Motivation Matters: How Diverse Reasons Enhance Household Energy Savings – A Statistical Analysis Using Propensity Score Matching on Household CO_2 Microdata –

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Abstract

This study examines the impact of energy-saving awareness on household energy consumption in Japan, using pooled data from the Ministry of the Environment's Household CO_2 Statistics (2020–2022). With Japan's "Green Growth Strategy" emphasizing the need for public awareness and engagement to achieve carbon neutrality, this research employed both multiple regression analysis and Propensity Score Matching (PSM) to estimate the energy-saving effects of various awareness motivations. First, distinct motivations, such as cost-saving, climate change, and peer influence, were analyzed individually, revealing limited energy-saving effects when these motivations exist alone. Second, combinations of these motivations showed significantly amplified impacts on energy savings, especially when cost-saving was combined with other motivations. Third, this outcome aligned with Self-Determination Theory (SDT), which posits that combining intrinsic (e.g., climate-related) and extrinsic (e.g., economic) motivations fosters stronger, more lasting behavior changes. The findings suggested that awareness-building strategies combining intrinsic and extrinsic motivations were likely more effective for encouraging sustained energy-saving behavior than approaches that rely solely on economic incentives. Furthermore, promoting diverse motivations could enhance household energy-saving behavior, providing valuable insights for energy policy design. This study also identified the potential applicability of PSM as a policy evaluation method for measuring the impact of energy policies.

Key words: Propensity Score Matching, Self-Determination Theory, Energy Conservation, Motivation, Behavior, Awareness

1. Introduction

The importance of public awareness with regard to decarbonization and energy conservation has frequently been emphasized in relation to achieving carbon neutrality goals. For example, the "Green Growth Strategy" (2021)[1] published by the government of Japan notes that it is essential for each citizen to understand the importance of carbon neutrality and take autonomous action to achieve it. In addition, the White Paper on Land, Infrastructure, Transport and Tourism in Japan, 2021 (2021) [2] states that awareness of long-term sustainable decarbonization on the part of society as a whole, while taking the diverse awareness of people into account, is important for efforts toward decarbonization. Furthermore, the 6th Strategic Energy Plan (2021) [3] also states that in order to achieve the 2050 carbon neutrality goals, it is necessary for not only companies and energy providers, but also each individual citizen to be aware of taking ownership of the decarbonized society and acting proactively. Accordingly, the importance of cultivating an awareness of decarbonization and energy-savings in the household sector is being increasingly recognized for the transformation of society toward carbon neutrality.

With regard to Japan's carbon neutrality targets, the Plan for Global Warming Countermeasures (2021) [4] sets forth the 2030 energy-derived CO_2 emissions targets for each sector, but as of FY2022, the achievement rate for the household sector is the farthest behind compared to other sectors, [5] and immediate action is required. In light of this situation, it is increasingly important to understand the state of energy-saving awareness, the drive behind purchases of energy-saving equipment and daily energy-saving behavior, and the impact it has on energy consumption.

On the other hand, much of policy and research on energy-saving to date has focused on hardware factors, such as highly energy-efficient equipment, and policy and research on so-called soft factors, such as energy-saving awareness, has been limited. Reasons for this include the belief that the energy-saving effect of the so-called soft factors is smaller than that of technological factors, and the fact that it is difficult to quantify human awareness, such as energy-saving awareness, meaning that data gathering primarily depends on questionnaires and interviews.

To address these issues, the Ministry of the Environment launched the Statistical Survey on CO_2 Emissions in the Household Sector (Household CO_2 Statistics) [6] in 2017 to identify opportunities for reduction in the housing sector and identify appropriate measures to do so. Under the Household CO_2 Statistics, a major questionnaire is issued to approximately 13,000 households throughout Japan each year. Because the use of the microdata for research purposes is allowed, it has broadened the scope of analysis that is possible. With the addition of questions regarding energy-saving awareness from FY2020 in particular, a platform for analyzing the relationship between energy-saving awareness and energy consumption in detail is becoming available.

In light of these developments, this research pooled the microdata from the Household CO_2 Statistics for the three-year period of 2020 through 2022 and examined the energy-saving effect of energy-saving awareness by employing both multiple

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regression analysis and Propensity Score Matching (PSM). PSM is a method that produces results similar to randomized experiments by performing pseudo-randomization on the observed data. The aim of this study is to examine the impact of energy-saving awareness on reducing energy consumption in the housing sector, and we use PSM in addition to multiple regression analysis to ensure the robustness of the analysis.

The results of this study confirmed that when there is a single motivation for energy-saving awareness, there are cases when there is an energy-saving effect and when there is not. However, when motivations are combined with others, even motivations for which an effect was not found in isolation, a significant energy-saving effect emerges. This result can be explained by the Self-Determination Theory (SDT) by Deci & Ryan (1985).[7] According to the SDT, people's behavior is stronger and more lasting when they have both intrinsic (e.g., to protect the environment) and extrinsic (e.g., to reduce utility costs) motivations. This study offers a new approach to conventional analysis of energy demand in that it examines the effects of the ambiguous concept of energy-saving awareness using large-scale data and new analytical methods. Furthermore, the new finding of this study, which quantitatively verifies that multiple energy-saving awareness motivations increase energy-saving effectiveness, is that it suggests a need to encourage diverse motivations rather than a single motivation in policies that promote energy-saving behavior in the household sector.

