Nudges by School Children and Electricity Conservation: Evidence from the "Project Carbon Zero" Campaign in Singapore

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Abstract

Can children effectively nudge their parents to change their energy consumption behavior? This study sets up a *quasi-experiment* using the "Project Carbon Zero" campaign, an energy-saving contest in Singapore, to empirically test the effectiveness of school children nudges in bringing electricity conservation messages home and influencing behaviors of their families and neighbors. Based on the 2 kilometers (km) home-school distance as an identification, our results show that families living within 2 km from participating schools (treatment group) used 1.8% less electricity at the block level than other families outside the 2 km school zone (control group) during the contest period. The electricity savings effects are persistent with an estimated marginal savings 1.6% in the post-campaign months. The results imply that policy makers and advocates for energy conservation could use school children nudges in public campaigns, instead of pecuniary interventions, to drive home behavioral changes in electricity conservation of families.

Keywords: *Energy conservation; Behavioral Intervention; Peer effects; Income Effect; Selective intervention*

JEL Code: D1, D4, R2, R3

1. Introduction

Behavioral intervention is an effective way of organizing collective actions in energy conservation, even in the absence of pecuniary incentives. The research in this field has attracted increasing interest in the economic literature. There are various non-pecuniary nudges being used to inculcate voluntary commitments in individuals for energy conservation, which include public appeals (Pallak and Cummings, 1976; Katzev and Johnson, 1983; Reiss and White, 2008) and peer comparisons (Allcott and Roger, 2014; Ayres et al., 2013; Costa and Kahn, 2013). Getting children to nudge their families to follow good electricity consumption practices is also an effective way of organizing voluntary commitments in conserving energy. Using an energy-saving contest in a quasi-experiment, this study aims to test the effects of nudges by school children in driving behavioral changes of their families in energy conservation in Singapore.

Households account for about 15% of the total electricity consumption in Singapore.[1] Therefore, understanding how behavioral interventions could be effectively applied to reduce electricity consumption of households has important implications from the public policy perspective. In April 2008, the National Environment Agency (NEA), a government agency entrusted with the roles of promoting resource efficiency and conservation, launched the "10% Energy Challenge" campaign to challenge households to reduce energy consumption by 10% or more. In the campaign, the NEA organized road shows, media events and exhibitions, and sent households brochures on energy-saving tips to encourage households to practice energy-saving habits. The NEA also partnered with the Singapore Environment Council (SEC)[2] to organize an energy-saving contest known as "Project Carbon Zero" for primary and secondary schools in Singapore.

We set up a policy experiment using housing block-level electricity consumption data and a list of schools participating in the 2009 contest provided by the NEA to test if behavioral interventions via school children's nudges are effective in reducing electricity consumption of

[1] Refer to the statistic in the Singapore Energy Statistics 2014 report by the Energy Market Authority (EMA). (Page 29; https://www.ema.gov.sg/cmsmedia/Publications_and_Statistics/Publications/EMA_SES%202014.pdf).

[2] The Singapore Environment Council (SEC) is a non-profit non-government organization (NGO) championing the issues relating to sustainability and environmental courses in Singapore.

Singaporean households. Based on a 2km home-school distance[3] identification strategy, we find significant savings in block-level electricity consumption for households in the treatment areas (≤2km) relative to households outside the 2km (control) areas. The energy-saving campaign creates positive behavioral intervention effects that lead to a reduction in electricity consumption by 1.8% for the treatment group during the contest period (May to August) compared to the reference period (January to April). The effects persisted into the post-contest months with an estimated energy saving of 1.6% for households in the treatment blocks relative to those in the control blocks. The results suggest that children of participating schools could nudge their family members to save electricity, and the nudging effects could also spill over to the neighbors. When we use different treatment boundaries of 1.5km and 3.0km, the results remain significant, though the intervention effects are slightly smaller during and after the contest months.

We conduct various robustness tests on the significance and persistence of the treatment effects. The results show that primary school students have stronger nudges on electricity conservation than the secondary school students during the intervention periods; however, the nudging effects by the older (secondary school) students are more persistent. Building design is also an important factor in determining the savings on electricity consumptions. More energy-efficient private housing blocks show greater response to the treatment effects relative to less energy-efficient public housing blocks. The income effects interacted with building design factor will influence households' elasticity to energy conservation. We find that low income households in less energy-efficient buildings and high income households in more energy-efficient buildings are less responsive to non-pecuniary nudges by students.

The findings of this study imply that for policy makers and advocates for energy conservation, they could design public campaigns that leverage on school children's nudges, instead of pecuniary interventions, to drive home behavioral changes in electricity conservation of households. However, the non-pecuniary interventions may be less effective on low income households in less efficient buildings. For high income households living in energy-efficient buildings, they are price inelastic to consuming electricity, and their responses to children

[3] The 2km perimeter is chosen to coincide with the primary school allocation rule of the Ministry of Education (MOE) of Singapore that gives priority in the allocation of placement to families within a 2km radius from the chosen school.

nudges are stickier. Different forms of nudges may be required to change their electricity consumption behaviors.

The remainder of this paper is organized as follows. Section 2 introduces the related studies and Section 3 describes "Project Carbon Zero", an energy-saving contest launched in conjunction with the "10% Energy Challenge" campaign, which is aimed at selected schools in Singapore. Section 4 discusses the empirical methodologies, which include the home-school distance identification strategy, data sources and empirical models. Section 5 analyzes the empirical results. Section 6 concludes with the policy implications of the study.

2. Literature Review

Using more energy-efficient appliances (Gardner and Stern, 1996) and adopting stringent building design codes (Costa and Kahn, 2011; Jacobsen and Kotchen, 2013) could reduce electricity costs. Consumers respond to sharp increases in energy prices by adopting new technologies and better building design (Reiss and White, 2005; Allcott, 2011a and 2011b). However, the net saving effects in electricity consumption are nullified, if efficiency gains are accompanied by high energy consumption by consumers. The tradeoff to efficiency gains associated with efficient technology is known as the rebound effect (Berkhout et al., 2000). The rebound effects can also be induced by a price cap intervention as observed in San Diego, which increased energy demand by 8% following the price cap's imposition (Reiss and White, 2008). Agarwal et al. (2016b) study the electricity consumption of households in response to negative externality from nearby construction sites, and find no rebound effects in electricity consumption by households after negative externalities have been removed.

Behavioral interventions through providing real-time information (Sexton et al., 1987; Jessoe and Rapson, 2013; Agarwal, et al., 2016), soliciting voluntary commitments (Katzev and Johnson, 1983), creating public appeals via media campaigns (Pallak and Cummings, 1976; Reiss and White, 2008) and instilling peer comparisons (Nolan et al., 2008; Schultz et al., 2007; Allcott and Roger, 2014; Ayres et al., 2013; Costa and Kahn, 2013) provide effective nudges to inculcate and promote more sustainable electricity consumption behaviors in households. Governments and public utilities organize various media campaigns to change individual electricity consumption behavior without distorting private incentives (Pallak and Cummings, 1976; Katzev and Johnson, 1983; Reiss and White, 2008). Opower's home electricity reports

(HER)[4] have been used to create effective social comparisons to encourage households to reduce electricity consumption (Nolan et al., 2008; Schultz et al., 2007; Allcott 2011; Thaler and Sunstein, 2008; Allcott and Mullainathan, 2010; Ayres et al., 2013; Costa and Kahn, 2013; Allcott and Rogers, 2014). Allcott (2011) shows that the non-price intervention program significantly reduces energy consumption by 2%. In a separate study, Winett et al. (1978) show that households who received an energy audit used 21% less electricity relative to the control group. Hirst and Grady (1982) find that households saved 1% to 2% more on gas usage than the control group.

Unlike the behavior interventions that aim at promoting energy conservation such as Opower's HER, providing real-time information on consumption is another form of nudging widely used in energy-related behavioral intervention experiments (Sexton et al., 1987; Jessoe and Rapson, 2013). In one of the demand response programs that aim at cutting down peak-hour consumption, Jessoe and Rapson (2013) conducted a randomized controlled trial (RCT) that attempts to isolate the salience effect from pricing elasticity of households. In the RCT, they installed in-home devices to display real-time electricity usage and costs to the treatment households, and exposed the treatment households to price increases of 200 to 600 percent at the same time. They show that providing feedback about residential electricity usage significantly increases the price elasticity of demand. They show that the group that is subject to the price treatment and also provided with real time feedback achieved 8% to 22% reduction in electricity consumption relative to the control group. Agarwal et al., (2016a) conducted a RCT on water used in shower by installing 828 smart shower devices, known as "Amphiro", for 525 households in Singapore; and they find that real time information reduces water usage during shower by 9.3% per shower.

Commitment and goal setting (antecedent interventions) are effective nudges in reducing energy consumption, when used in combination with other interventions (Becker, 1978; Katzev and Johnson, 1984; McCalley and Midden, 2002; Abrahamse et al., 2005). In Becker's goal-setting experiments, households who received a challenging goal (20% reduction of electricity usage) conserved 15.1% more electricity than households with an easy goal (2% reduction). Consequence interventions in the forms of monetary rewards and incentives can also be used

[4] Opower uses home electricity reports (HER), which are personalized energy reports containing information on energy use, to provide social comparisons in its efforts to promote energy conservation.

to motivate households to conserve energy (Winett et al, 1978; McClelland and Cook, 1980).

3. “10% Energy Challenge” Campaign

The NEA[5] has organized the “10% Energy Challenge” campaign in Singapore since April 2008 to encourage families to embrace an energy-efficient lifestyle at home, and take up environmental ownership and care for the environment as a way of life. During the campaign, the NEA organized road shows and media events, and sent households information kits on energy-saving tips to raise public awareness on energy-efficient appliances and inculcate energy conservation habits (antecedent interventions).

