Evaluation of an Energy Efficiency Program in a Regional Context

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ABSTRACT

The Central Victoria Solar City (CVSC) research trial is part of the Australian Government's $94 million Solar Cities program. Managed by renewable energy company, Sustainable Regional Australia (SRA), the program encourages residents to test energy efficiency technologies and services designed to reduce energy use and reliance on non-renewable energy sources. The trial involves collecting data from over 3,500 households (including a control group of 750) across central Victoria and recording changes to their energy consumption until 30 June 2013. CVSC is in its early stages of implementation, with about one third of participants recruited. In energy program evaluations, much of the data is hierarchical in nature (e.g. household energy readings over time). An issue with such data is that conventional statistical methods (e.g. OLS or Logistic regression) assume independency between observations, which is likely to be violated by longitudinal data. Techniques to address this problem have been a major area of research during the past 10 years. Such developments have led to analytical tools (e.g. Linear Mixed Models), which allow for modeling of dependencies between measures. Early analysis has confirmed the hierarchical nature of the data, with 76% of the variance in pre-program energy consumption occurring between (rather than within) households. A preliminary baseline model based on regional, climatic and household characteristics explains 40% of variation in household electricity consumption. Initial findings suggest that household electricity consumption is most strongly influenced by regional factors (e.g. climate, reticulated gas availability), number of occupants, house size and income.

Introduction

The Australian Government's $94 million Solar Cities program is designed to test new sustainable models for electricity supply and use. It is being implemented in seven separate regions across Australia, including Central Victoria. Central Victoria Solar City (CVSC) encourages central Victorian residents to test the effectiveness of different energy efficiency and renewable energy products and services in reducing energy use and reliance on non-renewable energy. CVSC is funded by the Australian Government through the Department of the Climate Change and Energy Efficiency, Sustainability Victoria, the Sustainability Fund and the Central Victoria Solar City Consortium. Managed by Sustainable Regional Australia, CVSC's consortium members include Bendigo and Adelaide Bank, Central Victorian Greenhouse Alliance (CVGA), Origin and Powercor.

CVSC is a complex project with the recruitment of more than 3,500 households (including a control group of 750) and involves recording changes to their energy consumption for up to four years (until 30 June 2013). The study will test the impact of four interventions on the demand for electricity. These include:

- Free Home Energy Assessments
- Retrofits package ($500 rebate on $2,000+ energy efficiency investments)

- Solar Hot Water
- Household Solar Photovoltaics (1.5 Kw system)

The CVSC evaluation has been designed to: monitor and evaluate the impact of the program; identify confounding factors that influence household energy consumption and adoption of energy efficiency technologies; and inform public policy and future research. This study, by conducting a longitudinal study of electricity use, will identify the drivers of efficient consumption and inform public policy by developing an energy-saving optimization model. In particular, this will enable an assessment of the program's influence on electricity consumption savings, in the form of estimated gross savings, estimated savings attributable to the program (net savings) and estimated co-benefits (e.g. avoided emissions). Key research questions identified include:

1. What influence do technological, behavioral, social and economic factors have on energy consumption?
2. What is the influence of these factors on household adoption of solar energy technologies?
3. How do demographic, geographic and attitudinal characteristics influence the use of technological interventions and the demand for energy?
4. Which combinations of measures provide the best cost route to achieving the most carbon efficient energy consumption?
5. What are the characteristics of a predictive macro model that explain the impact of household demand and supply management on future energy use and carbon emissions?
6. How can results from such programs be effectively communicated to users?