Chapter 2 of this paper examines the existing domestic and international literature that uses the Household CO_2 Statistics for the analysis of the energy-saving effect itself, and of the energy-saving effect of energy-saving awareness. We found that the primary research theme for analysis of the energy-saving effect using the Household CO_2 Statistics to date has been the technological aspects of energy-saving. Furthermore, while we found multiple studies that treated energy-saving awareness as one variable in the energy supply-demand model, research that analyzed energy-saving awareness in depth was limited. In Chapter 3, we organize the combination patterns regarding the motives for energy-saving awareness based on the Household CO_2 Statistics questions, and in Chapter 4, we analyze the verification of energy conservation effects for each motive pattern of energy-saving awareness using multiple regression and propensity score matching (PSM). Chapter 5 offers a summary and the conclusions of this study.

2. Previous Studies

2.1 Analysis of the Energy-Saving Effect Using the Household CO_2 Statistics

Research on energy demand analysis using the Household CO_2 Statistics has been carried out from diverse perspectives since it began in 2017. For example, Ishikawa et al. (2018, [8] 2024 [9]) examined factors behind CO_2 emissions nationwide and by region using multiple regression analysis to estimate the CO_2 emissions per household by municipality, while Iwafune et al. (2020) [10] estimated the potential for converting to electric household equipment and private cars and the associated CO_2 reduction effect, again using multiple regression analysis, suggesting that the adoption of energy-saving equipment may contribute to the reduction of household CO_2. Meanwhile, Shimomura et al. (2019-), [11] Mori et al. (2022), [12] and Ueno et al. (2022) [13] have each developed simulation models capable of detailed analysis of energy consumption and CO_2 emissions in the housing and transportation sectors by region, respectively. Nishio (2021) [14] analyzed the actual utility costs according to the period when houses were constructed using gradient boosting decision trees and SHAP values, and in a subsequent study in 2024, [15] examined the electricity consumption reduction effect for households that adopted HEMS using multiple regression analysis as well as propensity score doubly robust estimation. Hoshino et al. (2021) [16] organized the ratio of energy expenditure to household income and the energy burden rate by income group, broken down by region, and used multiple regression analysis to compare price elasticity by detailed region and household income in order to make policy recommendations based on those results.

Meanwhile, there also exist studies that have used the Household CO_2 Statistics to analyze energy-saving awareness. Washizu et al. (2020) [17] used multiple regression analysis to examine the number of household members, the age of the head of the household, and the rate of energy-saving behavior as factors influencing the energy consumption rate, confirming that energy-saving behavior significantly contributes to a reduction in energy consumption. Hoshino (2022) [18] also pointed out that one of the factors affecting the adoption of electric vehicles in households is the presence or lack of energy-saving awareness. Iwafune et al. (2021) [19] analyzed the changes in energy consumption over time according to life stage, noting that energy-saving awareness has an effect on CO_2 emissions reductions at each life stage. Accordingly, it is clear that energy-saving awareness has been subject to analysis as one element in analyzing energy demand.

2.2 Domestic Analysis of Energy-Saving Awareness

The following studies have been carried out to analyze energy-saving awareness in Japan. Kumeimura et al. (2024) [20]

conducted an online questionnaire targeting 1,500 residents of Tokyo, Kanagawa, Chiba, and Saitama prefectures to track changes in energy-saving awareness and behavior from September 2012 to August 2022 during the period following the Great East Japan Earthquake. While energy-saving awareness showed a declining trend from 2012 through 2016, it recovered to 2012 levels by 2022. Factors suggested for this change, a change that influenced energy-saving awareness, included rising utility costs, the situation in Ukraine, and pressure on the electricity and gas supply, in addition to the experience of the Great East Japan Earthquake itself. Incidentally, that study also included questions on the questionnaire regarding reasons for not saving electricity. The top responses from the 2022 survey were "physical discomfort" at 42.4% and "inconvenience in daily life" at 39.9%, with "physical discomfort" a common answer among the elderly and "inconvenience in daily life" common among younger segments. Hotta et al. (2023) [21] surveyed 19 households that were using an energy usage visualization system over an extended period, regarding their energy usage and user evaluation of the system, to ascertain changes in energy consumption and user awareness before and after adopting the system. The study showed that users found that the ability to regularly review feedback reports on home energy usage over fixed periods of time, along with comparative data, made the information more accessible. The study suggested that the ability to compare home energy usage to other homes or to past usage in the same home may lead to an awareness of energy-saving behavior. Hirayama et al. (2021) [22] conducted a randomized controlled trial (RCT) of 450,000 households in different regions and climates and examined the CO_2 saving effect of sending home energy reports (HER) using difference in differences (DID) analysis. The results showed an energy-saving effect in all regions for almost all months starting from the month when the HERs started to be sent. Furthermore, they examined the sustainability of the intervention effect in a follow-up study by comparing 80,000 households to which HERs were sent in the treatment group with a control group of 100,000 households determined through RCT. While the treatment group showed a slight elevation over the control group in terms of daily energy-saving awareness and intent after the reports were ceased, the difference was not statistically significant. Sasa (2018) [23] conducted a questionnaire on the implementation and continuation of energy-saving behavior among 134 female university students, while simultaneously measuring ambient temperature around the body, daily behavior, air conditioning usage, and self-reporting for 12 test subjects, to examine the effect on awareness and behavior from the receipt of energy-saving messages via social media. The results showed that energy-saving awareness was raised through receipt of the messages, confirming the effect of promoting energy-saving behavior. Takada et al. (2017) [24] combined a questionnaire with a survey of actual energy usage to analyze the relationship between parent and child energy-saving awareness and behavior and energy consumption in the home. Specifically, a questionnaire and survey on actual energy usage were conducted for 11 monitor households, and an intervention strategy was adopted for the surveyed households, including the presentation of energy-saving targets and reflection on daily life. While the presentation of targets did have some effect on increasing energy-saving awareness and behavior, it did not have an effect on actual consumption. The results suggested that reflecting on daily life led to a reduction in water consumption, but did not have a significant effect on gas and electricity consumption. Mori et al. (2016) [25] argued that it is possible to apply concepts of motivation from psychology to the cultivation of energy-saving awareness, and discussed the sustainability of energy-saving awareness by dividing motivations into extrinsic motivation, or evoking behavior through external factors such as reward and punishment, and intrinsic motivation in which behavior results from finding interest and enjoyment in the behavior itself. A field study was conducted by recruiting 69 households from the public residing in Asahikawa City to survey the effect of intrinsic motivations for energy-saving behavior on energy consumption over a one-year period. As a result of continuing the study for one year, it was found that the higher the intrinsic motivation, the lower the actual energy consumption and the higher the frequency of energy-saving behavior, according to self-reporting. The study also suggested that in order to promote sustainable energy-saving behavior, long term intervention is more effective than short-term temporary intervention. However, the study also pointed out that because there are many difficulties and limitations to maintaining constant external intervention, it was necessary for people to become able to maintain the behavior autonomously after the intervention ceases.

