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Solar rebound effects: Short and long term dynamics

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ABSTRACT

Rooftop solar is increasingly promoted as a source of low-carbon household energy; however, there is a plausible concern that solar installations might influence energy consumption patterns in ways that undermine potential environmental benefits. In this study, we examine the impact of residential rooftop solar panels on energy usage in Vietnam. Leveraging a comprehensive and unique panel dataset, we employ a difference-in-differences identification strategy to estimate the effects of solar installation on consumption. Our models reveal that households installing solar panels reduce grid consumption (typically carbon-intensive) by approximately 3.6 %. This reduction occurs concomitantly with an increase in total consumption of around 16 %, indicating a substantial rebound effect from solar panels. Nonetheless, dynamic models suggest a diminishing trend over time for both the decline in grid usage and the rebound effect, leveling off to 1.5 % and 3.5 %, respectively, within one year of solar installation. Acknowledging the marked differences in household consumption behavior and electricity demand dynamics between developing and developed nations, our research provides valuable insights into the understanding of the solar rebound effect and its dynamics over time.

1. Introduction

Replacing fossil fuels with renewable energy sources is considered one of the most viable options for mitigating climate change [1]. However, the success of solar installations in reducing carbon emissions depends heavily on their ability to substitute for other sources of energy, particularly grid electricity that runs on fossil fuels. If households that adopt solar panels also substantially change their energy consumption patterns, it is possible that the overall carbon emissions associated with energy use may be relatively unchanged. This phenomenon is known as a “rebound effect”, where increased supply fails to induce substitution between solar and grid energy.

In this paper, we investigate the efficacy of residential solar energy in mitigating carbon-intensive energy consumption. Our motivation stems from the possibility that a rebound effect may occur through various behavioral changes, some of which could paradoxically counteract the environmental benefits of adopting clean energy. Renewable energy adoption is influenced by both non-financial motivations and financial incentives [2–4].

Regarding non-financial motivations, there is a consensus that solar adoption is both encouraged by and encourages more environmentally responsible behavior [5,6]. However, the effectiveness of these behavioral interventions may be observable only over short periods or may not always be sustained over the long term [7,8]. The rebound effect can be explained by moral licensing, wherein solar users may consume more energy under the assumption that they have already taken a morally responsible action by installing solar PV [9,10]. On the financial front, the rebound effect may manifest when consumers perceive solar energy as synonymous with “free electricity.” This perception is particularly pronounced in contexts like Vietnam, where the initial phase of promoting rooftop solar power installation employs the net metering mechanism. Under this mechanism, the solar power output generated is essentially free for consumption, given that the marginal price of electricity is zero [11].

We address this issue through an analysis of a distinctive panel dataset encompassing approximately 3500 households in Hanoi, Vietnam, focusing on their energy consumption patterns. Employing a difference-in-differences methodology, we assess the structural shifts in solar and grid energy utilization before and after households adopt solar panels. Our model findings indicate a modest 3.6 % reduction in grid electricity consumption among solar energy adopters, relative to non-solar households. Conversely, post-solar system installation, total

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power demand among solar users exhibits a 16 % increase compared to homes without solar energy. Thus, the potential of household solar panels to substantively mitigate carbon emissions seems to be adversely affected.

We further explore the temporal dynamics of both total electricity demand and grid power demand over a twelve-month period following the installation of solar systems. Our findings reveal a significant initial expansion in the gap between the total electricity demands of rooftop solar owners and non-solar households, as mentioned above at 16 %, which gradually diminishes over time, ultimately converging to 3.5 % after the twelve-month observation period. Simultaneously, an opposing trend is observed in grid electricity consumption. Initially, the reliance on the grid by solar prosumers is 3.6 % lower than that of non-solar households, yet this disparity contracts to 1.5 % over the same period. These dynamics suggest a partial reversion in the behavior of solar owners towards increased dependency on the grid. This trend may be attributed to factors such as a less attractive feed-in tariff, limited adoption of battery technology, and the persistence of entrenched long-term behavioral patterns.

After obtaining these baseline results, we perform a set of model diagnostics related to causality/identification. These include an examination of parallel trend assumptions, running a placebo regression, and using stability assessments to simulate the potential effects of unobserved confounding. Our models perform well in all instances, suggesting that our estimates are likely to be causal.

Our results are associated with the rebound effect, a conservation or energy economics concept on an adverse behavioral response to new technologies, which are usually more economical or efficient. The rebound effect was initially known as Jevons' [12] paradox and revisited in Khazzoom [13] before being widely adopted in a series of analyses for various energy services, especially papers focusing on energy efficiency. Some examples of this include but are not limited to studies by Du et al. [14], Wei & Liu [15], Zhang & Lin Lawell [16], Turner [17], Freire González [18], Mizobuchi [19], Frondel et al. [20], Dimitropoulos [21], and Bentzen [22]. The detailed surveys of the rebound effect in earlier literature can be found in studies by Sorrell et al. [23] and Greening et al. [24].

The solar rebound effect has become a focal point in scholarly discourse, with recent empirical studies consistently reinforcing findings from earlier research on this phenomenon. Notably, Beppler et al. [25] observed a rebound effect of 28.5 % in the eastern United States. Boccard & Gautier [26] contributed evidence revealing a significant rebound effect in consumption, often resulting in oversized installations due to a generous subsidy scheme in Wallonia, Belgium. Qiu et al. [27] reported a positive indication of a rebound effect in Arizona, showcasing an 18 % increase in electricity consumption from solar energy production. Investigations into Australian households identified a rebound effect ranging from 16 % to 20 % in the consumption patterns of solar owners in Sydney from 2007 to 2014, with the prospect of a more pronounced effect under a higher feed-in tariff [28–30].

Our study modestly contributes to the emerging field by investigating the solar energy rebound effect in a developing country context. Recognizing that household consumption behavior and electricity demand dynamics in developing countries differ significantly from those in developed nations, our research adds valuable insights to the understanding of the solar rebound effect. Leveraging a substantial, distinctive, and up-to-date panel dataset, we unveil a substantial rebound effect that challenges the presumed environmental advantages of residential solar energy. We are also (to our knowledge), among the first authors to study the dynamics of this process and show that both the primary effect and the rebound effect tend to diminish over time.

The paper is structured as follows. Section 2 introduces the data set and variables. Section 3 presents our baseline estimates and discusses the immediate implications. Section 4 studies the dynamic properties of our data and Section 5 undertakes some causal diagnostics. Section 6 discusses some policy implications and Section 7 concludes.

2. Data

We employ two datasets, household-level panel data and aggregated district-level panel data of Hanoi Capital, Vietnam. The household data are an unbalanced panel of more than 3550 households in Hanoi from 2015M1–2021M11, in which 1688 households are solar energy consumers and 1862 households do not use solar energy. It contains detailed monthly information on electricity demand and bill, solar system capacity, production, and installation time. This data are collected from the customer database of Hanoi Power company with encrypted identity information for privacy purposes. Meanwhile, the district-level data are a balanced panel dataset that provides aggregated social economics information of Hanoi's 30 administrative regions (districts) in the same period. Because not all households' socioeconomic and demographic were available, we adopted district-level data as proxies for exogenous impact factors to overcome that situation. The district-level data are balanced data published annually in Statistical Yearbooks by the Vietnamese Statistics Office.

