REBOUND EFFECT IN ENERGY EFFICIENT APPLIANCE ADOPTING HOUSEHOLDS

An Undergraduate Research Scholars Thesis

by

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TABLE OF CONTENTS

ABSTRACT

Rebound Effect in Energy Efficient Appliance Adopting Households. (May 2015)

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This paper uses data from smart meter technology to estimate the occurrence of energy rebound--the phenomenon that improving the energy efficiency of an appliance reduces the price-per-use and thus can increase use of the appliance and mitigate energy savings. This causes households to have more income that they could potentially use to increase their appliance use, cutting their true energy savings. Smart meter readings are provided by Pecan Street Incorporated and provide minute level energy use for a household's washing machine. This data grants the ability to count actual laundry loads of a household from observing when washing machines energy consumption changes from zero to positive. Utilizing a treatment effect created by a partnership with LG and Pecan Street Inc. to provide select households with energy efficient washer and dryers, I estimate that load rebound is not statistically different from zero with the upper bound of a 95% confidence interval that households would at most increase their loads of laundry by 20%. Likewise, I estimate energy rebound to be not statistically different from zero with a 95% confidence interval of -20 to 80 kilowatt-hours for a household month.

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CHAPTER I

INTRODUCTION

Many households and businesses have turned to energy efficient appliances in order to reduce their energy footprint. Moreover, policies, such as tax rebates, are being designed to incentivize the adoption of this new technology (Doris et al. 2009). Economists note that improvements in energy efficiency do not necessarily lead to proportional decreases in energy consumption – this is called the "rebound effect" (Gavankar and Geyer 2010). Because improvements in energy efficiency reduce the cost of using an appliance, the adoption of energy efficiency appliances can increase utilization and, in extreme cases, reverse energy savings. I use unique household-level data on energy consumption, facilitated by new smart meter technology, for laundry machines to test for a rebound effect both for direct energy rebound as well as rebound measured by extra laundry loads done by a household. Utilizing a difference in difference model, I estimate that load rebound is not statistically different from zero with 95% confidence intervals of -6 to 7 extra loads of laundry a month. Likewise, I estimate energy rebound to be not statistically different from zero with 95% confidence interval of -20 to 80 kilowatt-hours. From this result, I rule out the possibility of rebound greater than 20%.

Theory behind Energy Rebound

The "rebound effect" was first formally conceptualized by Stanley Jevons in 1865. Jevons asserted that the increased efficiency of the steam engine allowed the price of coal to fall causing greater utilization of coal by the economy as a whole. Thus, the demand for coal increased such that more coal was used after the improvement of the steam engine than before it (Jevon 1845). This same concept can be attributed, more modernly, to cars with higher fuel efficiency. While a person will save fuel during routine use of their vehicle if they had a hybrid sedan versus an old SUV, they also might be willing to take more vacations with longer driving distances due to a decreased price-per-mile, assuming gas prices stay relatively constant.

The rebound effect can be thought of in three different ways: direct rebound effects, secondary fuel use effects, economy wide effects. (Greening et al. 2000). Direct rebound effects occur on the microeconomic level where a firm who has saved amount “X” energy decides that they can increase production by “Y” leading to the excess “X” being used. Although, due to the “Y” increase in production, an increase of demand for other inputs for production could curb use of energy as cost of those inputs rise. But, since energy is a low cost input, the firm may adopt new energy using technology to decrease the need of other inputs and improve productive efficiency. This exemplifies secondary fuel use effects. If more firms adopt energy efficient technology this opens up avenues for economic growth. (Greening et al. 2000). Which, while this may cause energy use to rise, there are significant gains to the economy. Thus, often the rebound effect is economically efficient (Gillingham et al. 2014).

In recent years, with the advent of “Energy Star” appliances, new concern exists over the occurrence of energy rebound on the household level. In a recent study of a “Cash for Coolers” program by Davis, Fuchs, and Gertler, it was found that government subsidies for new refrigerators decrease energy consumption by residents by 8%, one quarter of what was predicted at the funding of the program (2013). Replacing old air conditioners, however, causes energy use to increase. This implies that consumers not only adjust usage due to decreased cost of energy, but also exaggerate their energy savings. Thus, a better understanding of household rebound effect could prevent inefficient policies such as this one.