2.3 International Analysis of Energy-Saving Awareness

Similar studies on energy-saving awareness have been conducted outside Japan as well. Some of the leading studies thereof are discussed here. Pekez et al. (2024) [26] conducted workshops on energy efficiency and climate change at elementary schools in Serbia to increase environmental knowledge and track changes in environmental awareness across generations. As a result of the workshops on children's attitudes towards energy efficiency and climate change, and a survey conducted to measure the transfer of the knowledge gained from the children to their parental guardians to evaluate their changes in awareness before and after the workshop, the study suggested that raising awareness through knowledge may have a significant effect on the attitudes not only of the students, but their parents as well. Baidoo et al. (2024) [27] conducted a survey of 396 households from nine communities in the Cape Coast metropolitan region of Ghana, selected through random sampling, to analyze the relationship between household energy-saving practices and the level of energy-saving awareness education. The study showed that the principal factors influencing the selection of home appliances with high energy efficiency were the academic background, income level, expenditure, age of the head of the household, and the number of power outages experienced per day. The study offered an overall assessment that the level of energy-saving awareness in the household was low in Ghana, and suggested that this was caused not only by the inadequacy of energy-saving and conservation campaigns, but a lack of methods for communicating those to households effectively. The study recommended the implementation of energy literacy programs to raise awareness of practicing energy efficiency in the home by ensuring energy cost conservation, environmental protection, and climate change mitigation. Keller et al. (2021) [28] measured the effectiveness of a campaign using public service advertising on television and websites in Rocky Mountain City. First, they identified common hurdles to energy-saving using a focus group (40 people). They then examined changes in energy-related behavior through self-reporting by implementing a survey before and after implementing the campaign. The study used the Population Health Management (PHM) framework from health psychology for the energy-saving advertising campaign, including bringing awareness of the severity of energy waste, increasing self-efficacy (awareness that one has the ability to achieve a goal) to conserve energy, and increasing response efficacy (awareness that the presented method can help reduce risk) to conserve energy. As a result, the subjects showed a positive change towards replacing lightbulbs, and an increased motivation to lower thermostat temperatures, unplug devices, and turn off lights. The study noted that a follow-up study was required to examine the precise mechanism of the psychological processes, while pointing out, based on analysis, that both self-efficacy and response efficacy were important as elements required to transform behavior. Webb et al. (2013) [29] used the framework of Self-Determination Theory to analyze consumer motivation in energy-saving behavior in the home. An online survey was conducted for 200 consumers who were motivated by energy-saving in the home, and the relationship between the motivations and behaviors was analyzed using confirmatory factor analysis (CFA) and structural equation modeling (SEM). The study examined the effects of intrinsic and extrinsic motivations on energy-saving behavior, and the results suggested that the higher the intrinsic motivations of the consumer, the more proactive their energy-saving behavior.

2.4 Issues of Previous Studies and Positioning of this Study

In light of these previous studies, the following three points are offered regarding the issues with those studies and the positioning of the analysis in this study.

First, many of the previous studies on energy-saving awareness used specific, limited samples of several tens to several hundreds of subjects. This is likely because the standard approach has been to construct data through questionnaires and interview questions, because energy-saving awareness is a variable that cannot be quantified, but if those questionnaires and interviews are implemented on a national level, it would require an unreasonable amount of time and cost. With regard to this issue, it is believed that in Japan, the Household CO_2 Statistics survey conducted by the Ministry of the Environment, which covers a massive nationwide sample exceeding 10,000 subjects each year, may compensate for this deficiency to some degree.

Second, we found that the main research theme of previous studies that analyzed the energy-saving effect using the Household CO_2 Statistics tended to be the technological aspects of energy-saving. While we found multiple studies that treated energy-saving awareness as one variable in the energy supply-demand model, research that analyzes energy-saving effects in depth was limited.

Third, while the range of analytical methods available is expanding because analysis using large scale microdata sets has been made possible by the Household CO_2 Statistics, and some studies have attempted demand analysis using new approaches based on machine learning, to date, the trend has continued to be analysis primarily based on multiple regression analysis for both measuring the energy-saving effect and energy demand analysis.

In light of these three issues, this study pooled the data from the Household CO_2 Statistics for the three-year period starting in 2020, when the questions on energy-saving awareness were added, until the latest year to measure the energy-saving effect of energy-saving awareness using a microdata set of roughly 30,000 subjects. Specifically, we examined the effect of energy-saving awareness patterns with a variety of motivations on energy consumption using multiple regression analysis, while adopting propensity score matching (PSM) as a new analytical method. PSM is a method that is considered to be superior at eliminating confounding bias, able to produce results similar to randomized controlled trials by using quasi-randomization with observational data. The use of PSM in addition to the standard multiple regression analysis ensures the robustness of the measurements of the energy-saving effect on fluctuating energy-saving awareness.