As part of the campaign, the NEA partnered with the Singapore Environment Council (SEC) in organizing the “Project Carbon Zero” competition, targeting school children. The competition sets a goal for students to reduce overall electricity usage at home by 10% or more. In the participating schools, teachers in science and social studies classes would educate students on the importance of energy conservation, and share with them specific energy-saving tips and advices. For instance, students are advised not to leave appliances on standby mode, and to set their air-conditioners at 25°C to save energy at home. Students are expected to bring these energy-saving messages home and nudge their family members to do their parts in reducing electricity usage.

60 schools consisting of 36 primary schools and 24 secondary schools participated in the 2009 competition. Students are required to bring their monthly household electricity bills to school[6] for verification and tracking purposes. During the competition, students of the participating schools report their electricity consumption for the months before and after the announcement of the competition from January 2009 to August 2009 via a designated website. Students’ entries are also used for the inter-school and the intra-school categories of the competition. The school-level competition is based on the aggregate of electricity savings from participating

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[5] The National Environment Agency (NEA) is a government agency formed in 2002 and entrusted with the responsibilities to improve and promote a sustainable clean and green environment in Singapore.

[6] Singapore Power (SP) is the corporation that owns and operates electricity and gas transmission and distribution businesses, and provides energy market support services in Singapore. The SP Services division sends electricity bills once a month to its customers, and the bills are sent out on the same day. However, utility meter readings are only done once every two months. For the month when the meters are not read, the bill is estimated based on the last two actual meter readings. We conduct further robustness tests to explicitly deal with adjustment errors, if any, in the billing cycles when meter readings are not done.

students' families. Prizes and certificates are given to the top three students with the largest reduction in electricity bills and the top three schools with the largest number of students who reduce at least 10% in electricity bills during the contest months. Book vouchers are given to reward students who achieve 10% or more reduction in electricity bills during the contest period.

The total electricity consumption in kilowatt hour (kWh) for each participating student's family is calculated for the two different 4-month periods. The reference period is before the announcement of the competition from January to April, and the treatment period is from May to August. The difference in total electricity consumption between the two periods is then computed. For example, the following electricity consumption data (in kWh) was submitted by one of the participating families:

Reference period: January to April				
January	February	March	April	Total
239	234	214	257	944
Comparison period: May to August				
May	June	July	August	Total
252	182	210	149	793

Source: NEA

A total reduction in the electricity consumption for the 4-month comparison (treatment) period is computed at 151 kWh, which is equivalent to 16.0% of the electricity consumption in the reference period from January to April.

In the 2009 "Project Carbon Zero" contest, 291 students from 30 participating schools submitted electricity consumption bills for the full periods from January to August (Table 1). Participation by students are voluntary. Based on the 30 participating schools' data, 18.90% of the participating families recorded reductions in electricity bills in the contest (treatment) period relative to the base period, and only 4 primary schools and 2 secondary schools (3.78% of the total sample) saved more than 10% in electricity bills. Given an increasing trend in electricity consumption during the typical hot months from April to August in Singapore

(Department of Statistics, Singapore, 2010), the low saving effects recorded in the contests are not unexpected.

[Insert Table 1 here]

4. Experimental Design and Data

4.1. Identification Strategy

The home energy reports by Opower use non-pecuniary interventions to encourage energy conservation in the US; the "Project Carbon Zero" contest, however, uses nudges of school children to inculcate good energy consumption habits at home. School children participating in the energy-saving contest are encouraged to follow good energy saving tips and also influence their family members to save electricity at home. Like in some media campaigns in the US (Reiss and White, 2008; Costa and Kahn, 2013), the behavior intervention effects could spill over through social interactions to their neighbors, which may indirectly impact energy savings at the block level. However, the children are less likely to influence the behavior of families living outside their school zones. Therefore, the nudging effects are likely to be stronger in neighborhoods that are located close to the participating schools, and the home-school distance is a reasonable identification to capture the treatment effects.

In Singapore, the Ministry of Education (MOE) employs a distance-based policy that gives priority in school allocation to students living within a 2km radius from a school.[7] Agarwal et al. (2016c) also show that there is a strong preference of parents to enroll their children to schools that are close to their homes. Therefore, in the absence of the home address data of participating students, the home-school distance (DISTANCE) that demarcates a school attendance zone is a reasonable identification to spatially define the treatment areas within which energy saving messages from school children participating in the contest have the most direct impact on families living within this zone.

In the baseline model, we use the 2km home-school distance to sort the sample housing blocks into the treatment group, where students living in these blocks are subject to the treatment of the energy-savings contest; and other housing blocks outside the 2km school zone are sorted into the control group. The two groups are identified by a dummy variable, "TREAT", which

[7] All the schools involved in the "10% Energy Challenge" are public schools.

has a value of 1 if a sample is subject to the interventions (DISTANCE ≤ 2km), and 0 otherwise for the control group (DISTANCE > 2km). As Yangzheng Primary School, one of the participating schools, is located far from housing neighborhoods and has thin matched data on housing block-level electricity consumption, it is dropped from our tests. The final sample in our experiment includes only 29 participating schools (indicated by red triangles in Figure 1).

[Insert Figure 1 here]

As the home-school distance rule is not applicable to secondary schools, the 2km boundary is a lower bound of the treatment effects for secondary school students. Robustness tests are conducted to test the treatment effects using different home-school distances. We also conduct additional tests that use only primary school samples to allow for a cleaner identification of the treatment effects.

4.2. Data on Electricity Consumption

We obtain the monthly electricity consumption data for a large sample of 5,320 public (HDB[8]) and 2,750 private (condominiums and apartments) housing blocks from the NEA. The electricity consumption data are aggregated on a monthly basis at the block (building) level for a 12-month period from January to December in 2009. Figure 2 shows the geographical distributions of the private and public housing blocks and the participating schools. We define two time dummies: (i) "TEST_TIME" that has a value of 1 for the contest period from May to August, and 0 otherwise, and (ii) "POST_TIME" that has a value of 1 for the post-intervention period from September to December, and 0 otherwise. The "TEST_TIME" dummy captures the contemporary intervention effects, and the "POST_TIME" dummy measures the persistence of the intervention effects.

[Insert Figure 2 here]

After removing the sample blocks with missing records and winsorizing the outliers[9], we keep

8 The Housing and Development Board (HDB) is a government agency that is responsible for developing and selling affordable housing flats to eligible Singaporean citizens at concessionary prices. Only Singaporean families with a monthly household income of less than S$10,000 are eligible to apply for new HDB flats.

9 We winsorize the 20th percentile samples at both tails, and reduce the variations in electricity consumption to a range between 16,392 kWh and 65,569 kWh. In our robustness tests, we use stricter winsorization criteria that remove the 25th percentile, 30th percentile, 35th percentile and 40th percentile of the samples at the two

a final sample of 6,631 blocks, which include both the treatment and the control blocks, with 69,257 block-month observations. Figure 3 shows that electricity consumption followed a normal distribution with a median electricity consumption of 41,613 kWh.[10] Figure 4 shows the changing patterns of the average (unconditional) monthly electricity consumptions (kWh) at the block-level for the treatment and control groups for the full experiment periods from January to December 2009. The lowest average monthly energy consumption (kWh) was estimated in February 2009, and the highest average energy consumption month was estimated in June 2009. The household electricity consumption is generally lower in the first four months of the year from January to April, compared to the months from May to August. As May to August are the hottest months in Singapore and families are likely to use more air-conditioning,[11] the high average monthly electricity consumptions from May to August could be correlated with the hot weather and increased use of air-conditioning during the period.

[Insert Figures 3 and 4 here]

When we sort the block-level monthly average electricity consumption by the treatment and control groups, families living close to the schools participating in the energy-saving contest consistently consume less electricity than other families that are not likely to be influenced by the contest. We observe a consistent pattern in electricity consumptions between the two groups in the pre-intervention months (January to April), but the consumption gap widens after May 2009. The two vertical lines in the chart mark the energy-saving contest periods.

The NEA electricity consumption data do not contain building attributes, such as building height, number of housing units, housing unit size and household income. We use the six-digit postal code fixed effect to control for the heterogeneity of building. In Singapore, each housing block is identified by a unique six-digit postal code.

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tails. The marginal intervention effects remain significant, and the signs are correct. Due to space constraints, the results are not presented in the paper.

[10] Based on the Singapore's Energy Statistics, the (overall) average monthly household electricity consumption in 2012 was 476.6 kWh, and the median block-level electricity consumption of 41,613 kWh. The two statistics translate into an approximately 87 households per block, on average.

[11] The household energy consumption profiling survey conducted by the NEA under the Energy Efficient Singapore ("E2 Singapore") initiative shows that air-conditioning accounts for 36.7% of the total electricity consumption of a typical Singaporean home. Source: (http://app.e2singapore.gov.sg/DATA/0/docs/Voluntary%20Agreement/Household/Executive%20Summary%20%20Key%20Findings.pdf).

4.3. *Empirical Model Specifications*

The "Project Carbon Zero" contest is a public campaign aimed at bringing good electricity saving habits to families through school children. We use the 2km home-school radius to sort the housing blocks located within the 2km boundary into the treatment group denoted by "TREAT =1", and those located outside the 2km zone as the control group denoted by "TREAT =0". We test the intervention effects by comparing the energy savings of these two groups of housing blocks between the intervention period from May to August ("TEST_TIME =1") and the reference period from January to April, and the persistence of the intervention effects into the post-contest months, ("POST_TIME = 1"), using the two interactive terms, ("TREAT×TEST_TIME" and "TREAT×POST_TIME") in the difference-in-differences (diff-in-diff) model.