2.1. Electricity demand variables

Total electricity consumption, y^1_{it}, and electricity purchased from the grid network, y^2_{it}, are monthly data of household i in month t.[1] They are measured in kilowatt-hour (kWh) and transformed into logarithmic form before being adopted into the models. Values of y^1_{it} and y^2_{it} are identical for those households that do not install or had not installed solar energy systems. Notably, all homes in the dataset did not possess solar batteries, but none fed solar energy into the national grid. It means all solar owners either consumed all solar production or wasted it, and the solar energy output always equals the subtraction of y^1_{it} to y^2_{it}.

2.2. Electricity price variables

The retail electricity tariff in Vietnam for residential purposes is the tier rate, in which the rate will increase after every 100 kWh of electricity consumed. It means that the individual household power price is endogenous to the demand. Thus, we calculate the average monthly electricity price for the whole administrative region, $aveprice_{dt}$, based on total bill and total demand at the district, d in month t. The variable ce_{dt}, which is measured in Vietnam Dong per kilowatt-hour, is then deflated and transformed into logarithm form before being input into the models. This proxy satisfies the price variable's exogenous requirement.

In addition, the impact of average electricity price on household demand could be influenced by the urbanisation rate of each district, i.e. $urban_{dt}$. Specifically, the more developed the district is, the more dependent households are on electronic devices. Consequently, the influence of electricity prices on consumption in lower urbanisation areas

[1] In the initial phase of promoting the development of residential solar power systems, the Vietnamese government actively endorsed a net-metering initiative. As part of this initiative, households in Hanoi installing rooftop solar power systems were mandated to have bi-directional electricity meters, ensuring the compulsory monthly recording of solar power self-consumption, and any surplus electricity transmitted to the grid. However, this program faced a setback due to the absence of guidance on finalization, payment schemes, and invoicing mechanisms from the Ministry of Industry and Trade and the Ministry of Finance. Consequently, the implementation of this initiative had to be halted.Subsequently, a new payment scheme for rooftop solar projects was introduced in the form of the feed-in-tariff (FIT). During the FIT policy period, electricity generated by rooftop solar power projects was consistently metered independently. The electricity supplied by Hanoi Power to consumers, including rooftop solar power investors, underwent regular metering procedures similar to those applied to other households and consumers. Therefore, the monthly total electricity consumption of each household is recorded as the sum of the power obtained from the grid and the actual amount used from the rooftop solar system.

could be more substantial than that in more developed districts. Thus, an interaction term between price and urbanisation rate, $aveprice_{dt} \times urban_{dt}$, is included in models to capture this effect.

2.3. Income variables

We use aggregate-level income averaged by districts as a proxy for each households' economic status. We use this approximate method as unit record data on household income is not available. This approximation is likely to be reasonable given the spatial associations in socioeconomic well-being usually seen in microdata [31–33]. Variable $income_{dt}$, measured in Vietnam Dong, is deflated and transformed into logarithm form. We also include a quadratic term of log of income into our model to allow for any potential nonlinear effects.

2.4. Other social demography variables

Other socio-demographic covariates, which potentially influence the power demand, are also included in our model. For instance, the number of families living in the same house, $family_{it}$, may positively correlate to the demand. Meanwhile, the urbanisation rate ($urban_{dt}$), the employment rate (emp_{dt}) and the rate of households having more than two children ($thirdchild_{dt}$), which reflect the socioeconomic development of each district, are also adopted. Finally, the number of new rooftop solar installed in the district each month, $solarcount_{dt}$, helps capture the solar adaptation level of the neighbourhood.

The descriptive statistic of the dataset is provided in Table 1.

Table 1
Descriptive statistics of the dataset.

Variable	Description	Mean	Std. dev.	Min	Max
y^1_{it}	Total electricity demand (log form)	5.79	0.82	3.69	8.35
y^2_{it}	Amount of electricity purchased from the network (log form)	5.71	0.81	0.00	8.34
$month_t$	t-1 dummy variables for t months	44.66	23.99	1.00	83.00
D_{it}	Dummy variable of the installation period - $D_{it} = 1$: the solar system is installed - $D_{it} = 0$: not installed yet	0.13	0.34	0.00	1.00
$family_{it}$	No. of families in the household	1.11	0.44	0.00	8.00
$income_{dt}$	Log of average households' income (by district)	8.99	0.21	8.30	9.51
$price_{dt}$	Log of average electricity retail price (by district)	7.57	0.15	6.22	7.77
$urban_{dt}$	Urbanization rate (by district)	60.92	45.78	1.56	100.00
emp_{dt}	The employment rate (by district)	37.85	22.56	2.25	125.18
$solarcount_{dt}$	Number of the new solar system installations (by district)	1.12	2.96	0.00	44.00
$thirdchild_{dt}$	The rate of households have more than two children	4.62	4.39	0.10	20.20

Notes.
- Table 1 presents the descriptive statistics of the data used in this study.
- The first column displays the names of variables, which are included in the model in Eq (1). Meanwhile, the second column shows the meaning and how to transform variables from the raw dataset.
- The dataset is unbalanced panel data, consisting of observations of 3550 households in 83 months from January 2015 to November 2021. In the data, 1688 solar energy consumers reflect the whole population; and 1862 households are samples of non-solar houses, which are randomly provided without any intervention or influence by the authors.

3. Analysis of the rebound effect

3.1. Baseline models

We are interested in assessing the changes in household consumption behaviour after installing solar systems, reflected in power consumption and grid electricity demand. We set up a difference-in-differences (hereafter, DID) design, in which solar energy adoption was not geographically specified and the installation point is time-variant by households.[2]

Let y_{it} denotes the electricity demand of household i at months t; D_{it} is a dummy for the treatment, i.e., solar installation, that distinguish by households and time[3]; α_i are households' time-invariant fixed-effects; λ_t are time fixed-effects; and, $\mathbf{x}_{it}$ is the vector of exogenous variables and interaction terms. For potential unobserved variables, the fixed effects estimation will help to capture their impacts. We define baseline models, including a model for total electricity demand and a model for power demand from the grid, as follows:

$$y^E_{it} = \alpha^E_i + \lambda^E_t + \theta^E y^E_{it-1} + \delta^E D_{it} + \mathbf{x}'_{it}\boldsymbol{\beta}^E + \varepsilon^E_{it} \quad (1)$$

where the superscript E is to distinguish a model for total electricity demand, i.e., y^1_{it}, from a model for power demand from the grid, i.e., y^2_{it}. In addition, residential power consumption is usually serially correlated, even after applying controlling methods like time-variant fixed-effect dummies. It is potentially caused by the accumulation of electrical devices or the stability of household financial conditions in the short term [30]. Thus, we accepted the setup with both fixed effects and lagged dependent variable, y^E_{it-1}.

Baseline models in Eq. (1) can be estimated by least squares, and estimation outputs are displayed in Table 2. In Table 2, the dependent variables in columns (1) and (2) are the logarithm of households' total electricity consumption, $\log(y^1_{it})$. Meanwhile, dependent variables in columns (3) and (4) are the logarithm of grid electricity demand, $\log(y^2_{it})$. All models included households' time-invariant fixed-effects and time fixed-effects, but they are not shown in the output for simplicity of exposition. The only differences between models in each pair are the inclusion or exclusion of exogenous variables, and those differences are to test the consistency of the estimations.

3.2. Implication of static estimates

The estimation of the treatment dummy, D_{it}, in Model (1) showed a highly significant and positive impact on households' total electricity demand. It implies that solar installations immediately increased the total electricity demand by approximately 16.3 %, i.e., suggesting the existence of a rebound effect of solar installation. The parameter of D_{it} in Model (2) also provided a similar pattern, which was 18.1 %, to confirm that the estimations are only marginally different regardless of the presence or absence of other exogenous variables. These results were analogous to the findings in studies of Qiu et al. [27] and Deng and Newton [30], in which increases in total electricity demand were 18 % in Arizona and more than 16.7 % in Sydney, respectively.

