Evaluation of Water Efficiency Programs in Single-Family Households in the UK: A Case Study

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Abstract

Current water supply worldwide is facing growing pressure as a result of climate change and increasing water demand due to growing population and lifestyle changes. The traditional way of fulfilling the growing demand-supply gap by seeking new water supply options such as exploiting new fresh water resources and investing in the expansion of infrastructure is no longer considered environmentally or economically sustainable. A diverse portfolio of water efficiency measures is now a requirement for the majority of water companies in the UK. This paper presents results from a statistical analysis of a unique water efficiency program case study. The study evaluates the effectiveness of installing water-saving devices in single-family households in areas where a major UK water supply company operates. Using multilevel models, the study accurately measures the water savings achieved through the efficiency program and defines the factors that affect a household's potential to save water. Analysis illustrated a mean 7% decrease in consumption, explicitly attributable to the efficiency program. Research findings provide strong evidence that single resident and financially stretched households have a bigger potential to conserve water than larger and more affluent ones and also highlight the robustness of multilevel analysis, even in cases of data limitations.

Keywords

Domestic water demand, demand management, multilevel models, water conservation, water efficiency

INTRODUCTION

The new direction the water industry should follow at a global-scale is the management of water demand through innovative methods, tools and procedures that promote water conservation (Turner et al., 2010). The Integrated Resource Planning (IRP) framework is a comprehensive decision-making process in which a suite of both supply-side and demand-side alternative options are evaluated on the basis of predefined, often conflicting water planning objectives and uncertainty is explicitly considered (NWC 2011) and it is internationally considered as best practise. Leaders in IRP are the California Urban Water Conservation Council (CUWCC), the American Water Works Association (AWWA) as well as the Institute of Sustainable Futures (ISF) in Australia (Turner et al. 2010) that have established methodologies to account for projected future demand and plan for sustainable water conservation options. The IRP framework provides guidelines as to the methods that can be followed for an evaluation of a water efficiency program (Fyfe et al. 2010) and until today, this is the only comprehensive evaluation framework found in the water efficiency literature. In addition, robust methods for water savings evaluation such as end-use (micro-component) analysis are much more common in the Australian and USA literature (e.g. Makki et al. 2011; Willis et al. 2013) and they have only recently emerged in Europe (Parker 2013). Collection of end-use data is still uncommon for European water supply companies because of the technologically advanced equipment (smart meters and data loggers) that needs to be installed in advance. Thus water efficiency studies that use detailed micro-component analysis are very rare in the UK and European literature.

Australia is the leader in the successful implementation of residential water efficiency programs currently. This might be due to the major droughts that the country has experienced in the recent decades. Even in the case of Australian research, thorough publicly available information about water savings that were achieved is limited. Fyfe et al. (2009) documented savings of between 8.5 and 12.4 kl/household/yr for a showerhead exchange program in Melbourne while Turner et al. (2012) observed approximately the same levels of savings for another showerhead exchange program of Hunter Water Corporation (HWC) and savings of approximately 20 kl/household/yr for a toilet retrofit program.

A diverse portfolio of water efficiency measures is now an inevitable requirement for the majority of water companies in the UK too. Controlling domestic water demand is a priority for the UK. In fact, as the Department for Environment, Food and Rural Affairs (Defra) (2012) presents, factors such as population growth and land use change may affect water supply and demand more than climate change. Defra’s strategy (2012), aims at reducing residential water consumption from 150 l to 130 l per capita per day until 2030. Since 2010, Ofwat, the water industry economic regulator for England and Wales, has set minimum water efficiency goals for the water industry, equivalent to decreasing water use by 1 l per property daily. Several companies in the UK have taken major steps towards residential water efficiency by installing water meters, limiting leakage levels, launching information campaigns and by water using devices and fixtures retrofits at their customers’ homes. Water meters have been increasingly installed in British households during the last decade as a way to manage water demand effectively. However still only 41% of households are being metered and charged according to the water quantity that they use (Priestley 2015) in England and most importantly, little information is publicly available as to the magnitude of water savings that were achieved in the context of each water efficiency initiative.

CASE STUDY: RESIDENTIAL EFFICIENCY PROGRAM IN EASTERN ENGLAND

Anglian Water Services (AWS) is a company operating in the East of England, providing drinking water to 2.6 million properties. AWS report over 70% metering in the residential sector, one of the largest rates of metering penetration in the UK. It is forecasted that by 2019-2020 (AMP6), more than 95% of residential customers will have meters installed in their properties and more than 88% of them will be paying on the basis of volumetric charges, saving approximately 5.6 Ml/day (AWS 2015). During 2013 and 2014, the company embarked on a water efficiency program that involved a qualified plumber installing water efficiency devices in a sample of metered domestic properties free of charge. Some of the devices that were provided were left to the customers who could fit them later on themselves if they decided to. Each participating household received a number of the following: dual flush toilet converters, garden kits, hosepipe guns, Save-A-Flush devices, shower restrictors, Tap Magic spray inserts and shower timers, among others. A subset of this sample of properties completed a questionnaire, providing household-specific demographic and water use information.

