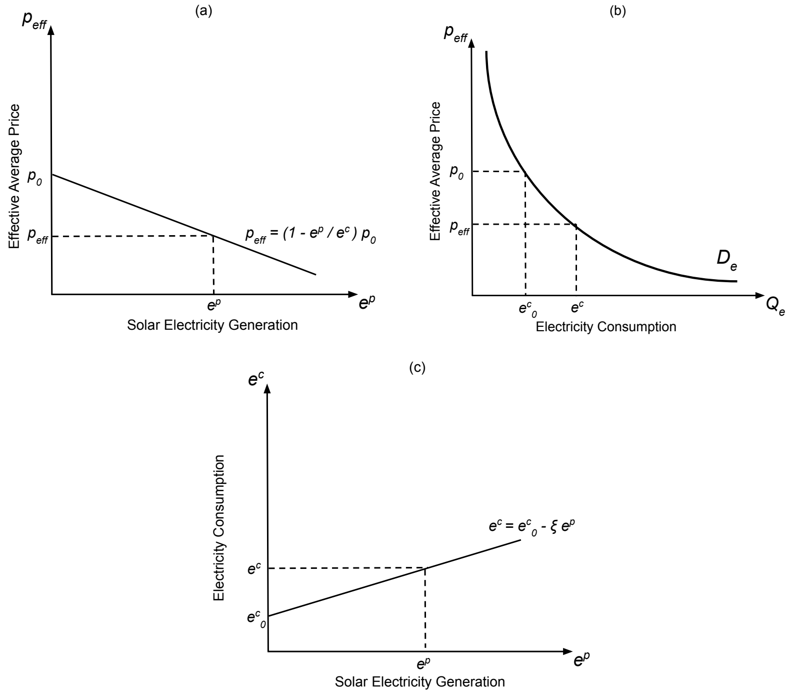
$$p_{eff} = p_0(1 - \frac{e^p}{e^c}) \tag{3.1}$$

where , e^c and e^p are electricity consumption before solar panel adoption and electricity produced by solar panels, respectively. Since $\frac{e^p}{e^c}$ is always non-negative, the effective average price is smaller than the average electricity price. Now, consider households' price elasticity of electricity, ξ, as follows:

$$\xi = \frac{\frac{\Delta e^c}{e^c}}{\frac{\Delta p}{p}} = \frac{\frac{\Delta e^c}{e^c}}{\frac{p_{eff}-p_0}{p_0}} = \frac{\frac{\Delta e^c}{e^c}}{\frac{p_0(1-\frac{e^p}{e^c})-p_0}{p_0}} = \frac{\frac{\Delta e^c}{e^c}}{-\frac{e^p}{e^c}} \rightarrow \Delta e^c = -\xi e^p \tag{3.2}$$

Based on equation (2), we observe that the change in electricity consumption depends on the elasticity (ξ) and the production by solar panels (e^p). Therefore, the change in electricity consumption after solar panel adoption is caused by the amount of electricity generated. In other words, the rebound effect of solar panel adoption is equal to $-\xi$. This relationship is illustrated in Figure 3.1.

Figure 3.1 Illustration of Rebound Effect



Notes: Panel (a) illustrates the relationship between the effective average price and the amount of electricity generated by solar, where p_{eff} denotes the effective average price, p_0 is the average electricity price from the grid, e_0^c is the electricity consumption prior to solar panel adoption and e^p denotes the amount of electricity generated by solar panels. Panel (b) shows the change in electricity demand after solar electricity generation, where e^c is the electricity consumption after solar panel adoption. The rebound effect is illustrated in Panel (c).

3.2 Empirical Model

The rebound effect is defined as the reduction in expected gains from a more resource-efficient technology as a result of behavioral or systemic change. In the context of domestic solar panel adoption, this effect equals the change in a household's electricity consumption resulting from solar electricity production. To estimate the rebound effect, we conduct a panel data analysis with the following empirical model:

$$e_{i,t}^c = \alpha + \beta_1 e_{i,t}^p + \beta_2 e_{i,t-1}^p + \beta_3 e_{i,t-2}^p + \delta_i + \gamma_t + \epsilon_{i,t} \tag{3.3}$$

where $e_{i,t}^c$ denotes the daily electricity consumption of household i on day t and $e_{i,t}^p$ denotes the daily solar energy production of household i on day t, which is our main variable of interest. Households equipped with solar panels may shift some of their consumption to the days with high levels of solar electricity generation.