Many studies have sought to measure the rebound effect, yet there is much disagreement to the severity of rebound with some studies claiming zero rebound, others claiming modest rebound of 10-20%, while others claiming up to 100% rebound (Nadel 2012). This disparity is likely due to a disagreement in how to measure rebound as well as trying to estimate rebound for specific appliances with aggregate household meter data.

Implications of Smart Meter Technology on Studying Rebound

There have been many new efforts to better understand consumer behavior resulting from exposure to new energy saving technologies and a “smarter” electrical grid. One effort is led by Pecan Street Inc (PSI). PSI, starting in 2011, has been recruiting households to install smart meters to record energy use. Participants in the Pecan Street Project must allow PSI access to their electricity, gas, and water consumption data for at least one year (Breen, Jones, and Wigg 2013). Recently, PSI partnered with LG to provide select households with energy efficient LG washers and dryers. This combination of real time utility consumption data and the distribution of energy efficient appliances to participants leads me to believe that PSI has created a golden opportunity to better measure the rebound effect in residential households.

One feature of the PSI data that gives a unique perspective on the rebound effect is electricity consumption by the minute for specific appliances. Most analysis of the rebound effect simply examines the difference in energy consumption between energy efficient appliance adopters relative to non-energy star appliance users. By flagging whenever an appliance's energy consumption changes from a zero to a non-zero, I estimate not only the electricity usage of said appliance, but how many times that appliance was turned on. This allows an estimate of how the quantity demanded of an appliance changes as the energy efficiency increases.

CHAPTER II

METHODS

In order to estimate how much someone's consumption of electricity directly changes when they adopt energy efficient technology, it can be difficult to see the true effect of the new technology. For example, while someone's consumption may decrease with the adoption of a new technology, they might use that saved consumption to operate other technology such as setting their AC to a more comfortable temperature. Thus, traditional meter data would not show whether a lack of change in energy consumption is due to the use of that specific technology. Another difficulty in measuring direct rebound effect results from varying energy consumption for different people, so one cannot simply compare technology adopters and non-adopters. Finally, the amount of energy a simple appliance uses compared to an energy efficient appliance can be hard to measure due to the small amount of electricity an appliance uses.

In order to overcome these challenges, I have chosen to utilize data from a smart energy grid project run by Pecan Street Incorporated. The PSI Database includes both electricity consumption data as well as survey done by Pecan Street participants. These surveys have extensive data including demographics of the household, date they enrolled with the pecan street project, and brand and model year of owned appliances. Electricity consumption data can be shown by the hour, fifteen minute, and one minute increments and it is time stamped and weather stamped.

One small scale treatment that has been made on some of the houses under PSI is a donation of high efficiency washing and drying machines from LG. Utilizing information of which houses adopted new washer and dryers around the beginning of 2013 under the LG program, I conduct a difference-in-differences approach in measuring the rebound effect in these households. However, it should be noted that given the youth of this program, meter data is limited. Thus, my dataset consists of three treated households out of sixteen total, each supplying data for the same three month period before and three month period after the treatment. For example, households were treated sometime in the spring and summer of 2014, thus I look at the November, December, and January months both before and after this period.

Specifically, I have a set of houses that I know changed to a more efficient laundry machine between January 2013 and December 2013 and I also have a set of houses that I know did not upgrade their machine. Assuming that these households would not vary there use of their laundry machine between this time except due to energy rebound, I can take a difference of the energy used previous to the switch to a more efficient machine as well as after. However, to control for time factors that could alter consumer’s laundry decisions, I also take the difference of energy consumption of people who did not change machines. By taking the difference of the average difference of people who changed and people who did not change, I should see no significant difference if there is substantial rebound effect.

