Do Customers Respond to Real-Time Usage Feedback? Evidence from Singapore

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Abstract

This paper studies the impact of providing a household with real-time usage feedback on its monthly energy consumption. The Singapore Energy Market Authority (EMA) implemented an Intelligent Energy System Pilot in which households were provided with in-home display (IHD) units that provided information on each household's real-time electricity consumption. To assess the impact of the real-time feedback provided by the IHDs, the monthly consumption of these households is compared to a control group of households that were not provided with these devices before and after this intervention. This data is used to estimate the average treatment effect associated with a randomly selected household having an IHD. We find that having a IHD unit leads to a reduction in electricity consumption of about 4% relative to the control group. This saving is equivalent to about 180 KWh annually for the average household in the sample which translates into roughly 50 Singapore dollars at the relevant retail electricity price. These results support more widespread deployment of real-time customer feedback technologies as a cost effective strategy for meeting Singapore's residential electricity demand.

*This paper does not represent the views of the Energy Market Authority (EMA) of Singapore.

1 Introduction

Electricity consumption is derived from the consumer's demand for the services provided by electricity-using capital equipment. A consumer demands hours of lighting, air conditioning, television viewing, and the others services provided by electricity-consuming appliances. However, few, if any, consumers understand how minutes of use of each of these electricity consuming appliances translates into kilowatt-hours (KWhs) of electricity used. With real-time feedback on its electricity consumption, a household can determine how use of each electricity consuming appliance translates into KWhs of electricity consumption. If the household knows the price of retail electricity, it can convert this magnitude into dollars on its monthly electricity bill.

With information about the cost using each electricity consuming appliance, a household has the opportunity to become a more efficient electricity consumer in the sense that it can compare the benefit from an additional hour of use of this appliance to a more accurate estimate of the cost of this action. In order to receive this information a household must have a real-time or interval meter that reports its electricity consumption for very short time intervals throughout the day. In addition, this high-frequency electricity consumption information must be conveyed to households in an easily digestible manner.

The Singapore Energy Market Authority's (EMA) Intelligent Energy System (IES) Pilot provided one such mechanism for making this real-time consumption and cost information available to households. A total of 1,147 households were chosen to receive a real-time meter and of those 126 randomly selected to receive an in-home display (IHD) unit that presents real-time information on the household's electricity consumption and the cost of this electricity consumption, as well as information on the household's cumulative electricity consumption and its total cost at daily, weekly and monthly historical time intervals. By the above logic, customers armed with this infomation can become more efficient electricity consumers relative to similar households that do not have access to this information. To investigate the validity of this hypothesis about the impact of providing real-time feedback on a household's electricity consumption, data on the billing cycle-level electricity consumption was collected from both treatment and control customers before and after the installation of IHDs.

A difference-in-difference estimation methodology is applied to this data to compute the average treatment effect associated with the installation of an IHD. The installation of an IHD is found to reduce a household's monthly electricity consumption by 4 percent, which amounts to an approximate annual saving for customers in our sample of 180 KWh annually. Valuing this annual KWh savings at the average retail price for our sample period of 0.279

Singapore dollars per KWh, implies an annual savings of approximately 50 Singapore dollars. Assuming a 10-year life for the IHD and a discount rate of 5 percent, implies a discounted present value of savings for the life of the device of approximately 380 Singapore dollars.

Extrapolating these results to all Singapore residential electricity consumers implies that rolling out real-time meters with IHDs to all Singapore households would more than pay for the cost this policy and therefore yield significant net benefits to the Singapore economy. In 2012, total household electricity sales in Singapore was 6,640 gigawatt-hours (GWh). Assuming a 4 percent reduction in this value is associated installing real-time meters and IHDs in all Singapore households, implies 266 GWh less consumed annually. Valuing this at 0.279 Singapore dollars per KWh implies an annual savings of 74.1 million Singapore dollars. Assuming these annual savings last for the assumed 10-year life of the real-time meter and IHD, and applying a 5 percent discount rate to these savings yields a discounted present value of savings of more than 572 million Singapore dollars.

Several possible extensions of these results are exploreed. First, the hypothesis that the average treatment effect of an IHD varies with the dwelling type of the household is examined and the null hypothesis that it is the same for the two household dwelling sizes is not rejected. Second, the null hypothesis that the average treatment effect of an IHD is same for each of the five months of the post-IHD installation date time period is also not rejected. Third, different household-specific characteristics are found to predict different average treatment effects for an IHD. For example, households that chose to take a pre-intervention survey were found have larger in absolute value average treatment effects if they had more occupants and more air conditioning units than households that declined to take the survey.