For instance, a person may choose to postpone a routine task, like laundry, in anticipation of high electricity production, increasing the electricity consumption for that future day. This type of consumption shifting behavior does not increase the overall household electricity consumption, and can therefore be easily missed in standard estimation procedures. However, when not taken into account, these shifts may lead to overestimation of the rebound effect. To address this issue, we introduce lagged electricity production variables ($e^p_{i,t-1}$ and $e^p_{i,t-2}$) into our model with the depth of two periods.[1] Aggregation of the β coefficients gives us the rebound effect. Individual and date fixed-effects (δ_i and γ_t, respectively) are also included in the model in order to control for household-variant and time-variant unobservables. Finally, $\epsilon_{i,t}$ denotes the error term.

[1] We limit the depth of our time lags to two periods because further lags did not show statistical significance, as seen in Table 4.1, Column 6.

4. RESULTS

We start our analysis with an Ordinary Least Squares (OLS) estimation, where we regress daily electricity consumption on daily electricity generation. Then, we introduce household fixed-effects and date fixed-effects to control for possible unobservable confounders that are fixed for a household or during a time period. Lastly, we include lagged PV electiricity generation to control for consumption shifting, which can inflate our estimation of rebound effect. Table 4.1 reports the OLS estimation results. When we introduce household and date fixed effects, we estimate a rebound effect of around 29 percent (column 3). However, this result might also capture potential shifting behavior. After adding lagged production as control variables, the estimated rebound effect decreases to 7.7 percent (column 5). It is worth noting here that the coefficient for the lagged variable at period $t-3$ is not statistically significant, as shown in column 6. Thus, we will focus on the model with two periods of lagged production as our main specification. The estimated instantaneous effect suggest that 1 Wh increase in generated electricity results in an instantaneous increase of 0.58 Wh in consumption within that day. Because of the time shifting behavior, this decreases the electricity consumption for the next day by 0.45 Wh and by 0.05 Wh 2 days later. That is to say, the carbon emission gains of reduced grid consumption that result from solar PV electricity generation are dispersed over time.

Table 4.1 Main Model

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Total effect	0.157***	0.177***	0.291***	0.098***	0.077***	0.074***
	(0.015)	(0.013)	(0.014)	(0.015)	(0.016)	(0.017)
Daily electr. prod. at t	0.157***	0.177***	0.291***	0.592***	0.582***	0.572***
	(0.015)	(0.013)	(0.014)	(0.016)	(0.017)	(0.017)
Daily electr. prod. at t-1				-0.494***	-0.453***	-0.430***
				(0.017)	(0.018)	(0.019)
Daily electr. prod. at t-2					-0.052***	-0.064***
					(0.009)	(0.009)
Daily electr. prod. at t-3						-0.006
						(0.009)
Household FE		Yes	Yes	Yes	Yes	Yes
Date FE			Yes	Yes	Yes	Yes
Constant	8,697.112***	8,619.022***	8,168.732***	8,784.800***	8,829.964***	8,822.548***
	(150.147)	(75.748)	(71.764)	(67.899)	(66.207)	(64.819)
Observations	75,097	75,096	75,096	69,460	65,218	61,861
R-squared	0.025	0.418	0.521	0.566	0.562	0.559

Notes: The dependent variable is daily electricity consumption(Wh). The analysis is based on a sample of 317 households on the Dutch island of Texel for the period March 2014 to February 2015. The standard errors are clustered around season-household pairs, controlling for autocorrelation, and are reported in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Observing within-day changes in electricity consumption is more relevant for estimating the reductions in peak-hour electricity demand, while investigating the existence of within-day rebound effects is intriguing in itself. With the high-frequency data available for September 2014 onwards, we conducted a series of analyses for within-day electricity consumption, starting from 15-minute intervals and aggregating towards daily intervals. This approach also allows us to control for time-variant unobservables in a more refined manner. Table 4.2 reports the results for this within-day analysis and shows rebound effects varying between 5.3% to 9.4%, which is in compliance with our daily data analysis. However, consumption shifting appears to be milder than in the daily data analysis. This should mostly be explained by the response time of the households to the generated electricity. Households should be less likely to respond to electricity generation within the same 15 minutes, whereas it is more likely that they will respond within the same day.

