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Impact of the Adoption of Photovoltaic System on Households' Energy Consumption: The Evidence from the Urban Area in Jaffna District in Northern Sri Lanka

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ABSTRACT

Photovoltaic system (PV) is a classic example of renewable energy sources and a potential alternative for fossil fuels to satisfy the energy needs of households and industries. However, the adoption of PV at the household level remains very low, especially in the developing countries. This study investigates the effect of the adoption of PV on the electricity usage of urban households in Jaffna district in northern Sri Lanka using the primary data collected from the sample of 303 households including both the adopters and non-adopters of PV who were randomly selected from urban population. To account for selection bias, this study employs propensity score matching method and estimate the impact of adopting PV on households' energy consumption. The outcome of average treatment effect and average treatment effect on the treated prove that the adoption of PV has a significant positive effect on household's energy consumption, coefficients with a value of 45.743 ($P < 0.01$) and 29.372 ($P < 0.1$) respectively. The results clearly show the adoption of PV at the household level significantly and positively increases household's total electricity consumption, suggesting the significance of promoting renewable energy sources as a potential way to tackle the issues of climate change and ensure clean development.

Keywords: Energy Needs, Electricity Consumption, Photovoltaic System, Propensity Score Matching, Renewable Energy Source
JEL Classifications: Q2, Q4, Q5

1. INTRODUCTION

Sustainable energy is an increasingly critical and innovative concept, necessitating serious attention due to rising energy costs, a growing global population, environmental pollution, and the depletion of natural resources. Addressing these obstacles through sustainable energy solutions is necessary for prospective economic and environmental stability (Bandara and Amarasena, 2020). Solar energy is widely regarded by experts as one of the most promising technologies, harnessing the sun's abundant radiation as a renewable energy source. It is the most plentiful energy resource on Earth, offering significant potential for sustainable energy production (Thennakoon et al., 2023). The fundamental principle of Photovoltaic (PV) technology, converting sunlight into electricity, highlights its potential to address energy poverty, reduce carbon emissions, and drive economic advancement, thereby contributing to sustainable development goals (Li et al., 2023; Mulyani et al., 2024).

Sri Lanka's rapid growth in economy during the late twentieth century has been favorably associated to a significant rise in the country's total use of energy. Sri Lanka's energy policies and measures strongly emphasize the development of both conventional and non-conventional clean energy sources for power production, with a significant focus on promoting domestic energy resources (Koswatte et al., 2024). Sri Lankan Net electricity generation for the year 2021 was recorded as 16,715.6 GWh. It is a 6.4% increase compared to the last year (Ceylon Electricity Board Annual Report, 2021). The Soorya Bala Sangramaya program, in cooperation with the CEB and Lanka Electricity Company, which was well above the 400 MW targeted for 2021, it was reported that over 36,640 solar rooftop systems were interconnected with the national grid, providing an aggregate capacity of 410 MW under this program (SLSEA, 2021). The northern region, like Jaffna, and the eastern regions around Trincomalee and Kalmunai, have higher PVOUT values, based on the map, which was created by World Bank Group and Solargis, indicating their high solar irradiance and suitability for PV installations.

On the one hand, the accrued benefits of adopting PV systems at the household level is well-understood. Adoption reduces electricity bills for households with installations by reducing dependence on grid power, hence exposure to energy price volatility, on the rise. This is also for the potential additional revenue stream that may be opened by the Net Metering, Net Accounting, and Net Plus rooftop solar schemes. This enabling financial incentive model indeed has made the investment in a PV system viable and profitable for a household (Ceylon Electricty Board, 2022).

On the other hand, despite this rosy future ahead, there are numerous key hurdles on the widespread use of PV systems. However, detailed studies on the adoption of PV systems are scare in the literature. Moreover, the influencing factors on PV adoption are mostly context-specific. Therefore, identifying the local factors influencing PV deployment is crucial for crafting effective policies and incentives. By understanding the factors, policymakers can design targeted strategies to address specific barriers and opportunities, enhancing the effectiveness of promotional efforts and encouraging greater PV adoption. This approach ensures policies that are well-suited to regional conditions, facilitating robust and widespread solar energy integration (Jayaweera et al., 2018).

This study aims to investigate on the adoption of PV systems and its impact on households' energy consumption in the Jaffna urban area in northern Sri Lanka, and probes into the influence factors for its adoption. This is mainly to find out how the integration of the PV system influences economic well-being, Energy usage patterns, as well as the region's overall quality of life. The findings of this study may enhance the capability of policymakers in designing and implementing strategies that ensure the uptake of renewable energy technologies equitably and sustainably, improving household welfare and contributing to broader global sustainability goals.

