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Energy Saving Potential of Replacing the Old Refrigerator: Evidence from Comparative Case Study of Japanese Household

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Abstract

This paper empirically analyzes the causal effect of the replacement of an old refrigerator using household data. We adopt the synthetic control method to capture this effect. The result is intuitively an energy saving potential, and is based on consumer behavior data. Our analysis shows the replacement effect to be around 30 kWh per month and its reduction ratio around 49 percent. Furthermore, the energy saving is attained regardless of the choice of the refrigerator, which gives the impression of an increase in electricity, and our observations provide the possibility to enhance welfare.

JEL classification numbers

C29; D12; Q40; Q48; Q54

Keywords

Energy Efficiency Gap; Effect of replacing appliances; Synthetic Control Method; Energy Saving Potential; Causal Inference

1. Introduction

Considering the causal effect on energy consumption of replacing appliances with energy-efficient ones seems challenging. Most previous studies confine themselves to energy conservation, because such implications are difficult to use in persuading consumers to buy more energy-efficient appliances. Here, we investigate the impact of refrigerator replacements on energy consumption using household level data, and encourage energy saving through replacement. Particularly, we regard the replacement as a policy, and attempt to capture its causal effect through the synthetic control method (SCM).

Energy saving is a cost-effective approach to enhancing energy security and reducing energy-related CO_2 emissions. However, previous literature often points out the possibility of not attaining energy saving at an expected level, despite positive net-present-value energy-efficient investments. This is often called the energy efficiency gap (EEG). If it exists, it means there is energy saving potential. As such, EEG attracts attention among both policy makers and analysts. Regarding future energy demand in Japan, an energy-saving potential of 1,950 GJ is projected by 2030, which accounted for approximately 14 percent of the final energy consumption in 2013 (METI, 2015). Conversely, energy consumption in the private and transport sectors increased (ANRE, 2015). Therefore, it is important to consider the time-honored issue of EEG in the energy and related markets.

There are two points worth mentioning from previous EEG studies: one is the theoretical consideration of EEG and the other is capturing its impact. Recent survey studies summarized the issues to realizing an EEG based on economics as mainly per two economic theories: neoclassical and behavioral economics (Gillingham, Newell, and Palmer, 2009; Gillingham and Palmer, 2014). The neoclassical theory pointed out market failures that left consumers and entrepreneurs unable to make the optimal decision on energy-efficient investments. On the other hand, behavioral economics advocated behavioral failures to be induced by some anomalies, which are due to the difference between decision and experienced utility (Kahneman and Tversky, 1979).

These theories can account for EEG, but the opinions on its magnitude are divergent in literature. There are two approaches to measuring magnitude: one is an economic approach to allowing individual decision-making and the other is an engineering approach to calculating the net present value of costs on energy saving potential. The energy saving potential is defined as the difference between energy the consumption baseline and consumption after the future high energy-efficient technology has been applied. Compared to the economic approach, engineering does not consider decision-making when highly energy-efficient technologies are adopted (Arroyo-Cabañas, Aguillón-Martínez, Ambríz-García, and Canizal, 2009; Johnson, Alatorre, Romo, and Liu, 2010a; McKinsey & Company, 2009). However, the economic approach often measures the difference between the market interest rate and the implicit discount rate (IDR). IDR is calculated using observed data from the investments on energy-efficient durables, manufacturing plants, or energy management services (Anderson and Newell, 2004; Hausman, 1979; Houston, 1983).

Fowlie *et al.* (2015) focused on the Weatherization Assistance Program (WAP), and analyzed EEG using the program's method of evaluation. WAP is the US federal social services program that provides weatherization services to low-income families, using the latest technologies for home energy upgrades. The study captured the impact of the program on household energy consumption by applying the observed data from the participants within a quasi-experiment. The sample data was divided into two groups: one is the treatment group to be randomly assigned and encouraged to apply for WAP and receive significant application assistance, and the other is the control group, which was eligible for applying but was not contacted.

Davis *et al.* (2014) analyzed the effect of replacing energy inefficient refrigerators and air-conditioners in the household using the data from the large-scale appliance replacement program in Mexico. In their analysis, the energy consumption data at the household level was used and let them adopt the difference-in-difference. Their study is similar in the data to our analysis. The treatment group is to replace appliances with new ones in a household, and the control group was collected from the sample not to participate the program whose location and electricity consumption are similar to those of the treatment group.

We attempt to incorporate these insight into capturing the impact of household replacements of refrigerators on electricity consumption, but the size of treatment group (i.e., all households to replace their refrigerators in our analysis) is very small and less reliable regarding outcomes. Therefore, we use SCM for the comparative case study, which focuses on the replacement effect. The SCM was developed by Abadie and Gardeazabal (2003) and Abadie *et al.* (2010), and the data-based procedure is to calculate the counterfactual in the policy intervention. SCM can be applied in the small size of the treatment group, even if only one treatment group, hence it is widely used in the recent economic studies (Billmeier and Nannicini, 2013; Kim and Kim, 2016; Nannicini and Billmeier, 2011).

The focus on refrigerators in the household is motivated by their utilization pattern and the energy efficiency standard program in Japan. Shutting off power affects cold storage, which is an essential purpose of using a refrigerator, for which it must always be in use from the time its operation commences. When we capture the impact of the appliance's energy performance shift on energy consumption, it is straightforward to use the refrigerator as a case study. Moreover, the energy standard program on energy end-user appliances in Japan heightens the possibility of purchasing more energy-efficiency appliances. The top-runner program, which is the energy efficiency standard program for refrigerators as well as other major appliances, mandates makers to supply a product portfolio with a weighted average of energy efficiency meeting the target standard levels for the target year. When the households to replace the old refrigerator can be particularized, the impact of energy efficiency improvement of the refrigerator on energy saving can be obtained from an investigation of its electricity consumption.

The remainder of this paper is organized as follows. Section 2 reviews previous studies, whose argument is the difference in the measurement of EEG between the engineering and economics approaches. The summary of these approaches may be helpful in identifying the features of our analysis in empirical studies related to EEG. Section 3 explains the empirical models and the data used in this paper. Section 4 provides results of our estimations. Section 5 discusses the policy implication, considering our results. Section 0 concludes the paper.

2. Literature Review

2.1 Different Impacts of Energy-Efficient Investments on Energy Saving

The energy saving from energy-efficiency investments is widely known as a cost-effective approach to enhancing energy security and reducing CO_2 emissions. Particularly, the replacement of appliances with more energy-efficient ones seems to be a coherent and rapid way for energy end-users to conserve energy use. Hence, the impacts of energy-efficient investments have been an important subject of scientific analyses for several decades, with some studies showing opposite results from what is initially expected, that is, the observed energy saving in the studies is underperforming.

These contradictory results come from different methodologies, divided into two main types: the engineering and economics-based approaches. The engineering approach has been inducted with a critical commentary on its overestimate of the energy saving potential by studies using the economics-based approach. From the economics standpoint, the critical commentary mainly derives from a lack of modeling to describe a behavior as an investment in energy efficiency. However, there are some differences in the terms of each approach. We summarize each methodology for energy saving potential in these studies focusing on their clarifications, and we refer to the features of our analysis found in empirical studies related to EEG.