The diff-in-diff model with the log-electricity consumption of housing block *i* in month *t*, denoted by log (Y_{it}), as the dependent variable is defined as:

$$Log(Y_{it}) = \alpha_1 + \beta_1(\text{TREAT}) + \beta_2(\text{TEST\_TIME}) + \beta_3(\text{TREAT} \times \text{TEST\_TIME}) + \beta_4(\text{TREAT} \times \text{POST\_TIME}) + \beta_5(PRIVATE) + \lambda_i + \varepsilon_{it} \quad (1)$$

where α_i is an intercept term; ε_{it} is an *i.i.d* error term; and [$\beta_1, \beta_2, \beta_3, \beta_4$] are estimated coefficients that capture both the spatial-dependent and the time-dependent intervention ("treatment") effects. We control for the housing type using a dummy variable, "PRIVATE", to differentiate between public (PRIVATE =0) and private (PRIVATE =1) housing blocks. We control for unobserved spatial heterogeneity in the building-level electricity consumption using either the 2-digit housing block postal code (district level) or the 6-digit school location postal code (school level), which is also known as the fixed effects, (λ_i), in the model. The model is estimated using both the Ordinary Least Square (OLS) estimator that imposes a strict heteroscedastic error restriction, and the Generalized Linear Model (GLM) that allows for correlated error terms.

β_2, if not significantly different from zero, captures seasonal variations in electricity consumptions between the treatment months (May to August) and the other months in the year. The three hypotheses are defined to test the treatment (intervention) effects of the energy saving contest: First, [$\beta_1 = 0$], if significantly rejected, shows positive intervention responses of families participating in the energy saving contest ("treatment group") by reducing their energy consumption relative to families of non-participating schools ("Control group"). Second, $[\beta_3 = 0]$, if significantly rejected, implies that the public campaign creates effective behavioral interventions on students' families in the treatment area with significantly larger reductions in electricity consumptions relative to other families in the control areas. Third, $[\beta_4 = 0]$, if significantly rejected, shows persistence in behavioral interventions for the "treatment" families that continue to embrace good practices in energy conservation in the post-contest period. However, instead of changing the energy consumption habits, our results could not rule out the possibility that the contest may have motivated families of participating school children to switch to more energy efficient installations at home and make permanent shifts in energy saving behaviors.

The behavioral intervention effects of the energy-saving campaign hinge strongly on the 2km distance used in our identification strategy. We conduct robustness tests by other "DISTANCE" measures: 1 km to 1.5km (lower bound) and 3 km to 3.5km (upper bound), to verify the spatial-bound treatment effects. As the MOE applies the distance-based prioritization rule only to primary school allocations, the distance identification is likely to be stronger for primary schools. We further test this presumption by dropping the secondary schools from the sample.

5. Empirical Results

5.1. Base Regression Results

Each of our sample housing blocks is geo-coded; and the shortest distance of housing blocks to one of the 29 treatment schools participating in the energy-saving contest is measured. Table 2 shows the results of the log-electricity consumption regression models with the treatment effect identified by the 2km home-school distance, ["TREAT =1, if DISTANCE≤ 2km" and "TREAT=0, if 2km < DISTANCE ≤ 5km"]. We control for boundary discontinuity by setting a 5-km outer boundary for the control group such that the sample blocks located outside the 5-km boundary are not included in the regression estimation.

[Insert Table 2 here]

Columns (1) to (3) of Table 2 present the results for the baseline models, where column (1) is estimated using OLS estimator, and columns (2) and (3) are estimated using the GLM estimator. The "Treat" coefficients are statistically insignificant, which suggest that the average electricity consumptions between the treatment group and the control group are not different without interventions. The two time dummies representing the contest periods ("TEST_TIME") and the post-contest periods ("POST_TIME") are statistically significant and position indicating an uptrend in electricity consumption after the reference period (January to April), where electricity consumptions increase by 11.1% and 7.3%, on average, in the May-August and the September-December periods, respectively.

The coefficients on the two interactive variables ("TREAT×TEST_TIME" and "TREAT×POST_TIME") are statistically significant at less than the 1% level, and the coefficient signs are negative. The results show significant behavioral intervention effects in the experiment. The treatment households respond to the behavioral interventions of the energy-saving contest by using 1.8% less electricity at the block-level per month relative to the control households. The treatment effects persist with an average saving of 1.6% in monthly electricity bills for housing blocks near the participating schools relative to housing blocks in the control group in the post-contest months (September to December). There is no attenuation in the treatment effect after the contest period.

We control for unobserved heterogeneity using the district (two-digit postal code of the housing blocks) (Column 2) and the school location (six-digit postal code of the treatment schools) (Column 3) fixed effects, respectively, in the GLM models. The intervention effects are still significant, and the coefficients remain the same in both the contest (-1.8%) and the post-contest (-1.6%) periods. We do not reject the hypothesis that school children participating in the "Project Carbon Zero" contest effectively nudge their families to embrace good energy saving habits and reduce the electricity consumptions during the contest and the post-contest periods.

The coefficients on the private housing type dummy ("PRIVATE") are statistically significant and positive in all three models indicating that the electricity consumption in private housing blocks is 28% lower than in the public housing blocks. The results could possibly be related to building design factor, where public housing blocks are usually high-rise and densely built containing more housing units in each block. More robustness tests are included in the subsequent section.

In Singapore, the SP Services, a division of SP, sends electricity bills to its customers once a month, and the bills are sent out on the same day. However, utility meters are only read once every two months. For the months when the meters are not read, the bill is estimated based on the last two months' meter readings. Customers could also opt to submit their meter readings through the self-help channels. Adjustments to estimation errors in billing cycles are made in the following month, when meter readings are done. The two-month reading frequency and the billing cycle apply consistently to housing blocks in the same neighborhood that are billed on the same day, but they could be different for housing blocks in different neighborhoods.[12] We conduct two additional tests to avoid biased results caused by possible meter-reading errors.[13]

Columns (1) to (3) of Table 3 repeat the estimation of Models in Table 2, but we exclude the May and August data, which are more likely to be subject to meter-reading errors in the adjustment months. The results are consistent except that the treatment effects are slightly lower at about 1.6%, compared to 1.8% in the early baseline models (Table 2) during the contest months. In columns (4) to (6) of Table 3, we use the bi-monthly aggregated electricity data, where we treat the odd month as the estimated month, and the even month as the actual meter-reading month, to reduce errors in electricity bill estimations. The estimated coefficient of 1.8% during the contest period is not significantly different from that found in Table 2 reaffirming that the intervention effects are still significant.

[Insert Table 3 here]

5.2. Home-School Distance

In our robustness tests, we experiment with two different distance measures (1.5km and 3.0km) to separate the treatment area from the control area, and repeat the early log-electricity consumption models. While we could use a tighter home-school distance of 1.5km, instead of the 2km, to improve the treatment intensity, the tighter treatment area may also exclude some

[12] For example, for the treatment neighborhoods that have June's electricity meters estimated from April (actual reading) and May (estimated March and April readings) bundled data, June's reading could be over-estimated for the treatment blocks relative to the control blocks. The meter reading errors could cause the under-estimation of actual treatment effects.

[13] We would like to thank the anonymous referee for the constructive comments on the meter reading errors.

families from the school boundary. If we expand the treatment school boundary to 3km, we may risk including families with no children attending the participating schools in the treatment group.

The results in Table 4 show that while the treatment effects are significant, the savings in block-level electricity consumption for the treatment group are smaller compared to the early results in Table 2. In columns 1 to 3 of Table 4 and with a tighter intervention zone (1.5km home-school distance), we find 1.0% reduction in electricity consumption, on average, for housing blocks in the treatment area relative to those outside the treatment area. The post-treatment effects are stronger with electricity savings ranging from 1.2% to 1.3% for the treatment group. Despite having a smaller number of sample blocks in the treatment group, we cannot reject the hypothesis that the energy-saving contest generates effective student nudges that change families' electricity consumption behaviors during and after the contest periods.

[Insert Table 4 here]

When the treatment area is expanded to 3km as in columns 4 to 6 of Table 4, we find that the coefficients on the two interactive variables ("TREAT×TEST_TIME" and "TREAT×POST_TIME") are still significant and with the same negative signs. The results show that families living within 3km from the schools participating in the energy-saving campaigns consume 1.6% less monthly electricity than families that are not "treated" by the campaign. The strong persistence of the treatment effects are shown in the estimated 1.5% reduction in energy consumption after the contest months. The results reaffirm that the energy-saving campaigns create positive nudges to inculcate electricity conservation behaviors in families' of participating students.

5.3. Primary and Secondary Schools

The MOE's prioritization rules that are only applicable to primary school allocations improve the home-school distance identification for behavioral interventions on participating primary school students, but not directly on secondary school students. Nudging effects could also be different between secondary school students and primary school students because of their age. Using the 2km home-school distance measure to demarcate the treatment and control groups for the two types of schools, we test the intervention effects for the primary school and secondary school students using the same diff-in-diff regressions. The regression results are separately summarized in Table 5.

[Insert Table 5 here]

The intervention effects during the contest period from May to August are significant in both primary and secondary school models. However, the effects are stronger in the primary schools than in the secondary schools. Housing blocks within 2km from the participating primary schools (treatment) use 2.1% less electricity than other housing blocks that are not “treated” by the energy-saving contest (control). For the secondary schools, the intervention effects are significant, where housing blocks within a 2km boundary from the participating schools save 1.5% more in electricity consumption than housing blocks outside the 2km boundary. We find that the marginal electricity savings are insignificant after the contest periods implying that behavioral changes of the primary school students’ families are not persistent. The results, however, show that nudges from secondary school students are persistent. Families in the secondary school treatment zone use 2.1% less electricity in the post-campaign period than in the reference period.

In summary, the energy saving contest is effective in using nudges of school students to encourage their families and neighbors to conserve electricity during the intervention periods. However, nudges to cultivate conservation habits from elder secondary students persist even after the post-intervention period.