3. The Household CO_2 Statistics

3.1 Overview of the Household CO_2 Statistics

The Survey on the Actual Conditions of Carbon Dioxide Emissions from Residential Sector (Household CO_2 Statistics) is a general statistical survey carried out by the government of Japan, launched by the Ministry of the Environment in 2017 to track the state of energy consumption and CO_2 emissions in the household sector. The survey covers roughly 13,000 households each year, including an investigator survey based on random sampling from the Basic Resident Registry, and an online monitor survey selected from survey monitors registered with private companies. The survey gathers a wide variety of data on household demographics, home characteristics, and energy consumption.

One of the characteristics of the Household CO_2 Statistics is the ability to handle detailed energy consumption data based on the factors and energy usage background that differ from household to household. For example, in addition to physical characteristics such as family composition, annual household income, and age of the home, the survey also began including questions on the presence or lack of energy-saving awareness from the 2020 survey.

3.2 Motivational Patterns for Energy-Saving Awareness

As noted in section 3.1, a question on energy-saving awareness was added to the Household CO_2 Statistics from the 2020 survey. The specific question that was added is, “Does the following description apply to anyone in your family (including you)? *Reply “Yes” if there is even one person to whom the description applies.” There are five answer choices for this question.

1. *Anyone who is mindful of energy-saving to save on utility costs.*
2. *Anyone who is mindful of energy-saving for global warming.*
3. *Anyone who is mindful of energy-saving because other households are doing so.*
4. *Anyone who is mindful of energy-saving for a reason other than the above.*
5. *Anyone who is mindful of energy-saving without a clear reason.*

Note that being “mindful of” energy-saving for a variety of reasons means always keeping it in mind or being aware of or cautious of it, and this study has abbreviated the term as “energy-saving awareness” for the sake of simplicity.

Also, because multiple answers are allowed for choices 1 through 5, many combinations of those choices are conceivable, such as households that select both “to save on utility costs” and “for global warming,” or households that select only “because other households are doing so.” Due to the structure of this question, households can be categorized into multiple patterns based on the energy-saving awareness of each (Table 1), and there are households that practice energy-saving for multiple reasons, households that practice energy-saving for one reason, and even households without energy-saving awareness. Therefore, this study will analyze the energy-saving effects for each combination of energy-saving awareness reasons. Note that for choice 4, “a reason other than the above,” and choice 5, “without a clear reason,” the motivations are unclear and difficult to interpret. Households that include those reasons are very likely to include a wide range of reasons depending on values and situation, which tends to obscure the results of the analysis. Accordingly, this study will focus on analyzing the effects of the three motivations, which are clearer, including “to save on utility costs,” “for global warming,” and “because other households are doing so.” Note that for this study, the treatment group, consisting of households with energy-saving awareness with any of the above three reasons, is called “households with energy-saving awareness,” while the control group of households without any of the above three reasons is called “households without energy-saving awareness.” This is because even if a given household is carrying out energy-saving behaviors, a clear energy-saving awareness cannot be confirmed if they do not fall under one of the above three reasons. In summary, categories B1 through B7 on the table represent the treatment group, while category B8 represents the control group.

Table 1: Energy-saving awareness motivations Combination Patterns

Group No.	Description	Utility costs	Global warming	Other households	Combination Pattern	Observations
B1	Mindful of energy-saving to save on utility costs	1	0	0	100	6,755
B2	Mindful of energy-saving for global warming	0	1	0	010	275
B3	Mindful of energy-saving because other households are doing so	0	0	1	001	42
B4	All three reasons are present (utility costs, global warming, other households)	1	1	1	111	9,472
B5	Two reasons (utility costs, global warming)	1	1	0	110	7,732
B6	Two reasons (utility costs, other households)	1	0	1	101	628
B7	Two reasons (global warming, other households)	0	1	1	011	73
B8	None of the three reasons (utility costs, global warming, other households)	0	0	0	000	3,985

Source: Created from the Ministry of the Environment's Household CO_2 Statistics [6]

4. Methods for Analyzing the Measurement of the Energy-Saving Effect

4.1 Overview of the Analysis

This chapter will quantitatively analyze the effect on energy consumption in the household sector of each combination of energy-saving awareness motivations, as shown in Table 1. The data used in the analysis is microdata pooled from the Household CO_2 Statistics for the years 2020 through 2022, during which the question on energy-saving awareness was included, including a total of 28,962 samples of the 29,298 responses after subtracting the 336 samples for which the answers were unclear. Furthermore, samples were excluded from analysis when there were missing values in explanatory variables, resulting in a total of 23,722 samples that were actually used.

Previous studies on energy demand analysis widely use multiple regression analysis, so this study first implements multiple regression analysis using the energy consumption per household as the explained variable. The advantages of using multiple regression analysis are that trends can be understood for the data overall by using all samples, and the ability to measure the effects of individual explanatory variables on the explained variables when multiple explanatory variables are used. On the other hand, there are cases in which the effects of confounding factors cannot be adequately controlled. Therefore, after using multiple regression analysis, we used propensity score matching (PSM), which is superior at controlling the effects of confounding factors, to estimate the amount of energy-saving effect of energy-saving awareness to ensure the robustness of the analysis.