[2] In other words, the difference between this model and an ordinary DID model is that the treatment group is not naturally assigned, and some households get treated at particular times while others do not. Nonetheless, the DID panel model is still suitable because we have panel data of the same families over time [41].

[3] The pre/post-treatment periods are identified by dummy variables, D_{it}, while the identity of treatment/control groups is omitted because the model already includes time-invariant household variant fixed effects. Thus, variable D_{it} indicates two different periods, before ($D_{it} = 0$) and after ($D_{it} = 1$) installing the solar system, for each solar energy owner. Households that do not have a solar system will have $D_{it} = 0$ in all observations.

Table 2
Estimates output of baseline models.

	(1)	(2)	(3)	(4)
Solar installation (treatment)	0.163***	0.181***	−0.036***	−0.032***
	(0.006)	(0.006)	(0.005)	(0.005)
Log of total electricity demand (lagged)	0.693***	0.699***		
	(0.005)	(0.005)		
Log of grid electricity demand (lagged)			0.701***	0.702***
			(0.005)	(0.005)
Average electricity price (log)	−0.150***		0.025*	
	(0.017)		(0.014)	
Urbanisation rate (%)	0.004		0.011**	
	(0.005)		(0.005)	
Average electricity price (log)* Urbanisation rate	0.002***		−0.00007	
	(0.000)		(0.000)	
Income (log)	3.454***		2.261***	
	(0.470)		(0.467)	
Squared income (log)	−0.191***		−0.126***	
	(0.026)		(0.026)	
Number of families	0.017**		0.019**	
	(0.007)		(0.008)	
Employment rate	−0.001		−0.001**	
	(0.000)		(0.000)	
Rate of household having more than 3 kids	0.0003		−0.0003	
	(0.001)		(0.001)	
Observations	223,562	223,562	223,562	223,562
R-squared	0.660	0.658	0.594	0.594
Groups	3544	3544	3544	3544
Average group size	63.08	63.08	63.08	63.08
Panel-level standard deviation (σ_u)	0.720	0.195	0.427	0.217
Standard deviation of ϵ_{it} (σ_e)	0.286	0.287	0.294	0.295
Adjusted R-squared	0.660	0.658	0.594	0.594
R-squared within model	0.660	0.658	0.594	0.594
R-squared overall model	0.507	0.852	0.647	0.842
R-squared between model	0.559	0.991	0.721	0.997

Notes.
- The dependent variables in models (1) and (2) are the household's total electricity consumption (in log form).
- The dependent variables in models (3) and (4) are the household's grid electricity demand (in log form).
- All models include households' time-invariant fixed-effects and time-variant fixed-effects.
- Standard errors are clustered at the household level and reported in parentheses.
- ***,**, *: significant at the significant level of 1 %, 5 % and 10 %.

In the following estimations, the coefficient of D_{it} in Model (3) expressed a decrease of 3.6 % in grid power demand. A similar estimate of D_{it} in Model (4) highlights the robustness of this result. Jointly, these estimates imply that solar adaptation contributed to replacing a part of the household's electricity demand from the grid network to reduce the dependence on the grid; however, that contribution was relatively small. Furthermore, the dataset indicated that no residential solar owner in Hanoi had sold solar power production to the grid. This implies the solar power production has been topped-up to the solar owner's total demand and was not conducive to reducing the carbon footprint of the power generation industry.

4. Dynamics of the rebound effect

4.1. Modelling the dynamics

The preceding estimations revealed a notable surge in a household's overall energy consumption subsequent to the installation of solar panels, coupled with a slight reduction in grid demand compared to non-solar homes. This observed phenomenon may be indicative of a rebound effect, wherein behavioral responses lead to increased consumption following the adoption of a more economical energy source. Conversely, it could stem from a natural uptick in usage when individuals have an additional energy source to meet previously constrained demand. Furthermore, there is a plausible suggestion that these effects are dynamic, contributing to short-term spikes in household consumption that may not necessarily represent long-term adaptations. To address and scrutinize these concerns, we adapt our model in Eq. (1) as follows:

$$y_{it}^E = \alpha_i^E + \theta^E y_{it-1}^E + \lambda_t^E + \delta_k^E D_{it-k} + \mathbf{x}_{it}^{'}\boldsymbol{\beta}^E + \varepsilon_{it}^E \quad where \;\; k = 0, \dots, 12. \tag{2}$$

The difference between models in Eq. (2) to the models in Eq. (1) is the existence of twelve lagged treatment dummies, D_{it-k} where $k = 0, 1, \dots, 12$. In more detail, thirteen estimations of parameter $\delta_k^{E=1}$, i.e., $\delta_0^1, \delta_1^1, \dots, \delta_{12}^1$, reflect the impact of solar adaptation on the total electricity demand immediately after installation and in the next twelve months. Similarly, thirteen estimations of parameter $\delta_k^{E=2}$, i.e., δ_0^2, δ_1^2, …, δ_{12}^2, reflect the difference in the impact of solar adaptation on the grid power demand of rooftop solar owners in the same period. Estimations of parameters $\delta_k^{E=1}$ and $\delta_k^{E=2}$, then had been plotted in Fig. 1 (a1) and (b1), respectively. Besides, Fig. 1 (a2) and (b2) demonstrated $\delta_k^{E=1}$ and $\delta_k^{E=2}$ when exogenous factors were excluded in Eq. (2) estimations as a robustness check.

The dynamic of coefficients $\delta_k^{E=1}$ in Fig. 1 (a1) suggests that the impact of solar installation was remarkable in the first two periods, which caused total power demand to increase by approximately 16.5 % higher than in non-solar households. However, that difference diminished and reached about 3.5 % after thirteen months. Meanwhile, Fig. 1 (b1) displayed an opposite dynamics pattern of coefficients $\delta_k^{E=2}$. It showed that installing rooftop solar energy helped households reduce the grid energy demand by approximately 4 % in the first two months compared to homes without solar power. Nonetheless, this gap also faded out and reached approximately 1.5 % after thirteen months.

4.2. Dynamic effects

Three implications emerge from the dynamic impacts of solar installation on electricity consumption. Firstly, the diminishing trends observed in the gaps between total electricity consumption and grid power demand suggest that the associated demand shocks are transient and expected to dissipate over the long term. Consequently, it is reasonable to assert that the increase in total consumption was not instigated by restrained demand. If it were, we would anticipate an expanding demand gap after solar installation, which remains stable in the long term. Given Vietnam's 100 % electrification, the absence of severe power shortages, and the relative affluence of households in Hanoi, who can afford ample energy, the dynamic points to a significant short-term rebound effect experienced by rooftop solar prosumers upon acquiring a cost-effective energy source, namely solar energy.

Secondly, a discernible trend indicates the reduction of gaps in both total electricity consumption and grid demand between rooftop solar users and non-solar households over a thirteen-month period. This phenomenon suggests a gradual diminishment in the disparity of electricity usage behavior between the two household groups. It is plausible that these households were initially committed to altering their usage patterns of electrical appliances to maximize the utilization of solar energy. However, considering that a substantial portion of power consumption, particularly for essential activities such as cooking, studying, and entertaining, predominantly occurs during nighttime when solar energy is unavailable, these solar energy consumers may gradually revert to their established dependency on the grid, potentially leading to a reduced reliance on solar energy.[4]

Third, the reversion to previous consumption patterns may partially explain the dynamics of the rebound effect; however, it raises lingering questions regarding the decrease in solar energy consumption among

[4] This phenomenon could be seen more obviously in the analysis of solar production in Section 6.