5.4. Building Design

The early results of the baseline models in Table 2 show that families living in public housing blocks consume 28% more electricity, on average, than families living in private housing blocks. One possible explanation for the negative coefficient on the “PRIVATE” in the log-electricity consumption models is related to building design and physical attributes of the two housing types. In the land-scarce Singapore, high-rise housing blocks are the norm for both private and public housing. Public housing is densely built with more units being built into a block to reduce development (land) costs, and ensure that public housing prices are affordable to low and median income Singaporeans. However, the government imposes stricter restrictions on the density of private housing sites. The density restrictions coupled with other controls, such as open space, high ceiling and other requirements, limit the number of units that can be built in a private housing block. Private housing units are a more expensive housing form usually equipped with more energy-efficient appliances compared to public housing units.[14] Therefore, at the building block level, building design and energy-efficient features could explain why households in public housing blocks collectively consume more electricity than households in private housing blocks. Do building design and energy-efficient fixtures influence households' responses to non-pecuniary nudges (the energy saving contest)?

We test the treatment effects by running separate log-electricity consumption regressions as in Equation (1) for the two housing types: public housing blocks ("PRIVATE" =0) and private housing blocks ("PRIVATE" =1). Table 6 shows that there were clear upward trends in the electricity consumptions in the two types of housing blocks in the contest period (TEST_TIME) and the post-contest period (POST_TIME); but the average electricity consumptions in the public housing blocks (12.2% and 8.8%) are relatively higher than in the private housing blocks (5.19% and 2.79%).

For the public housing blocks, the treatment effect (TREAT×TEST_TIME) is only significant at the 10% level in column 2 with the fixed district effect. The results show that public housing blocks near the participating schools reduce electricity consumptions by 0.9% more than other public housing blocks (control) in the contest period. However, the results show that private housing households respond more positively to the interventions, where private housing blocks within a 2km radius from the participating schools reduce average monthly electricity consumptions by 2.5% to 2.7% (Columns 4 to 6) during the intervention period, compared to other private housing blocks outside the participating school area (control).

The intervention effects on families in the public housing blocks persist in the post-intervention periods, but the magnitude of the reduction in electricity consumption in the public housing blocks is smaller ranging from 1.16% to 1.22% in the post-contest period. The persistence of a larger treatment effect with 2.4% savings in electricity consumptions was found in the private housing blocks in the post-contest period from September to December relative to the reference months, when the district fixed effects are controlled for in the model (Column 5).

[14] Studies in the US have shown that more energy-efficient buildings built under stringent building codes could offset rising energy consumption effects induced by higher income and bigger footage areas of houses (Costa and Kahn, 2010; Jacobsen and Kotchen, 2013).

The results show that the treatment effects are found in both housing types, but electricity savings in in private housing blocks are larger than in public housing blocks during the contest period. The persistence effects are also stronger in the private housing blocks, though the effects are only found when the errors are clustered within the planning district. Public housing families that consume more electricity at the housing block level have smaller elasticity to save electricity than private housing families. One possible explanation is that public housing blocks contain more units, especially those from non-participant families, which may weigh down the treatment effects. Another explanation is that families in more energy-efficient private housing blocks are more likely to adjust their electricity consumption behaviors in response to non-pecuniary nudges by their children. The results are consistent with Reiss and White (2008) that families in more energy-efficient buildings exhibit lower price elasticity to conserve electricity than families in buildings with less energy-efficient systems. However, we also could not rule out the income effects of families; and more robustness tests would be conducted in the next section.

[Insert Table 6 here]

5.5. Income Effects

The income effect hypothesis argues that differential treatment responses between private housing families and public housing families are correlated with price elasticity to changes in electricity consumption. The income effect on elasticity of electricity savings is likely to be stronger for low income families than high-income families; and the latter are more likely to respond to interventions for reasons other than economic value of energy savings. In Singapore, families living in private housing blocks have generally higher average income relative to families living in public housing blocks.[15] However, the housing type is not a clean measure of household income, and the earlier results of private housing families saving more electricity during the contest period could be correlated with the building design factor. We conduct further robustness tests to separate the building design effects from the income effects in the intervention experiments.

[15] In Singapore, public housing are developed and sold by the Housing and Development Board (HDB), the public housing agency of Singapore, to families with monthly income of not more than S$10,000 at subsidized price. The income eligibility cap is, however, not applicable to private housing purchases.

Based on a unique database of 180,000 customers of a leading bank in Singapore[16], we compute the block-level average income and merge the data into the block-level electricity consumption database using the six-digit postal code identifiers of the sample blocks. Figure 5 shows a two-way sort of the sample blocks by the 2km home-school distance ("TREAT") and the housing type ("PRIVATE") variables. The between group variations in income are significant, where the median monthly incomes of private housing families and public housing families are estimated at S$8,378 and S$4,078, respectively. However, the within group variation in income is insignificant. The income of the treatment group families (housing blocks within 2km from the participating schools) is not significantly different from the income of the control group families.

[Insert Figure 5 here]

We use the median income to separate the high-income families (the top 50th percentile housing samples), denoted by the dummy "HIGH_INCOME=1", from the low-income families, denoted by "HIGH_INCOME =0", for the respective housing type groups. We re-run equation (1) using two triple diff-in-diff terms in the models, ["TREAT×TEST_TIMES×HIGH_INCOME", "TREAT×POST_TIME×HIGH_INCOME"], and the results are shown in Table 7. The results show that the intervention effects are significant and negative for the top 50th percentile of families in public housing. After controlling for the school fixed effects (column 3), the above-median income families reduce their electricity consumption by 2.32% more during the treatment period, and by 2.80% more in the post-treatment period relative to the lower income families in public housing blocks. For private housing families, the treatment effects on the electricity consumption are significant, but the coefficients are positive at 4.58% and 4.42% during and after the intervention periods, respectively.

The results imply that the nudging effects are relatively small for the low-income public housing families (with less energy efficient design). One possible explanation is that low-income families in less energy efficient buildings (public housing) have already paid due attention to save and optimize electricity consumptions, and further reductions in electricity consumptions are less noticeable. However, for private housing blocks with more energy-

[16] We would like to thank Agarwal and Qian (2014) for sharing the block-level income data used in their paper "Consumption and Debt Response to Unanticipated Income Shocks: Evidence from a Natural Experiment in Singapore."

efficient design, high income families' elasticity to change energy consumption is stickier. The children's nudging is less effective on both the low income families living in less energy-efficient buildings (public housing) and the high income families living in more energy-efficient buildings (private housing).

6. Conclusion

Public appeals have been used to create positive behavioral interventions on household energy conservation in the US (Reiss and White, 2005 and 2008). In Singapore, the NEA, in partnership with the SEC, launched the "Project Carbon Zero" contest for primary and secondary schools in 2009. We use the data on housing block-level electricity consumption and a list of schools participating in the 2009 contest provided by the NEA to conduct a policy experiment to test the effectiveness of students' nudges in creating interventions that induce households to reduce electricity consumptions.

Using the home-school distance of students participating in the contest as an identification, we show that the energy-saving campaign is effective in reducing the block-level electricity consumptions for households living within a 2km radius of the participating schools (treatment) relative to households living outside the 2km radius of the participating schools (control). The behavioral interventions reduce electricity consumptions of the treatment group by 1.8% during the contest period from May to August relative to the reference period from January to April in 2009. The treatment effects are persistence with 1.6% electricity more savings recorded by the treatment housing blocks than the control housing blocks in the post-contest months from September to December in 2009.

In the absence of the household-level data, the use of the home-school distance as an identification may subject to some limitations; and this may yield the lower bounds for the true treatment effects in this study for several reasons.[17] First, the 2km school zone may include families that have no school going children,[18] or more specifically, those with no children

[17] We would like to thank the referee for the comments on the possible factors causing under-estimation of average treatment effects of the "Project Carbon Zero" campaign.

[18] The Census of Population Report (2010) (Source: shows that children aged between 5 to 14 years account for 12.2% of the total resident population in Singapore; and children of married households attending either a primary school or a secondary school account for 42.7% of the total resident households in 2009 (Source: Department of Statistics, Singapore, 2010). The households are evenly distributed across neighborhoods.

attending the schools participating in the contest. Second, the distance identification is not perfect. When we use 1.5km and 3km home-school distance cutoffs in the robustness tests, non-participants could be falsely assigned to the treatment group, and/or participants could be falsely assigned to the control group. However, we still find significantly negative, but conservative (weaker) treatment effects. Third, as the “Project Carbon Zero” is an event run under the “10% Energy Challenge” campaign targeting at schools, the average treatment effects could have been diluted due to other concurrent activities that have also raised the public awareness of energy conservation during the campaign period.

We conduct various robustness tests on the above results. First, we use different home-school distances (1.5km and 3km) to identify the treatment area, and find that the treatment effects remain significant. We next test the treatment effects on school children of different age groups (primary schools versus secondary schools). The nudging effects of primary school students are stronger during the contest period, but the effects of secondary school students are persistent into the post-contest period. The building design effect is also tested by splitting the housing block type into public housing blocks and private housing blocks. Private housing blocks that are less densely built and also equipped more energy-efficient fixtures are found to conserve more electricity in response to students’ nudges during the intervention period. However, the building design factor interacted with block-level household income in explaining the intervention effects. Low income families in less energy efficient public housing blocks, and high income families in more energy efficient private housing blocks have relatively inelastic responses to children nudges during the intervention period.