2 IES Pilot Treatment and Control Samples

This section describes the data collected for the treatment and control groups. The raw data is compiled from monthly billing cycle-level consumption data for each household. This data is converted to average daily-values for the calendar month for each customer as follows. For each billing cycle, the customer's total consumption is first converted to an average daily value. The average daily consumption for each calendar month is computed as the day-weighted average of the average daily consumption values for all of the billing cycles that have days in the calendar month. For example, if one billing cycle has 10 days in the calendar month and a second billing cycle has the remaining 21 days of the 31-day month, the average daily consumption for the calendar month is 10/31 times the average daily consumption for the first billing cycle plus 21/31 times the average daily consumption for the second billing cycle in the calendar month. The raw billing cycle-level data starts in June 2010 and runs through March 2013 for customers in both the treatment and control groups, which yields a calendar month panel dataset from July 2010 to February 2013. The treatment period is assumed to start with the calendar month that the household's IHD device is installed. Because there was a rollout period for the installation of the IHDs, the exact treatment date differs across households during the months of October and November of 2012. This is accounted for in the construction of the regressor used to estimate the average treatment effect for the installation of an IHD in a household's dwelling described in Section 4.

The dataset is unbalanced in the sense that the number of calendar months of data available differs across customers. This is the result of the fact that customers have different start and end dates for their billing cycles and that some households move out of a dwelling and other customers move into the dwelling during the sample period. There was missing data or obvious data recording errors for certain customers in the treatment and control groups that required reducing the initial control group size from 1,203 to 1,147 customers and initial treatment group from 128 to 126 customers. A size 0.05 test of the null hypothesis that the missing data proportions for the treatment and control groups are equal is not rejected the using a two-sample binomial proportions test. For the final dataset, all customers in the treatment and control groups have monthly consumption observations for at least twelve calendar months and all customers in the treatment group are observed before and after the intervention for a minimum of 3 calendar months.

3 Experimental Design

This section describes the experimental design underlying the measurement framework employed to compute the average treatment effect associated with installing an IHD in a household's dwelling. Various statistics are presented to show that the pre-IHD installation date distribution of monthly consumption for the treatment and control groups are the same unconditionally and conditional on observable differences between the two groups of households. The only observable difference between households is the type of premise that the household occupies. There are two types of premises observed in the data called HDB04 and HDB05, with the former dwellings having one less room than the latter dwellings. Table 1 shows the breakdown of treatment and control groups by dwelling type. The fraction of treatment households is not statistically different across the two dwelling types with p-value of 0.40 using Fisher's (1922) exact test for s $2x2$ contigency table.

To test whether the distribution of monthly consumption across households is same for the treatment group (those that receive an IHD) and the control group (those that do not receive an IHD), I rely on the two-sample Kolmogorov-Smirnov test of equality of two distributions. Let Q_{im}^k be the average daily consumption of customer i of type k during calendar month m, where k indexes the control or treatment group. As described above, all monthly consumption is expressed in terms of average daily consumption during that calendar month to account for the fact that there are different numbers of days during the different months of the year.

Suppose there are M months during the pre-intervention period which ends September 2012, the calendar month before the first IHD was installed for any consumer in the treatment group. Suppose there are N_{km} customers in group k during pre-intervention month m. Define the empirical distribution of average daily consumption in month m for group k as:

$$F_m^k(t) = \frac{1}{N_{km}} \sum_{i=1}^{N_k} I(Q_{im}^k \leq t)$$

where $I(X \leq t)$ is an indicator variable that takes on the value 1 if X is less than or equal to t and zero otherwise. Under the assumption that the Q_{im}^k, $i = 1, 2, ..., N_{km}$ are independent and identically distributed within month m for each group k with population distribution equal to $G_m^k(t)$, we can perform the hypothesis test: $H : G_m^k(t) = G_m^h(t)$ versus $K : G_m^k(t) \neq G_m^h(t)$, where group k is the treatment group and group h is the control group, using the two-sample Kolmogorov-Smirnov statistic

$$KS(m) = \underset{t}{sup}\ |F_{mt}^k(t) - F_{mt}^h(t)|.$$

Table 2 reports the monthly values of the mean daily consumption for the treatment and control groups for each calendar month from January 2011 to September 2012. The last column of the table reports the p-value associated with null hypothesis, $G_m^k(t) = G_m^h(t)$. For all months, the p-value is greater than 0.05, indicating that the null hypothesis of equality of the two distributions would not be rejected for a size 0.05 test of the null hypothesis for any month from January 2011 to September 2012. Tables 3 and 4 repeat the analysis presented in Table 2 separately for the two different dwelling types in the sample–HDB04 and HDB05. Because HDB05 dwellings contain one more room than HDB04 dwellings, they also have a higher mean daily consumption of electricity. Once again the p-values for the null hypothesis of equality of the two distributions are all larger than 0.05 for all months for both dwelling types. Taken together these results suggest that assignment of customers to the treatment and control groups was random both conditional on the dwelling type and unconditionally.

