Analyzing Micro-Level Rebound Effects of Energy Efficient Technologies

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Abstract

Energy preservation is central to prevent resource depletion, climate change and environment degradation. Investment in raising efficiency of appliances is among the most significant attempts to save energy. Ironically, introduction of many such energy saving appliances increased the total energy consumption instead of reducing it. This effect in literature is attributed to the inherent Jevons paradox (JP) and optimism bias (OB) in consumer behavior. However, the magnitude of these instincts vary among different people. Identification of this magnitude for each household can enable the development of appropriate policies that induce desired energy saving behaviour. Using the RECS 2015 dataset, the paper uses machine learning for each electrical appliance to determine the dependence of their total energy consumption on their energy star rating. This shows that only substitutable appliances register increase in energy demand upon boosted efficiency. Lastly, an index is noted to indicate the varying influence of JP and OB on different households.

1 Introduction

Climate change is one of the greatest environmental challenge in today's era. Increasing amount of greenhouse gas (GHG) emissions is among the crucial factors for this deterioration [1]. According to a 2021 report by the Intergovernmental Panel on Climate Change (IPCC) [2], there has been a significant rise in the concentration of GHG emissions since the pre-industrial period. Increased usage of energy, even in the form of electrical energy, has been one of the most contributing factors for the rise in GHG concentrations in the atmosphere [3]. Consequently, a vast amount of research has been conducted to engineer energy efficient technologies and consumer goods [4].

However, time and again, previous literature has shown a rebound effect of introducing energy efficient technologies. This effect is much more significant at the level of end consumers of such technologies. Herring and Roy [5] have shown that technological advancements modify the lifestyle and attitude of people. They further state that even if the product in itself consumes less energy per

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unit time, an increased usage of it by the consumers nullifies/reduces the benefits. This is in coherence with the well-known *Jevons paradox* (JP), formulated by Stanley Jevons in 1865 [6]. It diminishes the expected benefit from the newer technology. Apart from JP, human psychology also plays a crucial role in defining their behavior/response to any change. Several researchers in the domain have claimed that people possess *optimism bias* (OB) [7, 8]. It is a tendency of humans to underestimate negative events for themselves or from their actions. This raises a possibility that post adoption of energy efficient appliance, consumers might start to further underestimate the environmental impact of consuming the appliance and thereby increasing their demand for electrical energy.

In short, it is deemed that people consume limited electrical energy primarily because of two main factors, namely, 1) monetary cost of electricity, and 2) environmental impact. Since the adoption of energy efficient technologies is expected to reduce both of these factors, electricity demand might increase corresponding to the effects of JP and OB, respectively. This intuition is validated at a macro-level in previous studies. Greening *et al.* [9] consolidated the results from previous research to identify the behavioural influences upon introduction of appliances with higher energy efficiency. The results showed a net increase in the electricity demand. In another national level study, Frondel [10] showed that the introduction of a more efficient technology influence the behavior of consumers for worse. More recently, Li *et al.* [11] showed that without proper policies, technological progress does not reduce energy consumption. Focusing on regional data, they further identified significant spatial variations in the rebound effects. Thereby further strengthening the requirement of more micro level analysis of rebound effects to identify the exact variations of JP and OB at the level of individual households and for different technologies.

Every individual (or household) is different in terms of their lifestyle, level of education, and concern for environment. Thus, to make direct and concrete claims about the influence of JP and OB on their energy consumption patterns, we need to analyze the consumption patterns of each individual for both non-energy efficient technologies and energy efficient technologies in otherwise similar, yet parallel, universes. Since such data is not yet available, we need alternate measures to estimate the influence of JP and OB on consumer behaviour.

Using a dataset of total energy consumption of different appliances, their energy efficiency ratings, and household characteristics, this paper uses machine learning to identify the appliances where rebound effects can be observed in the community as a whole. Additionally, an index is noted to estimate the varying influence of JP and OB on individual households.