Behavioral Energy Research

Existing studies on household energy behavior are typically based on concepts from economics, psychology and sociology. The 1970s energy crisis in the United States prompted increased interest in understanding how households could reduce energy consumption in response to increased energy costs (Stern 1992). This lead to a body of research designed to understand the main factors influencing energy consumption behavior. Some recent literature reviews summarize the studies conducted in this area (cf. Abrahamse et al. 2005; Lutzenhiser 1993; Wilson and Dowlatabadi 2007). The primary purpose of these studies has been to stimulate behaviors that are more energy efficient and/or will reduce energy-consuming behaviors. Despite the prevalence of research in this area, understanding energy behavior still presents many complexities. Such issues include difficulties in identifying and measuring the factors that influence energy-consumption and the nature of each influence on behavior (Ritchie et al. 1981). Stern (1992) suggests potential factors include psychological, social structures, economic and technological variables. Similarly, Abrahamse et al. (2005) propose that energy consumption is a complex interaction between macro-level factors (e.g. technological, economic, demographic and institutional factors) and an individual's views, preferences and abilities.

Barr et al. (2001) sought to provide a broader understanding of environmental behavior, through a conceptual framework that suggests consumption is mainly influenced by social and environmental values, situational variables and psychological factors. The link between values and conservation behavior builds on previous studies, which have found that social values are associated with environmental practices (Cameron et al. 1998; Corraliza & Berrenguer 2000; Stern et al. 1995). The most common measure of environmental values in the literatures is Dunlap and Van Liere's (1978) New Environmental (or Ecological) Paradigm (NEP). A wide range of social science studies have employed the NEP scale to examine the influence of environmental values on behavior. In general, such studies have failed to provide convincing evidence supporting the influence of values on behavior (e.g. Scott & Willits 1994; Vining &

Ebreo 1992). Similar studies have found that energy consumption attitudes are associated with knowledge and self-reported activities, not actual conservation behavior (Heslop, Moran, & Cousineau 1981; Neuman 1986). A possible reason for not finding such a relationship could be attributed to the moderating and mediating effects of situational variables (e.g. physical infrastructure, geographical location, socio-economic structure and knowledge) or psychological variables (e.g. attitudes, social norms), which have received considerable attention in the past 40 years (Fishbein & Azjen 1975; Stern et al. 1992).

Despite the prevalence of literature into the determinants of energy consumption, such factors are rarely taken into consideration when evaluating the effectiveness of energy programs. Indeed, Abrahamse et al. (2005) found that only 25% of studies reviewed controlled for behavioral determinants. Such omissions inhibit the ability of these evaluations to investigate counterfactual explanations for changes in energy consumption by program participants. The present evaluation seeks to consider such confounding effects, by conducting a large-scale longitudinal analysis of household energy consumption, which will simultaneously compare the influence of program interventions in the context of other determinants of energy use. Such determinants outside the program's interventions have been considered in developing this study's conceptual framework.

Conceptual Framework

A review of the literature has highlighted the need to understand the characteristics of households as well as the context in which they live to understand energy behavior and how it might be changed. The study's conceptual framework (refer Figure 1) proposes that energy behavior (and behavioral intentions) is a function of situational variables (which act as enablers / disablers for undertaking certain behavior), social/environmental values and psychological factors that motivate or act as barriers for households to use energy in a particular way. This conceptual framework has been used as a basis to guide the design of the evaluation and construction of associated survey instruments.