4 Empirical Strategy

This section presents the econometric modeling framework used to estimate the average treatment effect from the installation of an IHD in household's dwelling on its electricity consumption. Let Q_{im} be the average daily electricity consumption in calendar month m for customer i. Define the variable IHD_{im} which equals the fraction of days in month m that customer i has an IHD installed in his dwelling. For all months but the first month an IHD is installed in a customer's dwelling, this variable takes on the value 1. For all months that the customer does not have an IHD installed it takes on the value zero. During the calendar month that the IHD is installed, this variable take on a value between 0 and 1. For example, if the IHD was installed on the 16th day of a 31-day month then the value of IHD_{im} is equal to 15/31, the fraction of days in that month that the household had an IHD installed in its dwelling. All regressions reported in the next two sections are estimated using data from 5-months before the first IHD was installed and 5 months after first IHD was installed, from May 2012 through February 2013 (the last calendar month of data available).

The basic econometric model estimated takes the form:

$$y_{im} \ = \ \delta_i \ + \ \gamma_m \ + \ IHD_{im}\beta \ + \ \epsilon_{im},$$

where δ_i is the fixed effect for each household i, γ_m if the fixed effect for month-of-sample m, β is the average treatment effect associated with having an IHD installed, and ϵ_{im} is a mean zero disturbance that is uncorrelated with the fixed effects and the value of IHD_{im}. All models are estimated for y_{im} equal to Q_{im} and $ln(Q_{im})$, so that β measures the average treatment effect of installing an IHD in kilowatt-hours (KWh) of average daily consumption or as the percentage change in the customer's average daily consumption from the installation of an IHD in the household's dwelling.

Table 5 reports the results of estimating these models for both the level of average daily consumption (Levels) and the logarithm of average daily consumption (Logs). The results are reported with the conventional ordinary least squares (OLS) standard error estimates and clustered standard errors that allow for arbitrary autocorrelation of the ϵ_{im} across months for the same household as discussed in Arellano (1987).

Table 6 also reports the random effects estimator that treats the δ_i as draws from a distribution with mean zero and variance σ^2_δ that is uncorrelated with IHD_{im} and the γ_m. The fixed-effects estimates and random effects estimates yield very similar point estimates of β. In fact, a size 0.05 Durbin-Wu-Hausman test of the null hypothesis that the probability limit of the difference between the fixed effect estimate of β and the random effects β is equal to zero is not rejected for either the Levels or Logs specification.

The Levels average treatment effect and the Logs average treatment effect yields similar quantitative results for impact of having an IHD. Dividing the Levels average treatment effect point estimate of 0.458 KWh per day by the sample mean of Q_{im} for the control group for the period October 2012 to February 2013 of 13.07 KWh and multiplying by 100 yields 3.5 percent. The Logs specification yields a percentage average treatment effect of approximately 4.1 percent. To understand how the treatment effect various across the distribution of average daily consumption, Figure 1(a) plots the histograms of the residuals from the regression of $y_{im} = \delta_i + \gamma_m + \epsilon_{im}$ for $y_{im} = Q_{im}$ for the treatment and control groups during the post-intervention period. This graph shows that the treatment effect from the installation of an IHD in the household's dwelling is approximately the same across the percentiles distribution of average daily consumption. Figure 1(b) repeats this plot for residuals from the same regression using $y_{im} = ln(Q_{im})$ as the dependent variable. This figure is also consistent with an approximately uniform treatment effect across the percentiles of distribution of $ln(Q_{im})$.

5 Potential Heterogeneity in Average Treatment Effect

This section investigates the extent to which the average treatment effect associated with installing an IHD in customer's dwelling differs across households based on observable characteristics or over time. I first investigate whether the treatment effect differs across the two dwelling types. Then I examine whether the magnitude of the treatment effect differs across months of the treatment period. Finally, I investigate the extent to which the treatment effect differs across responses to a pre-intervention survey sent to all households in the treatment and control group.

Table 7 reports the result of estimating the equation

$$y_{im} = \delta_i + \gamma_m + IHD_{im}\beta + IHD_{im} * HDB04_i\lambda + \epsilon_{im}$$

where $HDB04_i$ is an indicator variable that equals 1 if household i's dwelling type is HDB04 and zero otherwise. The coefficient on $IHD_{im} * HBB04_i$ is the difference in the average treatment effect for households's in HDB04 dwellings versus those in HDB05 dwellings. For both the conventional standard error estimates and clustered standard error estimates, the null hypothesis that $\lambda = 0$ is not rejected at 0.05 level of significance. This result implies that data provide no evidence against the null hypothesis that the treatment effect is the same for both HDB04 and HDB05 households. Clearly, one explanation for this result is the much smaller number of households of dwelling type HDB04 versus HDB05 shown in Table 1, because the point estimates in Table 5 are consistent with a smaller average treatment effect in both levels and logs for the HDb04 households.