2 Dataset and Pre-Processing

The data was obtained from the 14^{th} iteration of the residential energy consumption survey (RECS) program, 2015 [12]. The survey was conducted by the Independent Statistics & Analysis group, U.S. Energy Information Administration. More specifically, this study uses the publicly available 'microdata' which consists of data from more than 5600 randomly sampled households. The dataset provides features for both appliance level data and the data on household characteristics as follows:

- census 2010 urban type - rural/urban
- whether the house is owned or rented
- total number of rooms in the house
- level of insulation in the house
- if on-site solar electricity is generated
- electricity payment by self or landlord
- number of household members
- number of days someone is at home
- annual gross household income
- energy assistance scheme participation
- climate zone of the household
- household race
- highest level of education
- employment status of respondent
- age of respondent

From the appliance level data, the total energy consumption of each appliance (say, i) in `kWh` (KWH^i), and a binary flag describing whether the appliance is energy star qualified or not (ESQ^i), are considered in this paper. Since the study is to be conducted separately for each appliance i, to compare the impact of ESQ across the appliances, the readings of KWH^i were scaled down to $[0, 1]$ using min-max normalization:

$$nKWH^i = \frac{KWH^i - min(KWH^i)}{max(KWH^i) - min(KWH^i)};\ \forall i. \tag{1}$$

During pre-processing, all households for which the information for these features was not sufficient/known were removed. However, the omission is done separately for each appliance's case such that the lack of information/availability of just one appliance in a household's case will not affect its eligibility to be considered in the analysis of another appliance. This means that for each appliance, we obtain different number of households that can be considered. Following is the list of appliances that were considered in this study along with the number of households (hh) that remain eligible against each appliance.

- Clothes Dryer (CD) – $4,101$ hh
- Clothes Washer (CW) – $4,172$ hh
- Dish Washer (DW) – $3,501$ hh
- Freezer (FZ) – $1,700$ hh
- Refrigerator (RF) – $4,717$ hh
- Light Bulbs (LB) – $4,738$ hh
- Water Heater (WH) – $4,724$ hh

3 Methodology

The study aims at visualizing behavioral shifts in consumers when they use an energy efficient technology. To proxy the behavioral response, this study analyzes how people use energy efficient appliances. As an indicative test, the study models the appliances-wise energy consumption over the energy efficiency of those appliances. If JP and OB indeed exist among individual energy consumers, the following hypothesis should be valid:

Hypothesis H_0. *Consumers using an energy efficient appliance will consume more power than their counterparts.*

Since the coefficients of a linear regression model can be easily interpreted, as compared with the parameters of other complex machine learning models, linear regression was chosen as the optimal machine learning model for this study. Consequently, a series of multi-variate linear regressions are performed by considering the $nKWH^i$ as independent variable, ESQ^i as dependent variable and the rest of the defined 15 household characteristic variables (say, $hhCh_n, \forall n \in \{1, \ldots, 15\}$) as controls. For each appliance i, the equation for linear regression can be written as:

$$nKWH^i = \alpha^i \cdot ESQ^i + \sum_{n=1}^{15} \beta_n^i \cdot hhCh_n + \gamma^i. \tag{2}$$

While the data pre-processing (and results post-processing) was done in *python*, the regression analysis was performed in *Stata* [3]. Once the coefficients (α, β_n, and γ) are estimated, the impact of ESQ over KWH is determined from the model as $\frac{\partial nKWH^i}{\partial ESQ^i} = \alpha^i$.

Note that ESQ^i is 1 for an energy star qualified (or an energy efficient) appliance and 0 otherwise; and $nKWH^i$ is a direct representative of energy consumption of the appliance i. Hence, a positive value of α^i will validate the initial hypothesis H_0 whereas a negative value of α^i will invalidate H_0. Lastly, obtained values of α^i were validated using t-test [13] for significance. Absolute value of the t-statistic must be greater than 1.96 for the α^i to be considered significant.

4 Results and Discussion

The coefficients of ESQ for each appliance is shown in the figure 1, along with their 95% confidence intervals and the value of t-statistic. While 2 appliances, i.e. CD and DW, validate the initial hypothesis H_0, 3 others, namely, CW, RF, and LB, do not. Since the results for WH and FZ are statistically insignificant, they will not be involved in the discussion.

It should be noted here that the 2 appliances which validate H_0 are all substitutable appliances. In consumer theory, a substitutable product/service is defined as the one which can be replaced by another means [14, pp. 108]. Previous research has shown that people don't mind cleaning dishes by hand and hence DW could be considered as substitutable [15, 16]. Similarly, for CD, people tend to use it for partial drying instead of full/complete dry [17]. On the other hand, the 3 appliances which

[3] With the spirit of reproducible research the *python* and *Stata* scripts used to conduct the experiments in this study can be accessed at: `https://github.com/jain15mayank/Behavioural-Study-Indicative-Tests`

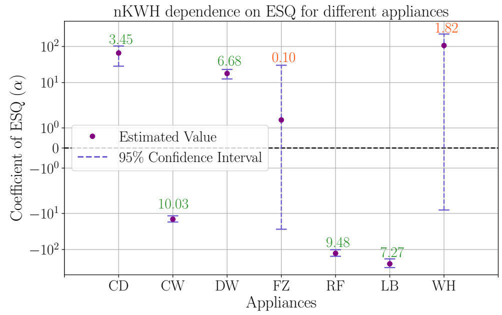

Figure 1: Plot showing normalized KWH dependence on ESQ for different appliances. Estimated value of the dependence parameter (α)), its 95% confidence interval and the absolute value of t-statistic are reported for each appliance. If $\alpha > 0$, appliance consumes more electricity in general when it is energy star qualified.