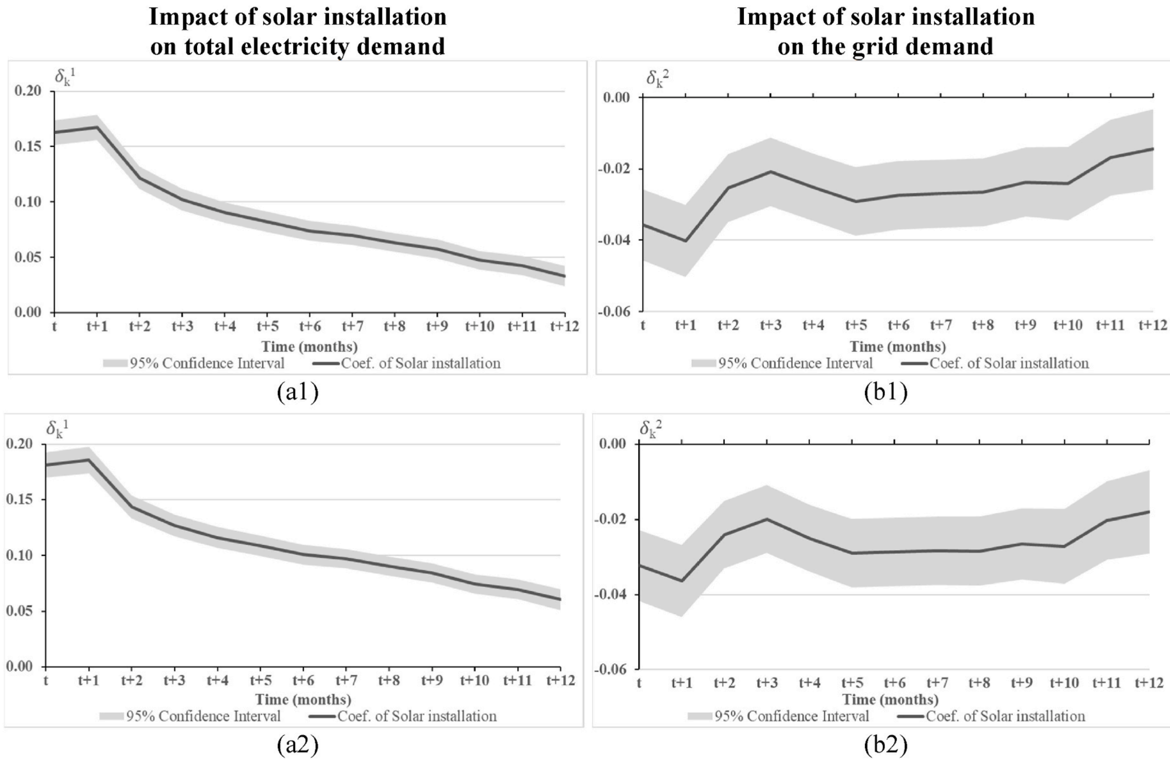


Fig. 1. Dynamics of rooftop solar installation's rebound effects
Notes:
The figures (a1) and (a2) illustrate solar adaptation's impact on the total electricity consumption in 13 months compared to non-solar households.
- The figures (b1) and (b2) illustrate the difference in solar adaptation's impact on the grid power demand between rooftop solar owners and non-solar consumers in 13 months.
- The difference between models in figures (a1) versus (a2) and figures (b1) versus (b2) is the inclusion or exclusion of exogenous variables, respectively. And the purposes of figures (a2) and (b2) are to double-check the consistency of figures (a1) and (b1).

solar energy owners, who refrained from selling excess outputs to the grid.[5] This phenomenon can be attributed to factual inadequacies in technology application and policy implementation, exemplified by the minimal adoption of solar batteries among residential consumers in Hanoi. Consequently, households installing solar panels faced a 'take it or leave it' scenario, unable to store surplus solar energy for nighttime use when power-intensive activities predominantly occur. Thus, those households were unable to mitigate their dependence on the grid, although they were determined to lean toward solar energy. In addition, the Vietnamese Government applies a feed-in-tariff policy to encourage households to sell unused solar power to the grid. However, the feed-in tariff, which is 8.38 cents/kWh,[6] is lower than most tiers' marginal prices in the retail electricity price.[7] Meanwhile, households need to complete a tax registration procedure to be able to sell solar energy to the grid. Therefore, solar energy consumers may not have enough incentive to sell their solar production.

5. Discussion on installed capacity and production

Our results above do not actively address differences in installed capacity and production that will vary across households. In this section, we explore these variables and search for their potential to explain the rebound effect analysed earlier.

We demonstrate the installed capacity distribution trend of household rooftop solar in Hanoi in Fig. 2. While most households selected a capacity smaller than 10 kW-peak (kWp) and mainly in the range of 3–7 kWp in 2019, adopters in 2020 chose a higher range of 5–10 kWp or even more than 15kWp. This could be a response to a dramatic reduction of 58 % in terms of the levelized cost of solar PV during the period 2016–2020 in Vietnam [34]. However, it is plausible that households are over-capitalising on solar investment and are creating excess supply, which may be linked to the behavioural responses hypothesised above. The potential solar energy production in Hanoi is about 3.3 kWh/kWp per day or approximately 100 kWh/kWp/month [35,36]. Based on that, the installed capacities required to fulfil the total electricity demand for households are approximately 1 kWp, 2 kWp, 3 kWp, and 4 kWp, respectively, for the households with consumption in Tier 2, Tier 3, Tier 4, and Tier 5. Thus, the illustration in Fig. 3 implies that the majority of solar energy owners in Hanoi have oversized installations.

Oversized installation could bring some potential benefits that include revenue from selling solar energy or independence on the grid for the owners, as well as reducing the peak load for the national system. However, those benefits were ambiguous or nonexistent in our study. Previously we found that the dependence on the grid was reduced by only approximately 4 %, while the whole solar energy output was added up to the owner demand. In addition, residential solar energy owners have zero revenue from selling the output based on our data in this

[5] This is observed from the declined trends of the gaps in both total electricity demand and grid electricity demand between solar energy consumers and non-solar households.

[6] Decision no 13/2020/QD-TTG issued on 06/04/2020 about the mechanism to encourage the development of solar power in Vietnam.

[7] The residential electricity retail price is following six tiers:Tier 1 (0–50 kWh): 7.24 UScent/kWh- Tier 2 (51–100 kWh): 7.48 UScent/kWh- Tier 3 (101–200 kWh): 8.69 UScent/kWh- Tier 4 (201–300 kWh): 10.94 UScent/kWh- Tier 5 (301–400 kWh): 12.22 UScent/kWh- Tier 6 (>400 kWh): 12.62 UScent/kWhThe feed-in tariff of rooftop solar (8.38 cents/kWh) is only higher than tier 1 and tier 2 marginal prices.