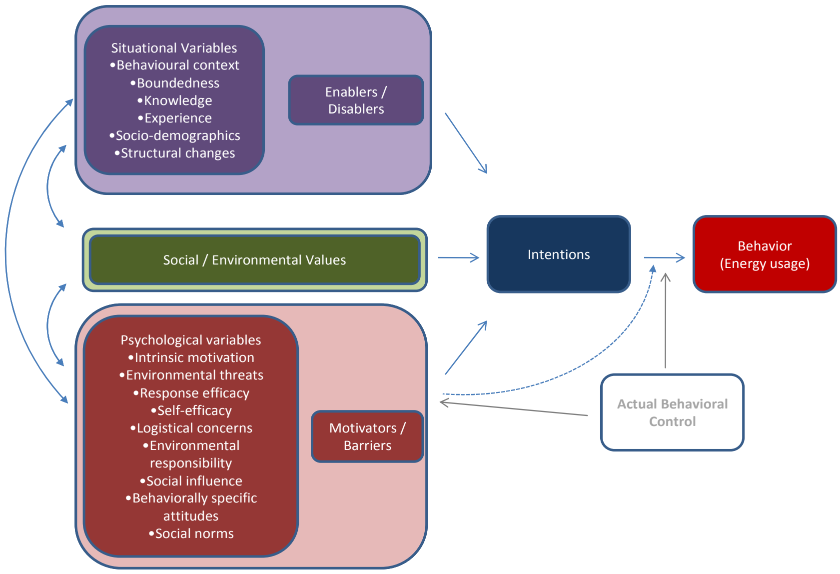

Figure 1. Conceptual Framework: Adapted from Barr & Gilg (2007) and Ajzen & Fishbein (1980, 2005).

Methodology

The study will be directed to address the key research questions and provide:

- baseline analysis, including energy consumption and its relationship to weather and household profiles;
- longitudinal statistical analyses of changes to energy use for different assumptions on the effects of demographic, income, household, behavioral, attitudinal, housing and meteorological covariates; and
- longitudinal statistical analyses of long-term changes to behavioral and attitudinal indicators, cost-benefit analysis, optimization and demand management modeling of different strategies needed to reduce household consumption patterns.

The voluntary nature of participation in energy efficiency programs often means that a true experimental design with randomly assigned treatment and non-treatment (i.e. control group) groups is not possible. As intervention groups for CVSC are self-selected, a nonequivalent groups quasi-experimental design (NEGD) has been adopted for this study. An inherent limitation of observational studies is that the patterns of characteristics that occur in the study sample cannot be tightly controlled, leading to a lack of statistical balance in the data. With such data, it is not necessarily possible to attribute outcomes to particular factors unambiguously. For example, if most of one intervention group were located in a hot weather area and most of another intervention group were located in a much cooler area, it would be difficult to separate completely the differences between the effects of the two interventions from the differential weather effects. Use of a pre-post design and matched control groups reduces problems of attribution in an observational study, but does not eliminate them. The results of any data analysis will therefore be considered in light of this limitation.

Participants

The program administrator, Sustainable Regional Australia (SRA), will organize the intervention group of 3,000 participants. CVSC is still in the early stages of implementation. At the time of writing, more than one third of this target has been recruited, with the remainder expected to sign up by the end of 2011. The target numbers for each intervention group are presented in the following table:

Table 1. Intervention targets

Intervention[1]	Target
Home Energy Assessment	3,000
Retrofit	500
Solar Hot Water	200
Household Solar Photovoltaics	600

Prospective control group participants were recruited using a short environmental values telephone survey with randomly selected households in the target area to recruit. During this process, 4,954 households completed the initial survey, with 2,894 (58%) agreeing to receive further information about

[1] All program participants receive a Home Enery Assessment with the option of participating in one of the other trials

joining the program's control group. After distributing these information packages, a quarter of recipients (25%) elected to join the project, which resulted in a Control Group of more than 700 households.

Data Collection

A longitudinal design has been employed, with measurements at baseline (and before baseline for some measures) and at intervals throughout the remainder of the project. The evaluation's data collection began in 2010 and will continue until the conclusion of the project (June 2013). Three major types of variables will be collected and monitored for this study:

- measures of electricity consumption, the primary response variable;
- covariates collected via household surveys, demographic, housing, attitudinal, and behavioral characteristics; and
- geographical covariates, meteorological characteristics.

Measures of electricity consumption. The data needs for the evaluation require collection of half-hourly energy use data from all participating households. This interval meter data will be collected by the region's electricity distributor (Powercor) from all households in both intervention and control groups, from the time of commencement until the conclusion of the project. Information about prior metered electricity use is also being provided retrospectively, for up to three years. Data on energy use from gas or other sources will be collected by self-reporting of household bills.