Table 8 reports the results of estimating the equation

$$y_{im} = \delta_i + \gamma_m + IHD_{im}\beta + IHD_{im} * Oct12_m\lambda_1 + IND_{im} * Nov12_m\lambda_2$$

$$+ IHD_{im} * Dec12_m\lambda_3 + IHD_{im} * Jan13_m\lambda_4 + \epsilon_{im}$$

where $MonYR$ is an indicator that equals 1 during month "Mon" and year "YR" and zero otherwise. The 0.05 size joint test of the null hypothesis that $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0$ is not rejected for the Levels or Logs regressions using either standard error estimates. These hypothesis testing results are consistent with the conclusion that the average treatment effects for both the Levels and Logs specification do not differ across the months of the intervention period from October 2012 through February 2013.

All customers in the treatment and control groups were invited to take a pre-intervention survey to collect information on their observable demographic characteristics and their attitudes towards energy consumption. Table 9 reports the number of treatment and control households that elected to take the survey before the intervention occurred. Table 10 reports the results of estimating

$$y_{im} = \delta_i + \gamma_m + IHD_{im}\beta + IHD_{im} * Survey_i\lambda + \epsilon_{im}$$

where $Survey_i$ is equals to 1 if customer i took the pre-intervention survey and zero otherwise. For both the Levels and Logs specification and the conventional and clustered standard error estimates, the 0.05 test of the null hypothesis that $\lambda = 0$ is not rejected. This implies that the data provide no evidence against the null hypothesis that the treatment effect is the same for households that chose to take and chose not to take the pre-intervention survey.

The survey collected information on the number of occupants in the household, the number of air conditioner (AC) units in the dwelling, the monthly income bracket of the household, highest level of education obtained by the survey respondent and the respondent's attitude towards saving energy. For each of these observable characteristics, I run the following regression

$$y_{im} = \delta_i + \gamma_m + IHD_{im}\beta + IHD_{im} * Survey_i\lambda + IHD_{im} * Survey_i * Z_i\prime\theta + \epsilon_{im}$$

where Z_i is a vector of observable characteristics of household i. This regression quantifies the extent to which the treatment effect differs across households depending on their responses to the pre-intervention survey.

Table 11 reports the results of estimating this equation with Z_{im} equal to the number of occupants in the household. These results imply a larger treatment effect for households with more occupants. Figure 2 plots the average treatment effects for the Levels regression for survey respondents as function of the number of occupants in the dwelling. The pointwise 95 percent confidence interval for each number of occupants using the conventional standard error estimates is also plotted in this figure. Households that responded to the survey with more than four occupants have a treatment effect associated with an IHD that is larger in absolute value than the treatment effect associated with those that did not respond to the survey. For smaller households that responded to the survey, the number of occupants does not yield an average treatment effect that is statistically different from zero. Figure 3 plots the histogram of the number of occupants per household for treatment households that took the pre-intervention survey.

Table 12 reports estimation results with Z_{im} equal to the number of AC units in the household. The absolute value of the average treatment effect is increasing in the number of AC units in the household for those households that took the pre-intervention survey. Figure 4 plots the treatment effect for the Levels regression for households that took the survey along with pointwise 95 percent confidence intervals constructed using the conventional standard error estimates. These result show that the absolute value of the treatment effect is statistical larger in absolute value for households that took that survey living in dwellings with more than three AC units than households that did not take the survey. Figure 5 plots the histogram of the number of AC units in the household for treatment households that took the survey.

Table 13 reports estimates for the case of Z_{im} equal to a vector of indicator variables for ranges of total household income. For both the Levels and Logs models and the conventional and clustered standard errors, the null hypothesis that the elements of the vector θ and λ are jointly zero is not rejected at a 0.05 level of significance. This result indicates that the average treatment effect for households that took the survey does not vary with the household's income. Table 14 gives the number of survey respondents in each income range.

Table 15 reports estimates for the case of Z_{im} equal to a vector of indicator variables for the highest level of education obtained by the survey respondent. For survey respondents in the treatment group, the average treatment effect is roughly increasing in absolute value in the highest level of education obtained by the survey respondent. Specifically, survey takers with Polytechnic, Secondary and University education have larger in absolute value average treatment effects. Figure 6 reports the change in the average treatment effect for survey takers as function of their education level, along the 95 percent confidence interval for this change in the average treatment effect. For all but the No_Qualification category, this difference is negative and different from zero, indicating a significantly larger in absolute value average treatment effect for survey takers with higher education levels. Table 16 gives the number of survey respondents in each education group.