2.2 Engineering Approach

The engineering approach often offers the expectation of a relatively larger potential in discussing future energy savings and CO_2 emission reduction, but its results seem to encounter a skeptic reception from economists. The reason is that the engineering approach overlooks the significance of modeling consumer behavior, and calculations thus result in an overestimation (Gillingham and Palmer, 2014).

The engineering approach accounts for the physical flows of the energy end-use product (Worrell, Ramesohl, and Boyd, 2004). Therefore, when calculating energy saving potential during a time horizon, this approach incorporates the product lifecycle of the energy end-use product into the calculation. Energy consumption depends on the product lifecycle of the energy end-use equipment. In a product market, new models appear on the market and older models of the same product disappear gradually from the market. These models can be thought to follow their respective product lifecycle. When the new and old model maintain the same level of the energy efficiency, the model with a relatively longer product life-cycle brings the larger energy consumption during its life. As such, many developing and developed countries implement energy policies to urge producers to design and produce more energy-efficient models, where the energy policy can cause a change in product lifecycle.

In this approach, the *energy potential* is defined as the difference of energy consumption between the business as usual, which is often called the reference case, and its alternative in the engineering approach. The energy consumption is described as a multiplication of energy consumption per activity unit by the activity quantified for using energy. In the case of a car, the energy consumption is obtained from the product of fuel economy and traveled distance. When the energy saving (or CO_2 abatement) cost is estimated, the additional cost of the energy-efficient product, compared to the inefficient product, which is assumed to be the business as usual case, is used.

The engineering approach regards the energy use of energy end-use products as a certain type of mechanical systems, and the calculation of the energy saving potential uses heuristics for best performance. The basis of the engineering approach is the technological evaluation using ex-ante information about the relative efficiency of various types of energy end-use equipment, existing deployment, and assumptions about usage patterns.

2.3 Economics-Based Approach

Although the engineering approach is a practical methodology to forecast the future energy saving potential, there are some criticisms from the economics perspective. Many economists have found that the consumer understated the future benefit from the energy-saving investment. They attribute the slow progress on the energy conservation in consumers' attitude: the consumers' undervaluation dampens their spending on energy-efficient appliances, even if they know that the investment has a positive net-present-value projection. The issues arising from the mismatch between decision and awareness is known as the "energy efficiency gap," which means an unfilled interval between the ideal and real energy saving.

There are many studies that provide the possibility that consumers undervalue future energy conservation. For example, Hausman (1979) empirically analyzed the implicit discount rate when the consumers purchase durable goods. The rate was calculated from the consumer's preferences, using airconditioner expenditure and running cost and has shown a higher discount rate than the engineering calculations. Meier and Whittier (1983) calculated the implicit discount rate, assuming the additional expenditure on a highly energy-efficient refrigerator is equal to the net present value of future energy saving. Their straightforward calculation also showed a high discount rate. Revelt and Train (1998) analyzed consumers' choice considering the randomness of preference, and adopted a model on refrigerator choice in a household. They also found a high consumer implicit discount rate based on their estimation result.

The undervaluation is believed to be due to market and behavioral failures. Market failure involves imperfect information, a principal-agent problem, credence goods, and other relevant topics. First, the imperfect information or lack of accurate information on energy performance could lead to an unwillingness to pay the contribution of energy saving (Zhou and Bukenya, 2016), but adequate information only cannot achieve energy saving. Anderson and Newell (2004) showed that the adopted project plants as a result of consultancy by specialists represented around half the projects recommended by energy audits. Low cost of investment and high gain certainty are dominant in decision-making, making benefits from energy saving have a lower priority. Second, the principal-agent problem is applied to the issue that arises in different groups in contractual relations, which have a different attitude toward energy saving based on their own interests (IEA, 2007).

Behavioral economics also explains the mechanism of EEG. An explanation is the lack of self-control regarding investment in energy-efficient products. Behavioral analysis explained self-control as a personal choice using delayed discounting (Rachlin, Raineri, and Cross, 1991), and the choice of energy conservation is also found to be affected by the timing of receiving benefits from investment in energy-efficient (durable) goods. Tsvetanov and Segerson (2013) analyzed the impact of energy policies on welfare for EEG, and the mechanism of the gap they considered was based on temptation and self-control. They showed the possibility that the Pigovian tax, in collaboration with the energy efficiency standard, led to increased welfare.

The various economics theories have explained the mechanism of EEG, but there are is no agreement on the degree of EEG in economics literature (Gillingham and Palmer, 2014). Furthermore, previous literature has not extensively offered direct estimations of the gap. As such, it is important to provide the estimate of EEG. To resolve this issue, we apply a recent method of program evaluation for the estimate of the gap.

We define an individual energy saving potential as the difference between before and after replacement for an appliance. SCM is suited for calculated the estimate of the difference, because it can capture the causal effect of policy on outcomes in a small number of treatment cases. Our analysis is conceptually similar to the engineering approach, but uses consumer behavior data.

3. Data and Empirical Method

3.1 Applying the Replacement Effect with SCM

SCM is one of the methods to capture the causal effect of policy on outcomes, proposed by Abadie and Gardeazabal (2003). It is widely utilized as an analysis tool for causality in economic issues, and we also use it empirically capture the replacement's effect. The reason is that our sample may fit the matching method.

Following Abadie *et al.* (2010), we assume there are $j+1$ households, where the first household replaces their old refrigerator and the others are potential controls. We denote Y_{it}^{N} as the outcome of i-th household without replacement (HWOR) at month t, and a number from 1 to $j+1$ is assigned to each household. A household is assumed to replace its refrigerator at a point during periods $t=1,\cdots,T$, and the period before the replacement is T_0. The periods can be divided into pre- and post-replacement, and described as $1\leq T_0 < T_0+1 < T$.

When the i-th household replaces an old refrigerator, Y_{it}^{I} is denoted as the observed outcome that the household generates through the replacement at time t. The i-th household has been affected by the intervention for the periods from T_0+1 to T. Y_{it}^{N} denotes the observed outcome that the i-th HWOR generates at time t, and the period is $t=1,\cdots,T$.

Before the first household exposed to the intervention buys the new refrigerator, there is no difference in the observed outcome between pre- and post-replacement, and $Y_{jt}^{N}=Y_{jt}^{I}$ is obtained. Let α_{jt} be the effect of replacement for the first household at time t, which is called the treatment effect, and can be represented as $\alpha_{jt}=Y_{jt}^{I}-Y_{jt}^{N}$ during the periods $T_0+1,\cdots,T$. We assume that the household that faces the intervention is the first household, and then the effect is represented as $\alpha_{1t}=Y_{1t}^{I}-Y_{1t}^{N}$. α_{1t} becomes 0 in the pre-intervention, because $Y_{1t}^{N}=Y_{1t}^{I}$ for the periods from 1 to T_0.