Table 4.2 Within Day Analysis

Variables	(1) 15 min.	(2) Hourly	(3) Two hours	(4) Four hours	(5) Half day
Total Effect	0.056***	0.053***	0.064***	0.094***	0.084***
	(0.012)	(0.013)	(0.013)	(0.015)	(0.026)
at t	0.093***	0.095***	0.084***	0.080***	0.134***
	(0.013)	(0.013)	(0.012)	(0.013)	(0.017)
at t-1	-0.032***	-0.050***	-0.043***	-0.015	-0.005
	(0.005)	(0.006)	(0.007)	(0.007)	(0.016)
at t-2	-0.005	0.009**	0.023***	0.029***	-0.045***
	(0.005)	(0.006)	(0.008)	(0.009)	(0.012)
Household FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Constant	99.733***	400.897***	798.407***	1,579.398***	4,694.887***
	(0.547)	(2.196)	(4.378)	(8.820)	(32.838)
Observations	3,293,218	836,299	418,702	209,139	68,915
R-squared	0.243	0.319	0.369	0.420	0.536

Notes: The dependent variable is electricity consumption(Wh) at time *t*. Time intervals for the analysis are given on their respective columns. The analysis is based on a sample of 282 households on the Dutch island of Texel for the period September, 2014 to February, 2015. The standard errors are clustered around season-household pairs, controlling for autocorrelation, and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.1 Robustness Checks

We perform a series of analyses to check the robustness of our estimations. Table 4.3 reports the results of these analyses. First, we check comparability of solar and non-solar households on observable variables, so that we can establish a credible estimate of the counterfactual for the solar households. Thus, we conduct a propensity score matching (PSM) analysis on the sample that participated in the household survey. Based on the results of the survey, we generate scores for environmentalism, savings and energy literacy as previously mentioned. We estimate propensity scores for solar panel adoption, using a probit model with these scores, age, education level and average electricity consumption of the month with lowest mean PV electricity generation. Radius matching with 0.075 caliper is used to match these observations, since this results in the smallest median bias. Yet, other matching algorithms have been applied as well and yielded similar results[1]. Figure A.2 shows the common support after the PSM. Then, we utilized these matches in a WLS model with two-way fixed effects. As can be seen in Column 2-3 in Table 4.3, the estimated rebound effect does not alter significantly, when comparing the OLS and PSM approaches for the sample of survey participants.

[1] See Table A.1 in the Appendix for examples.

Table 4.3 Robustness Checks

Variables	(1) Main Model	(2) Survey Participants (OLS)	(3) Survey Participants (PSM)	(4) No Bungalows	(5) Only Solars	(6) Monthly Analysis
Total Effect	0.077***	0.059***	0.049**	0.054***	0.150***	0.118***
	(0.016)	(0.019)	(0.020)	(0.018)	(0.026)	(0.020)
at t	0.582***	0.577***	0.569***	0.595***	0.580***	0.118***
	(0.017)	(0.022)	(0.024)	(0.021)	(0.023)	(0.020)
at t-1	-0.453***	-0.453***	-0.458***	-0.472***	-0.368***	
	(0.018)	(0.024)	(0.026)	(0.023)	(0.024)	
at t-2	-0.052***	-0.065***	-0.062***	-0.069***	-0.062***	
	(0.009)	(0.011)	(0.011)	(0.010)	(0.013)	
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	8,829.964***	9,901.575***	10,056.964***	9,788.317***	8,575.368***	8,852.892***
	(66.207)	(74.147)	(67.113)	(68.912)	(162.832)	(92.387)
Observations	65,218	38,355	35,513	40,950	36,358	3,201
R-squared	0.562	0.636	0.643	0.640	0.564	0.798

Notes: The dependent variable is daily electricity consumption for columns 1-5. The dependent variable is monthly average electricity consumption in column 6. The analyses are based on the sample of households on the Dutch island, of Texel during the period September 2014 to February 2015. The number of households was 317, 171 (survey participation), 171, 209, 108, 187, 317 in columns 1-6, respectively. The standard errors are clustered around season-household pairs, controlling for autocorrelation, and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Second, a small portion of our sample consists of holiday bungalows. To assess whether energy behaviour differs between these holiday homes and the more conventional standard homes, we re-estimate the rebound effect using a stratified sample without holiday bungalows as reported in Column 4 in Table 4.3. These estimates appear to be in accordance with our main results, with only minimal differences compared to our main model estimation in Column 1.