Table 17 assesses the impact of attitudes towards energy savings of survey respondents on the estimated average treatment effect. In this case, Z_{im} is the indicator variable for whether the respondent agreed with the statement, "I would be willing to save energy if it did not require hard work." In this case the treatment effect is statistically significantly smaller for both the Levels and Logs model and both the conventional and clustered standard error estimates. In fact, the overall treatment effect for survey respondents that agree with this statement, which the equivalent to the null hypothesis that the sum of β, λ and θ ix zero, is not statistically different from zero at an 0.05 level of significance. This result suggests that a household's attitude towards energy savings is an important predictor of the effectiveness of installing an IHD in their dwelling. This result implies that households taking the survey that expressed an unwillingness to save energy if it required hard work, did not save any energy as a result of having an IHD installed in their dwelling. Table 18 lists the number of suvey respondents that answered "Yes" and "No" to the question, "I would be willing to save energy if it did not require hard work."

6 Implications of the Results

Assuming a 13 KWh daily average consumption for households in our sample, a 4 percent average treatment effect implies an annual electricity consumption reduction of approximately 190 KWh as result of installing an IHD in the household's dwelling. The average retail price during 2012 is 0.279 Singapore dollars per KWh. This implies roughly 50 Singapore dollar per year savings for households with IHDs. Assuming a 10-year life for the real-time meter and IHD and a discount rate of 5 percent, implies a discounted present value of savings for the life of the two devices of 386 Singapore dollars.

Extrapolating these results to all Singapore residential electricity consumers implies that rolling out real-time meters and IHDs to all Singapore households would more than pay for the cost this policy and therefore yield significant net benefits to the Singapore economy. In 2012, total household electricity sales in Singapore was 6,640 gigawatt-hours (GWh). four percent of that figure is 267 GWh. Valuing these annual savings at 0.279 Singapore dollars per KWh implies an annual savings of 74.2 million Singapore dollars. Assuming these annual savings last for the assumed 10-year life of the real-time meter and IHD, and applying a 5 percent discount rate to these savings yields a discounted present value of savings of more than 568 million Singapore dollars.

These results reinforce the importance of actionable information provided in a timely fashion to encouraging more efficient consumption of electricity by households. Kahn and Wolak (2012) found similar magnitudes of electricity savings from providing households with information about the nonlinear pricing schedules that households faced and how their electricity consuming actions both increase and decrease the household's monthly electricity bill computed using this nonlinear price schedule.

The installation of interval meters and IHD device leaves open the opportunity to capture further demand-side savings. By implementing dynamic pricing plans where the price a household pays for electricity varies with the hourly wholesale price can increase the potential savings that consumers can achieve from these technologies. As Wolak (2011) and (2007) demonstrates, dynamic pricing programs can produce 10 to 20 percent reductions in electricity demand during peak hours of the day and these programs are only technologically feasible if the household have a real-time meter.

7 Conclusions

This paper evaluates the efficacy of real-time usage feedback to households. EMA's IES Pilot provides the ideal environment to study the impact of real-time usage and cost feedback on a household's electricity consumption. A simple difference-in-difference estimator applied to a variety of samples of treatment and control households shows that IHD units are associated with a 4 percent reduction in consumption. This translates into a 50 dollar per year saving in electricity consumption per household. Scaling these savings to all households in Singapore yields substantial aggregate benefits associated with the widespread adoption of these devices. The results of this analysis are consistent with those obtained from other information provision experiments. They also suggest that even greater savings are possible if dynamic pricing programs were adopted for households with interval meters.

8 References

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1 Pre-Treatment Balance

1.1 Sample Sizes

	PREMISE_TYPE				
Streetname	HDB03	HDB04	HDB05		Total
	No.	No.	No.	No.	No.
PUNGGOL DR	630.0	3,892.0	82.0	10.0	4,614.0
PUNGGOL FIELD	0.0	8,455.0	19,871.0	56.0	28,382.0
PUNGGOL PL	953.0	6,550.0	146.0	12.0	7,661.0
PUNGGOL RD	534.0	2,785.0	96.0	10.0	3,425.0
	7,322.0	147,268.0	126,003.0	1,740.0	282,333.0
Total	9,439.0	168,950.0	146,198.0	1,828.0	326,415.0