It is possible to observe Y_{jt}^{N} for the post-intervention, and if the counterfactual is obtained, the effect of the replacement can be thus evaluated. Abadie *et al.* (2010) assumed that Y_{it}^{N} can be assessed by a factor model and showed that the counterfactual can be expressed as the weighted average of the outcome of the i-th HWOR at month. Let w_j^{*} be the optimal weight for the j-th household as the control unit, and estimated treatment effect is as follows:

$$\hat{\alpha}_{1t} = Y_{1t}^{I} - \sum_{j=2}^{J+1} \mathrm{w}_j^{*} Y_{jt}^{N},$$

for $t \in \{T_0 + 1, \cdots, T\}$.

A choice of the weight of HWORs as SCM decreases the difference in the pre-intervention characteristics between the household with replacement (HWR) and the synthesized household using the weight and the characteristics of the HWOR. Let $\mathrm{X}_1 = \left(\mathrm{Z'}_1, \overline{\mathrm{Y}}_1^{\mathrm{K}_1}, \cdots, \overline{\mathrm{Y}}_1^{\mathrm{K}_\mathrm{M}}\right)'$ be a $(k \times 1)$ vector of the pre-intervention characteristics for HWR, and X_1 comprises the a $(r \times 1)$ vector of observed covariates, Z_1, and the linear combinations of pre-intervention outcomes[1], $\overline{\mathrm{Y}}_1^{\mathrm{K}_\nu}$ for $\nu = 1, \cdots, \mathrm{M}$. Similarly, X_0 is formed by a $(k \times J)$ matrix, composed of the same variables for the HWOR, and its j-th column of X_0 is $\left(\mathrm{Z'}_j, \overline{\mathrm{Y}}_j^{\mathrm{K}_1}, \cdots, \overline{\mathrm{Y}}_\mathrm{j}^{\mathrm{K}_\mathrm{M}}\right)'$.

The optimal weight is calculated to minimize the norm, $\|X_1 - X_0 W\|_V = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)}$, where V is a $(k \times k)$ symmetric and positive semidefinite matrix. When the matrix of V is choosen, we can use a matrix whose elements are composed of an arbitrary number. Abadie and Gardeazabal (2003) chose V among positive definite and diagonal matrices to minimize the mean squared prediction error of the outcome variable during the pre-intervention. We choose the matrix to resemble the outcome variable of the household in replacing the old refrigerator during the pre-intervention.[2] To obtain the counterfactual under this method, the optimal weight W^{*} is calculated, leading to minimizing the distance between the treated and weighted average of the controls group during the pre-intervention.

3.2 Tests

3.2.1 Placebo Test

The placebo test is widely used when the significance of the treatment effect (i.e. the difference between the treatment and control groups) is assessed using SCM (Abadie et al., 2010; Abadie, Diamond, and Hainmueller, 2015; Ando, 2015; Billmeier and Nannicini, 2013). The test is based on the permutation test and its procedure is to apply SCM to each household, including the control group, iteratively. In our

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[1] The linear combination of pre-intervention outcomes is defined as $\overline{\mathrm{Y}}_\mathrm{i}^{\mathrm{K}} = \sum_{s=1}^{T_0} k_s Y_{is}$, and there are M combinations.

[2] We use the STATA packages synth and synth-runner to execute SCM (Abadie, Diamond, and Hainmueller, 2011; Galiani and Quistorff, 2016b). Abadie *et al.*(2011) is the explanation in running the command on R, and is also available on STATA.

analysis, if a householder in the control group believes to have receive treatment, the electricity consumption of his refrigerator would drop below the level of no intervention.

Galiani and Quistorff (2016) calculated the proportion of intervention-free effects exceeding the estimated effect through SCM. Let $\hat{\alpha}_{1t}$ represent the estimated effect after the replacement and $\hat{\alpha}_{1t}^{PL}$ a set of the estimated effects in the control group by the placebo test. $\hat{\alpha}_{1t}^{PL}$ represents $\{\hat{\alpha}_{jt}: j \neq 1\}$ as a set and their proportion is considered as a two-sided p-value from the analogy of the permutation test:

$$\text{two} - \text{sided } p - \text{value} = \Pr(|\hat{\alpha}_{1t}^{PL}| \geq |\hat{\alpha}_{1t}|) = \frac{\sum_{\iota=2}^{J} \mathbf{1}(|\hat{\alpha}_{\iota t}| \geq |\hat{\alpha}_{1t}|)}{J},$$

where $\mathbf{1}(\cdot)$ is an indicator function taking the value 1 when $\hat{\alpha}_{1t}^{PL}$ surpasses the estimate effect of household replacement, $\hat{\alpha}_{1t}$, and 0 when the event does not occur. As stated by Abadie *et al.* (2015) the above p-value can be interpreted as a usual p-value if and only if the treatment group is assigned randomly.

3.2.2 Alternative Hypothesis Test: Difference in Means

The placebo test, which is based on the nonparametric permutation test, may be effective in illustrating the performance of estimation results. However, when estimation results are tested according to the placebo test, a portion of the information from these results may remain unutilized. The test proposed by Galiani and Quistorff (2016) focuses on the proportion of the intervention-free effect in exceeding the estimated effect under the placebo test. The information on the magnitude of the estimated effect, for example, large/small or high/low, is used in the test. This is related to the fact that the permutation test may be more efficient than standard tests such as *t*-test when the sample size is large and/or the population distribution is not normal.

Furthermore, in many situations, the treatment is not assigned randomly, hence we should note that the existing placebo test is not perfect in evaluating the estimated results under SCM. Our research objective is to shed light on the magnitude of replacement towards more energy-efficient refrigerators on electricity consumption. As such, for robustness checks the conventional hypothesis test is also used (i.e., the test of the difference in means of two normal populations).

3.3 Data

3.3.1 Actual Electricity Consumption and Household Characteristic

For the most part of our analysis, we depend on the survey results from the Center for Low Carbon Society Strategy (LCS), who investigated the actual electricity consumption of refrigerators used by households during the study time frame. Moreover, LCS also inquiries about the household's attributions through a questionnaire (LCS, 2013). The questionnaire results provide information on the characteristics of households and are utilized as covariates in our analysis.

The investigation covered 232 households mainly in the Kanto region in Japan,[3] and the study time frame was from January to December in 2014. There were some households that started or abandoned the investigation in the middle of the study period. Hence, there is some data unavailability.

The actual electricity consumption was measured by a watthour meter installed in the households. It can measure the electricity consumption per minute, and the measurements are saved as half-hour data, as well as minute-by-minute data. These measurements were sent to a server over the internet. The watthour meter assigns accurate timing to measurements. For internet interruption, some actual consumption data were resumed as long as the watthour meter resent the data. However, it was impossible to measure consumption when the watthour meter faced breakdowns.

Consequently, there are missing values in the measurements. The monthly data for our analysis is aggregated from the measurements, and missing data is imputed. The procedure of aggregation and imputation is reported in the Appendix.