4.2 Multiple Regression Analysis

For the analysis, we use a standard multiple regression model shown in (1).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \quad \ldots(1)$$

Here, Y is the energy consumption per household, while X_1 through X_n are dummy variables representing energy-saving awareness and the household attributes (floor area, household income, family composition, etc.). β_0 is the intercept, β_1 through β_n are the regression coefficients for each explanatory variable, and ϵ is the error term. We selected the explanatory variables to use by referring to structural energy consumption analysis for the household sector in previous studies [15][17] while considering such factors as statistical significance, the sign, and the avoidance of multicollinearity. Note that since energy demand is determined through the complex interaction of numerous elements, this model includes variables thought to be important from the standpoint of understanding the household energy demand structure, while considering the overall fit with the model, rather than only considering the statistical significance of each variable in isolation. Energy consumption per household was used as the explained variable, while dummy variables for each energy-saving awareness pattern for the “without energy-saving awareness” group used as the control group, were used as explanatory variables. Factors were included that are thought to have an effect on energy consumption, such as household income, family composition, and housing type, as shown in Table 2.

4.3 Propensity Score Matching Analysis

Propensity score matching (PSM) was proposed by Rubin and Rosenbaum in 1983 as a method to estimate causal effects by adjusting covariates in observational studies where random assignment is difficult and confounding is likely to occur [30]. PSM estimates the probability, or propensity score, that each subject has of receiving a treatment, and then matches the individuals in the treatment and control groups with similar propensity scores, thereby mimicking the conditions of a random controlled trial. We believe that this approach reduces confounding bias and allows for estimation of the effect of energy conservation awareness itself more precisely.

The procedure of analysis is as follows. First, the propensity score is calculated using the logit model in formula (2) and using each of the seven groups in Table 1 with energy-saving awareness (the treatment group) as the explained variables.

$$P(T = 1 \mid X) = \frac{e^{(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}}{1+e^{(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}} \quad \ldots(2)$$

P(T=1 | X) in the above equation denotes the probability that the sample belongs to the treatment group (T=1), X'β is the linear combination of the covariate X and the corresponding regression coefficient vector β, and e is the Napier number. In this study, a variety of energy-saving awareness patterns were set as the treatment groups, and with reference to the method used by Nishio (2024) [15], the variables used for the multiple regression analysis in 4.2 were used as covariates with the exception of household energy consumption, which is used as the explained variable for propensity score matching.

Then, each treatment group sample was matched with the control group sample with the closest propensity score. This study analysis. First, a caliper was set as an upper limit (the maximum allowed distance between the propensity scores of samples to be matched), and matching was not performed when the given distance exceeded the caliper. The caliper distance was set at 0.25 times the standard deviation used by Rosenbaum & Rubin (1985) [31]. Second, we established a common support range using the conditions shown in formula (3) below and excluded samples outside the range.

$$\min(P(T = 1 \mid X)) < P(T = 0 \mid X) < \max(P(T = 1 \mid X)) \ldots(3)$$

Here, P(T=1|X) and P(T=0|X) are the propensity scores for the treatment and control groups, and the common support range is defined as the overlap between the two ranges. Furthermore, this study evaluated the balance of each covariate based on the standardized mean difference (SMD), shown in formula (4), in order to confirm whether the covariates were appropriately balanced between the treatment and control groups.