The “Project Carbon Zero” competition encourages students in primary schools and secondary schools to nudge their family members to conserve energy at home. During the competition, teachers teach students about the importance of energy conservation and its impact on climate change. They provide energy-saving tips for students to reduce their electricity consumption at home, and encourage them to influence energy consumption behaviors of their parents and neighbors. Energy-saving campaigns are carried out in many schools across the world, and some successful campaigns have been documented in the North America. For instance, the Campus Conservation Nationals (CCN) has organized the largest electricity and water reduction competition in the world since 2010. In the 2014 contest, 265,000 students from 109 colleges and universities in the US and Canada collectively saved over 2.2 million kWh of electricity and 476,000 gallons of water (US Green Building Council, 2014) over a three-month period. California Public Utilities Commission organized an annual energy-conservation competition that involves a three-week bill-tracking campaign for K-12 students in late October each year. Since 2014, they have organized five contests with California schools, and saved a total of $51,657, 335,795 kWh, and 234,450 pounds (lbs) of CO_2 (Energize Schools, 2016).

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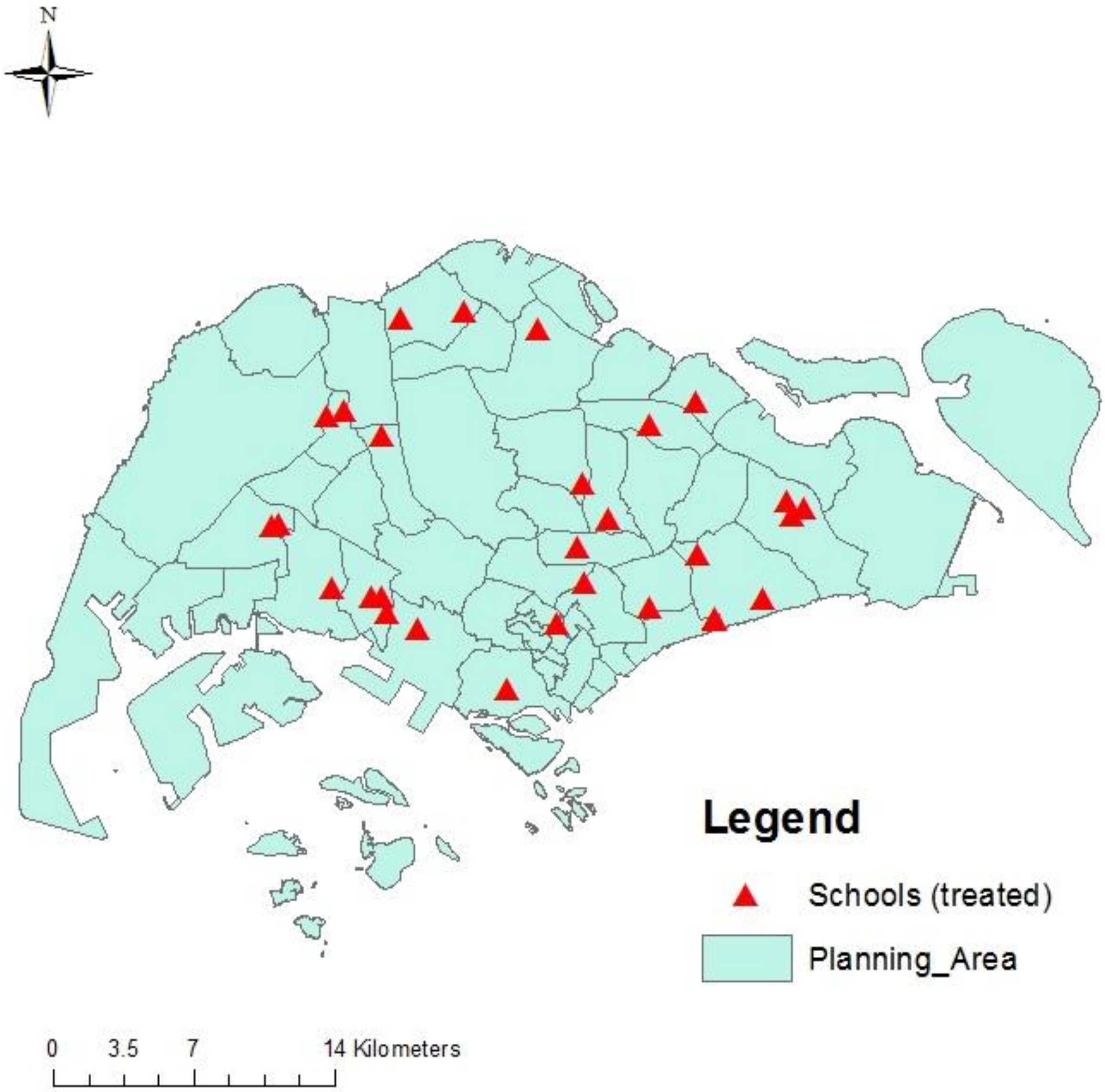

Fig. 1. Distributions of Sample Schools (primary and secondary) Participating in Energy Saving Contest in 2009 *Note: The figure shows the locations of the 29 schools that participated and completed the submissions in the "Project Carbon Zero" contest in 2009. The sample schools are used in our empirical analyses. The boundaries demarcated by the lines indicate the planning areas in Singapore. The image is obtained through ArcGIS using geographical information systems (GIS) data. Data on the treated schools is obtained from the NEA.*

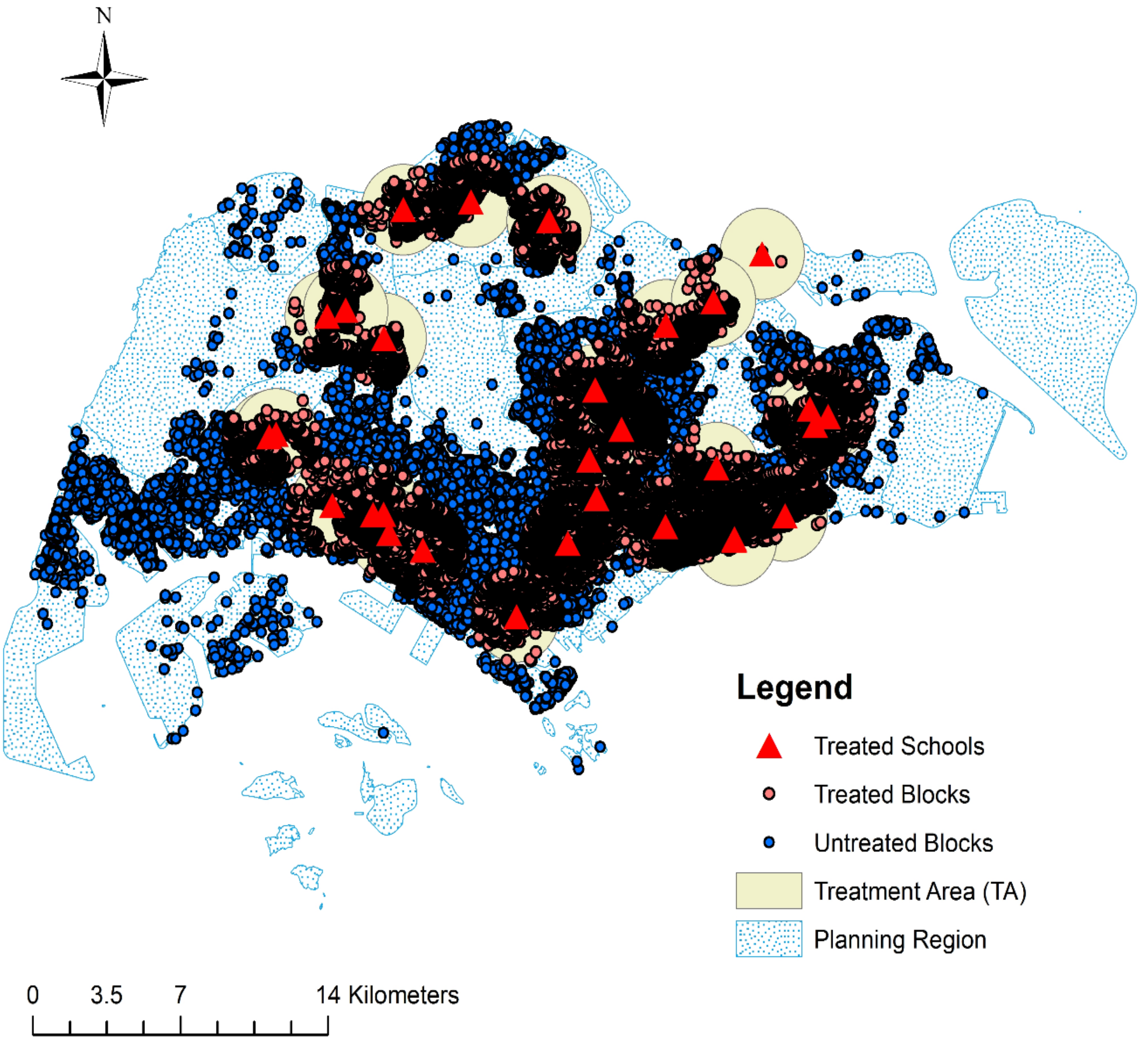

Fig. 2. Boundaries of Treatment Areas (≤2km) and Control Areas (>2km) Surrounding the Participating Schools *Note: The figure shows the locations of the sample housing blocks, treatment areas (demarcated by circles) and control areas with reference to the treated schools. The treatment area is defined by a home-school distance of less than 2km, and the control area includes other housing blocks located outside the 2km radius. The image is obtained through ArcGIS v 9.1(specifically with buffer and intersect) using geographical information systems (GIS) data on properties in Singapore. Data on the treated schools is obtained from the NEA.*