2. METHODOLOGY

2.1. Study Design and Study Area Description

The study was conducted in the Jaffna District, located in the Northern Province of Sri Lanka. Jaffna spans a total land area of 1,025 square kilometers. The district is administratively divided into 435 Grama Niladhari (GN) divisions, serving as the smallest administrative units.

According to the most recent census, the population of Jaffna stands at 627,796 individuals. Of this population, 84,846 (13%) reside in urban areas, while the remaining 542,950 (87%) live in rural areas. The district is home to a total of 206,574 families, resulting in a population density of approximately 612.48 persons per kilometer square.

2.2. Methods of Data Collection and Quality Control

A quantitative method was employed in the study to enable the collection of further data on existing variables as discussed in the study literature. A survey research methodology was utilized, where a structured questionnaire was prepared to collect primary data. The questionnaire was designed to collect conjoint data across two sections. The first portion included a series of questions about the respondents' socioeconomic status and demographics. This part asked questions about age, gender, household income, education level, employment status, number of household members, and marital status. The second section of the questionnaire contained details about the respondents' knowledge and factors related to household PV technology.

The survey was conducted between July and September, involving 151 households with photovoltaic (PV) installations and 152 households without PV systems across the Jaffna District. Information was gathered through personal interviews with household members using a well-structured questionnaire. The households were selected through a purposive random sampling method to ensure representativeness. The respondents in this study were cooperative and provided the necessary information without hesitation, actively engaging with all the questions posed. Most respondents were heads of households, ensuring that the data collected reflected the perspectives and experiences of those directly responsible for household decision-making.

2.3. Conceptual Framework of Study Variables

The conceptual framework presented in Figure 1 illustrates the multifaceted factors that influence adoption to rooftop photovoltaic systems on households. These factors are categorized into three main groups: demographic, house-related and awareness on incentives.

Demographic factors encompass key characteristics such as the age, gender, education status, and family income of the household. House-related factors focus on aspects related to the ownership of the household, number of rooms and number of electrical appliances using in the house.

This framework provides a comprehensive overview of the diverse elements that shape households' adoption to rooftop photovoltaic systems, highlighting the interplay between individual characteristics, house-related aspects and awareness on incentives.

2.4. Propensity Score Matching (PSM)

This study used the Propensity Score Matching model to study the impact of rooftop photovoltaic installation on household electricity consumption. PSM is a statistical technique utilized to decrease bias in observational studies by matching treated and control groups based on their propensity scores (Weisburd, D et.al.,2022; Kaliendo and Kopeinig, 2008; Rubin, 2006). Because such scores intrinsically represent the probability of being treated conditional on a certain set of observed covariates, hence they are able to balance the observed covariate distribution between the treatment and control groups, reducing biases in the estimation of treatment effects. Diagnostics on balance are needed to check the performance of the matching process. Most diagnostics available, and usually considered after matching, involve the computation of standardized mean differences and variance ratios, while others are graphical techniques, including propensity score distribution and Love plots (Austin, 2011).

2.5. Testing the Matching Quality

Before and after matching, characteristics of individuals compared to determine the possibility of any differences after accounting for the propensity score thereby the matching quality was ensured. Accordingly, the purpose of balancing tests is to assess the adequacy of balance achieved by the propensity score. In essence, such tests attempt to answer the question of whether a given characteristic shows similar distributions across the treatment and comparison groups at every value of the propensity score (Caliendo and Kopeinig, 2008).

2.6. Data Analysis

The purpose of using PSM is to assess the welfare impact of photovoltaic (PV) installations on households. To understand the effect of PV installation on households' energy consumption, the observed energy consumption outcomes of households with PV systems must be compared with the hypothetical outcomes had these households not installed PV systems. However, there are only energy consumption outcomes of the households with PV systems observed.

PSM is a sophisticated statistical technique developed to estimate the effect of PV installations on the welfare of a household, considering the issue of selection biases. Such a step will make a better comparison possible between the treated group of the households that have PV installations and the control group that does not have PV installations. This data includes 23 variables and 303 observations. Some important variables of our analysis include "Adopt", represents the PV adoption, age, gender, education level, number of rooms, number of refrigerators, number of AC, number of washing machines, number of fans, family income, home ownership, awareness of incentives, energy usage.