Next, some might expect that solar households have different characteristics than non-solar households that led them to adopt solar panels. For example, solar households may inherently consume more electricity than non-solar households prior to solar panel adoption. Therefore, our estimations might be reflecting those inherent differences rather than an actual increase in consumption after solar panel adoption. To elucidate this matter, we run a regression solely on solar panel households, which should constitute a more homogeneous sample. As reported in Column 5, the estimated rebound effect is still statistically significant and larger than our main results (15 percent versus 7.7 percent). This difference might be explained by the fact that the solar households constitute a sample with higher solar electricity production. Recalling from Figure 2.4, the rebound effect seems to increase as electricity production increases. We further verify this potential non-linearity in the rebound effect in the next section.

One of the reasons that we use lagged independent variables is to control for consumption shifting. To check the validity of this approach, we estimate the rebound effect by using monthly average electricity consumption and generation, where the effect of consumption shifting should be minimal. In Column 6 of Table 4.3, we can see that this rebound effect is estimated to be around 11%, which is relatively high compared to the estimated rebound effect using daily and high frequency data. This difference can be due to other confounders that we are able to control with the daily data. Nevertheless, this monthly estimate is still significantly lower in contrast to the estimate in Column 3 of Table 4.1, which clearly indicates the necessity of controlling for consumption shifting.

Lastly, some doubts may arise about our estimates since the data we use is collected as a part of an experiment, and that experiment might have an effect on our rebound effect estimates. In order to address this issue, we run the following regression:

$$e^c_{i,t} = \alpha + \boldsymbol{\beta} \begin{pmatrix} e^p_{i,t} \\ e^p_{i,t-1} \\ e^p_{i,t-2} \end{pmatrix} + \boldsymbol{\lambda} \begin{pmatrix} e^p_{i,t} \\ e^p_{i,t-1} \\ e^p_{i,t-2} \end{pmatrix} D_i + \delta_i + \gamma_t + \epsilon_{i,t} \tag{4.1}$$

where D_i is the experiment outcome dummy that becomes zero for households that reported no savings associated with the experiment in the survey and vice versa. As seen in Table 4.4, the interaction variable does not have a statistically significant coefficient in neither of the time periods, whereas our estimation of the rebound effect keeps its significance and it does not vary significantly from our estimate reported in Table 4.3 Column 2. Thus, we fail to find any statistically significant effect that can be attributed to the experiment.

Table 4.4 Rebound Effect by Experiment Outcome

Variables	
Total Effect	0.041*
	(0.021)
Total Effect*D	0.023
	(0.034)
Daily electr. prod. at t	0.578***
	(0.027)
Daily electr. prod. at t-1	-0.466***
	(0.029)
Daily electr. prod. at t-2	-0.071***
	(0.013)
*Daily electr. prod. at t*D*	-0.009
	(0.042)
*Daily electr. prod. at t-1*D*	0.007
	(0.045)
*Daily electr. prod. at t-2*D*	0.024
	(0.018)
Household FE	Yes
Date FE	Yes
Constant	9,931.121***
	(77.162)
Observations	34,360
R-squared	0.644

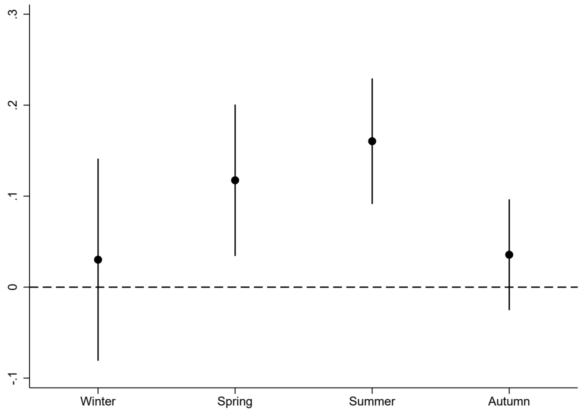
Notes: The dependent variable is daily electricity consumption(Wh). The analysis is based on a sample of 171 households on the Dutch island of Texel for the period March 2014 to February 2015 that participated in the survey. "Experiment Outcome Dummy" variable takes the value zero if the household reported no savings related to the experiment in the survey and vice versa. The standard errors are clustered around season-household pairs, controlling for autocorrelation, and are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1