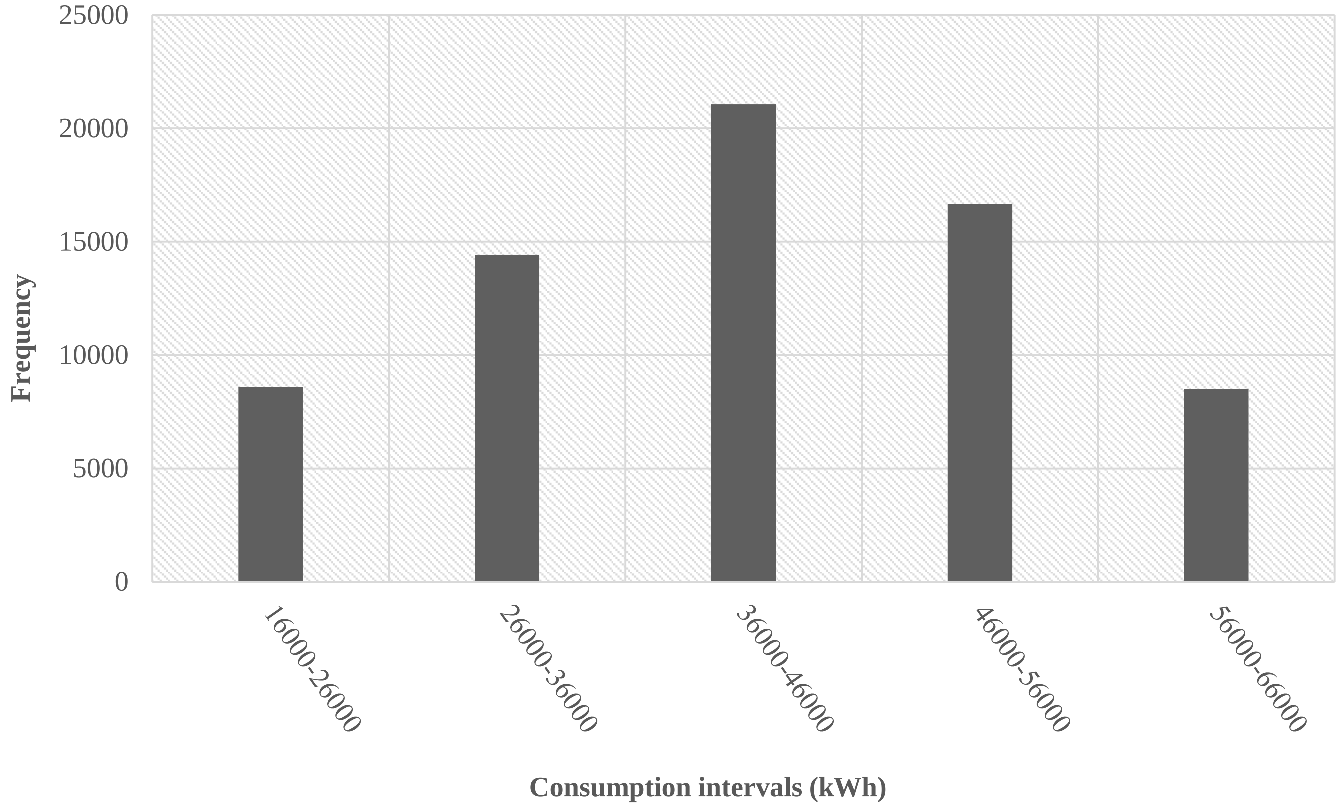

Fig. 3. Distributions of Electricity Consumptions for Public and Private Housing Blocks in Singapore (2009) *Note: The figure shows the distributions of electricity consumption of the samples of public housing (HDB) and private housing ("PRIVATE"=1) blocks (in kWh) during the behavioral intervention study periods in 2009. The bars are plotted with the range of 10,000 kWh, and the electricity consumption shows a normal distribution, with the middle bar of 36,000-46,000 kWh indicating the highest frequency of electricity consumption of Singaporean households. The electricity consumption data is provided by the NEA.*

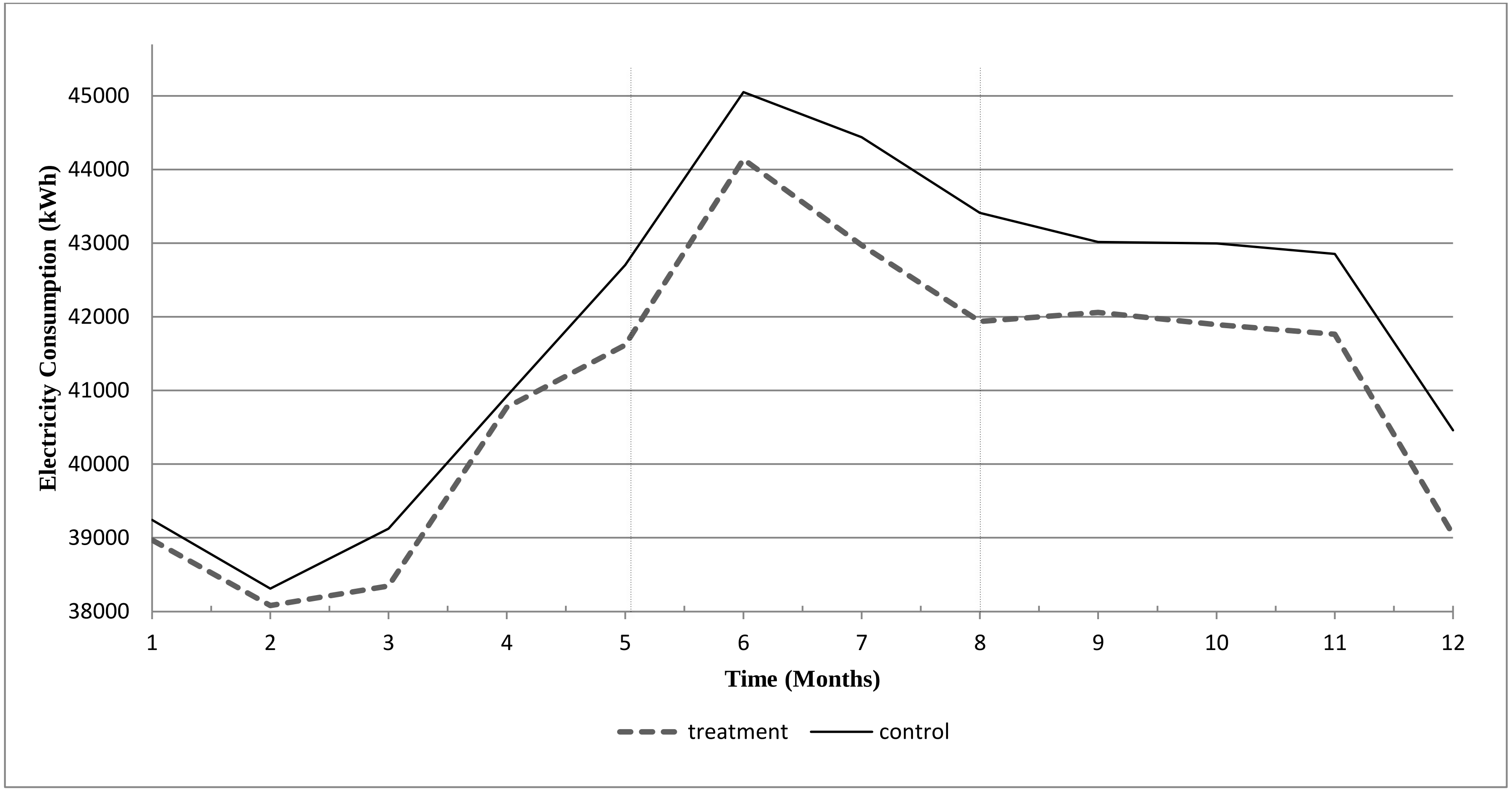

Fig. 4. Average Electricity Consumptions of the Treatment and the Control Housing Blocks in 2009 *Note: The figure plots the average monthly electricity consumption at the block level between the treatment group (dashed line) and the control group (solid line) during the year of the intervention study in 2009. The two vertical dotted lines at "5" and "8" indicate the intervention periods (May to August), during which the savings in electricity by households are computed with reference to the base months from 1 to 4 (January to April). The electricity consumption data are provided by NEA.*