Normally, unobservable characteristics that determine PV installation may also affect welfare outcomes. For example, highly innovative households may be more likely to install PV systems and tend to use more electricity. Therefore, the predicted treatment effect will be biased until the issue of sample selection is addressed. The Propensity Score Matching (PSM) model is a common method for formalizing the sample selection problem and assessing the treatment effect. In the case of a binary treatment, the dummy variable for the treatment (Di) is 1 if a household has installed PV and 0 otherwise.

As a first-step of the analysis, the estimation of the propensity score-that is, the probability of installation of the PV system by households given observables-by means of logistic regression was the first step of this analysis. This was done using STATA 15, which is an environment fitted with robust tools both in terms of estimation of propensity scores and subsequent matching.

In the next step, by comparing the propensity scores of the households in the treatment and control groups estimated above, we matched households in the treatment and control groups based on their propensity scores. The matching has thus equilibrated the sample so that the only significant difference between the groups pertains to the presence of the PV installations. Matching methods First, we used one-to-one propensity-score matching and kernel matching. In general, the balance of the matched sample was investigated, and it has been demonstrated that the balance between the treated and controls was much better in the match.

Indeed, the impacts of PV installation on household welfare are heterogeneous. In estimating such treatment effects, two measures can be taken into consideration: First, ATE, or the average treatment effect-the impact of installing PV systems on a randomly picked households from the population; second, another average treatment effect of the treated, ATET, is the impact showing households that have installed PV systems.

The potential outcomes are determined by the treatment, Qi (Di), for household i. The treatment impact for a household i can be described as:

$$\tau_i = Q_i(1) - Q_i(0) \quad (1)$$

Each household has only one observed outcome. To estimate the household treatment impact (τi), the unobserved outcome (counterfactual outcome) is required. The Average Treatment impact on the Treated (ATET) is defined as:

$$\tau_{ATET} = E[\tau||D=1] = E[Q(1)||D=1] - E[Q(0)||D=1 \quad (2)$$

The counterfactual outcome (unobserved outcome) for individuals under treatment is defined as $E[Q(0)||D=1]$**.** There would be self-selection bias since the outcomes of households in the treatment group would differ from those of households in the comparison group even if treatment was not provided. Thus, ATET can be stated as:

$$E[Q(1)||D=1] - E[Q(0)||D=0] = \tau_{ATET} + E[Q(0)||D=1] - E[Q(0)||D=0] \quad (3)$$

The true parameter τ_{ATET} is only identified if the 'self-selection bias's is equal to 0:

$$E[Q(0)||D=1] - E[Q(0)||D=0] = 0 \quad (4)$$

To address the'self-selection bias' issue, some identifying assumptions should be made. The mean effect of treatment is defined as the average difference between the treated and untreated groups' results. The Average Treatment Effect (ATE) is defined as:

$$\tau_{ATE} = E[Q(1) - Q(0)] \quad (5)$$

In the matching method, a matching household for each household in the treatment group is found from among the comparison group by identifying households with similar observable characteristics. The probability of finding a match decreases as the number of characteristics considered in the matching process increases (Caliendo and Kopeinig, 2008).