The questionnaire was answered by households undertaking the measurement of electricity consumption for their refrigerators by the watthour meter. The questions include the family structure, daytime activities of the household members, income, and the attitude toward energy efficiency in their personal life. This investigation inquired about whether the household replaced their old refrigerator or not and the model number of the refrigerator, that is, both model numbers (old and new) for HWR. There are six households out of the 232 surveyed who bought a more energy-efficient refrigerator than previously.

3.3.2 Other Data

The survey results from LCS offer most of the data required for our analysis, but there are other data to be made available for the covariate. First, energy prices and demand for food are important. Although the crude oil price in the international market decreased in 2014, energy prices on the Japanese domestic market increased due to the yen's weakness during the same year. Therefore, the price index of electricity for consumers in 2014 increased 5.83 percent from the previous year. Clearly, the price of electricity is important, and we use it in our analysis. Additionally, the electricity consumption of refrigerators can be affected by the volume of stored food and other goods, as well as other factors, the demand for food thus playing a key role in the covariates. The consumer price indices (CPI) for electricity bills and food are also used in our dataset.

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[3] The data include households in the Nara prefecture, Kansai region.

Second, the temperature around a refrigerator affects its electricity consumption, making temperature an important variable in our analysis. LCS's survey did not inquire about the temperature in the space the refrigerator is installed, and we use regional temperature[4] as a proxy.

Data on CPI and city-level temperature are not available for the precise location where the individual respondents in LCS's survey live. Therefore, we use data on CPI and temperature in the cities with local governments which dominates the prefecture including the respondent's neighborhood. We attempt to use these data, which are compounded from the survey results and regional data, and the results of our analysis based on these data are discussed in the next section.

4. Analysis Results

4.1 Data Synopsis

We start by examining the characteristics of the sample. Table 1 summarizes the descriptive statistics of the electricity consumption for refrigerators, average temperature, and CPI. These descriptive statistics are calculated using the entire dataset.

In our sample, the average refrigerator electricity consumption in a household was 572.72 kWh in 2014, while a household in Japan consumed an average of 428.2 kWh per month in the same year,[5] and the refrigerator's share in total electricity for a household is roughly 11.1 percent. CPI of food and electricity also increased to 102.2 and 134.2 from the base year of 2005 to 2014, respectively. The food price cross elasticity of electricity and the power price elasticity of electricity are expected to be negative.

The electricity price may have an effect not only power demand, but also the decision of replacement. When an individual shapes his/her expectation of the price increase from fluctuations in electricity prices, the household regards fluctuations as a chance to replace an existing refrigerator with a more energy-efficient one. However, the electricity market for home users was deregulated on April 2016 in Japan, and the households in the sample experienced regulated electricity prices before liberalization. The sample period is from January to December in 2014, and our analysis has the limitation of investigating the effect of the electricity price on the decision by estimating the counterfactual using the CPI of electricity.

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[4] Historical meteorological data are available from the website of the Japan Meteorological Agency (http://www.jma.go.jp/jma/menu/menureport.html).

[5] Family Income and Expenditure Survey in 2014, Statistics Bureau, Ministry of Internal Affair and Communications, Japan.

Indoor temperature affects the energy use of a refrigerator. The dataset does not include these data, and we utilize local monthly temperature data as a proxy. The average temperature was 15.42 in 2014, and below the average temperature (16.3 degrees Celsius) in Tokyo from 1981 to 2010.[6]

On the difference between HWORs and HWRs, Table 2 provides information on the share of the two types of households in the sample and the different power consumption, volume, and energy performance of the refrigerators between them. HWRs comprise around 3 percent of the total sample, consuming 449.5 kWh of electricity from refrigerators in 2014, and the figure for HWORs is around 1.3 times larger. Refrigerator volume in HWR is relatively larger than in HWOR in 2014, and the post-replaced refrigerator has larger volume than the pre-replaced.

Finally, on the cycle of replacement in the HWR, Figure 1 shows a distribution of the model year of the refrigerator in the sample households. The HWRs in the sample spent about 12.7 years using the pre-replaced refrigerator (see the vertical line in the figure). This is consistent with the survey results of the *Consumer Confidence Survey* (Cabinet Office, Japan).[7]

TABLE 1

TABLE 2

Figure 1

4.2 Results of SCM

We construct synthetic households using the group of HWORs, and the group is similar in some predictor values before the replacement to the HWR. The synthesis can be expressed as the linear combination of HWORs.

There are three kinds of predictors in our analysis. The first type is the outcome variable at the pre-intervention, measured by monthly electricity consumption of the refrigerator in a household. The second type is the time-varying covariate during the pre-intervention period, and its variables are CPI and the monthly average temperature. The last type is the constant covariate during the period, and its variables are data on attributions in a household.

Table 3 summarizes some characteristics of these predictor variables in actual and synthesized HWR and its average values in control group in the pre-replacement period. Some predictor variables in the average of control group have distinct deviations from the actual and synthesized HWR. Particularly, average monthly electricity consumption for the control group is smaller than that for all treatment groups

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[6] Data source is the Japan Meteorological Agency.

[7] We have checked the data from 1991 to 2014 in this survey, and the average years of usage are around 11.

except (c) during the pre-replacement period. The reason for the control group's smaller value is that the control group's data includes the monthly electricity consumption in the household that had replaced its old refrigerator before the sample dataset was collected (see Figure 1). On the other hand, the synthesis has fewer deviations from HWR. Analyzing the causal inference in effect of the replacement to the new (and energy-efficient) appliance, it is significant to consider the counterfactual through SCM.

Table 4 shows the weight of the synthetic household for the HWR. The treatment group's monthly electricity use of the refrigerator is reproduced by the synthesized households using these weights. The table provides some information on the synthesized households. First, the maximum weight is over 50 percent and there is a household in the control group that is similar to the household in the treatment group. Second, we can find that the households used in synthesizing have less common components. Then, we can judge whether each synthesized household is independent.

Figure 2 illustrates the monthly electricity consumption of the HWR refrigerator and its counterfactuals during 2014. The vertical line in each figure means the month that the household has replaced the old refrigerator. The refrigerator electricity consumption for each synthesized HWR closely follows actual consumption of the treated household during the pre-replacement period. We can recognize that the synthesized electricity consumption of HWR is an adequate counterfactual.

The effect of the replacement of the old refrigerator on its electricity consumption is measured by the difference between the refrigerator's electricity consumption in HWR and in the synthesized households after replacement. The immediate impact of the month in which the old refrigerator has replaced is exhibited in the results, except for households (b) and (c). The replaced month was reported by the household. Therefore, electricity consumption in the reported month is a combination of the consumption of pre- and post-replaced refrigerators in the HWR.

We can see a clear impact of the replacement on electricity consumption from the results, except for household (c). Refrigerators operate intensively in the summer season to chill food, drinks, and others. The electricity consumption in both real HWR and its synthesis increases in this season and decreases as the temperature drop. The expected energy reduction of households (e) and (f) is larger than for households (a) and (b). We can distinguish these household groups by the refrigerator's electricity consumption in January 2014. There is a different use of refrigerators for various family attributions, and the energy saving potential from the replacement likely depends on individual characteristics.