4.2 Heterogeneity Analysis

So far, we estimated the rebound effect of solar PV electricity generation in a sound manner and demonstrated the robustness of our results. However, some questions might arise regarding the external validity of our results, since our sample consists of Dutch households. Thus, it might be helpful to test the heterogeneity in the rebound effect under different circumstances or for differing household characteristics.

First, there may be a heterogeneity in the rebound effect related to differences in climate or in electricity generation levels. Therefore, we estimate the rebound effect separately across the different seasons. Figure 4.1 illustrates these results. Interestingly, we observe higher rebound effect during seasons with higher solar electricity generation. The rebound effect in the summer is about 16% and statistically significant, whereas, it is around 3% during winter and lacking statistical significance. These results also indicate a non-linear relationship between consumption and electricity generation. Monthly estimates are also reported in Figure A.1 in Appendix.

Figure 4.1 Rebound Effect by Seasons

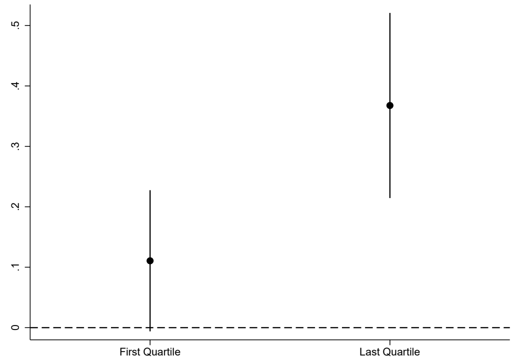


Notes: The dependent variable is daily electricity consumption. The analysis is based on the sample of households on the Dutch island of Texel for the period September 2014 to February 2015. The standard errors are clustered around season-household pairs. Each marked point indicates the estimates for the corresponding season and lines indicate the corresponding 95% confidence intervals.

To dig deeper into the matter of non-linear relationship between consumption and electricity generation, we also estimated the rebound effect for solar households by dividing them into sub-samples by quartiles according to the average electricity generation of the households. As shown in Figure 4.2, households with less electricity generation demonstrate a lower rebound effect compared to the households with greater average electricity generation. More precisely, solar households in the first quartile of the distribution according to their average electricity generation show a rebound effect around 11% [2], whereas the households in the last quartile of the distribution exhibit a rebound effect around 36%.

[2] This estimate is statistically significant at 10% level with a p-value of 0.063

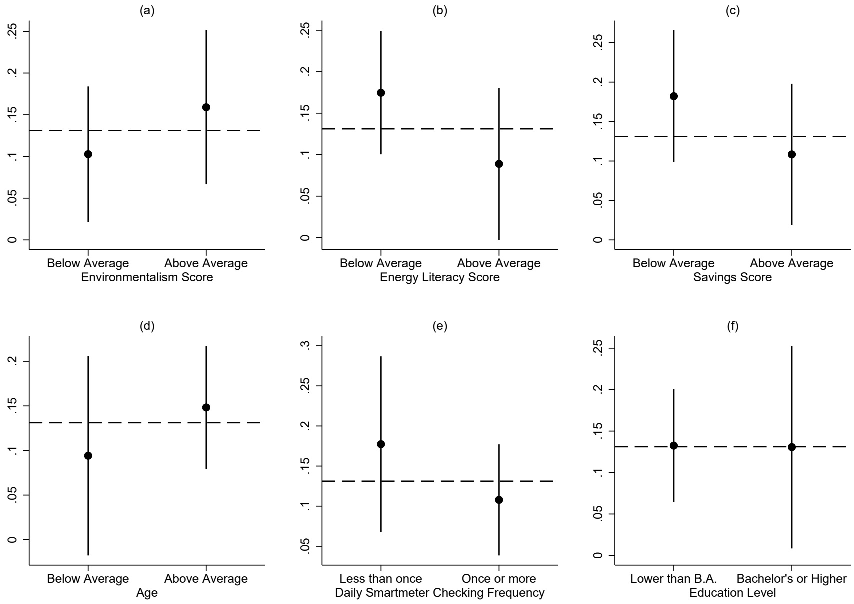
Figure 4.2 Rebound Effect by Average Electricity Generation of Households