Figure 1: Conceptual framework

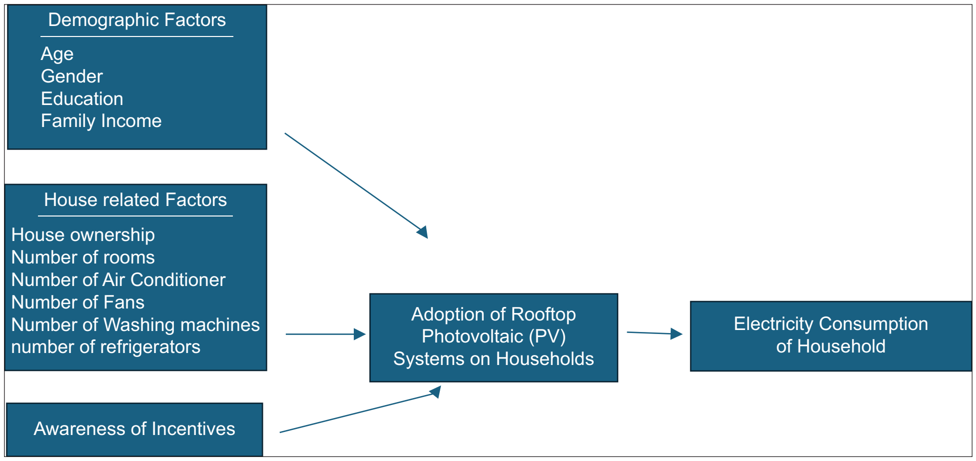


Figure 2: PV capacity distribution in Jaffna

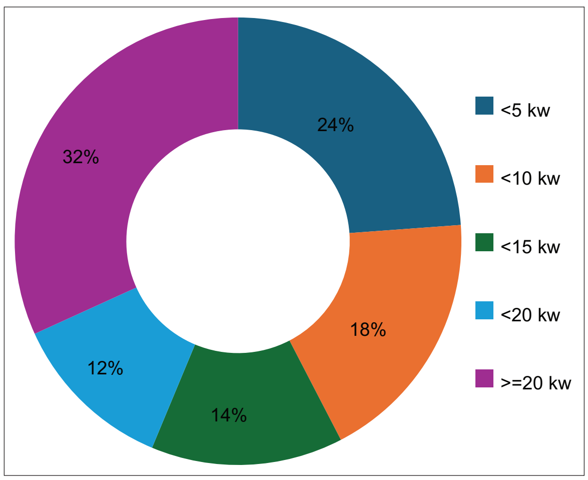
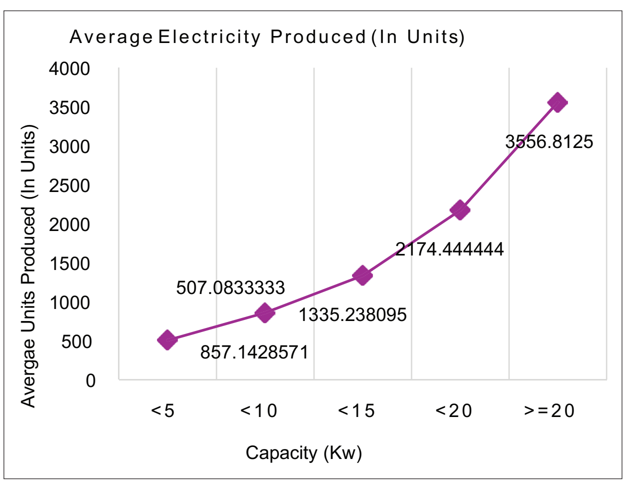


Figure 3: Average electricity generation with PV capacity

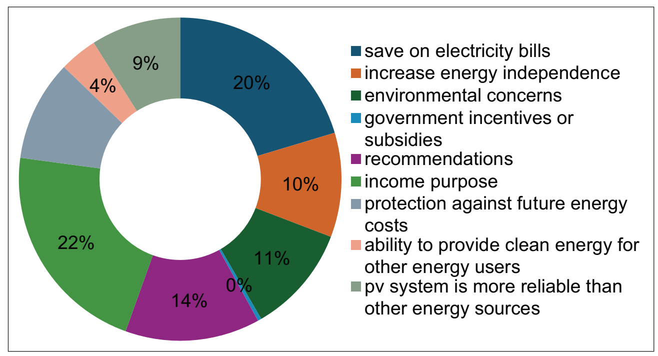


3. RESULTS AND DISCUSSION

3.1. Descriptive Analysis

Table 1 shows the descriptive statistics of socio-economic and house-related characteristics of the total households that surveyed in the study.

Figure 4: Primary motivations of household PV system adoption in Jaffna district



3.1.1. PV capacity distribution in Jaffna District

According to Figure 2, the Capacity of solar PV systems as recorded at households ≥20 kW is the biggest part with 32%, <5 kW is 24%, 5-10 kW makes 18%, 10-15 kW takes 14% and 15-20 kW makes 12%. This graph also further confirms that larger capacity PV installations are recent trends, while the number of smaller-sized systems installed is considerable.

3.1.2. Electricity generation with PV capacity

As many as 32% of the households prefer a capacity of 20 kW or higher because of the high generation of electricity. As shown in Figure 3, the average amount generated by those operating photovoltaic systems rated below 5 kW is 507.08 kWh compared to the average generation of 3556.81 kWh for those operating at over 20 kW capacities. This large deviation depicts the economies and efficiency in energy production from the higher capacities of photovoltaic installations that are enabled, for example, by such instruments as the feed-in tariffs.