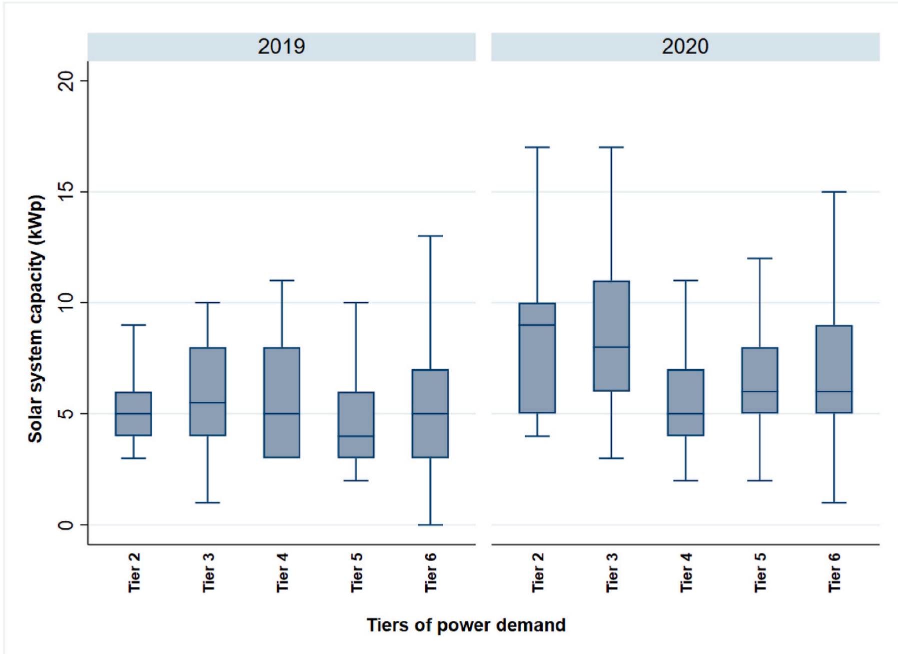


Fig. 2. Distribution of installed capacity of the household solar systems in Hanoi
Notes:
Fig. 2 demonstrates the distribution of installed capacity of the household solar systems by tiers of electricity consumption. The data are from two years, 2019 and 2020, which recorded the installation of most households in Hanoi
- Each boxplot displays the median, lower and upper quartiles of the capacity. The upper and under adjacent values are respectively determined by the formulas: $Q3 + 1.5 \times$ *Interquartile range* and $Q1 - 1.5 \times$ *Interquartile range*. Outliers are not presented in this figure.
- The consumption range in each tier of power demand is explained in footnote 3 of this study.
- In this figure, a household will be assigned to a specific tier based on its highest monthly consumption before installing solar energy.

study, collected up to November 2021. Thus, installation of residential rooftop solar in Hanoi seems inefficient, resulting in higher total costs for the owners.

We illustrate the self-consumption of residential rooftop solar power in Hanoi, organized by installed capacity across four distinct seasons, using scatter plots in Fig. 3. Additionally, we compare this data with the potential output calculated from a trial installation project conducted by Thanh et al. [36], represented by the red lines. The findings from Fig. 4 suggest that only a limited number of households utilized their solar power output to its full potential, matching the capacity of their installed solar PV systems. Conversely, a significant proportion of homes consistently consumed considerably less solar power than their systems could practically generate, irrespective of the season or installed capacity. Notably, the absence of records indicating households selling solar power to the grid implies that a substantial amount of the produced solar power has gone unused or been wasted.

One plausible reason for this inefficiency is insufficient power storage due to inadequate evaluation. The most common mistake solar owners had was relying on cost-benefit analysis only but overlooking the technical analysis, which is also seen in many studies or policy recommendations. For example, Thanh et al. [36] considered that a 3kWp solar system without storage is about 45 % cheaper and has only almost half the payback period of the same system but with power storage. However, this result could be different if the fact that most residential power-consumed activities occur at night is counted. Then, if a solar owner does not sell solar output to the grid, the output can only be minimally consumed by certain frequently plugged-in appliances such as refrigerators. Without the storage, cost-benefit analysis may be misleading.

Another possible reason for the inefficiency of residential solar energy in Hanoi is the lack of incentives in promoting policies. As discussed above, the feed-in tariff regulated by the Government is only 8.38 cents/kWh, lower than most tiers' marginal prices, while the procedure to apply to sell solar output has many red tapes. As a result, solar owners would rather waste their solar power than sell it back to system. A higher feed-in tariff, which is encouraging enough to motivate solar energy owners to produce and sell, is needed. However, what threshold is appropriate requires further study as there are evidence that high feed-in tariffs cause rebound effects to be more severe [28,29].

6. Models diagnostics

6.1. Parallel trend assumption

We first examine the electricity demand trends of two groups, solar owners and non-solar households. Specifically, we aim to verify the parallel trend assumption that the difference between the demands of two groups in the absence of solar installation is constant over time. Fig. 4 demonstrates the results for the total electricity demand (Fig. 4-a) and the network electricity demand (Fig. 4-b). It is noteworthy that the parallel lines are not required to be linear, depending on the nature of the data [37]. In this case, demand lines reflect the well-known seasonality of electricity consumption. In addition, there is no apparent time boundary between before and after installation, and the lines depicting solar owners in two periods overlap in Fig. 4. This is because households installed rooftop solar systems at different points, so each solar PV owner moved from the pre-treatment sub-group to the post-treatment sub-group at various times.

As illustrated in Fig. 4-a and 4-b, households without solar power installations exhibit similar electricity usage patterns. Upon the installation of rooftop solar systems, distinct shifts in the trend lines for total electricity demand and grid power demand become evident among solar power users. For instance, in Fig. 4-a, the green dashed line representing the total electricity demand of solar power users experiences a notable