Notes: The dependent variable is daily electricity consumption. The analysis is based on the sample of solar households on the Dutch island of Texel for the period September 2014 to February 2015. Households are divided into sub-samples delimited by quartiles according to their average electricity generation. The standard errors are clustered around season-household pairs. Each marked point indicates the estimates for the corresponding season and lines indicate the corresponding 95% confidence intervals.

Next, as there might be heterogeneities in the rebound effect associated with differing household characteristics, we estimate the rebound effect for a series of solar household sub-samples based on the characteristics as shown in the Figure 4.3. These estimates suggest that individuals with higher energy literacy and with a higher savings score are associated with lower rebound effects. This might suggest that financial and energy awareness reduces the rebound mechanism. On the other hand, people that have more environmental awareness tend to experience higher rebound effects. This result might look counter-intuitive at first sight, however, it needs to be noted that overall electricity consumption is lower for households with above average environmental awareness and they just respond relatively more generously to PV electricity generation. Besides, these households might experience a stronger rebound effect due to the decreasing environmental cost of their future electricity consumption. In addition, the older households in our sample are associated with a slightly higher rebound effect, whereas, differences in education levels appear to have no effect at all on the rebound. Lastly, households that check their smart meters more frequently experience a lower rebound effect, which can be interpreted as an indication for the information feedback mechanism. However, we should note that because sample size is relatively small in these subgroups, all these observed differences are lacking statistical significance.

Figure 4.3 Rebound Effect by Different Household Characteristics



Notes: The dependent variable is daily electricity consumption. The analysis is based on the sample of solar households on the Dutch island of Texel for the period September 2014 to February 2015. The standard errors are clustered around season-household pairs. Each marked point indicates the estimate for the corresponding sample, while lines indicate the corresponding 95% confidence intervals. Dashed line indicates the estimate for the full sample of solar households that participated in the household survey.

5. CONCLUSION

By exploiting electricity consumption and solar PV electricity generation data of Dutch households, we observed changes in consumer behavior related to solar panel adoption. Our estimations suggest that a household increases its electricity consumption by 0.07 kWh when generated solar PV electricity increases by 1 kWh, indicating a rebound effect of around 7%. We also find that solar PV electricity generation decreases the net electricity consumption from the grid, but these consumption gains are dispersed over time. In addition, our heterogeneity analysis also shed light on the circumstance that booster this rebound effect. For instance, we observe a higher rebound effect during seasons that are associated with higher solar irradiance, which might indicate that the rebound effect may be higher in geographical regions with higher solar irradiance and vice versa. When we look at differences in socio-demographic characteristics, we find that households experience lower rebound effects when they have more energy literacy or a stronger tendency to save. On the other hand, people with higher environmental awareness experience a higher rebound effect. These household differences in the rebound effect are not statistically significant, but may offer some guidance for further research.

A proper estimation of the solar rebound effect is essential for policy evaluations. When assessing the impact of distributed solar panel adoption, neglecting the rebound effect would result in improper and somewhat optimistic conclusions. The benefits of solar panels to the consumer may be overstated if the rebound effect is ignored, since the future value of such investment would co-depend on it. Furthermore, reductions in energy imports or carbon emissions may be overestimated, as the rebound effect would result in a slight increase in electricity consumption. The timing of those reductions is another matter to consider. One of the benefits of distributed solar panels is that they lead to a reduction in distribution infrastructure load and peak-hour electricity demand from the grid. Our results show that reductions in demand from the grid are not fully instantaneous. Instead, grid electricity demand is diffused more over time. This should be considered when planning for the fulfillment of peak-hour demand or considering reductions in carbon emissions due to point-of-demand electricity production, since it leads to a decrease in distribution infrastructure load that is intrinsically inefficient.