Household Surveys. To collect information about the determinants of energy consumption, baseline surveys have been conducted with all participating households as part of the sign-up process. Follow-up surveys will also be conducted on two further occasions during the life of the project. Based on the study's conceptual framework and the program's reporting requirements, there will be a common core of questions. There will be specific provision for baseline and follow-up versions and for extra aspects that are specific to particular interventions.

The baseline surveys involve distributing two separate questionnaires to participating households. Each survey was designed, produced, and administered following Dillman's *total design method* (Dillman 2007). The first survey is a self-administered mail survey that mainly focuses on household characteristics such as site details, appliances, lighting, energy bills, gas and other energy sources and energy efficiency measures. On returning the first survey booklet, participants are provided with a second questionnaire in the form of a mail, web or a telephone survey, depending on the respondent's preference. This second survey provides information on environmental values, knowledge, views and opinions on energy use, information sources and demographic characteristics.

Follow-up surveys will include: a review of demographic characteristics, characteristics of buildings, appliances, knowledge and attitudes; retrospective information regarding use of reticulated gas and other energy sources; and questions specific to particular interventions. These questions will address issues of process, behavior of individuals within the household, household dynamics, barriers and facilitators, free riders and spillovers, and other items as appropriate.

Geographical covariates: meteorological characteristics. Local weather and climate data is sourced from the 14 Local Government Areas involved in the program. It is expected that relevant environmental covariates will included meteorological measures such as heating degree days, cooling degree days, apparent temperature, wind speed, cloud cover, rainfall and relative humidity.

Data Analysis

The data analysis will be directed toward identifying, quantifying and comparing the outcomes attributable to each intervention with regard to levels and patterns of energy use. These analyses will be directed to addressing the evaluation's key research questions. An important consideration for the data analysis phase is that as a longitudinal study, repeated measurements are observed at various intervals throughout the life of the project. Most traditional statistical analysis methods (e.g. OLS and logistic regression) assume that all observations are independent of one another (Singer & Willett 2003). This assumption might be reasonable in cross-sectional studies; however, when observations over time are clustered within households, such data are likely to be related (e.g. a household's energy consumption at one point in time is likely to be related to previous and later readings). Hierarchical linear modeling techniques (such as linear mixed models, varying coefficients mixed model and additive models) allow adjustments to be made by modeling such dependence between observations (McCulloch & Searle 2001; Raudenbush & Bryk 2002). Without such adjustments, estimates of standard errors are likely to be biased leading to an inflation in Type I errors (i.e. false positives).

Hierarchical linear modeling techniques provide an efficient method for analyzing the data in the present study. Particular advantages of these methods relate to their capacity to model different types of associations or correlations (i.e. within-household and between-household) and incorporate fixed and random effects, which take into account unobserved or unmeasured characteristics of participants (Everitt and Pickles 2000). In particular, the Linear Mixed Model approach is a recognized technique for dealing with specific issues often associated with large data sets, such as those expected in the current study. There is no need to assume that households have to be measured on the same number of time points (Laird 1988). This means that households with incomplete data across time may be included in the analysis. This represents an important advantage over alternative procedures that require complete data across time because it results in increased statistical power and is not as likely to suffer from bias associated with households with complete data not being representative of the wider population. When using linear mixed models in longitudinal studies, the *time* variable is treated as continuous. This means that households do not have to be measured at the same time points, which will be useful for future analyses where follow-up times are expected to be non-uniform across all households (i.e. they will join the program at different times). Therefore, both time-invariant and time-varying covariates can be included in the model. This implies that changes in household consumption may be due to both stable household characteristics such as regional location, structure or type of house, as well as characteristics that may change across time such as weather conditions, appliances, the number of people in the household, life events, attitudes or knowledge.