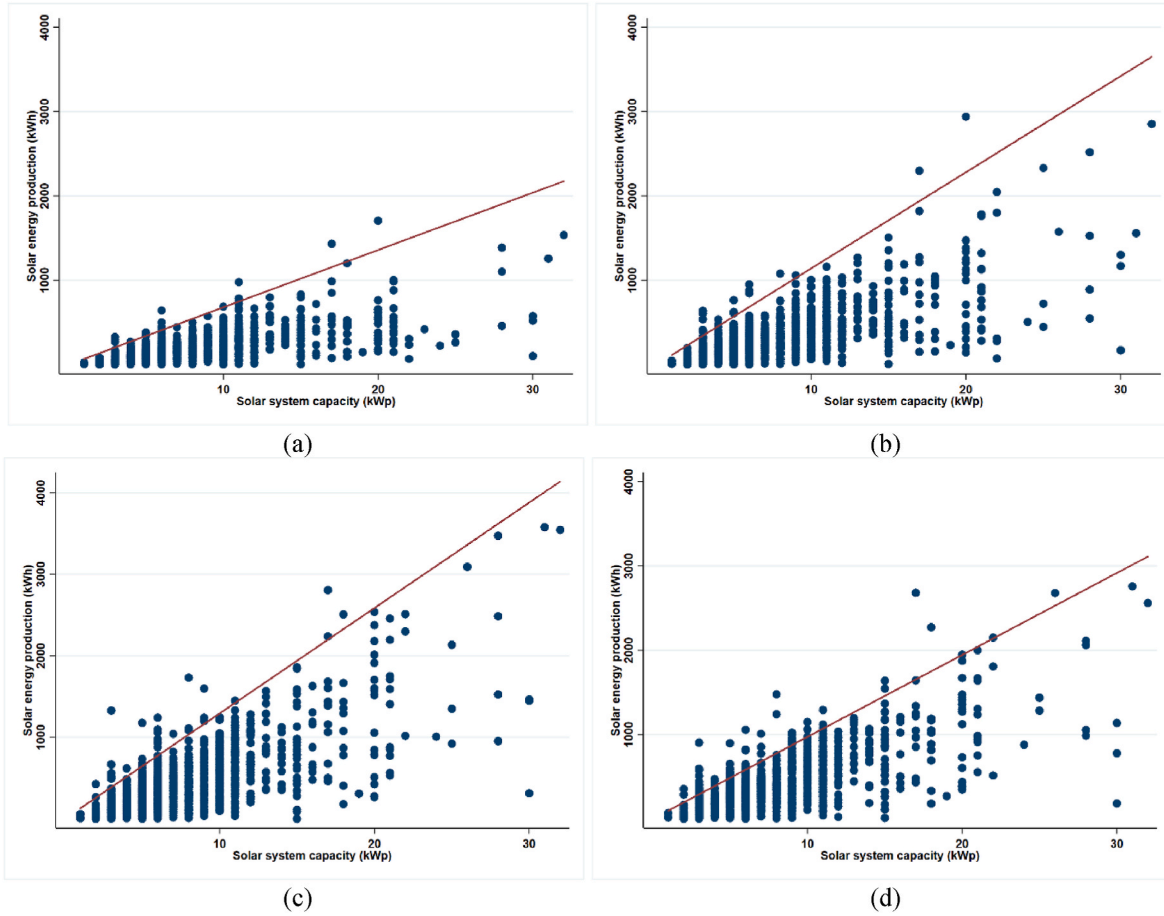


Fig. 3. Solar production consumed by households vs. potential output in four seasons
Notes:
Fig. 3 demonstrates the solar energy production consumed by households in our data versus the potential output of Thanh et al. [36] by solar energy capacities and four seasons.
- The actual solar energy production is depicted by the dots, and the potential output is depicted by the red lines
- Figures (a), (b), (c), and (d) respectively present four seasons, Spring, Summer, Autumn, and Winter.
- We only record solar power output data from the 4th month after installation to ensure that the data are not recorded too low in the first few months of operation.

increase, setting it apart from other households, particularly from mid-2018 onward. This divergence persists throughout the observed period. Conversely, the grid demand trend line for solar power users, as depicted in Fig. 4-b, initially exhibits a considerable decrease compared to other households but gradually converges with the original trend line over time. These visual trends serve as graphical evidence supporting the previously discussed rebound effect and its dynamic nature.

6.2. Stability analysis

Table 2 provides a comparison between our models of interest with all available covariates and the simplest models with only treatment variables, i.e. D_{it}. The results imply that the full models are reliable because the coefficients of interest, δ^E, are marginally affected when more covariates are added to the models. However, we caution that potentially poor measures of underlying cofounders could cause adding these variables to be meaningless or, more seriously, lead the estimation to problematic compositional changes. This can happen if the change in D_{it} is associated with changes in other explanatory variables, i.e., the solar installation is affected by some other factors included in the model.

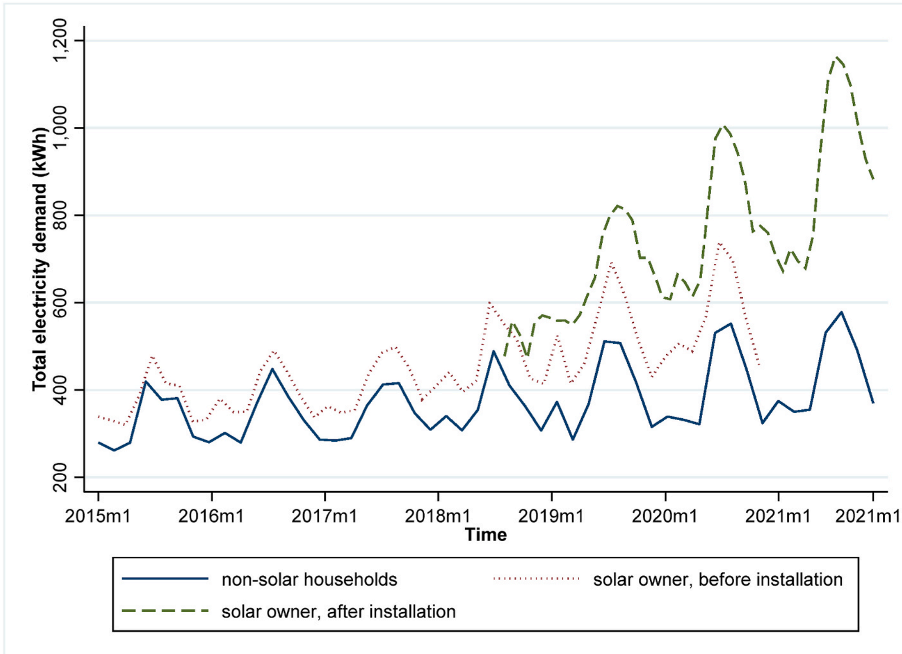
To examine this validity aspect of our models, we apply the process suggested by Pei et al. [38] to conduct balancing tests when putting covariates, $\mathbf{x}_{it}$, on the left-hand side (LHS). Pei et al. [38] argued that this strategy is more powerful than a conventional regression of D_{it} on other covariates, especially when the controls are bad measured. The LHS regressions are expressed by fixed-effects estimations in Eq (4):

$$\mathbf{x}_{it} = \alpha_i^{LHS} + \lambda_t^{LHS} + \pi D_{it} + u_{it}, \tag{4}$$

where, α_i^{LHS} are time-invariant fixed effects; λ_t^{LHS} are time fixed-effects. In addition, coefficient vectors π should be statistically equal to zero to verify the validity of our base models. The balancing tests against the null hypothesis that π equals zero are presented in Table 3. The results show that both individual and joint balancing tests cannot reject the null hypothesis at any significant level below 10 % so that all controls are statistically balanced. This suggests that the difference between solar energy owners and non-solar households is stable over time, and the causal impact of solar energy installation on demand is not associated with changes in the distribution of other factors.

7. Conclusion

This paper has studied the behaviour of household energy consumption in Vietnam before and after the installation of household solar panels. Using a difference in differences approach, we have shown that upon installation, households tend to sharply increase their energy consumption, with relatively little substitution occurring from grid electricity to solar energy. As a consequence, the scope for solar panels to reduce carbon-intensive energy usage appears partially compromised,



(a)