The robustness of the results is important. According to previous studies, significance is determined by the placebo test. We explain the test in the next subsection.

TABLE 3

TABLE 4

Figure 2

4.3 Tests

4.3.1 Placebo

In the context of SCM, a placebo test is conducted on the results to apply the method to each member in the control group under the intervention period of the treated member. It is natural that the actual outcomes of the so-called “placebo recipient” during pre- and post-intervention are in the proximity of the synthesized outcomes used by the pseudo control group, where the simulated “placebo recipient” is removed.

When the treatment effect is not significant, there is a paltry difference between the treatment and placebo effects. Galiani and Quistorff (2016) calculated the proportion of the intervention-free effect to exceed the estimated effect by SCM, and utilized the proportion to reject the null-hypothesis that there is no difference between the treatment and placebo effects.

Figure 3 and Table 5 show the results of the placebo test in our analysis. The light lines in each figure represent the difference in refrigerator electricity consumption between each household in the control group and its respective synthesized household. The thick and well-colored line describes the estimated effect of the replacement in the treated household. It is clear that the gap in the treated household is larger than the one for the “placebo recipient” in panels (a), (d), and (e), and the gap is relatively lower in panel (b). It is difficult to determine whether panel (c) is affected by the replacement.

Further considering the significance of the results, we check whether the proportion of the intervention-free effect exceeds the estimated effect by SCM (see Table 5).[8] The proportions in households (a), (d), and (e) falls below 5 percent on every month post-intervention. On the other hand, the proportions in (b) and (c) exceed 10 percent during the entire post-intervention period, and we cannot find a significant replacement effect in these households.

TABLE 5

Figure 3

4.3.2 Welch’s Test

To assess the robustness of result significance, we employ Welch’s t-test. We set two samples: one is the difference in monthly electricity consumption of the HWR refrigerator and its synthetic household during

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[8] The reported proportion was calculated using STATA (Galiani and Quistorff, 2016).

post-intervention and the other is the difference between each household in the control group and its respective synthesized household. We apply the statistical test to the pooled time series differences, which can be regarded as independent samples, making it appropriate to use Welch's t-test.

Table 6 summarizes the results of the test. The degrees of probability in households (a), (d), and (e) are smaller than the conventional level of 1 percent, and for (c) is than the level of 5 percent. Therefore, the null hypothesis of the same mean in these groups is unlikely. Household (c) cannot reject the hypothesis using Welch's test. This result is consistent with the result of the placebo test.

We can show the possibility that the replacement of the old refrigerator brings future energy saving at individual level. Using the results, we discuss the implication on macro energy policies in the next section.

5. Policy Implications

We empirically investigate the impact of a household's replacement of the energy-inefficient appliance on electricity consumption using the recent methodology to evaluate policy intervention. We can obtain statistically significant results to saving energy through the replacement, but the household nevertheless chooses a larger refrigerator than the previous one.

The results show that there is dispersion among treated households (see the sixth column in Table 6). A reason may be a different use of refrigerators derived from family attributions. For example, the pre-replaced refrigerator's age and volume in households (d) and (e) are approximately the same, but there are more households (e) than (d). The attributions lead to the conjecture that electricity consumption in household (e) may be larger than in (d), but the actual consumption in (d) is nevertheless larger than in (e) (see the monthly electricity consumption in these households during the pre-intervention period in Figure 2). One reason for this difference may be the relatively more intensive stance toward energy saving in household (e), implying that it is helpful to use more detailed household information to explore the energy saving potential at the individual level.

As previously noted, the engineering approach has a disadvantage in such a discussion on energy policy because it ignores individual behavior on energy efficiency. However, the output of the engineering approach is more explicit on the energy saving potential than the economics-based approach, and the same applies to SCM. Therefore, it enables us to compare the potential from the engineering approach with one from SCM directly, and the difference between these results can be recognizes as a measurement of the difficulties arising from market failure and behavioral bias.

Finally, the energy saving potentials for replacing the energy-inefficient refrigerator are shown. Table 7 shows the energy saving potential per refrigerator during 12.7 years, which is the average cycle of replacement in the sample, by energy reduction rate and yearly electricity consumption. In the case of the reduction ratio of 0.3, which is close to the average reduction ratio in our estimated results, the energy saving potential during the lifecycle ranges from 1,143 kWh (300 kWh per year) to 2,286 kWh (600 kWh per year). The maximum reduction ratio in our results is 0.498, and if the reduction ratio is 0.5, which is close to the maximum ratio in our results, the energy saving potential increases from 1,905kWh (300 kWh per year) to 3,810 kWh (600 kWh per year).

For the maximum ratio, the energy saving cost per unit is estimated to range from USD 449 to 897 during the 12.7 years.[9] The number of households in Japan was around 56.0 million in 2014,[10] and the share of households that used a refrigerator for more than 12.7 years in the model year is around 20.6 percent in the sample. In our case, where 20.6 percent of households replace old refrigerators, the CO_2 reduction is estimated to range from 12.2 Mt-CO_2 to 24.3 Mt-CO_2.[11]

It is interesting to consider whether our results of energy saving potential is larger than the potentials based on the other approaches or not. Davis *et al.* (2014) found that the replacement of energy inefficient refrigerator induced to save the household consumption of electricity by 8%, which is equal to a reduction of 12.4 kWh per month by replacing the old refrigerator in Mexico. Their estimates are the relatively small size than the engineering approach.

Johnson *et al.* (2010) applied the engineering approach to the analysis of CO_2 reduction potential in Mexico. In their analysis, the intervention effect is assumed to be 74.2 % reduction of 850 kWh per year in the case without replacement. Arroyo-Cabañas *et al.* (2009) calculated 4.7TWh in energy saving from replacing the old refrigerator in a household in Mexico. We convert their results to the consumption per unit, and the value is approximately estimated to be 310.5kWh per unit[12].

Compared with these studies, the averaged energy saving potential in our results seems to be close to the economics-based approach, and our results support the argument of the economics-based approach. However, our results show that some households attain the energy saving potential comparable to the engineering approach[13]. One interpretation of it is that there is friction, which is market failure and

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[9] We assume the electricity price is 25.91 JPY/kWh and the exchange rate is 110 JPY/USD.

[10] The number of households in Japan is derived from data in the Basic Resident Registration (Statistics Bureau, Ministry of Internal Affairs and Communications, Japan) for 2014.

[11] The coefficient of CO2 emissions from electricity in Japan is assumed to be 0.554 kg-CO2/kWh in 2014.

[12] The effect is the ratio of the estimated saving potential to the number of the refrigerators whose age is before 2000 in 2007. The number of refrigerator in each model year form one year ago up until ten years ago based on the year of 2007 is assumed to divide equally.

[13] It is often the case that the energy saving potential from replacing old refrigerator is treated as the

consumer's behavioral bias, in energy efficient investment but there is the household which dwindles EEG at the aggregated level.