1.2 All Dwelling Types

	Treatment Group		
mos	**Meter Only** Mean Daily Usage	**Treated** Mean Daily Usage	**K-S Test** ($H_0 : (1) == (2)$) P-Value
Jan2011	11.921	12.359	0.299
Feb2011	12.004	12.461	0.322
Mar2011	12.629	12.789	0.666
Apr2011	12.659	12.755	0.753
May2011	14.123	14.518	0.472
Jun2011	14.226	14.564	0.490
Jul2011	14.409	15.276	0.111
Aug2011	14.438	15.081	0.183
Sep2011	13.453	13.719	0.445
Oct2011	13.366	13.662	0.482
Nov2011	12.427	12.216	0.175
Dec2011	12.331	12.163	0.260
Jan2012	12.802	12.435	0.059
Feb2012	12.859	12.504	0.108
Mar2012	13.255	13.430	0.231
Apr2012	13.290	13.595	0.184

	treatment_group		
mos	**Meter Only** Count dailywtd	**Treated** Count dailywtd	**Total** Count dailywtd
Jan2011	884	113	997
Feb2011	887	113	1000
Mar2011	893	115	1008
Apr2011	897	116	1013
May2011	909	116	1025
Jun2011	915	116	1031
Jul2011	923	117	1040
Aug2011	937	119	1056
Sep2011	946	120	1066
Oct2011	954	120	1074
Nov2011	963	121	1084
Dec2011	977	122	1099
Jan2012	982	123	1105
Feb2012	989	124	1113
Mar2012	996	124	1120
Apr2012	1001	125	1126
Total	15053	1904	16957

1.3 HDB04

	Treatment Group		
mos	**Meter Only** Mean Daily Usage	**Treated** Mean Daily Usage	**K-S Test ($H_0 : (1) == (2)$)** P-Value
Jan2011	11.046	11.651	0.611
Feb2011	11.100	11.635	0.828
Mar2011	11.707	11.865	0.984
Apr2011	11.793	11.752	0.976
May2011	12.955	13.919	0.880
Jun2011	13.066	14.038	0.895
Jul2011	13.236	14.570	0.832
Aug2011	13.297	14.533	0.880
Sep2011	12.339	13.404	0.566
Oct2011	12.299	13.319	0.566
Nov2011	11.344	11.921	0.611
Dec2011	11.272	11.865	0.713
Jan2012	11.631	12.049	0.469
Feb2012	11.655	12.211	0.792
Mar2012	11.963	12.676	0.635
Apr2012	11.954	12.974	0.587

	treatment_group		
mos	**Meter Only**	**Treated**	**Total**
	Count dailywtd	Count dailywtd	Count dailywtd
Jan2011	269	36	305
Feb2011	270	36	306
Mar2011	273	37	310
Apr2011	274	38	312
May2011	277	38	315
Jun2011	279	38	317
Jul2011	279	38	317
Aug2011	281	38	319
Sep2011	283	38	321
Oct2011	283	38	321
Nov2011	284	38	322
Dec2011	287	39	326
Jan2012	288	40	328
Feb2012	288	40	328
Mar2012	289	40	329
Apr2012	292	40	332
Total	4496	612	5108

1.4 HDB05

	Treatment Group		
mos	**Meter Only** Mean Daily Usage	**Treated** Mean Daily Usage	**K-S Test** ($H_0 : (1) == (2)$) P-Value
Jan2011	12.304	12.690	0.087
Feb2011	12.400	12.848	0.141
Mar2011	13.035	13.227	0.312
Apr2011	13.040	13.244	0.360
May2011	14.634	14.809	0.616
Jun2011	14.735	14.819	0.688
Jul2011	14.917	15.615	0.121
Aug2011	14.927	15.338	0.201
Sep2011	13.928	13.866	0.365
Oct2011	13.815	13.821	0.351
Nov2011	12.880	12.351	0.106
Dec2011	12.772	12.303	0.124
Jan2012	13.288	12.621	0.253
Feb2012	13.354	12.644	0.243
Mar2012	13.783	13.789	0.225
Apr2012	13.840	13.887	0.184

mos	treatment_group		
	Meter Only	**Treated**	**Total**
	Count dailywtd	Count dailywtd	Count dailywtd
Jan2011	615	77	692
Feb2011	617	77	694
Mar2011	620	78	698
Apr2011	623	78	701
May2011	632	78	710
Jun2011	636	78	714
Jul2011	644	79	723
Aug2011	656	81	737
Sep2011	663	82	745
Oct2011	671	82	753
Nov2011	679	83	762
Dec2011	690	83	773
Jan2012	694	83	777
Feb2012	701	84	785
Mar2012	707	84	791
Apr2012	709	85	794
Total	10557	1292	11849

2 Average Treatment Effects

Treatment (IHD == 1, Meter == 1)
Control (IHD == 0, Meter == 1)

2.1 All Dwelling Types

	(1)	(2)	(3)	(4)
	ate_levels	ate_levels_clust	ate_logs	ate_logs_clust
did_ihd	-0.475***	-0.475*	-0.0379***	-0.0379*
	(0.141)	(0.256)	(0.0143)	(0.0228)
Observations	22252	22252	22232	22232

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	treated		
Premise type	**0**	**1**	**Total**
HDB04	222	29	251
HDB05	592	67	659
Total	814	96	910