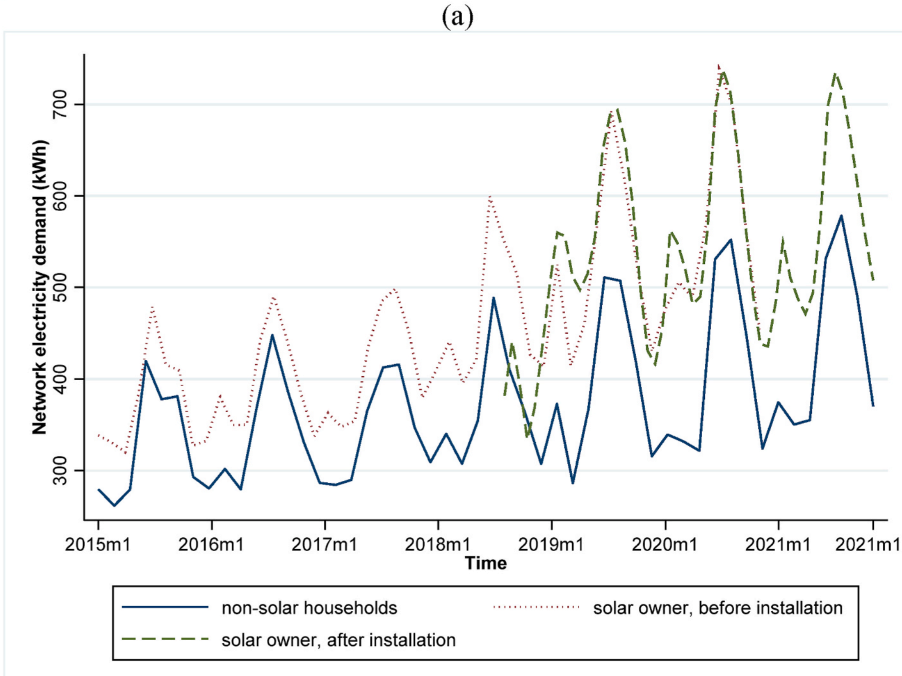


Fig. 4. Dynamics of rooftop solar installation's rebound effects
Notes:
Fig. 4 (a) illustrate the movement trends of total electricity demand, and Fig. 4 (b) depict the movement trends of network electricity demand.
- The lines depicting solar owners in two periods, before and after installation, overlap because households have different points installing solar PV systems.
- Demands are calculated based on the average monthly consumption of all households in each group
- Total electricity demands are identical to the network electricity demand for non-solar households and yet-to-be-installed solar owners. However, the two demands are different in the case of solar owners since the solar PV is installed.

at least for developing countries like Vietnam.

Furthermore, our findings indicate that the solar energy rebound effect manifested prominently in the short term but gradually diminished over time. To be specific, the total electricity demand of households with solar installations surged significantly by 16 % following the installation of solar systems, gradually tapering to approximately 3.5 % after a twelve-month period. While this decline might be viewed as a positive trend, it is indicative of a slow abandonment of solar energy over time, with potential adverse implications for both household welfare and carbon pollution. We contend that fostering improved energy battery adoption and implementing more incentivizing policies could contribute to mitigating this issue.

Since households that install solar panels may possess unobserved characteristics that distinguish them from households that did not, there is the potential for our results to be affected by unobserved confounding. However, across a range of diagnostic methods, we find little evidence

Table 3
Balancing tests the associations between D_{it} and $\mathbf{x}_{it}$.

	p-values of π
LHS balancing test:	
Individual:	
Average electricity price (log)	0.107
Urbanisation rate (%)	0.764
Average electricity price (log)* Urbanisation rate	0.442
Income (log)	0.151
Squared income (log)	0.144
Number of families	0.296
Employment rate	0.643
Rate of household having more than 3 kids	0.646
Joint:	0.5955

Notes: Table 4 expresses the result of the left-hand side (LHS) balancing test suggested by Pei et al. [38]- The LHS balancing test is estimated based on the first different estimator of equations$\mathbf{x}_{it} = \alpha_i^{LHS} + \lambda_t^{LHS} + \pi D_{it} + u_{it}$- The joint LHS balancing test is implemented by the *suest* command in Stata.

that endogeneity or misspecification issues may be biasing our results. As estimates need to be causal in order to meaningfully inform policy, the stability of our results is a major advantage.

Nevertheless, our study is subject to certain limitations. Firstly, detailed demographic and financial data at the household level were not within the scope of our data collection. Additionally, the available data lack granularity in terms of electrical appliance usage, which would have provided a more nuanced analysis of how rooftop solar owners adjust their consumption post-installation. Despite our efforts to conduct surveys in Hanoi for the collection of such data, all attempts were regrettably cancelled due to the Covid-19 epidemic. These limitations, acknowledged herein, underscore the need for future research endeavors to address these aspects comprehensively.

CRediT authorship contribution statement

Luan Thanh Nguyen: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis. **Shyama Ratnasiri:** Supervision. **Liam Wagner:** Supervision. **Dan The Nguyen:** Data curation. **Nicholas Rohde:** Writing – review & editing, Supervision, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Placebo regression

Estimates of solar energy installation on electricity demands, measured by δ^E in Eq. (1), could be invalid if the model is incorrectly specified. One way to diagnose potential specification errors is to run a *placebo regression.* , where the treatment is shifted into a period where no effect is expected to occur. If our model produces significant results in these placebo specifications, it suggests that some other factor may account for the results. To examine that effect, we apply a Granger-type causality framework [39] to Eq (1) by including three (03) leading values of the dummy variable D_{it}, which are D_{it+f} with $f = [1, 3]$. The test equations can be expressed as follows,

$$y_{it}^E = \alpha_i^E + \theta^E y_{it-1}^E + \lambda_t^E + \delta^E D_{it} + \sum_{f=1}^{3} \delta_f^E D_{it+f} + \mathbf{x}_{it}^{'} \boldsymbol{\beta}^E + \varepsilon_{it}^E \quad . \tag{3}$$

The estimation outputs provided in Table 4 suggest that all leading values D_{it+f} are insignificant. The Wald test further verified that three values of D_{it+f} ($with\, f = 1, 2, 3$) jointly equal zero. Therefore, we can reject the null hypothesis that the solar energy installation is anticipated by outcomes measured in earlier periods, considering up to three periods.

Table 4
Granger causality tests for the placebo effect

	(1)	(3)
Solar installation (treatment)	0.164***	−0.046***
	(0.010)	(0.009)
Solar installation (1-period lead, δ_1^E)	−0.005	−0.004
	(0.012)	(0.012)
Solar installation (2-periods lead, δ_2^E)	−0.010	−0.009
	(0.012)	(0.012)
Solar installation (3-periods lead, δ_3^E)	0.002	0.011
	(0.009)	(0.009)
Log of total electricity demand (lagged)	0.670***	
	(0.005)	
Log of grid electricity demand (lagged)		0.676***
		(0.006)
Average electricity price (log)	−0.137***	0.042***

(*continued on next page*)

Table 4 (*continued*)

	(1)	(3)
	(0.018)	(0.015)
Urbanisation rate (%)	0.004	0.011**
	(0.005)	(0.005)
Average electricity price (log)* Urbanisation rate	0.002***	0.000
	(0.000)	(0.000)
Income (log)	3.731***	2.333***
	(0.495)	(0.491)
Squared income (log)	−0.206***	−0.129***
	(0.028)	(0.028)
Number of families	0.021***	0.024***
	(0.008)	(0.009)
Employment rate	−0.001	−0.001**
	(0.000)	(0.000)
Rate of household having more than 3 kids	−0.0003	−0.001
	(0.001)	(0.001)
Observations	195,299	195,299
R-squared	0.651	0.592
Groups	3541	3541
Average group size	55.15	55.15
Panel-level standard deviation (σ_u)	0.751	0.446
Standard deviation of ϵ_{it} (σ_e)	0.275	0.281
Adjusted R-squared	0.651	0.592
R-squared within model	0.651	0.592
R-squared overall model	0.478	0.625
R-squared between model	0.529	0.694
Wald test for $\delta_1^E = \delta_2^E = \delta_3^E = \mathbf{0}$		
F(3, 3540)	0.83	0.62
Prob > F	0.4798	0.6021

Notes.
- The dependent variable in Model (1) is the log of the household's total electricity consumption.
- The dependent variable in Model (2) is the log of the household's electricity purchased from the grid network.
- All models include households' time-invariant fixed-effects and time-variant fixed-effects.
- Standard errors are clustered at the household level and reported in parentheses.
- ***,**, *: significant at the significant level of 1 %, 5 % and 10 %.