3.1.3. Primary motivations of PV systems adoption in Jaffna District

Figure 4 depicts main drivers for households to install the photovoltaic systems. The highest driver is that of income generation at 22%, hence oriented for monetary returns by feeding surplus electricity into the grid, made possible through policies such as feed-in tariffs. 20% said that the primary rationale is saving on electricity expenses.

3.1.4. Limiting factors of PV adoption in Jaffna District

Figure 5 shows that the most significant barrier for PV adoption is the high initial installation cost which accounts for 54% of the participants, and this is aligned with the previous studies (Jayaraman et al., 2017; Jayaweera et al., 2018; Mulyani et al., 2024). Therefore there is a policy need to cut down such capital costs through subsidy or financing options that will increase economic affordability for PV systems.

The second biggest barrier mentioned by 28% of those questioned was a lack of information about solar technology in general: its benefits, how it actually works. This reveals a strong gap in public awareness and education that may be provided by some information initiatives, workshops, or government-organized outreach events, which would improve understanding and confidence in solar energy adoption. An additional 14% stated that they had doubts about the advantages of the technology and indicated a state of unwillingness on the part of households to adopt, even if they are aware of the technology. This could perhaps be reduced if the long-term economic and ecological benefits of photovoltaic systems were shown more clearly. These rates can be improved if the policymakers and other stakeholders focus on reducing upfront costs and make access to reliable information about the benefits and viability of solar energy systems easier.

Figure 5: Impeding factors of household PV system adoption in Jaffna District

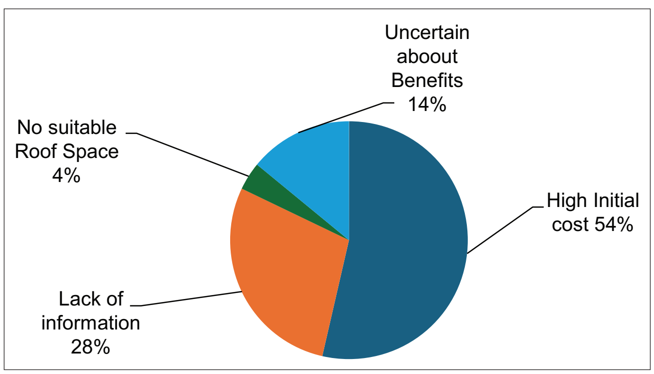
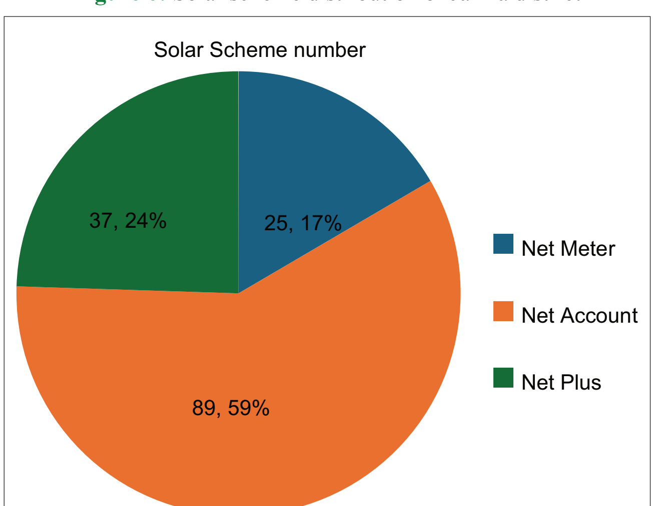


Figure 6: Solar scheme distribution of Jaffna district



3.1.5. Solar scheme distribution in Jaffna District

As shown in Figure 6, the most preferred arrangement is the Net Account, accounting for 59%, followed by the Net Plus arrangement with 24%. The Net Metering scheme, holding only a 17% share, will be the least distributed. This means under the Net Meter Scheme, generators selling electricity into the grid are not necessarily remunerated by the system for excess energy supplied.

However, excess energy supplied is credited and carried over for a maximum of ten years. The converse applies to generators under the Net Accounting Scheme, where generators can feed in electricity into the national grid and receive through a Feed in -Tariff as agreed upon by the ratified tariffs by Cabinet. Whereas in the Net Plus scheme, the producer is paid for all the electricity that he has produced, whereas he pays for the electricity cost himself.