Monthly water consumption data over a period of 43 months (2012–2015) comprising a sample of 72 properties across the company's area of operation were provided by the company and used for the subsequent analysis. Several extreme outliers were found in the AWS dataset using boxplots. All per capita consumption (pcc) values of more than 2000l/day were identified as extreme outliers and were subsequently removed. After removal of properties that presented a large number of outliers and periods of zero consumption, the dataset was reduced to 66 households. In parallel, monthly consumption data from a sample of 92 properties that did not participate in the water efficiency program were obtained for the same months. This sample was drawn from the same neighbourhoods as the participating households. The data used for the analysis are summarized in Table 1. The variable representing the take-up period for the water efficiency program for each household was a dummy variable which takes the value of either 0 or 1 to indicate the before and after program periods respectively.

Table 1. Data used for subsequent analyses

	Participants' sample
Monthly Water Consumption (litres/hh/day)	✓
Postcode	✓
Acorn class	✓
Number of Residents	✓
Intervention dates	✓
Weather data	✓

hh = household, Acorn = geodemographic segmentation of households, developed in the UK based on (among others) social/financial status and property size. Range: Acorn Category 1 (Affluent Achievers) to Category 5 (Urban Adversity) and Category 6 (Not Private hhs)

Figure 1 illustrates consumption patterns of the participants and non-participants groups for 43 months, including the program duration period. The graph shows non-monotonic consumption trends for both groups, for the whole period under consideration, possibly because of other external factors, such as weather conditions and household-specific changes. However, on the whole, it can be seen that following the intervention, the participants' consumption decreased, compared to consumption of the non-participants group. Although this is a sign of the program's effectiveness, further analysis is required to evaluate the water savings achieved.

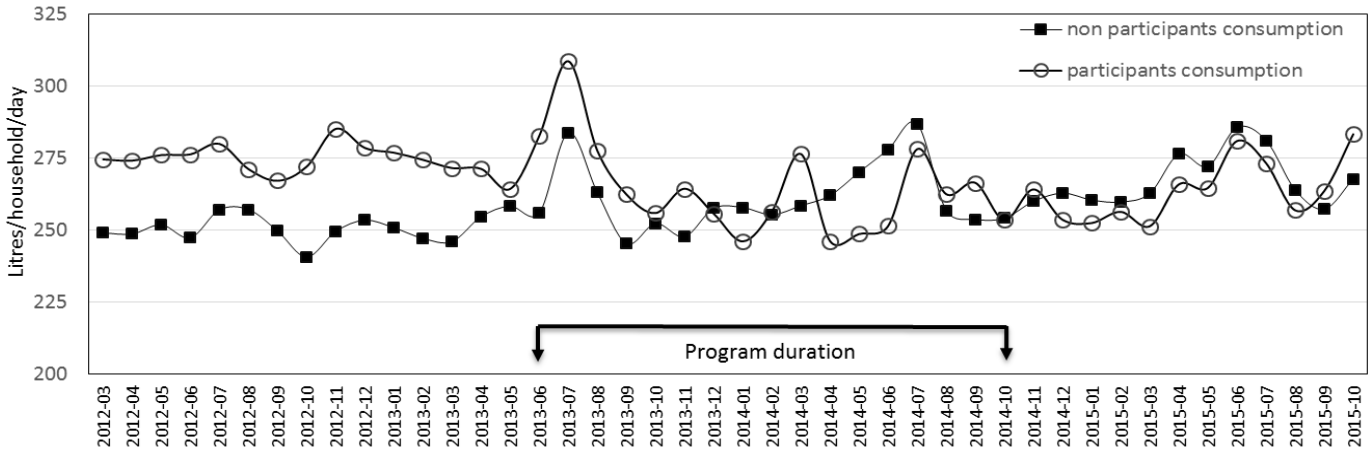

Figure 1. Water consumption of participating and non-participating households

TECHNIQUES FOR WATER SAVINGS EVALUATION

According to the literature, there are three main methods of residential water efficiency program evaluation: participant before-after parametric or non-parametric tests; participant-control means comparison methods, and regression techniques, including time series, covariate, cross-sectional and panel data regression (Fyfe et al. 2010). Before-after methods are subject to many sources of bias, as they do not account for external factors that may have a considerable effect on consumption. Participant-control comparison methods are designed to limit the bias caused by external factors. However, a control group should possess the same household characteristics and should be drawn from the same geographical area as the participants' sample for the comparison to be accurate. An alternative technique that effectively combines before-after testing with participant-control techniques is Matched Pairs Means Comparison (MPMC), developed by the Institute for Sustainable Futures, University of Technology in Sydney (Fyfe et al. 2010). MPMC is not discussed here. As for regression techniques, panel data regression is regarded as the most robust method for water savings evaluation. However, it is not frequently used in evaluation studies, as it is data-intensive and requires a certain level of statistical analysis skills.