There is a concern about the unified energy saving policy toward energy users. Previous studies pointed out the failure of the financial market, making it legitimate for the government to intervene in a market. A representative policy is a public support for the agent who cannot buy energy efficient appliances because of his/her insufficient funds. Nevertheless, using the newer appliance would bring him/her many benefits at the expense of private funds. Our results suggest that a distribution of public finances should be determined based on the evidence from data.

TABLE 6

TABLE 7

6. Concluding Remarks

This paper analyzes the causal effects of the replacement of energy-inefficient appliances using individual data for policy evaluation. As concerns about energy security and climate change increase, it is important to analyze the impact of the energy efficiency improvement on the society and market, but there is a difficulty in doing so: the possibility of EEG.

EEG has been explained by economic theories. The neoclassical theory pointed out that market failures and failures in general lead consumers and entrepreneurs apart from the optimal decision when they made energy-efficient investments. Behavioral economics advocated behavioral failures to be induced by some anomalies, which are due to the difference between decision and experienced utility. However, the opinions on the magnitude of EEG are divergent among engineering and economic approaches.

A clear difference between these approaches is whether to describe a behavior as an investment in energy efficiency improvement. According to previous literature, EEG is a friction to encumbering energy efficiency improvement, and it is irremissible not to incorporate individual behavior into theoretical models. This does not mean the energy saving level based on the engineering approach is irrelevant. Considering the engineering approach, we would better regard the output as a target that the energy efficiency improvement can achieve the ultimate saving without friction. The economic approach provides the energy saving level, including the market failure and the behavioral bias. A comparison of the level based on the two approaches offers information on energy saving potential to be induced by future energy policies.

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assumption.

This paper analyzes the energy saving potential of consumers who replaced their energy inefficient refrigerators using actual consumer behavior data. However, there is a difficulty in capturing the energy saving potential: the size of the treatment group is very small and it may be less reliable for the outcomes. Therefore, we use SCM for the comparative case study of a treatment small sample when we investigate the replacement effect.

Furthermore, there is a concern about identifying whether the household had bought the new refrigerator based on an energy-saving motivation from the data. The dataset includes energy performance and the volume of the refrigerator, and shows that households had chosen a more energy-efficient and larger volume refrigerator than the pre-replaced one. It is worth noting that our results show that the replacement leads to energy savings, regardless of the choice of refrigerator, which might give the impression of an increase in electricity consumption. Our observations thus provide the possibility to enhance welfare.

Finally, there are some extensions to our analysis. One example is expanding the coverage of appliances. We analyzed refrigerators, but air conditioners and lighting are used for daily needs. Their energy saving potentials should not be ignored. Moreover, it is important to increase the significance of the result from SCM, and there is a possibility to construct a methodology of statistical inference in SCM because of its recent development.

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Appendix

In this analysis we use the monthly data on the refrigerator's electricity consumption. The data is based on half-hour data measured by the watthour meter and it is necessary to aggregate the measurements into the monthly data. We define the half-hour data as $el_{01}^{MDH|S}$ and $el_{31}^{MDH|S}$ at an hour, H, on a day, D, of a month, M, in a household, S. $el_{01}^{MDH|S}$ and $el_{31}^{MDH|S}$ are the refrigerator's electricity consumption for the first and the last 30 minutes over each hour, H, respectively.

The watthour meter measures the consumption in watthours at one-minute intervals and saves the data which accumulates the one-minute electiricity consumption data as well as the time of the consumption. The half-hour data is the difference between in the cumulative consumption data between the first and the last 30 minutes over each sixty-minutes in a day; there are forty-eight each sixty-minutes intervals in a day. The half-hour data is defined as the difference in the data set.

At first, the hourly data, $el_{h}^{MD|S}$, is pulled from the pair of half-hour data, which is from $el_{01}^{MDH|S} + el_{31}^{MDH|S}$. If any of the half-hour data is missing, the hourly data is treated as missing. Secondly, the monthly data, el_{m}^{S}, in a household, H, in the month, m, is aggregated as the following:

$$el_{m}^{S} = \left(\sum\nolimits_{h \in \mathcal{H}} el_{h}^{MD|S}\right) \times D^{M} \cdot 24/\mathcal{H}$$

where D^{M} is the number of days in the month, M, and $\mathcal{H}$ is the number of hours of observation on $el_{h}^{MD|S}$ in the month, M. When there may be missing values of $el_{h}^{MD|S}$, $\mathcal{H}$ is the number of hours to multiply the number of missing values by an hour. An explanation of el_{m}^{S} with the missing values is represented by an instance. Measuring the electricity consumption of f-th household in September in 2014, there are three missing values of $el_{h}^{Sep.,D|f}$. $D^{Sep.} \cdot 24$ is 720 hours and $\mathcal{H}$ is 648 hours. Hence, el_{m}^{S} is estimated using the ration of 1.111. Obviously, the ratio is equal to one without the missing values of the hourly data, $el_{h}^{MD|S}$, in the month.

Table and Figure

Table

TABLE 1

Descriptive statistics

	Average	Max.	Min.	Range	Standard deviation	Sample size
Electricity Consumption in 2014 (kWh)	572.72	1,192.04	208.99	983.05	208.78	23,184
Monthly average temperature (in Celsius)	15.42	27.70	2.30	25.40	7.93	23,184
CPI, food (2005 ＝100)	102.02	107.60	99.70	7.90	1.58	23,184
CPI, electricity (2005=100)	134.06	138.50	121.60	16.90	4.35	23,184
CPI excl. food and elec. (2005=100)	99.63	102.40	97.40	5.00	1.16	23,184

TABLE 2

Characteristics of HWR and HWOR

	Ratio of the households	Electricity	Volume	before / after					
				elec.		vol.		Performance	
				Before	After	Before	After	Before	After
	%	kWh in 2014		kWh / month	kWh / month	L	L	kWh/year	kWh/year
with	3.8	449.5	466.2	50.1	35.9	406.5	476.8	453.3	236.7
w/o	96.3	577.2	416.3	48.1				353.6	

TABLE 3

Predictor means in the electricity consumption of household refrigerator

		Treated	Synthetic	Average of control group
(a)	*Elec(Jan)*	39,672	39,713	37,488
	Elec(Feb)	37,067	37,091	34,018
	CPI, food	103	101	100
	CPI, others	99	98	98
	Temperature	3	4	4
	Volume	404	420	420
	Num. of household	2	3	3
	Area of dwelling	255	98	98
	Income	400	751	741
(b)	*Elec(Jan)*	39,600	755	37,488
	CPI, food	103	39,766	100
	CPI, others	99	101	98
	Temperature	3	98	4
	Num. of household	4	4	3
	Area of dwelling	200	3	98
	Income	800	98	741
(c)	*Elec(Jan)*	38,609	38,409	37,488
	Elec(Feb)	34,584	34,441	34,018
	Elec(Mar)	36,365	36,806	40,041
	Elec(Apr)	39,062	38,990	42,071
	CPI, food	101	101	101
	CPI, others	99	98	98
	Temperature	8	8	8
	Volume	415	455	420