My model, which has similarities to rebound measurements by Davis, Gertler, and Fuchs (2013) is :

(1) $$E_{it} = \delta D_{it} + \sigma M_{it} + \alpha H_i + \varepsilon_{it}$$

In this above model, the endogenous variable E_{it} represents the energy use of household *i*'s laundry machine in month *t* in kilowatt-hours. The exogenous variable D_{it} is an indicator variable that the household was treated with a new energy star washer and dryers. M_{it} represents the month fixed effects for a household and H_{it} represents the fixed effects of a household, such as number of residents, which effect its laundry machines energy consumption. δ is the rebound effect.

Although the PSI dataset allows me to see specifically how someone changed consumption of their laundry machine due to smart metering, the energy consumption of a laundry machine for a single residency is not a huge amount. Thus, there may not be a significant difference between energy usages purely due to the low energy usage of a washer. However, if the rebound effect occurs, it would indicate that people would use their washing machine more. Thus, by using minute increment data, I flag when someone's laundry machine energy usage changes from zero to a positive number. This allows me to physically count how often a machine was used.

Due to being able to count loads based off of what the minute level consumption data looks like, I can also predict rebound effect using the model:

$$L_{it} = \delta D_{it} + \sigma M_{it} + \alpha H_i + \varepsilon_{it} \tag{2}$$

This difference in difference model works similarly as the one seen above. However, it seeks to predict how many loads of laundry *L* household *i* washes in month *t*.

CHAPTER III

RESULTS

As seen below, Table 1 displays the predicted energy rebound and load rebound of households caused by the adoption of the new energy efficient LG washers. From the model's prediction, both load and energy rebound are not statistically different from zero. This means that households most likely do not adjust the physical amount of loads of laundry they wash in response to the lower energy cost of their new laundry machine.

Table 1: Predicted Energy and Load Rebounds

Dependent variable	**Coef.**	**Std. Err.**	**t**	**p>|t|**	**95% CI-low**	**95%CI-Up**
E_{it}	**26.95**	**27.18**	**0.99**	**0.32**	**-27.21**	**81.12**
L_{it}	**0.45**	**03.42**	**0.18**	**0.89**	**-6**	**7**

Discussion of Results

With the size of the standard errors that govern my predicted load rebound (L_{it}), I cannot assert a positive or negative rebound. I can, however rule out the occurrence of a significant change in the number of loads of laundry households do in response to adopting higher efficiency washers. In the small chance that the true L_{it} is in the upper 95% confidence at 4- 7 extra loads of laundry a month, assuming the average number of loads of laundry a month by a household is 34 (EPA 2012), then the max possible rebound would be around 10-20%, which is a standard estimate of the rebound effect. However this number is not adjusted for energy or water savings per load, so one would expect energy rebound to be less.

The second set of results estimates the effect of treatment on energy consumption. High standard errors still make asserting a true rebound difficult, yet there is more evidence, given the larger t-statistic of .99, which indicates a positive rebound. If load rebound is truly zero, then one would predict that energy rebound should be negative. Given this is not the case, it suggests that there could be other ways that households adjust their energy consumption such as running more hot water or high intensity loads. Given that water heating contributes toward 90% of a laundry machine's consumption, this would be a reasonable assumption (DOE 2009). However, most energy increases come from the complementary use of the drying machine which, if there is not a significant increase of washing machine loads, then there should not be a significant increase in dryer energy consumption.

One limitation of utilizing smart meter data to test rebound is the relative youth of smart meter technology. In my data set, I had six months of information for 16 households. This contributed to higher standard errors. This study also only looks at direct rebound of a specific appliance. Further research may try to look at the energy rebound of an Air Conditioning system caused by the treatment of adopting a different energy efficient appliance to try to measure indirect rebound effects.

CHAPTER IV

CONCLUSION

This paper examined the theory of direct rebound effect which states that as consumers adopt energy efficient appliances, the cost of operating these appliances relative to income goes down causing consumers to use these appliances more. This, in turn, decreases energy savings. The severity of rebound effect plays a key role in intelligently creating policies that subsidize the purchase and manufacturing of energy efficient technology. While direct rebound has been studied before, new smart meter technology that measures specific appliance energy use at the minute level offers the ability for more precise estimates of direct energy rebound.