This evident preference for the Net Account scheme shows clearly that the possibility to be paid for excess energy is a significant incentive for households. This may prove especially helpful for policymakers and other relevant stakeholders in their efforts to enhance the diffusion process of PV systems. Investigation of the specific advantages offered by the Net Accounting scheme and, therefore, its popularity can also support the elaboration of more effective rooftop PV system policies.

3.1.6. Trend of PV users in Jaffna District

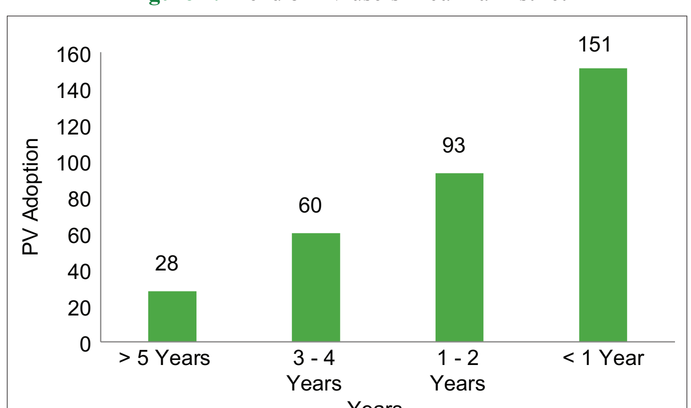
Figure 7 shows that cumulative distribution of respondents by period of using the photovoltaic system. The data falls into four distinct categories, which are: <1 year, 1-2 years, 3-4 years, and above 5 years. The highest number comes out to be 151, for those who have installed the photovoltaic system for less than a year.

3.1.7. Sources of information dissemination of PV technolgy in Jaffna District

Figure 8 showing that Utilization of various sources of information by the adopters and non-adopters of PV systems: The data is categorized into six types of sources of information, namely, television, radio, community events, word of mouth, the Internet, and newspapers.

The results show the importance of word of mouth, which got a total of 174 respondents out of which 93 adopted it as the main source of information. This underlines the importance of

Figure 7: Trend of PV users in Jaffna District



interpersonal communication and social influence for greater PV adoption, hence supporting the literature reviewed by placing trust and peer validation at the heart of the household decisions to adopt new technologies.

The Internet is the second source, 159 representatives and 86 adopters, showing that digital platforms are an important source of information for potential PV adopters. Online campaigns, easily reachable information portals, and active social networks can be very effective tools for the promotion of renewable energy solutions. A high level of digital media ranking shows the trend for more comfortable and bidirectional flows of information, especially in countries with higher growth rates of internet diffusion. The findings underline that for better diffusion and increased adoption, Future campaigns can build on this by developing more effective online content, facilitating grassroots advocacy, and encouraging peer interactions to leverage knowledge diffusion about PV systems. Where this is so, traditional media would perhaps require more focused approaches in pursuit of effective audience reach.

3.2. Empirical Analysis

3.2.1. Calculating propensity scores

The first step of the propensity score matching method was to determine the probability of being assigned to the treatment group. In the specific research context, the treatment groups consist of people who have installed rooftop photovoltaic systems, and their control groups will be comprised of those who have not. Logistic regression was used to estimate propensity scores for the installations of PV systems in households versus non-adopters.

Figure 8: Information dissemination of PV system in Jaffna District

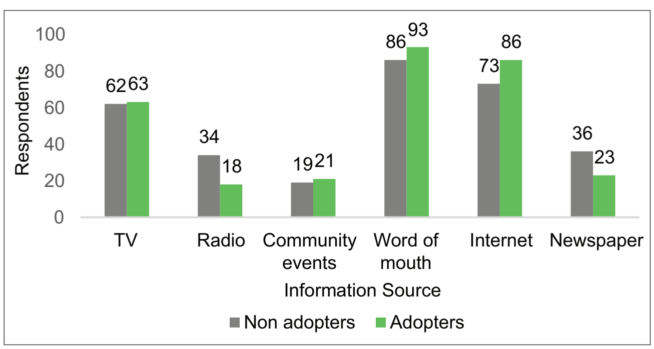


Table 1: Descriptive statistics of households

Variable	Mean	SD	Minimum	Maximum
PV adoption	0.495	0.501	0	1
Energy usage (non-PV installed)	90.237	51.633	10	350
Energy usage (PV installed)	196.113	97.326	40	850
Age	49.172	12.27	20	85
Income (rupees)	116624.17	188670.3	10000	3000000
Household size	4.106	1.266	1	8
House ownership	0.956	0.205	1	12
No of rooms	4.125	1.397	1	12
No of refrigerators	0.916	0.334	0	2
No of air-conditioners	0.333	0.67	0	6
No of washing machines	0.664	0.489	0	2
No of Fans	1.554	0.772	0	6

3.2.2. Determinants of households rooftop solar PV adoption

The analysis, based on 296 observations, revealed that the model is statistically significant, with a likelihood-ratio chi-square value of 141.07 and a p-value of 0.0000. The pseudo R^2 of 0.3438 indicates that the model explains approximately 34.38% of the variance in PV adoption.