As well as estimating an average change across time, as is the case with traditional approaches, linear mixed models can also estimate change for each household. Such estimates of individual change across time will be especially useful if it is found that some households present behavior that deviates from the overall average trend. The method will enable robust estimations of the strength of the relationship between electricity use and the variables that may drive use patterns and is therefore useful in formulating policy and program recommendations.

The following details preliminary analysis undertaken to prepare the present and model the study's data set using the linear mixed model method.

Results

Collection of data for CVSC project is ongoing. The analyses reported here are based upon 740 households of which 215 were involved in at least one of the intervention groups, while the remaining 525 households were from the Control Group. The sample size was restricted to those participants for whom it was possible to use a complete set of information for the variables used in the model. The purpose of this early analysis is to facilitate the initial design and calibration of statistical models to be used in future analyses. Models for such future analysis will be built upon as more data from participants becomes available.

A detailed analysis between specific interventions and the control group is not suitable at this stage. Such comparisons are dependent on sufficient numbers of participants fulfilling package requirements (e.g. retrofit receipts, installation of solar technologies). For this initial analysis, the intervention groups have been combined and treated as a homogenous group. In this way, broad comparisons can be made between participants in the control and intervention groups. Initially the analysis focuses on:

- establishing profiles of participant characteristics and differences between intervention group and control group participants;
- defining a baseline of energy use for the intervention group and control group; and
- exploring potential relationships between energy use and behavioral determinants.

Participant Characteristics

Preliminary analysis identified several differences between the intervention group and control group in terms of household characteristics. The intervention group were more likely to live in larger houses, be married, have higher income, be working full-time, have higher education qualifications, buy Green Power, have household solar electricity, be members of an environmental action group, undertake energy curtailment behavior (e.g. conserve water, minimize appliance use) and be more analytical (than impulsive) when making decisions about energy use. In contrast, control group participants were more likely to be renters and health care concession card holders. Although such discrepancies are not surprising for a voluntary energy conservation program, self-selection bias will need to be considered as part of the evaluation's on-going data analysis. Previous research has showed that such self-selection bias can lead to an over-estimation of program-induced energy savings (Hartman 1988).

Average Daily Consumption

At first, particular interest was shown in potential differences in electricity use between the control group and the combined intervention groups. Figure 2 shows the quarterly use patterns for individual households from both control and intervention groups based on historical records dating to the second quarter of 2007. Several points are worthy of note: use patterns are regular (reflecting seasonality), differences between the two groups are rather small, and there is a slight downward trend associated with the intervention group's consumption.

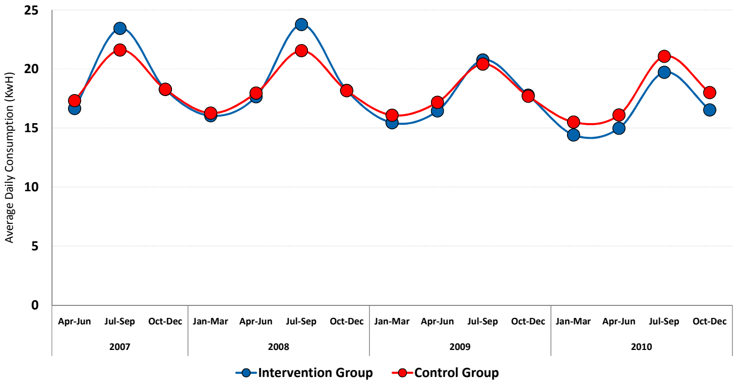

Figure 2. Average daily consumption per quarter: intervention group vs. control group

Clustering of the Data

To assess the proportion of variance that can be explained by the nested structure of the data (i.e. observations within households), an intraclass correlation coefficient (ICC) was calculated. This procedure revealed that 76% of the variance in household energy consumption occurred between (rather than within) households. This high ICC suggests strong dependence in the data, with homogeneity within households and heterogeneity between households. A design effect of 3.1 also indicated that if statistical techniques, which assume independence between observations were applied, Type I error rates would be inflated. Therefore, it is necessary to apply hierarchical statistical techniques that consider the nested structure of the data, such as linear mixed models.