2.2 HDB04

	(1)	(2)	(3)	(4)
	ate4_levels	ate4_levels_clust	ate4_logs	ate4_logs_clust
did_ihd	-0.233	-0.233	-0.0220	-0.0220
	(0.232)	(0.430)	(0.0262)	(0.0397)
Observations	6590	6590	6571	6571

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2.3 HDB05

	(1)	(2)	(3)	(4)
	ate5_levels	ate5_levels_clust	ate5_logs	ate5_logs_clust
did_ihd	-0.587***	-0.587*	-0.0448***	-0.0448
	(0.176)	(0.317)	(0.0172)	(0.0279)
Observations	15662	15662	15661	15661

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3 Average Treatment Effects – Interactions

3.1 Treatment x Month

	(1) levels	(2) levels_clust	(3) logs	(4) logs_clust
did_ihd	-0.928***	-0.928**	-0.0841**	-0.0841*
	(0.323)	(0.412)	(0.0329)	(0.0476)
did_ihd=1 x Jan 2013	0.563	0.563	0.0610	0.0610
	(0.379)	(0.350)	(0.0386)	(0.0411)
did_ihd=1 x Feb 2013	0.532	0.532	0.0505	0.0505
	(0.380)	(0.372)	(0.0386)	(0.0458)
F(Jan==Feb==0)	.29	.27	.27	.24
Observations	22252	22252	22232	22232

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.2 Treatment x Survey Respondent

	(1) levels	(2) levels_clust	(3) logs	(4) logs_clust
did_ihd=1	-0.200	-0.200	-0.0163	-0.0163
	(0.162)	(0.279)	(0.0165)	(0.0255)
did_ihd=1 × pre_survey_respondant=1	-1.033***	-1.033*	-0.0815***	-0.0815*
	(0.304)	(0.591)	(0.0309)	(0.0470)
Observations	22252	22252	22232	22232

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	pre_survey_respondant		
treated	**0**	**1**	**Total**
0	719	95	814
1	76	20	96
Total	795	115	910

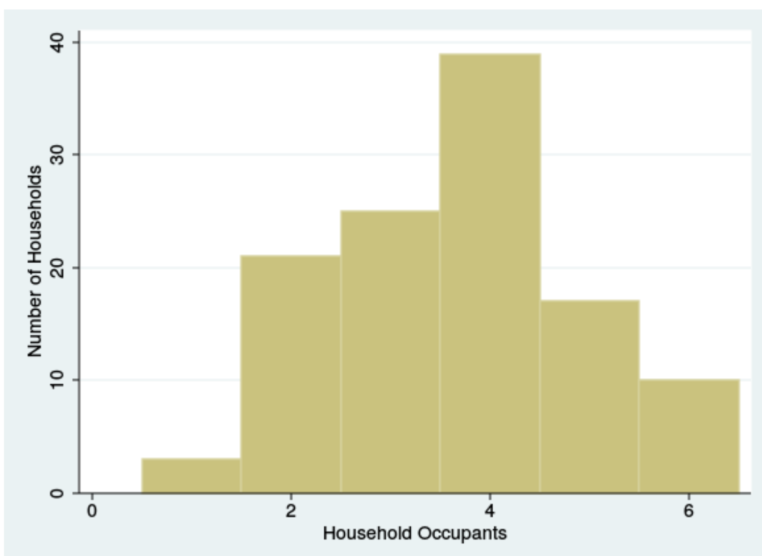
3.3 Treatment x Number of Occupants

	(1) levels	(2) levels_clust	(3) logs	(4) logs_clust
did_ihd=1	-0.199	-0.199	-0.0162	-0.0162
	(0.162)	(0.279)	(0.0165)	(0.0256)
did_ihd=1 × pre_survey_respondant=1	2.407***	2.407*	0.114	0.114
	(0.778)	(1.455)	(0.0792)	(0.119)
did_ihd=1 x Number of Occupants	-0.915***	-0.915**	-0.0521***	-0.0521*
	(0.190)	(0.447)	(0.0194)	(0.0278)
Observations	22252	22252	22232	22232

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Number of Occupants Per Household