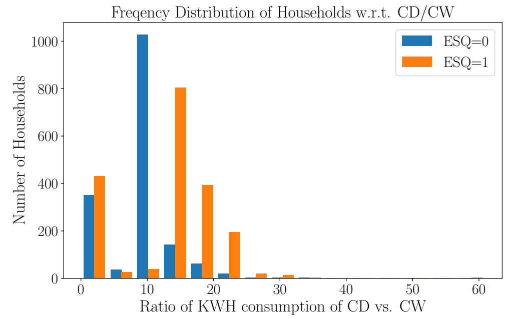

Figure 2: Frequency distribution of households that have both CD and CW, with respect to $^{KWH_{CD}}/_{KWH_{CW}}$. Blue bars: set of households whose both CD and CW are not energy efficient ($ESQ = 0$); Orange bars: set of households whose both CD and CW are energy efficient ($ESQ = 1$).

invalidate the H_0 are all non-substitutable appliances. RF normally runs 24×7 in a typical household, whereas most households in the west tend to use CW to wash their clothes. Also, CW generally has a fixed cleansing cycle for particular load/type of clothes. Operating times of LB depends on the individual habits and don't have practical substitutes.

Because people are not biased for non-substitutable appliances, they always consume them in fixed proportions irrespective of their energy efficiency rating. Hence, the operating hours of the appliances remain similar, and adopting an energy efficient alternative helps reduce the energy consumption as expected. Whereas, for the substitutable appliances, users tend to overuse them, if they have an energy efficient one, to reduce their manual labor.

The RECS 2015 also provides the information on usage frequency (number of times) for the appliances. It showed similar frequency trends for both CD and CW across the dataset. Hence, it is safe to assume that both CD and CW are mostly used together. Yet, the difference comes due to the variation in the degree of drying capacity in the case of CD. Because of this complementary use nature of CD and CW, the ratio of their energy consumption (i.e. $^{KWH_{CD}}/_{KWH_{CW}}$) for a particular household represents the knowledge about costs and benefits of altering the CD's drying capacity. The other subjective factors like household lifestyle, number of members in household, income, etc. get cancelled out.

Accordingly, figure 2 shows the frequency distribution of households with respect to the ratio $^{KWH_{CD}}/_{KWH_{CW}}$. Only households which have both CD and CW installed in their homes are considered. The set of households with both CD and CW as non-energy efficient (i.e. $ESQ = 0$), say S_0, are represented in blue color. Whereas the set of households with both CD and CW as energy efficient (i.e. $ESQ = 1$), say S_1, are represented in orange color. The figure clearly shows that the distribution of S_0 is heavily skewed towards the left as compared to that of the S_1, which is bimodal. The households either don't use CD at all, but whenever they use it, households with greater energy efficient CD makes full use of it, while those with non energy efficient CD dry their cloths only lightly. Therefore, an increased value of $^{KWH_{CD}}/_{KWH_{CW}}$ for most households in S_1 clearly reflects that they are acting under the influence of JP and OB. Hence, this ratio, subject to validation on datasets from other regions, might be used as an index to measure the influence of JP and OB on consumer behaviour on an individual household. A higher value of this index indicates higher influence.

5 Conclusion

While the previous literature shows the existence of rebound effects of energy efficient technologies at a macro scale, this work performs micro level analysis to identify the reason behind individual consumer responses upon increasing efficiency of any appliance. The paper makes use of the machine learning algorithm to draw its inferences. Consequently, the paper identifies that the degree of rebound effect varies across the individuals and can only be seen in appliances which are substitutable. Finally, the paper proposes an index to estimate the influence of the behavioral shifts, i.e. Jevons paradox

(JP) and optimism bias (OB), for each individual household. A machine learning model can further be used to learn and identify the people who have such behavioral biases based on regular survey information depicting household characteristics. Focused policy interventions can be targeted, if such identification is carried out. For instance, the environmental consequences and billing information must be carefully publicised for substitutable appliances; and the educational campaigns must be precisely targeted for the subset of population which is likely to be influenced more with JP and OB.

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