Data Preparation

Before the multivariate data analysis, the data was examined to ensure its distributional and measurement properties were consistent with the assumptions of the statistical tests to be applied. This involved assessment of missing data, normality and outliers. This examination resulted in the use of logarithms to normalize the dependent variable (average daily electricity consumption per quarter) and various covariates concerning the number of lights in the household. Missing value analysis was applied to explore the prevalence and nature of missing data from the sample. This analysis resulted in the imputation of missing data using the Expectation Maximization (EM) method (refer Allison 2001; Little & Rubin 2002 for more details on these procedures).

Baseline Model

The main purpose for modeling the data is to determine key confounding factors that influence the consumption of electricity and eventually attribute the influence of project interventions on usage. Due to the clustered and longitudinal nature of the data, a linear mixed model method has been selected for the baseline analysis.

For analyses using a linear mixed model approach, the covariance structure inherent in the data needs to be considered, both within households and between households. For within households an autoregressive covariance structure (AR1) for the repeated measures variable *Time* was used. This structure considers the high correlations between successive quarterly household consumption data. For between households a variance components structure for the random effects of *Intercept* and *Time* was used. This structure assigns a scaled identity (ID) matrix to each of the specified random effects. Exploration of other potential structures will be undertaken in future analyses.

Preliminary examination of the data suggested significant variation between households with respect to their electricity consumption. It was expected for households to have their own specific relationships between power consumption and time. This concept was used as the starting point for the baseline model that simply consisted of a random intercept. The ensuing procedure included the subsequent addition of covariates one group at a time. After each step, comparisons were made between the incremental model and the baseline to determine if there had been a significant improvement. This was a two-stage process, the first involving comparisons of (-2) log-likelihood differences using chi-square tests, and the second involving a proportional reduction in variance statistic to estimate the variance explained by each model (Raudenbush & Bryk 2002).

The model building continued until 10 incremental steps had been completed (refer Table 2). This considered most of the data collected from the baseline surveys and meteorological data. At this stage, it was inappropriate to proceed further as it could not be assumed the respective factor levels would have been constant over the preceding three years spanned by the historical data (e.g. daily occupancy, psychological factors).

Table 2. Development of the final model structure

Model Structure	**% V.E.**	**Effect Size (f^2)**	**-2 LL**
Model 0: *Intercept*			-6831.2
Model 1: *Intercept+Time*	1.4%	-	-6899.0*
Model 2: *Intercept+Time+Weather*	1.9%	0.005	-7559.1*
Model 3: *Intercept+Time+Weather+QTR*	2.8%	0.009	-7967.1*
Model 4: *Intercept+Time+Weather+QTR+Gas*	9.0%	0.069	-8028.0*
Model 5: *Intercept+Time+Weather+QTR+Gas+LGA*	16.4%	0.089	-8076.9*
Model 6: *Intercept+Time+Weather+QTR+Gas+LGA+CG*	16.5%	0.001	-8077.2
Model 7: *Intercept+Time+Weather+QTR+Gas+LGA+CG+Site*	29.9%	0.191	-8255.1*
Model 8: *Intercept+Time+Weather+QTR+Gas+LGA+CG+Site+Insul'n*	31.4%	0.021	-8275.9*
Model 9: *Intercept+Time+Weather+QTR+Gas+LGA+CG+Site+Insul'n+Lights*	32.9%	0.022	-8299.3*
Model 10: *Intercept+Time+Weather+QTR+Gas+LGA+CG+Site+Insul'n+Lights+Demog*	39.2%	0.104	-8390.9*

*p<0.05 (change from previous model)

The factors that resulted in the largest increments in % V.E. (i.e. had the largest impact) included *site* (i.e. physical characteristics of the house), *Local Government Area* (LGA), *gas connection* and *demographics* (e,g, income, number of occupants).