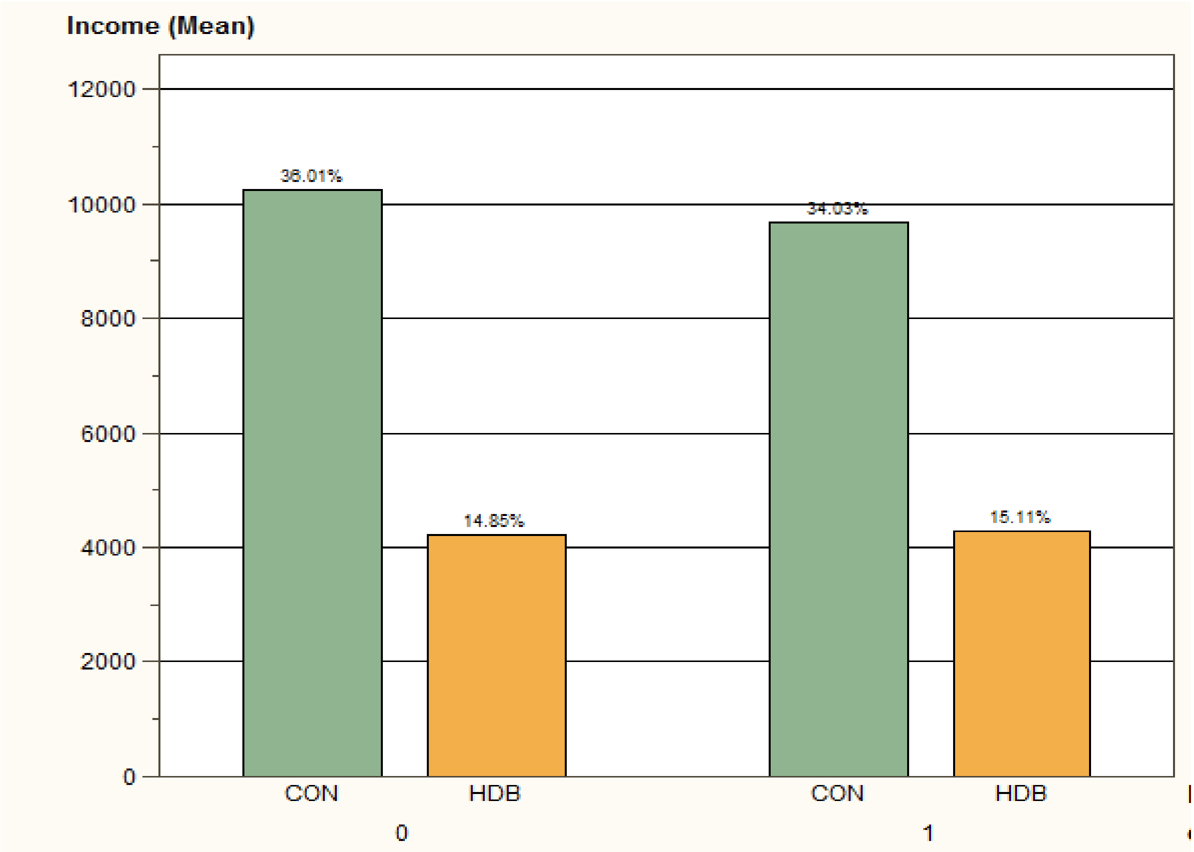

Fig. 5. Income Distributions for Public (HDB) and Private Condominium (CON) blocks in Singapore (2009) *Note: The figure shows the average income of households in 2009 at the block level for public housing groups (PUB) in orange and private housing groups (CON) in green. The samples are also sorted into the treatment group (1), which consists of housing blocks located within 2km from the participating schools), and the control group (0), which consists of housing blocks located more than 2km from the participating schools). The average household income (in Singapore Dollar) is computed using the data provided by Agarwal and Qian (2014) in the American Economic Review.*

Table 1
Final list of sample schools participating and completing the submissions in the Energy Saving Contest in 2009.

	School Name	Postal Code
Primary schools		
1)	Yew Tee Primary School	689100
2)	Yangzheng Primary School	556108
3)	St. Margaret's Primary School	228091
4)	Shuqun Primary School	649332
5)	Rulang Primary School	649295
6)	Radin Mas Primary School	099840
7)	Pei Tong Primary School	129857
8)	Pei Chun Public School	319320
9)	Ngee Ann Primary School	449149
10)	Kong Hwa School	399772
11)	Hong Wen School	327829
12)	Greenwood Primary School	737942
13)	Greenridge Primary School	677744
14)	Gongshang Primary School	529176
15)	Edgefield Primary School	828869
16)	De La Salle School	689285
17)	Clementi Primary School	129903
18)	Chongzheng Primary School	529392
19)	Anchor Green Primary School	544969
Secondary schools		
20)	Bedok North Secondary School	419612
21)	Chai Chee Secondary School	466781
22)	Chij Katong Convent	449150
23)	Chong Boon Secondary School	569250
24)	Commonwealth Secondary School	608784
25)	Fairfield Methodist School (Secondary)	139649
26)	Marsiling Secondary School	739110
27)	Nan Hua High School	129956
28)	Ngee Ann Secondary School	529283
29)	Yishun Town Secondary School	768610
30)	Zhonghua Secondary School	556123

Note: The table summarizes the name and postal code of the schools that participated in the 2009 "Project Carbon Zero" contest and submitted their complete electricity information. Participating schools that did not complete the submissions are not included in our test. One of the schools in the treatment zone, Yangzheng Primary School, which has limited housing samples is dropped from the tests. The school data is provided by the NEA.

Table 2
Household Behaviors in Electricity Consumption (Monthly frequency).

Data Frequency		Monthly Frequency[1]	
Model	(1)	(2)	(3)
Estimator	OLS	GLM	GLM
Treat	0.00579	-0.000303	0.00647
	(0.00399)	(0.00403)	(0.00436)
10%SAVE_TREAT	-0.00751**	-0.0187***	0.00523
	(0.00344)	(0.00382)	(0.00692)
TEST_TIME	0.111***	0.114***	0.112***
	(0.00444)	(0.00430)	(0.00442)
POST_TIME	0.0734***	0.0755***	0.0736***
	(0.00441)	(0.00426)	(0.00439)
TREAT_TEST_TIME	-0.0182***	-0.0180***	-0.0180***
	(0.00563)	(0.00544)	(0.00560)
TREAT_POST_TIME	-0.0168***	-0.0167***	-0.0165***
	(0.00559)	(0.00540)	(0.00556)
PRIVATE	-0.288***	-0.280***	-0.288***
	(0.00256)	(0.00378)	(0.00287)
Constant	10.60***	10.66***	10.59***
	(0.00314)	(0.0284)	(0.00904)
Observations	69,257	69,257	69,257
R-squared	0.168	0.224	0.176
District FE	No	Yes	No
School Postal FE	No	No	Yes

Notes: The table reports the regression results with the dependent variable is log electricity consumption per block per month. The regressions are estimated using OLS and Generalized Linear Model (GLM) estimators with the full sample of public HDB and private housing blocks in Singapore (8,070). The housing type is identified by the dummy variable "PRIVATE" that has a value of 1 for private condominium; and 0 otherwise. 29 sample schools that have participated (with complete submissions) in the energy savings contests are used in the tests. We use "Treat" to identify residential blocks that are located within 2 km radius from the nearest the participating school location. "TEST_TIME" indicates the contest months from May to August in 2009; and the "POST_TIME" indicate the post-contest months from September to December in 2009. "10%SAVE" is a dummy variable that identify the schools that have achieved 10% or more savings in electricity during the contest periods. We control for district fixed effects of the housing blocks and also the school postal code fixed effects. The standard errors are given in parentheses. *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.

Table 3
Household Behaviors in Electricity Consumption.

Data Frequency	Monthly Frequency[1]			Bi- monthly Frequency[2]		
Model	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	OLS	GLM	GLM	OLS	GLM	GLM
Treat	0.00564	-0.000570	0.00745*	0.00579	-0.000303	0.00647
	(0.00400)	(0.00407)	(0.00445)	(0.00399)	(0.00403)	(0.00436)
10%SAVE_TREAT	-0.00777**	-0.0184***	0.00453	-0.00751**	-0.0187***	0.00523
	(0.00377)	(0.00419)	(0.00757)	(0.00344)	(0.00382)	(0.00692)
TEST_TIME	0.132***	0.135***	0.132***	0.111***	0.114***	0.112***
	(0.00551)	(0.00533)	(0.00548)	(0.00444)	(0.00430)	(0.00442)
POST_TIME	0.0734***	0.0755***	0.0735***	0.0734***	0.0755***	0.0736***
	(0.00440)	(0.00426)	(0.00438)	(0.00441)	(0.00426)	(0.00439)
TREAT_TEST_TIME	-0.0162**	-0.0160**	-0.0158**	-0.0182***	-0.0180***	-0.0180***
	(0.00697)	(0.00675)	(0.00694)	(0.00563)	(0.00544)	(0.00560)
TREAT_POST_TIME	-0.0168***	-0.0167***	-0.0165***	-0.0168***	-0.0167***	-0.0165***
	(0.00558)	(0.00540)	(0.00556)	(0.00559)	(0.00540)	(0.00556)
PRIVATE	-0.284***	-0.275***	-0.285***	-0.288***	-0.280***	-0.288***
	(0.00280)	(0.00413)	(0.00314)	(0.00256)	(0.00378)	(0.00287)
Constant	10.60***	10.66***	10.59***	10.60***	10.66***	10.59***
	(0.00314)	(0.0304)	(0.00980)	(0.00314)	(0.0284)	(0.00904)
Observations	57,792	57,792	57,792	69,257	69,257	69,257
R-squared	0.168	0.221	0.175	0.168	0.224	0.176
District FE	No	Yes	No	No	Yes	No
School Postal FE	No	No	Yes	No	No	Yes

Notes: The block-level electricity consumption data grouped by monthly frequency and bi-monthly frequency to reduce possible meter-reading errors:

1 Monthly Frequency	2 Bi-monthly Frequency
Reference Period: Jan, Feb, Mar, Apr	Reference Period: Jan & Feb, Mar & Apr
Test Period: Jun, Jul	Test Period: May & Jun, Jul & Aug
Post Period: Sep, Oct, Nov, Dec	Post Period: Sep & Oct, Nov & Dec

The regressions are estimated using OLS and Generalized Linear Model (GLM) estimators with the full sample of public HDB and private housing blocks in Singapore (8,070). The housing type is identified by the dummy variable "PRIVATE" that has a value of 1 for private condominium; and 0 otherwise. 29 sample schools that have participated (with complete submissions) in the energy savings contests are used in the tests. We use "Treat" to identify residential blocks that are located within 2 km radius from the nearest the participating school location. "TEST_TIME" indicates the contest months from May to August in 2009; and the "POST_TIME" indicate the post-contest months from September to December in 2009. "10%SAVE" is a dummy variable that identify the schools that have achieved 10% or more savings in electricity during the contest periods. We control for district fixed effects of the housing blocks and also the school postal code fixed effects. The standard errors are given in parentheses. The assignment *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.