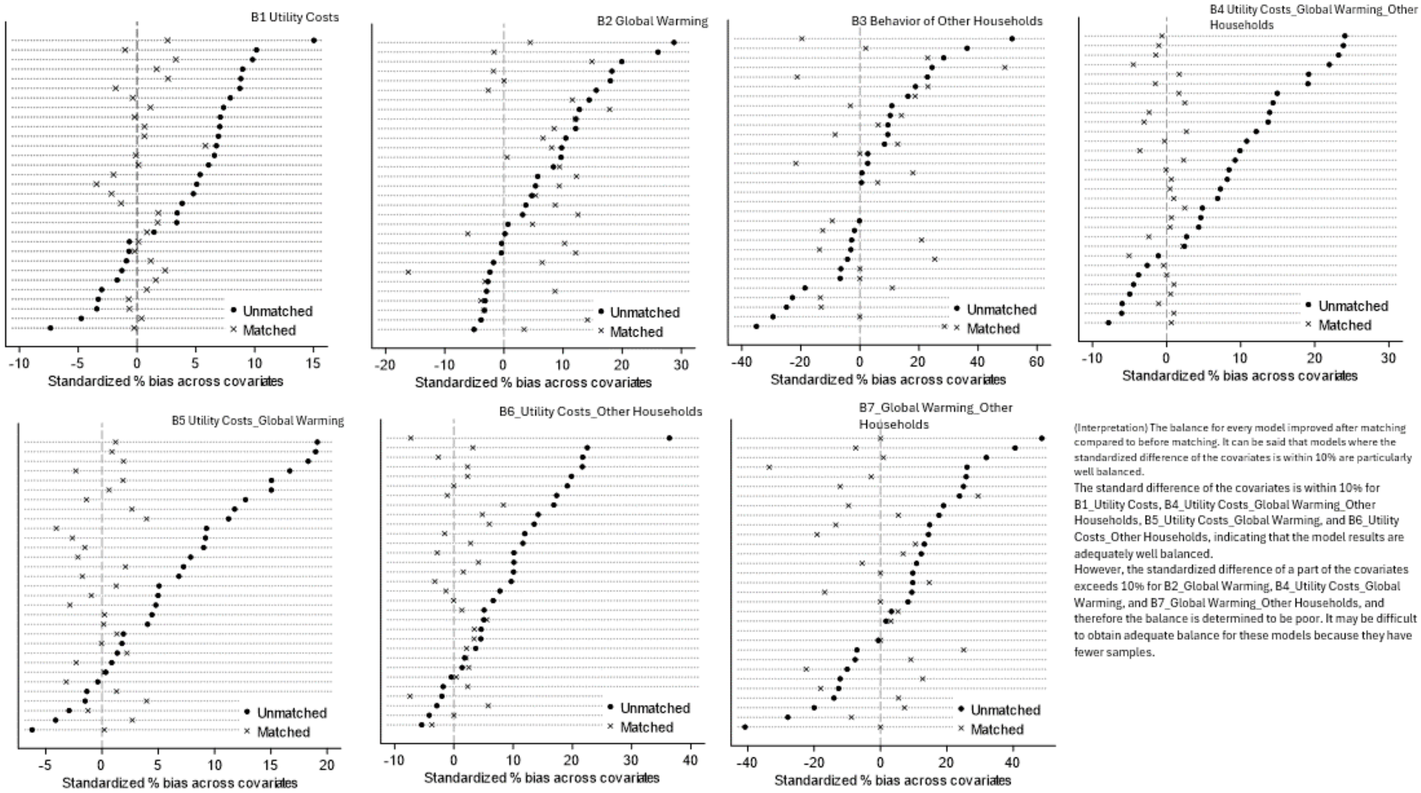

Figure 1: Standardized differences in covariates per model (unadjusted, adjusted)

used the nearest neighbor matching method to match the closest samples in the treatment and control groups. The advantage of using this method is that it limits the complexity of the calculations and enables comparison of samples with similar characteristics in the treatment and control groups, making the results easier to interpret. Furthermore, the following two processes were performed to increase the robustness of the

$$SMD = \frac{\bar{X}_T - \bar{X}_C}{\sqrt{\frac{\sigma_T^2+\sigma_C^2}{2}}} \quad \ldots(4)$$

Here, $\bar{X}_T$ and $\bar{X}_C$ are the average values for the treatment and control groups, while σ_T^2 and σ_C^2 are the standard deviations for the treatment and control groups. In accordance with Rosenbaum & Rubin (1985), [31] we determined each covariate to be balanced when the SMD was 0.1 or smaller, and to evaluate the overall model, we evaluated whether the covariates of the treatment and control groups were evenly distributed using a standard where the mean difference in propensity score for the treatment and control groups (value B) was 25% or less, and the variance ratio of the propensity scores for the treatment and control groups was within the range of 0.5 to 2 (value R). Figure 1 shows the change in bias before and after matching for the standardized mean differences for each model. The balance has been improved after adjustment for all models after the matching adjustment, compared to before matching.

After the preparations above, the average treatment effect on the treated (ATT) was obtained using formula (5).

$$ATT = \frac{1}{N_T} \quad \sum_{i \in T} \left(Y_i^T - Y_i^C\right) \quad \ldots(5)$$

Here, i ∈ T denotes that i is a sample belonging to the treatment group (T), N_T is the number of samples in the treatment group, Y_i^T is the energy expenditure of sample i in the treatment group, and Y_i^C is the energy expenditure of the matched control group sample i. The ATT represents the mean difference in energy expenditure between the matched treatment and control groups. In other words, it indicates the amount of energy-saving promoted by energy-saving awareness.

4.4 Estimation Results

Table 2 shows the multiple regression analysis for each energy-saving awareness combination, while Table 3 shows the results of the propensity score matching (PSM). As shown in formula (5), the ATT (average treatment effect on the treated) used here is an indicator of the extent to which energy-saving awareness contributes to a reduction in energy consumption on the part of households with energy-saving awareness, in the treatment group, compared to households without energy-saving awareness.

First, an effect of -2.92 GJ/household (an 8.4% energy savings over the average annual household energy consumption of 34.9GJ, the same applies below) was confirmed via multiple regression analysis, and an effect of -3.28 GJ/household (9.4%) was confirmed via PSM, for group B1 with the single motivation of “to save on utility costs,” demonstrating that economic motivations are a factor in promoting energy-saving behavior. However, no effect of statistical significance was found via both multiple regression analysis and PSM for group B2, with the single motivation of “for global warming,” and for group B3 with the single motivation of “because other households are doing so.”

The cases of particular interest are those that combine multiple energy-saving awareness motivations. For example, no energy-saving effect was found for the single motivation groups B2 (global warming alone) and B3 (other households alone), but the energy-saving effect was confirmed to have been amplified when combined with B1 (utility costs alone). Specifically, the energy-saving effects confirmed for group B4 (the case combining utility costs, global warming, and other households) were -04.38 GJ/household (12.5%) via multiple regression analysis and -5.01 GJ/household (14.3%) via PSM, demonstrating a significant rise in the energy-saving effect even when compared to the only single motivation group, B1 (utility costs alone), that showed a statistically significant effect. Similarly, the other combined energy-saving awareness patterns tend to produce an energy-saving effect when multiple motivations are combined. For example, the effects were -3.39 GJ/household (9.7%) via multiple regression analysis and -2.89 GJU/household (8.3%) via PSM for group B5 (combining utility costs and global warming), and -3.72 GJ/household (10.6%) via multiple regression analysis and -4.58 GJ/household (13.1) via PSM for group B6 (combining utility

Table 2: Estimation Results of Multiple Regression Analysis

Variable	Unit	Description	Regression coefficient	Standard Error (SE)
Constant term		Regression constant	178.9***	17.58
Household income	1K yen	Annual household income	0.005***	0.000
Residents	People	No. household members	6.121***	0.152
Weekdays present at home	Hours	Days/weeks present at home on weekdays	0.293***	0.053
Year built	Years	Year house built	-0.089***	0.009
Floor area	㎡	Residential floor area	0.036***	0.004
No. TVs	Units	No. TVs	1.061***	0.128
No. refrigerators	Units	No. refrigerators	3.826***	0.259
No. AC	Units	No. AC	1.469***	0.101
[Energy-saving awareness dummy] Standard: B8_Without energy-saving awareness				
B1_Utility costs	1=applicable 0=not applicable	For utility costs	-2.923***	0.351
B2_Global warming		For global warming	-1.859	1.219
B3_Other households		Other households	1.789	2.405
B4_Utility costs_Global warming_Other households		Utility costs, global warming, other households	-4.378***	0.344
B5_Utility costs_Global warming		Utility costs, global warming	-3.393***	0.349
B6_Utility costs_Other households		Utility costs, other households	-3.721***	0.794
B7_Global warming_Other households		Global warming, other households	1.269	3.243
[Household attribute dummy]				
Member under 19	1=applicable 0=not applicable	Are there any members under the age of 19?	-1.888***	0.364
Member over 65		Are there any members over the age of 65?	0.750**	0.253
Detached home		Detached home?	4.094***	0.297
Form of ownership		Type of home ownership (1=owner-occupied, 0=rental)	1.070***	0.299