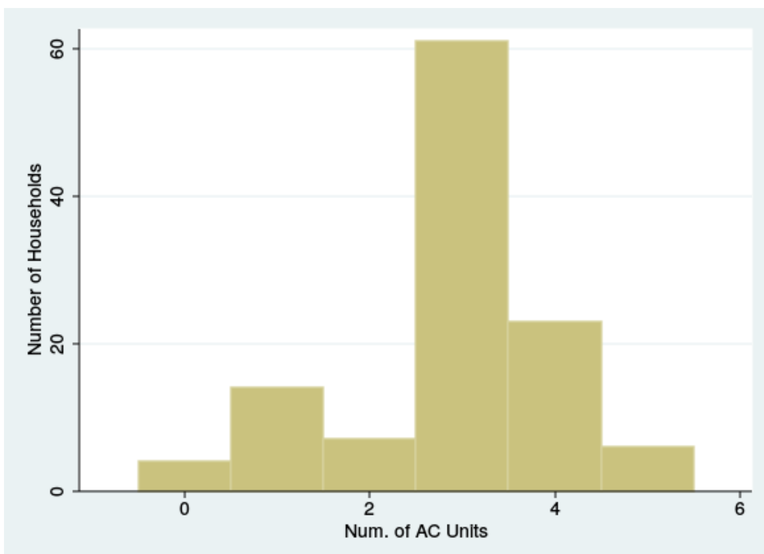
3.4 Treatment x Number of AC Units

	(1) levels	(2) levels_clust	(3) logs	(4) logs_clust
did_ihd=1	-0.200	-0.200	-0.0163	-0.0163
	(0.162)	(0.279)	(0.0165)	(0.0255)
did_ihd=1 × pre_survey_respondant=1	-0.216	-0.216	-0.0647	-0.0647
	(0.743)	(0.885)	(0.0756)	(0.0942)
did_ihd=1 x Number of AC Units	-0.282	-0.282	-0.00582	-0.00582
	(0.234)	(0.296)	(0.0238)	(0.0273)
Observations	22252	22252	22232	22232

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 2: Number of Air Conditioner Units Per Household



3.5 Treatment x Income Bracket

	(1)	(2)	(3)	(4)
	levels	levels_clust	logs	logs_clust
did_ihd=1	-0.200	-0.200	-0.0162	-0.0162
	(0.162)	(0.279)	(0.0165)	(0.0256)
did_ihd=1 × pre_survey_respondant=1	-1.880***	-1.880	-0.131**	-0.131*
	(0.518)	(1.477)	(0.0528)	(0.0748)
did_ihd=1 x Inc = $3001 - $6000	0.621	0.621	0.00939	0.00939
	(0.666)	(1.616)	(0.0678)	(0.101)
did_ihd=1 x Inc <$1500	1.309	1.309	0.0638	0.0638
	(0.956)	(1.715)	(0.0973)	(0.106)
did_ihd=1 x Inc >$6000	1.789**	1.789	0.143**	0.143
	(0.697)	(1.583)	(0.0709)	(0.105)
Observations	22252	22252	22232	22232

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Income	**Count**
$1501 to $3000	17
$3001 to $6000	42
= $1500	8
>$6000	48
Total	115

3.6 Treatment x Level of Education

	(1) levels	(2) levels_clust	(3) logs	(4) logs_clust
did_ihd=1	-0.201	-0.201	-0.0162	-0.0162
	(0.162)	(0.279)	(0.0165)	(0.0256)
did_ihd=1 × pre_survey_respondant=1	-3.160***	-3.160***	-0.199*	-0.199***
	(1.042)	(0.288)	(0.106)	(0.0663)
did_ihd=1 x No Qualificaiton	4.001**	4.001***	0.259	0.259***
	(1.695)	(0.103)	(0.173)	(0.0620)
did_ihd=1 x Polytechnic	1.230	1.230	0.100	0.100
	(1.172)	(1.882)	(0.119)	(0.113)
did_ihd=1 x Secondary	2.103*	2.103***	0.00730	0.00730
	(1.193)	(0.591)	(0.121)	(0.122)
did_ihd=1 x Univseriity	2.664**	2.664***	0.171	0.171**
	(1.095)	(0.547)	(0.111)	(0.0802)
Observations	22252	22252	22232	22232

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Education	**Count**
No Qualification	1
Polytechnic	32
Primary	3
Secondary	13
University	66
Total	115

3.7 Treatment x Attitude Towards Saving Energy

	(1) levels	(2) levels_clust	(3) logs	(4) logs_clust
did_ihd=1	-0.200	-0.200	-0.0163	-0.0163
	(0.162)	(0.279)	(0.0165)	(0.0255)
did_ihd=1 × pre_survey_respondant=1	-1.571***	-1.571**	-0.123***	-0.123**
	(0.349)	(0.756)	(0.0355)	(0.0597)
did_ihd=1 x Save Energy if Not Hard Work	1.770***	1.770**	0.136**	0.136**
	(0.566)	(0.767)	(0.0576)	(0.0588)
Observations	22252	22252	22232	22232

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Attitude	**Count**
I save energy even if it means hard work	62
I save energy if it does not require hard work	53
Total	115

4 Post-Treatment Survey

	post_survey_respondant		
treated	**0**	**1**	**Total**
0	658	156	814
1	96	0	96
Total	754	156	910