A logit regression model was designed with treatment assignment, in our case PV installation, as the dependent variable, and gender, age, education level, number of rooms, quantity of refrigerators, air conditioners, washing machines, fans, family income, and awareness of incentives as explanatory variables. This model provides a structure to calculate a propensity score for each observation. Table 2 shows the parameters obtained from the logit model, explaining the determinants of participation in PV installation.

The significant factors that influence the adoption of the PV systems are gender, the number of air conditioners, washing

Table 2: Determinants of households PV Adoption using Regression Logit Model

Variable	Coefficient	Std.Error	Z	P>Z
Age	−0.0198	0.1392	−1.43	0.154
Gender	0.8040**	0.3734	2.15	0.031
Education	0.0994	0.6955	1.43	0.153
No of rooms	0.1566	0.1280	1.22	0.221
No of refrigerator	0.7458	0.5456	1.37	0.172
No of A/C	1.1163**	0.3794	2.94	0.003
No of washing machines	0.9511**	0.3446	2.76	0.006
No of Fans	1.0303**	0.1904	5.41	0.000
Family income	8.88e-07	1.10e-06	0.80	0.421
Awareness of incentives	0.7937**	0.3145	2.52	0.012

***, **, * ==> Significance at 1%, 5%, 10% level

Table 3: Balancing covariates

Covariates	Means		Variance	
	Control	Treated	Control	Treated
Age	51.2162	47.0202	189.8033	101.5166
Gender	0.6689	0.8445	0.2229	0.01321
Education	13.1216	14.7905	6.6109	5.2551
No of rooms	3.8378	4.6351	1.3476	2.2605
No of refrigerators	0.7972	0.9932	0.1763	0.0611
No of A/C	0.0878	0.50675	0.806	0.6598
No of washing machines	0.3783	0.7905	0.2368	0.1939
No of fans	0.8378	1.554	0.9123	0.6297
Family income	87375	147966.2	8.03E+09	6.28E+10
Ownership	0.9324	0.9797	0.6343	0.0199
Awareness of incentives	0.3918	0.6486	0.2399	0.2294

Table 4: Covariate balance summary

Observation	Raw	Matched
Number of observations	296	592
Treated observations	148	296
Control observations	148	296

machines, and ceiling fans, and awareness of the incentives. The positive coefficient here indicates that, ceteris paribus, being male will enhance one's probability of adopting a PV system. Significant at 5%, it means that gender is one major factor considered in arriving at a decision on the adoption of PVs, this is contrast to findings that conclude that Females are more likely to adopt these systems (Bashiri and Alizadeh, 2018).

Greater awareness of the incentives offered for PV installation strengthens the possibility of installation. Household electricity use and information on incentives available make households more likely to invest in solar energy. In addition, non-significant variables include age, education, financial income, and house ownership, showing that these factors are not important determinants for the adoption of PV systems in the Jaffna district. The result underlines the need to address financial barriers through targeted incentives and improve awareness of the benefits of solar energy in order for the rate of adoption to be significant. The findings will assist policymakers and stakeholders in designing effective strategies to promote renewable energy adoption among households.

3.2.3. Balancing property test for propensity scores and model adequacy checking

Poor covariate overlap can lead to estimation bias. Therefore, checking the balancing property is become crucial in propensity score matching (King and Nielsen, 2019; Daw and Hatfield, 2018). Figure 9 suggests that the distribution of the propensity scores does indeed overlap between the treatment and comparison cohorts. One might further assess balance by stratifying the treatment cohort into five distinct blocks based on the propensity score and showing for any of the blocks, the average of the propensity score is not statistically significantly different between the treated versus comparison subjects. That is, for this test, the household covariates for the treatment and comparison groups are statistically identical across their respective blocks. It suggests that the propensity score is identically distributed across groups in each block, which further suggests that the propensity score has been properly specified.