Variable	Unit	Description	Regression coefficient	Standard Error (SE)
[Energy-saving equipment dummy]				
W/wo double sash	1=applicable 0=not applicable	Is there double sash?	0.292	0.222
W/wo HEMS		Is HEMS installed?	-0.483	0.686
W/wo storage batteries		Is there a storage battery?	1.622**	0.798
W/wo residential fuel cell		Is there a residential fuel cell?	17.15***	1.427
W/wo solar power generation system		Is there a solar power system?	-6.441***	0.488
W/wo solar heating system		Is there a solar heating system?	-2.495**	1.188
W/wo heat pump water heater		Is there a heat pump water heater?	-6.095***	0.336
W/wo central heating		Is there central heating?	12.45***	0.858
All-electric		Is the home all-electric?	-6.260***	0.307
[Region dummy] Standard: Kanto Koshin				
Hokkaido	1=applicable 0=not applicable	Do they live in Hokkaido?	23.38***	0.618
Tohoku		Do they live in the Tohoku region?	11.31***	0.448
Hokuriku		Do they live in the Hokuriku region?	6.445***	0.444
Tokai		Do they live in the Tokai region?	-2.906***	0.343
Kinki		Do they live in the Kinki region?	-0.781**	0.323
Chugoku		Do they live in the Chugoku region?	-2.361**	0.338
Shikoku		Do you they in the Shikoku region?	-3.504***	0.357
Kyushu		Do you they in the Kyushu region?	-4.651***	0.324
Okinawa		Do you they in Okinawa?	-7.618***	0.357
[Year dummy] Standard: 2020				
2021 dummy	1=applicable 0=not applicable	Dummy variable for 2021	-1.680***	0.255
2022 dummy		Dummy variable for 2022	-2.280***	0.236

Multiple regression model statistics F= 411.33, R^2= 0.5235, RMSE= 14.906, number of observations= 23,722, VIF= 1.56

***p<0.01: Significance level 1%, **p<0.05: Significance level 5%, *p<0.1: Significance level 10%.

costs and other households), confirming an expansion of the effects.

Accordingly, these results confirmed the energy-saving effect of energy-saving awareness via both multiple regression analysis and PSM, and we learned that the effect on reducing energy consumption tended to increase, particularly when multiple motivations are combined.

and the ability to understand the effects of individual explanatory variables on the explained variables when multiple explanatory variables are used at the same time. However, because it is necessary to assume the correct relationship between the outcome (explained variable) and the covariates (explanatory variables), it may not be possible to accurately control for confounding factors in the presence of nonlinear relationships or interactions between

Table 3: Estimation Results of Propensity Score Matching

Items	B1 Utility costs	B2 Global warming	B3 Other households	B4 Utility costs Global warming Other	B5 Utility costs Global warming	B6 Utility costs Other households	B7 Global warming Other households
After matching							
Treatment group mean	35.60	36.95	44.08	35.41	35.41	37.56	41.96
Control group mean	38.88	44.24	34.64	40.41	38.75	42.14	41.88
Average treatment effect (ATT)	-3.275***	-7.296**	9.442*	-5.012***	-2.893***	-4.581**	0.079
Standard Error (SE)	0.683	3.414	4.818	0.6801	0.6877	1.723	5.052
PsR2	0.002	0.035	0.358	0.002	0.003	0.014	0.197
Mean Bias	1.5	6.1	15.5	1.6	1.8	3.1	10.9
B value	10.2	44.8	134.4	11.2	12.5	28.2	112.2
R Value	1.07	1.16	1.44	1.06	1.07	1.15	1.16
Balance test	Good	Bad	Bad	Good	Good	Somewhat good	Bad
(Reference) Before matching							
Treatment group mean	35.74	37.06	44.08	35.41	35.43	37.50	41.96
Control group mean	38.88	36.74	36.6	36.74	36.74	36.74	36.67
Average treatment effect (ATT)	-1.124**	0.322	7.483*	-1.326***	-1.31**	0.7601	5.287
Standard Error (SE)	0.492	1.587	4.087	0.46	0.481	1.095	3.023
PsR2	0.023	0.042	0.098	0.033	0.025	0.037	0.115
Mean Bias	5.6	8.4	14.2	9.9	7.5	10.5	17.1
B value	36.2	55.3	111.9	44.6	38.4	50.4	114.3
R Value	0.97	1.51	0.66	0.99	1.19	1.11	0.78
Balance test	Bad	Bad	Bad	Bad	Bad	Bad	Bad

***$p<0.01$: Significance level 1%, **$p<0.05$: Significance level 5%, *$p<0.1$: Significance level 10%, achieving statistical significance.

Note: While value B in the results for group B6 slightly exceed the standard, the overall matching quality was categorized as "somewhat good" because all other values were good.

5. Conclusions

5.1 Analysis Results of This Study and Discussion Thereof

The following is a summary and discussion of the results obtained in this study.