Magnitude of Nickell bias

There are potential concerns in our dynamic panel data model regarding the inclusive of a first-order autoregressive model in a fixed-effect model, i.e. the appearance of y_{it-1} in Eq (1) [40]. Pischke [41] and Angrist and Pischke [42] emphasised that if the model with first-order autoregressive is correct, the use of the fixed-effects model will lead to an overstated positive treatment effect, i.e. δ is too big. Conversely, the mistaken use of the first-order autoregressive model, while the fixed-effects model is correct, leads to an understated positive treatment effect, i.e. δ is too small. For this, we conduct Born and Breitung's [43] portmanteau test for serial correlation in fixed-effects panel models to verify the inclusion of y_{it-1} in Eq (1). The result of this test is given in the Appendix.

Meanwhile, the model nest both lagged dependent variables and fixed effects could raise a downward biased if the time series (T) is short [40]. However, this issue can be neglected if T is "reasonably large", e.g., Beck et al. [44] considered that T = 40 is sufficient. Given that T = 83, the potential bias in our models is very small and could be considered as zero following that guidance.[8] We note that Nickell's bias can be solved by applying the generalized method of moments (GMM). However, because the Nickell bias could be considered not significant, we only report results by regular fixed-effects regression.

Portmanteau test for serial correlation in fixed-effects panel models

Born and Breitung's [43] portmanteau test for serial correlation in fixed-effects panel models is to test if the error term from ε_{it}^E from Eq (5) has serial correlation:

$$y_{it}^E = \alpha_i^E + \lambda_t^E + \delta_k^E D_{it-k} + \mathbf{x}_{it}^{'}\boldsymbol{\beta}^E + \varepsilon_{it}^E \quad k = 0, \ldots, 12. \tag{5}$$

$$\varepsilon_{it}^E = \sigma\varepsilon_{it-1}^E + e_{it}$$

where the difference of Eq (5) from Eq (2) is only the exclusion of the lagged dependent variable, y_{it-1}.

The test is stated as follows:

- H0: No auto-correlation of any order, i.e., $\sigma = 0$.
- Ha: Auto-correlation up to order 1, i.e., $\sigma \neq 0$.

[8] According to Nickell's [40] Monte Carlo simulation, the simple approximation of the bias in a within-group estimator is $-\frac{1+\theta}{T-1}$, where θ is parameter of lagged dependent variable y_{it-1}. Applying this approximation with $\theta = 0.69$ and $T = 83$, the bias in this study is approximately 2 %.

The result of the test (Table 5) rejects the null hypothesis and suggests the alternative that there is an auto-correlation issue. Thus, the inclusion of lagged dependent variable, y_{it-1}, is reasonable.

Table 5
Testing for serial correlation in the base models

	(1)	(2)
Solar installation (treatment)	0.475***	−0.049***
	(0.016)	(0.016)
Average electricity price (log)	−0.520***	0.154***
	(0.051)	(0.045)
Urbanisation rate (%)	0.023	0.041**
	(0.015)	(0.016)
Average electricity price (log)* Urbanisation rate	0.004***	−0.001
	(0.001)	(0.001)
Income (log)	9.129***	7.225***
	(1.479)	(1.534)
Squared income (log)	−0.507***	−0.402***
	(0.083)	(0.087)
Number of families	0.081***	0.088***
	(0.023)	(0.025)
Employment rate	−0.003**	−0.003**
	(0.001)	(0.002)
Rate of household having more than 3 kids	−0.0002	0.00004
	(0.004)	(0.004)
Observations	232,756	232,756
R-squared	0.312	0.171
Groups	3544	3544
Average group size	65.68	65.68
Panel-level standard deviation (σ_u)	2.040	1.383
Standard deviation of ϵ_{it} (σ_e)	0.421	0.436
Adjusted R-squared	0.312	0.170
Inoue and Solon [45] LM-test as post estimation		
IS-stat	1559.61	1387.41
p-value	0.000	0.000
N	3544	3544
maxT	82	82

Notes.
- The dependent variable in Model (1) is the log of the household's total electricity consumption.
- The dependent variable in Model (2) is the log of the household's electricity purchased from the grid network.
- All models include households' time-invariant fixed-effects and time-variant fixed-effects. The difference between these estimations and the ones in Table 2 is the exclusion of lagged dependent variable, y_{it-1}.
- The test for panel serial autocorrelation used Born and Breitung [43] implementation, initially described by Inoue and Solon [45]. This test can be conducted by *xtistest* command in Stata, implemented by Wursten [46].
- ***,**, *: significant at the significant level of 1 %, 5 %, and 10 %.
- Robust standard errors are reported in parentheses.

Estimations based on solar capacity explanatory variable

An alternative method for assessing the rebound effect of installing rooftop solar power involves utilizing installed capacity as an explanatory variable, in contrast to employing a dummy variable that signifies the periods before and after installation. This approach presents the advantage of capturing various levels of rebound effect, with higher capacity often associated with more pronounced rebound effects. However, it is crucial to acknowledge the potential correlation between capacity and household wealth, an additional explanatory variable for electricity demand. Consequently, the impact of solar capacity on electricity consumption and the rebound effect may be subject to bias due to multicollinearity.

Nevertheless, for comprehensive consideration, we introduce the estimation results of this alternative approach in Table 6 as a reference.

Table 6
Estimates output of baseline models based on installed solar capacity

	(1)	(2)	(3)	(4)
Installed solar capacity	0.021***	0.023***	−0.004***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Log of total electricity demand (lagged)	0.690***	0.697***		
	(0.005)	(0.005)		
Log of grid electricity demand (lagged)			0.701***	0.702***
			(0.005)	(0.005)
Average electricity price (log)	−0.164***		0.033**	
	(0.014)		(0.014)	
Urbanisation rate (%)	0.006		0.010*	
	(0.005)		(0.005)	

(*continued on next page*)

Table 6 (*continued*)

	(1)	(2)	(3)	(4)
Average electricity price (log)* Urbanisation rate	0.002***		0.000	
	(0.000)		(0.000)	
Income (log)	3.361***		2.289***	
	(0.477)		(0.468)	
Squared income (log)	−0.186***		−0.128***	
	(0.027)		(0.026)	
Number of families	0.017**		0.019**	
	(0.007)		(0.008)	
Employment rate	−0.001**		−0.001**	
	(0.000)		(0.000)	
Rate of household having more than 3 kids	0.000		−0.000	
	(0.001)		(0.001)	
Observations	223,562	223,562	223,562	223,562
R-squared	0.660	0.659	0.594	0.594
Groups	3544	3544	3544	3544
Average group size	63.08	63.08	63.08	63.08
Panel-level standard deviation (σ_u)	0.747	0.190	0.422	0.218
Standard deviation of ϵ_{it} (σ_e)	0.286	0.287	0.295	0.295
Adjusted R-squared	0.660	0.659	0.594	0.594
R-squared within model	0.660	0.659	0.594	0.594
R-squared overall model	0.498	0.852	0.650	0.841
R-squared between model	0.553	0.989	0.724	0.997

Notes.
- The dependent variables in models (1) and (2) are the household's total electricity consumption (in log form).
- The dependent variables in models (3) and (4) are the household's grid electricity demand (in log form).
- Installed solar capacity is zero for household does not have or have not installed rooftop solar.
- All models include households' time-invariant fixed-effects and time-variant fixed-effects.
- Standard errors are clustered at the household level and reported in parentheses.
- ***,**, *: significant at the significant level of 1 %, 5 % and 10 %.

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