		Treated	Synthetic	Average of control group
(e)	*Elec(Jan)*	77,647	78,099	37,488
	Elec(Feb)	67,803	68,222	34,018
	CPI, food	100	101	100
	CPI, others	97	99	98
	Temperature	4	6	4
	Volume	415	484	420
	Num. of household	2	3	3
	Area of dwelling	150	97	98
	Income	150	808	741
(f)	*Elec(Jan)*	61,536	61,121	37,488
	Elec(Feb)	55,618	55,247	34,018
	Elec(Feb)	70,072	69,645	40,041
	CPI, food	100	98	100
	CPI, others	98	96	98
	Temperature	6	6	6
	Volume	425	472	420
	Num. of household	4	4	3
	Area of dwelling	111	68	98
	Income	400	935	741

TABLE 4

Weight values in SCM

Control	Treatment				
variable	(a)	(b)	(c)	(d)	(e)
30	0.009	0.011	0	0.002	0.001
50	0.007	0.009	0.169	0.002	0
53	0.012	**0.024**	0	**0.796**	0.071
57	0.008	0.011	0	0.002	0.001
89	0.009	0.011	0	0.002	0.001
241	0.009	0.012	0	0.001	0.001
243	0.009	0.009	0.076	0.002	0
413	**0.071**	0.011	0	0.069	0.109
432	0.009	0.009	0.3	0.002	0
435	0.009	0.011	0	0.002	0.002
436	0.008	0.008	**0.455**	0.001	0
440	0.009	0.011	0	0.002	0.001
462	0.008	0.01	0	0.003	**0.748**
	115/115	115/115	4/115	110/115	58/115

TABLE 5

Placebo test (p-value)

Post intervention period	Treatment group				
	(a)	(b)	(c)	(d)	(e)
Jan-14					
Feb-14		0.61			
Mar-14	0.01	0.26		0.00	
Apr-14	0.01	0.17		0.00	0.01
May-14	0.03	0.43	0.94	0.00	0.00
Jun-14	0.03	0.21	0.65	0.00	0.00
Jul-14	0.03	0.23	0.76	0.00	0.00
Aug-14	0.04	0.20	0.63	0.00	0.00
Sep-14	0.03	0.17	0.48	0.00	0.00
Oct-14	0.02	0.17	0.91	0.00	0.00
Nov-14	0.02	0.13	0.89	0.00	0.00
Dec-14	0.03	0.13	0.33	0.00	0.00

TABLE 6

Welch test upper side test

Population of treatment group	t-value	p-value		Welch's DF	Difference of two means	Reduction ratio
(a)	-8.58	0.00	***	9.89	-25,916	-0.498
(b)	-2.08	0.03	**	11.30	-4,956	-0.101
(c)	-0.37	0.36	-	7.91	-1,161	-0.022
(d)	-8.70	0.00	***	9.95	-25,549	-0.491
(e)	-3.11	0.01	***	8.63	-11,070	-0.214

TABLE 7

Energy saving potentials

Reduction ratio	year	Electricity consumption of old refrigerators (kWh/Year)			
		300	400	500	600
0.1	12.7	381	508	635	762
0.2		762	1,016	1,270	1,524
0.3		**1,143**	**1,524**	**1,905**	**2,286**
0.4		1,524	2,032	2,540	3,048
0.5		**1,905**	**2,540**	**3,175**	**3,810**

Figure

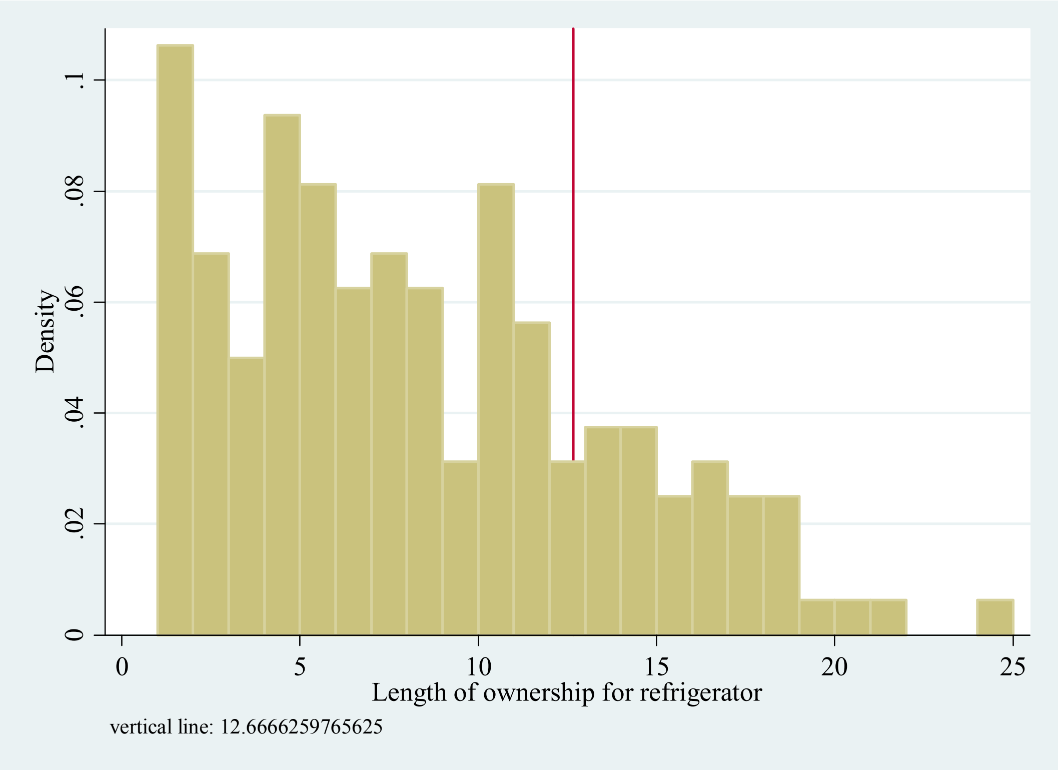
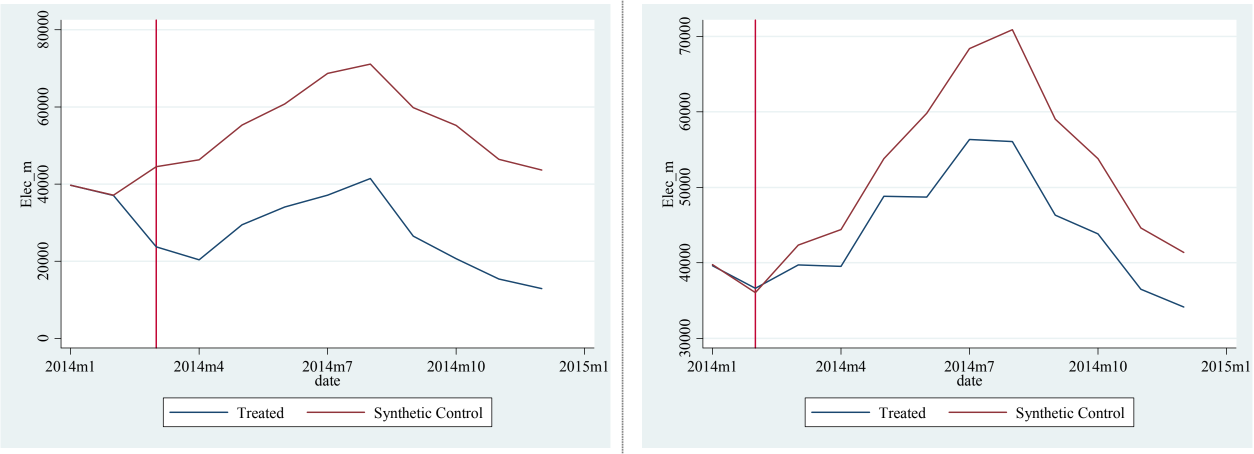


Figure 1 Disribution of the model year of the refrigerator.