First, the results suggest the potential of utilizing propensity score matching (PSM) in the analysis of energy demand. Similar analytical methods tried to date include inverse probability weighting using propensity scoring by Hirayama et al (2021) [32] for measuring the effects of adopting HEMS, and a double robust (DR) method using propensity scoring by Nishio et al (2024) [15], but the examples of applying PSM to the analysis of energy demand have been extremely limited. One reason for this may be the difficulty of collecting detailed data on energy demand. However, this study was able to apply PSM analysis because the use of an adequately large amount of microdata for research purposes was made possible thanks to the Study Group on Utilizing the Statistical Survey on CO_2 Emissions in the Household Sector of the Japan Society of Energy and Resources. The advantages of using multiple regression analysis are that trends can be understood for the data overall by using all samples,

covariates. In comparison, PSM focuses on treatment assignment rather than outcome modeling, making it a method that mitigates the influence of confounding factors by making the distribution of covariates similar in the treatment and control groups. Accordingly, PSM is well suited for measuring the effects of specific policy, and the use thereof in the analysis of the effects of future energy policy can be expected to increase.

Second, from the standpoint of the energy-saving effect of energy-saving awareness, the use of the two different analytical methods of multiple regression analysis and propensity score matching (PSM) demonstrated that an energy-saving effect from energy-saving awareness was verified from both methods.

Third, it was confirmed that the energy-saving effect was greater when multiple motivations for energy-saving awareness overlapped compared to when there was a single motivation. The results of this study confirmed that while individual motivations, such as "for global warming" or "because other households are doing so," did not show a statistically significant effect, combination with other motivations such as "to save on utility costs" produced a statistically significant energy-saving effect, and furthermore, that effect tended to exceed the effects of single motivations.

Fourth, we believe that the effects produced by the overlapping energy-saving awareness motivations observed in this study can be explained by Self-Determination Theory (SDT). [7] SDT is a theory for understanding motivations for human behavior proposed by psychologists Edward L. Deci and Richard M. Ryan in 1985. This theory explains why people engage in certain behaviors and how these behaviors are sustained, and focuses on two types of motivations: intrinsic motivation and extrinsic motivation. Dividing energy-saving awareness into its extrinsic and intrinsic motivations in accordance with SDT reveals the differences in the impact each has on energy-saving behavior. While extrinsic motivators, such as reward and punishment, bring about short-term behavioral transformation in consumers, that behavioral transformation typically only occurs in the form of backlashes or temporary compliance, and when economic incentives decline, behavior tends to revert to its former state (Kaiser et al, 2020). [33] For example, the energy-saving effect of increased energy costs through energy taxes in the household sector, where price elasticity is low, is not only limited (Hoshino et al, 2021) [16], but is also unlikely to lead to sustained energy-saving awareness (Mastria et al, 2023). [34] In comparison, intrinsic motivations are highly likely to trigger sustained behavioral transformations over the long term. Since intrinsic motivations are rooted in contributing to environmental protection and a sense of ethical responsibility, and behavior is sustained through fulfillment of the sense of autonomy and competence, an increase in intrinsic motivations evokes autonomous behavior without dependence on external pressure, so even when external economic incentives are removed, energy-saving behavior is more likely to be maintained (Silvi et al, 2021). [35] This suggests that, accordingly, it is difficult to sustain behavioral transformation purely through reward and punishment based extrinsic motivations, such as economic measures, in energy-saving policy.

As described above, it is likely that the potential for promoting effective and sustained energy-saving behavior can be increased by balancing extrinsic and intrinsic motivations in accordance with SDT (Duong et al, 2023). [36] A multifaceted approach from the standpoint of multiple motivations, including extrinsic and intrinsic motivations, is suggested by the results of this and previous studies, particularly regarding measures to cultivate an energy-saving awareness as the drive behind the adoption of energy-saving technology and energy-saving behavior, and measures to sustain that awareness.

5.2 Directions for Future Research

This study primarily analyzed the effects of the types and combinations of energy-saving awareness motivations on the reduction of energy consumption. The results suggested that, in addition to superficial aspects, such as the reasons and motivations behind energy-saving awareness, an awareness of the type of psychology that gives rise to that awareness is also an important clue in considering measures to cultivate sustainable energy-saving awareness among people. Particularly, it is likely that using self-determination theory (SDT) to categorize energy-saving motivations would be useful. On the other hand, there is a gradation between extrinsic and intrinsic motivations, and there are cases when it is difficult to divide them into clear categories. For example, a particularly large energy-saving effect was obtained through PSM analysis when combining “other households” with “to save on utility costs,” and it is possible that this can be categorized as both intrinsic and extrinsic motivation. It is possible that the social approval acquired through the “desire to fit in,” as an extrinsic motivation, combined with the sense of competence from believing that “if other households can do it, so can I” as an intrinsic motivation, brought about the motivation to tackle the challenge of saving energy. One issue for the future is a more in-depth analysis of energy-saving awareness that includes such diverse motivations.

Accordingly, for future research, an analysis of the specific behavioral transformations brought about by a wide variety of energy-saving awareness motivations is called for. For example, by clarifying how specific energy-saving awareness patterns influence such specific behaviors as practicing electricity conservation in the home, the purchase of high energy-efficiency equipment, or promoting the use of renewable energy, it will be possible to propose more specific and effective measures. Conducting factorial analysis of which energy-saving awareness motivation promotes behavioral transformation the most in particular, could serve as a reference for planning measures to evoke energy-saving behavior effectively. Furthermore, a deeper exploration of the relation of socioeconomic factors such as family composition, household income, region of residence, and educational level as factors behind energy-saving awareness would enable planning approaches geared toward specific regions and household characteristics.

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