Table 4

Treatment Effects with Different Home-School Distance.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	OLS	GLM	GLM	OLS	GLM	GLM
Treatment Distance	(A) Distance <1.5 km			(B) Distance <3.0 km		
TREAT	-0.00122	-0.00643*	0.000825	0.00340	-0.00295	0.0103*
	(0.00386)	(0.00381)	(0.00400)	(0.00542)	(0.00531)	(0.00565)
TEST_TIME	0.104***	0.107***	0.105***	0.114***	0.117***	0.114***
	(0.00357)	(0.00345)	(0.00355)	(0.00721)	(0.00697)	(0.00717)
POST_TIME	0.0684***	0.0703***	0.0687***	0.0759***	0.0787***	0.0758***
	(0.00354)	(0.00342)	(0.00352)	(0.00714)	(0.00691)	(0.00711)
TREAT□TEST_TIME	-0.0105*	-0.0103*	-0.0104*	-0.0161**	-0.0167**	-0.0158**
	(0.00553)	(0.00535)	(0.00551)	(0.00779)	(0.00753)	(0.00775)
TREAT□POST_TIME	-0.0130**	-0.0124**	-0.0128**	-0.0151*	-0.0159**	-0.0146*
	(0.00550)	(0.00531)	(0.00547)	(0.00772)	(0.00746)	(0.00768)
PRIVATE	-0.288***	-0.281***	-0.288***	-0.288***	-0.281***	-0.289***
	(0.00256)	(0.00378)	(0.00288)	(0.00255)	(0.00378)	(0.00287)
Constant	10.60***	10.65***	10.60***	10.60***	10.65***	10.59***
	(0.00255)	(0.0283)	(0.00836)	(0.00504)	(0.0286)	(0.00969)
Observations	69,257	69,257	69,257	69,257	69,257	69,257
R-squared	0.168	0.223	0.176	0.168	0.223	0.176
District FE	No	Yes	No	No	Yes	No
School Postal FE	No	No	Yes	No	No	Yes

Notes: The table reports the regression results with the dependent variable is log electricity consumption per block per month. The regressions are estimated using OLS and Generalized Linear Model (GLM) estimators with the full sample of public HDB and private housing blocks in Singapore (8,070). The housing type is identified by the dummy variable "PRIVATE" that has a value of 1 for private condominium; and 0 otherwise. 29 sample schools that have participated (with complete submissions) in the energy savings contests are used in the tests. We use "Treat" to identify the treatment residential blocks that are located near the participating school location. Two treatment distances: 1.5km and 3km are used in the test to sort the samples into the treatment group and the control group. "TEST_TIME" indicates the contest months from May to August in 2009; and the "POST_TIME" indicate the post-contest months from September to December in 2009. "We control for district fixed effects of the housing blocks and also the school postal code fixed effects. The standard errors are given in parentheses. *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.

Table 5
Intervention Effects between Primary Schools and Secondary Schools.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	OLS	GLM	GLM	OLS	GLM	GLM
School Type	(A) Primary Schools			(B) Secondary Schools		
TREAT	-0.0206***	-0.0200***	-0.0139**	0.0262***	0.0209***	0.0257***
	(0.00578)	(0.00577)	(0.00613)	(0.00533)	(0.00557)	(0.00567)
TEST_TIME	0.115***	0.119***	0.116***	0.108***	0.112***	0.108***
	(0.00654)	(0.00627)	(0.00649)	(0.00605)	(0.00587)	(0.00604)
POST_TIME	0.0739***	0.0768***	0.0742***	0.0732***	0.0753***	0.0732***
	(0.00647)	(0.00621)	(0.00643)	(0.00601)	(0.00583)	(0.00600)
TREAT×TEST_TIME	-0.0213**	-0.0209***	-0.0210**	-0.0159**	-0.0159**	-0.0155**
	(0.00832)	(0.00798)	(0.00826)	(0.00763)	(0.00739)	(0.00762)
TREAT×POST_TIME	-0.0118	-0.0118	-0.0114	-0.0211***	-0.0211***	-0.0207***
	(0.00825)	(0.00791)	(0.00819)	(0.00758)	(0.00735)	(0.00757)
PRIVATE	-0.289***	-0.289***	-0.295***	-0.288***	-0.276***	-0.284***
	(0.00370)	(0.00568)	(0.00425)	(0.00354)	(0.00516)	(0.00390)
Constant	10.62***	10.65***	10.60***	10.58***	10.69***	10.64***
	(0.00461)	(0.0321)	(0.00933)	(0.00427)	(0.0601)	(0.0148)
Observations	31,872	31,872	31,872	37,385	37,385	37,385
R-squared	0.178	0.245	0.189	0.163	0.216	0.166
District FE	No	Yes	No	No	Yes	No
School Postal FE	No	No	Yes	No	No	Yes

Notes: The table reports the regression results with the dependent variable is log electricity consumption per block per month. The regressions are estimated using OLS and Generalized Linear Model (GLM) estimators with the full sample of public HDB and private housing blocks in Singapore (8,070). The housing type is identified by the dummy variable "PRIVATE" that has a value of 1 for private condominium; and 0 otherwise. 29 sample schools that have participated (with complete submissions) in the energy savings contests are used in the tests. The schools are separated into two groups: primary schools and secondary schools, and the regressions are estimated using the two different sets of samples. We use "Treat" to identify residential blocks that are located within 2 km radius from the nearest the participating school location. "TEST_TIME" indicates the contest months from May to August in 2009; and the "POST_TIME" indicate the post-contest months from September to December in 2009. "We control for district fixed effects of the housing blocks and also the school postal code fixed effects. The standard errors are given in parentheses. *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.

Table 6
Building Design Effects.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	OLS	GLM	GLM	OLS	GLM	GLM
School Type		(A) Public Housing			(B) Private Housing	
TREAT	0.00543	-0.00775**	0.00636	-0.000764	0.0118	0.00729
	(0.00391)	(0.00388)	(0.00415)	(0.0107)	(0.0104)	(0.0113)
TEST_TIME	0.122***	0.126***	0.123***	0.0732***	0.0854***	0.0755***
	(0.00439)	(0.00422)	(0.00435)	(0.0125)	(0.0118)	(0.0123)
POST_TIME	0.0795***	0.0814***	0.0799***	0.0519***	0.0611***	0.0531***
	(0.00434)	(0.00418)	(0.00431)	(0.0124)	(0.0117)	(0.0123)
TREAT×TEST_TIME	-0.00887	-0.00962*	-0.00905	-0.0279*	-0.0256*	-0.0277*
	(0.00565)	(0.00544)	(0.00561)	(0.0151)	(0.0142)	(0.0149)
TREAT×POST_TIME	-0.0117**	-0.0122**	-0.0116**	-0.0244	-0.0242*	-0.0237
	(0.00560)	(0.00539)	(0.00555)	(0.0150)	(0.0142)	(0.0149)
Constant	10.59***	10.64***	10.62***	10.34***	10.22***	10.29***
	(0.00304)	(0.0246)	(0.0115)	(0.00878)	(0.0179)	(0.0152)
Observations	51,268	51,268	51,268	17,200	17,200	17,200
R-squared	0.035	0.107	0.051	0.004	0.117	0.028
District FE	No	Yes	No	No	Yes	No
School Postal FE	No	No	Yes	No	No	Yes

Notes: The table reports the regression results with the dependent variable is log electricity consumption per block per month. The regressions are estimated using OLS and Generalized Linear Model (GLM) estimators using only the private housing samples ("PRIVATE" =1). We sort the housing samples into two groups using the housing type dummy, "PRIVATE =1" for private housing; and otherwise "PRIVATE =0" for public housing. We use "Treat" to identify residential blocks that are located within 2 km radius from the nearest the participating school location. "TEST_TIME" indicates the contest months from May to August in 2009; and the "POST_TIME" indicate the post-contest months from September to December in 2009. We control for the school postal code fixed effects. The standard errors are given in parentheses. *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.

Table 7
Income Effects.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	OLS	GLM	GLM	OLS	GLM	GLM
School Type	(A) Public Housing			(B) Private Housing		
TREAT	0.00549**	-0.00960***	0.00537*	-0.0491***	-0.0189**	-0.0389***
	(0.00244)	(0.00254)	(0.00284)	(0.00939)	(0.00942)	(0.0102)
TEST_TIME	0.123***	0.124***	0.122***	0.0220**	0.0526***	0.0270**
	(0.00295)	(0.00285)	(0.00293)	(0.0111)	(0.0106)	(0.0110)
POST_TIME	0.0791***	0.0793***	0.0786***	0.00456	0.0315***	0.00846
	(0.00292)	(0.00281)	(0.00290)	(0.0112)	(0.0106)	(0.0110)
TREAT×TEST_TIME ×HIGH_INCOME	-0.0285***	-0.0200***	-0.0232***	0.0498***	0.0236*	0.0458***
	(0.00510)	(0.00496)	(0.00509)	(0.0134)	(0.0127)	(0.0132)
TREAT×POST_TIME ×HIGH_INCOME	-0.0331***	-0.0257***	-0.0280***	0.0476***	0.0203	0.0442***
	(0.00502)	(0.00488)	(0.00501)	(0.0134)	(0.0128)	(0.0133)
Constant	10.59***	10.65***	10.62***	10.38***	10.24***	10.32***
	(0.00241)	(0.0246)	(0.0114)	(0.00808)	(0.0176)	(0.0148)
Observations	51,268	51,268	51,268	17,200	17,200	17,200
R-squared	0.036	0.108	0.052	0.005	0.117	0.029
District FE	No	Yes	No	No	Yes	No
School Postal FE	No	No	Yes	No	No	Yes

Notes: The table reports the regression results with the dependent variable is log electricity consumption per block per month. The regressions are estimated using OLS and Generalized Linear Model (GLM) estimators using only the private housing samples ("PRIVATE" =1). We sort the housing samples into two groups using the housing type dummy, "PRIVATE =1" for private housing; and otherwise "PRIVATE =0" for public housing. We use "Treat" to identify residential blocks that are located within 2 km radius from the nearest the participating school location. "TEST_TIME" indicates the contest months from May to August in 2009; and the "POST_TIME" indicate the post-contest months from September to December in 2009. "HIGH_INCOME" dummy is used to sort the sample blocks by the median monthly income into a high group and a low-income group. The median incomes of S$4,078 and S$8,378 are used as the median income for the public housing and private housing, respectively. We control for the school postal code fixed effects. The standard errors are given in parentheses. *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.