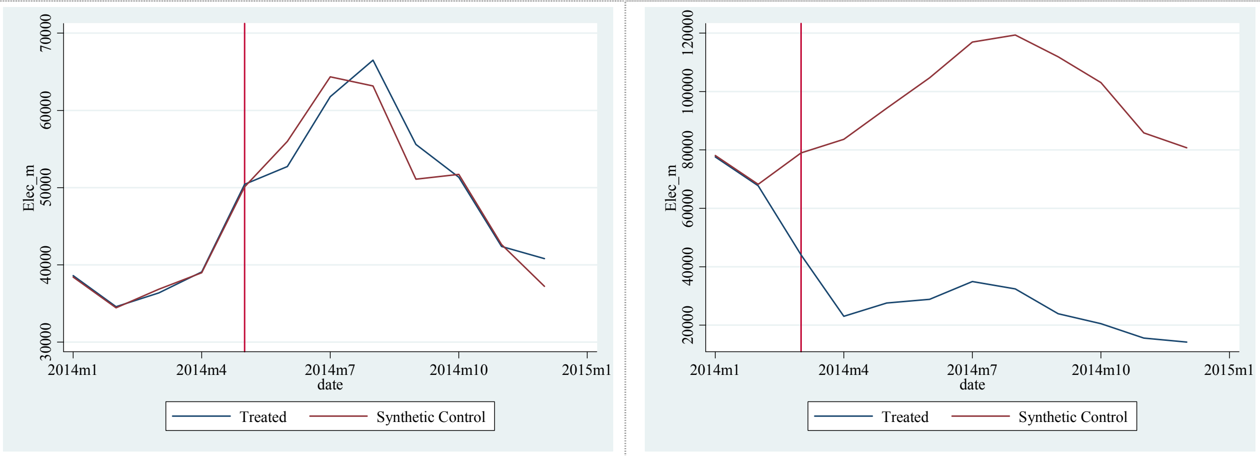
Note The histogram shows the difference between 2014 and the model year of the refrigerator in a household.

We use the the model year of the refrigerator before the replacement in the household with the replacement.



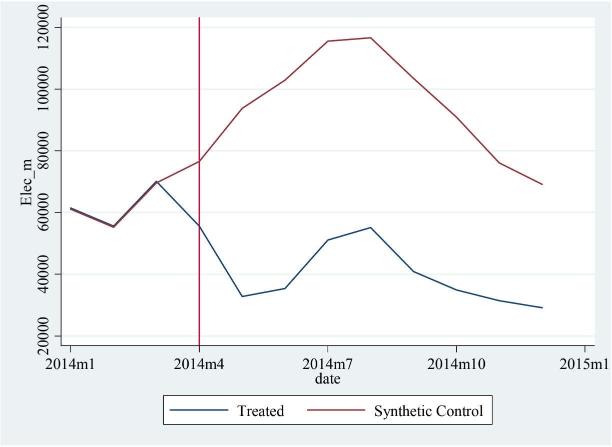
(a) household (a)

(b) household (b)



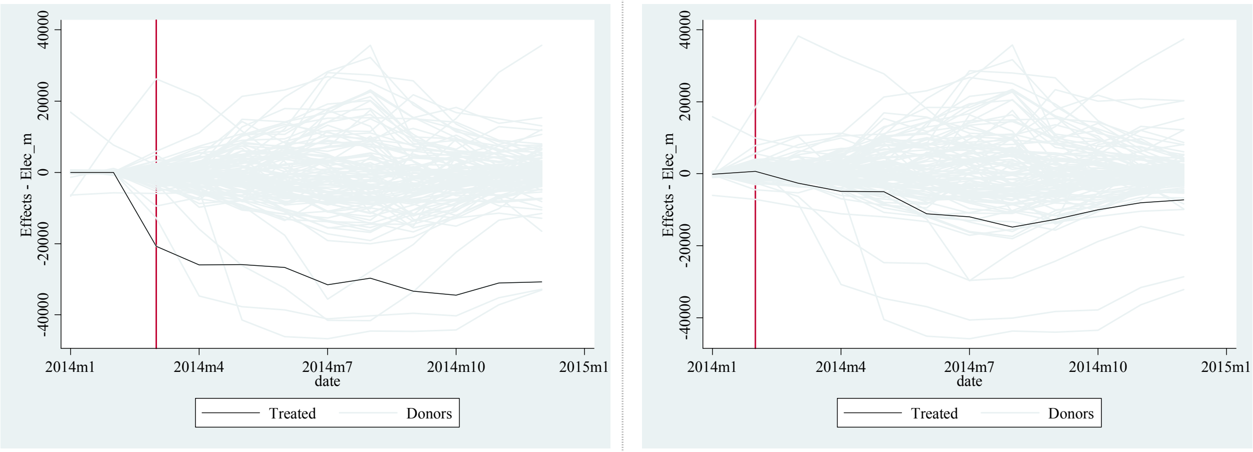
(c) household (c)

(d) household (d)



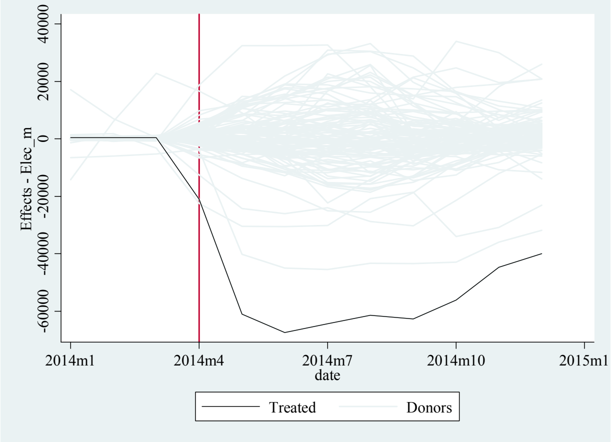
(e) household (e)

Figure 2 Results of the synthetic



(a) household (a) (b) household (b)

(c) household (c) (d) household (d)



(e) household (e)

Figure 3 Placebo test