3.2.3.1. Comparative summary of means and variance of key covariates

As shown in Table 3, matched treatment and control groups are similar by balancing these covariates. Differences in means and variances thereafter matching were at their minimum. That means groups are more comparable, and hence treatment effects could be estimated with more accuracy. Balance test was performed by comparing standardized differences, propensity score graphs of covariates, and propensity score graphs of the treated and control group before and after matching.

This table indicates that the matching process has doubled the number of observations for both the treated and control groups, ensuring a balanced comparison between the two groups.

3.3. Impact of Rooftop Solar PV Installations on Households Electricity Usage

Tables 5 and 6 shows estimates of the average treatment effect on the prediction of households with PV systems, ATET, and those that would be randomly selected from the population, ATE.

Figure 9: Propensity score matching graph

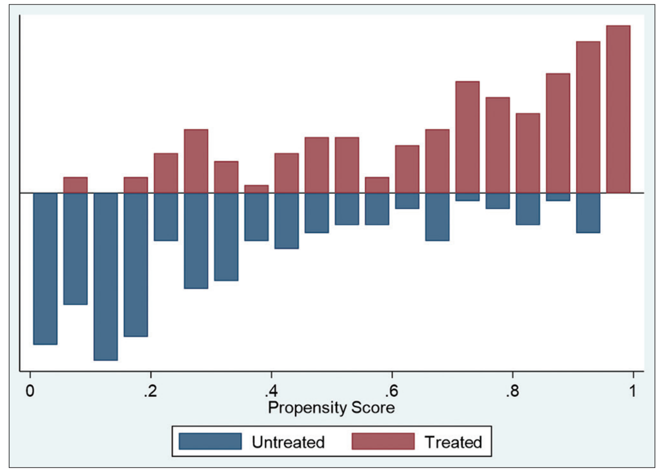


Table 5: ATE outcome of the analysis

Coefficient	Standard error	*Z*	P<*Z*	95% Confident interval	
45.74324***	10.80991	4.23	0.000	25.55621	66.93028

***, **, * ==> Significance at 1%, 5%, 10% level

Table 6: ATET outcome of the analysis

Coefficient	Standard error	*Z*	P<*Z*	95% Confident interval	
29.37162*	17.17284	1.71	0.087	−4.286585	63.02978

***, **, * ==> Significance at 1%, 5%, 10% level

The main results of the PSM analysis indicates large positive effects of PV installations on household welfare. Households that applied with PV systems tend to have higher levels of electricity use. These results suggest that incentives towards PV installations are important to match with increasing demand in household energy consumption and to foster sustainable development.

3.3.1. Average treatment effect analysis

The outcome of ATEs proves that the adoption of PV has a significant positive effect on electricity consumption, coefficients with a value of 45.743 ($P < 0.001$). This indicates that, on average, the families using PV systems consume 46 units of electricity more than those without PV system, indicating a considerable improvement in electricity consumption, which may symbolize improved energy access and an improvement in living standards.

3.3.2. Average treatment effect of treated analysis

ATET examines the impact of the installation of the photovoltaic systems on those households that installed them. In the same vein, the ATET results had coefficients of 29.37 with a $P = 0.087$ which show positivity but with reduced statistical significance when compared with ATE. This fact enables us to be confident about the robustness of our findings.

4. CONCLUSION

This study provides a comprehensive finding on the impact of PV installations on household level energy consumption. The key findings of this study indicate an increase in the average electricity usage by 46 units when a random household is installed with PV. In real households, when PV is installed, electricity usage is increased by about 29 units. We will infer from here that those households are better off. This research also establishes that, with awareness of the incentives for installing PV, its installation is likely to increase among households. It implies that creating awareness of the incentives for the installation of PV among households will increase the use of clean energy. Also, the number of electrical appliances used in the household (i.e., refrigerators, washing machines, table fans, air conditioners) increase the probability to install PV.

Furthermore, the descriptive results suggest that high upfront costs and information deficiency are major barriers to the adoption of PVs. These results indicate two urgent needs for policy intervention: one is financial incentives that alleviate such economic burdens; the other is a comprehensive education campaign for general citizens. In conditions of lower economic burden and increased public awareness, policymakers can move one step further along the diffusion process of the PV system toward greater household welfare and more sustainable energy consumption. In terms of future studies, a few longitudinal studies are still needed. These studies seek to measure the long-term impacts on household experiences because of the adoption of PVs. They shall provide a detailed insight into the effectiveness and sustainability of existing policies and programs.

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