As indicated by Table 3, many variables were found to have a significant influence on electricity consumption. These factors included climate (time of year and maximum temperature), the presence of a gas connection, house size and type, physical characteristics (floor type, number of floors), number of occupants, insulation measures (floor and window awnings), income and lighting. Some of the factors that were identified as not having a significant influence on energy consumption included housing material, building age, roof color, roof type and several insulation measures (e.g. wall insulation, double glazing, window tinting, draft stoppers and skylights). A significant difference between households in the control group and those in the combined intervention groups was identified. This finding suggests that even when controlling for other elements in the model, the intervention group is different from the control group in terms of energy consumption; although the size of this difference appears to be relatively small. A key component of future analysis will be to see what influence integrating environmental and psychological variables into the model has on this discrepancy and whether this difference is consistent across the program's four interventions.

Whether a particular variable or factor contributes significantly in explaining variation in household consumption of electricity will depend on many things and indeed interactions between factors. As more data is collected, the analysis will take such interactions into account, along with the mediating and moderating effects of variables.

Table 3. Estimates of Fixed Effects (significant parameters)

Parameter	Estimate	Std. Error	P value
Intercept	1.56	.13	.00
QTR= Jan-Apr vs. Oct-Dec	-.04	.01	.00
QTR= May-Jun vs. Oct-Dec	-.08	.02	.00
Gas connection = Yes	-.14	.02	.00
LGA = 1 versus 6	.18	.04	.00
LGA = 5 versus 6	.09	.03	.01
Intervention Group = Yes	-.06	.02	.00
Residence Size = Small vs. Medium	-.08	.02	.00
Residence Size = Large vs. Medium	.09	.02	.00
Residence Type = Apartment vs. House	-.10	.03	.00
Floor Type = Concrete Slab vs. Timber	-.05	.02	.03
Single Floor vs. Multiple Floors	-.07	.03	.03
Grid connected Solar Panels = Yes	-.06	.02	.01
Floor insulation = Yes	-.07	.03	.04
Window awnings = Yes	-.04	.02	.01
Income = <$20K vs. >$150K	-.15	.04	.00
Income = $20K-$50K vs. >$150K	-.09	.04	.02
Income = $50K-$100K vs. >$150K	-.08	.03	.02
Income = $100K-$150K vs. >$150K	-.08	.04	.04
Time	.01	.00	.00
Time (squared)	.00	.00	.00
Maximum Temperature	-.03	.00	.00
Maximum Temperature (squared)	.00	.00	.00
No. of Fluorescent lights (log)	.05	.02	.05
No. of outdoor solar lights (log)	.06	.02	.00
No. of household occupants	.05	.01	.00

Dependent variable: Average Daily Consumption by Quarter (log)

Conclusions

The Central Victoria Solar City (CVSC) research trial offers incentives to local residents to test energy efficiency technologies and services and is part of the Australian Government's $94 million Solar Cities program. Managed by renewable energy company Sustainable Regional Australia (SRA), it encourages central Victorian residents to test the effectiveness of these technologies and services in reducing energy use and reliance on non-renewable energy. The project's evaluation will simultaneously compare the influence of program interventions in the context of other energy use determinants. Preliminary analysis suggests a need to account for the hierarchical nature of the data in this study. An issue with such a data structure is that conventional statistical methods (e.g. OLS/Logistic regression) assume independency between observations. Hierarchical models (such as Linear Mixed Models) allow such dependencies to be considered. An initial baseline model identifies that the four most influential factors affecting household energy consumption were site details, location, gas connection and household demographics (i.e. income, number of occupants). A major finding from this analysis is differences between program participants and the control group, both in terms of demographic characteristics and energy consumption. This self-selection bias will need to be considered as the analysis progresses to attribute energy savings to program participation. With further recruitment of intervention participants and interval data becoming available during the next 12 months, more detailed analyses will be undertaken to compare the influence of program interventions in the context of other determinants of energy use.

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