Facilitated by smart meter data provided to me by Pecan Street Incorporated, I estimate both the added energy consumption caused by the adoption of energy efficient washer and dryers as well as the actual extra loads that households wash. This is made possible through an LG Washer and Dryer program that supplied select households involved with the Pecan Street smart meter project with LG energy star washer and dryers. This allowed me to measure a treatment effect without the bias of the fact that people who choose to purchase more energy efficient technology are likely to be more energy conscious. Minute level energy consumption readings allowed me to count laundry loads for load rebound estimates.

My estimates predict that, with 95% confidence, that households are not experiencing direct rebound above 20% for loads and energy consumption. However, my estimated coefficient predict that load rebound, for the washing machine, could be non-existent. The estimated energy rebound coefficient suggests positive rebound, meaning that households could be responding to new washing machines by washing with hot water more frequently.

Lack of smart meter readings for treated households presents the greatest limitation to this study. In total, I was only able to observe six months of data for three treated households. With the higher frequency of smart meter use, a replication of this study with more data points could allow for precise direct rebound effect estimates for various appliances.

This study does not explore the possibility of indirect rebound effect caused by households utilizing other, less energy efficient, appliances more in response to their cost savings from their adopted energy efficient technology. Smart meter data, though, could also allow this comparison by applying the treatment of incentives to adopt energy star appliances to the energy consumption of indoor climate control units. Thus, further economic research in energy rebound will benefit greatly from wider adoption of smart meter technology.

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APPENDIX

Table 2: Difference in Difference Energy Rebound

var	*Coef.*	*Number of Observations*	*t*	*P>t*	*Lower Level 95%*	*Upper Level 95%*
D	**26.9 (27.1)**	**96**	**0.99**	**0.325**	**-27.2**	**81.1**
M_1	**36.4 (18.3)**	**96**	**1.98**	**0.051**	**-.21**	**73.0**
M_2	**32.4 (19)**	**96**	**1.70**	**0.093**	**-5.5**	**70.4**
M_3	**10.2 (19)**	**96**	**0.54**	**0.594**	**-27.7**	**48.2**
M_4	**54.0 (19)**	**96**	**2.83**	**0.006**	**16.0**	**92.0**
M_5	**28.8 (18.3)**	**96**	**1.57**	**0.121**	**-7.7**	**65.4**
constant	**70.1 (24.4)**	**96**	**2.87**	**0.005**	**21.4**	**118.8**
Household fixed effects Applied	**Yes**					

Table 2 shows the predicted coefficients for the difference in difference model for energy rebound. Month and household fixed effects are shown by month and dataid respectively. The interaction variable represents the treatment effect of energy efficiency

Table 3: Difference in Difference Load Rebound

var	*Coef.*	*Number of Observations*	*t*	*P>t*	*Lower Level 95%*	*Upper Level 95%*
D	**.45 (3.4)**	**96**	**0.13**	**0.89**	**-6.3**	**7.2**
M_1	**2.6 (2.3)**	**96**	**1.16**	**0.24**	**-1.9**	**7.2**
M_2	**2.6 (2.3)**	**96**	**1.13**	**0.26**	**-1.9**	**7.2**
M_3	**4.1 (2.4)**	**96**	**1.74**	**0.08**	**-.61**	**8.9**
M_4	**1.2 (2.4)**	**96**	**0.51**	**0.61**	**-3.5**	**6.0**
M_5	**5.2 (2.4)**	**96**	**2.18**	**0.03**	**.44**	**10.0**
cons	**15.6 (3)**	**96**	**5.10**	**0.0**	**9.5**	**21.8**
Household fixed effects applied	**Yes**					

Table 3 shows the predicted coefficients for the difference in difference model for load rebound. Month and household fixed effects are shown by M and H respectively. The variable D represents the treatment effect of energy efficiency.