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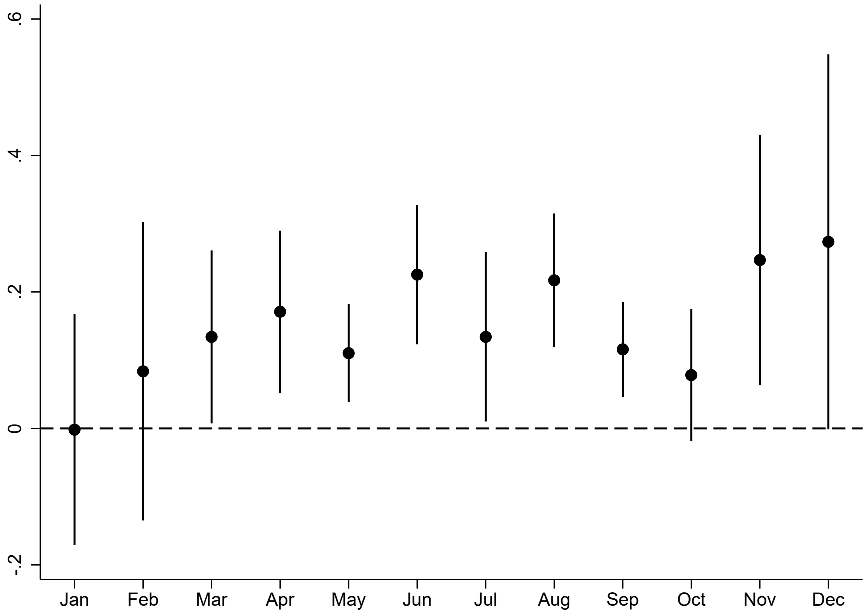
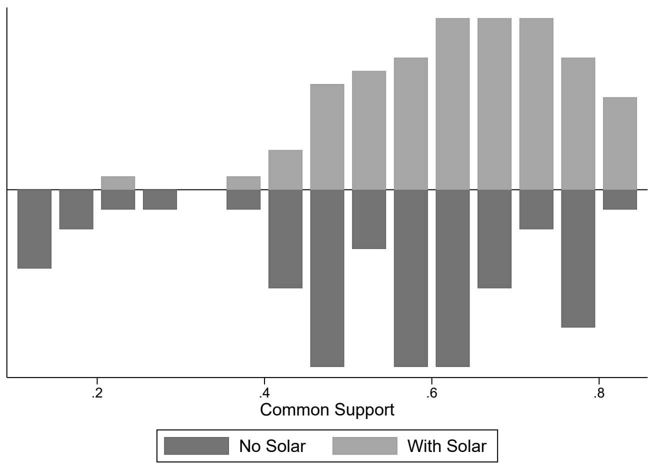
APPENDIX A

Figure A.1 Rebound Effect by Months



Notes: The dependent variable is daily electricity consumption. The analysis is based on the sample of households on the Dutch island of Texel for the period September 2014 to February 2015. The standard errors are clustered around season-household pairs. Each marked point indicates the estimates for the corresponding month and lines indicate the corresponding 95% confidence intervals.

Figure A.2 Common Support for PSM



Notes: This graph shows the common support between treated and untreated households after the PSM.

Table A.1 Different Matching Algorithms for PSM

Algorithms	(1) Radius (0.075)	(2) Radius (0.05)	(3) Radius (0.1)	(4) Nearest Neighbor (N = 3)	(5) Kernel
Total Effect	0.049**	0.053***	0.048**	0.051**	0.053***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
at t	0.569***	0.570***	0.569***	0.565***	0.570***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
at t-1	-0.458***	-0.457***	-0.459***	-0.454***	-0.457***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
at t-2	-0.062***	-0.060***	-0.062***	-0.060***	-0.060***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Household FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Constant	10,056.964***	10,048.413***	10,090.672***	9,902.443***	10,068.704***
	(67.113)	(66.695)	(67.572)	(70.241)	(66.757)
Observations	33,928	33,644	34,574	33,928	33,644
R-squared	0.662	0.657	0.658	0.669	0.657

Notes: The dependent variable is daily electricity consumption. The analyses are based on the sample of households on the Dutch island, of Texel during the period September 2014 to February 2015. The number of households was 171 (survey participation). The standard errors are clustered around season-household pairs, controlling for autocorrelation, and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1