The decision of which method to use depends on the type of available data, their quality and sample sizes; but also on the skills and expertise available for the data analysis and interpretation of results. Most water companies both in the UK and worldwide experience data limitation problems that do not allow them to perform a robust evaluation of water savings. Common limitations include:

- Absence of high-quality, small-interval meter readings (e.g. monthly, 2- or 6-monthly readings without consecutive periods of missing data).
- Unknown program take-up dates for each participating household.
- Small participating households sample sizes.
- No information on participating household demographics (e.g. number of occupants, average household income etc.).
- No information on non-participating household demographics, such as the number of occupants, which leads to the incapability to compare participant and control samples using pcc efficiently,

rather than aggregated per household consumption, and to select a control sample that matches the participants' one.

- Major intervention date differences among households and limited consumption records before and after the intervention dates. This common problem makes before-after techniques inapplicable.

Improving the accuracy of before-after and participant-control methods

It is very common that water companies in the UK do not possess household-related information such as household size, property size or average household income when deciding to embark on a water efficiency program. However, these data are essential for a robust water savings estimation using mixed-effects models. If a water company wishes to explore the impact that a water efficiency initiative had on consumers of different social classes/property sizes and thus to draw important information that can be referenced when a similar program evaluation is needed in the future, the Acorn classification can prove to be useful. Even if no other demographic information is available for the participating household sample and for a sample of non-participating ones (which could be used as a control group), before-after means comparisons could be undertaken by disaggregating the participants' sample into subsamples of the same Acorn classes and running t-tests. It should be stressed, however, that a sufficiently large sample of households belonging to each Acorn class would be necessary for this analysis to be possible.

In a similar manner, if Acorn class and per household consumption are known for a sufficiently large sample of households that did not take part in the program and are located in the same geographical area as the participating homes, the change in consumption for the former group can be used as a representative reference case for comparison to the latter group's consumption change after the efficiency program launch.

Multilevel Modelling (Mixed Effects Models)

It is very common that social data have hierarchical (nested) structures. A well-known form of nested data are panel data (observations over time that are nested in different subjects). In the context of this study, the subjects are the households, and the overtime observations are monthly water consumption readings and monthly weather-related data. Nested data are not statistically independent; thus, linear regression and other techniques such as ANOVA that require statistical independence are not suitable, as they would produce extreme Type I errors if they were to be used. Multilevel regression (i.e. hierarchical linear regression) is designed for application to hierarchical data structures as it accounts for the statistical dependence among sequential observations in the same group. It is an extension of regression; its difference lies in the fact that the parameters can be allowed to vary. Multilevel models also ignore the assumption of homogeneity of regression slopes; they can handle missing data with much greater ease than other statistical procedures; and, most importantly, they make use of data for each and every observation or time point, increasing the power of analysis (Goldstein 2003; Field 2012).

As far as this study is concerned, multilevel models offer a more appropriate and powerful analysis of the particular dataset than simple Ordinary Least Squares regression, as they allow for the full exploitation of the data, providing the opportunity to make use of both time-varying and time-invariant variables in the same analysis. In order to perform the analysis, the *Nlme* package in R software was used (Pinheiro et al. 2016). The first model that was developed was an unconditional means (empty) model which is equal to a one-way analysis of variance (ANOVA), followed by a step by step addition of fixed effects. The fixed effects components include weather and household demographic variables as well as a dummy variable representing the water efficiency program. Finally, several interactions between variables of interest were added to the models, completing the formation of a two-level random slopes model with cross-scale interactions. The level-1 unit of analysis are the separate consumption observations in time whereas the level-2 unit under which level-1 units are nested, is the household.

Model Development

Properties identified as flats were removed from the participants' sample; thus only single-family participating households were used in the analysis. Pcc was not normally distributed; thus the natural logarithm of pcc was used as the dependent variable. To ensure normal distributions, all continuous independent variables were transformed to their natural logarithm. Multicollinearity can become a serious problem in mixed models especially when the model contains cross-level interactions (interactions that cross levels in the hierarchy) (Field et al. 2012). For this reason, it is suggested that predictor variables are centred before the analysis. By centring variables, we transform them into deviations around a fixed point and typically, level-1 variables should be centred. Centring predictor variables does not change the model's fit. There are two ways to centre data, namely group mean centring and grand mean centring. In the group mean centred model, the variables are centred around the group mean whereas in the grand mean centred model, the variables are centred around the grand mean (Field et al. 2012). For this study, grand mean centring was used for the level-1 weather variables.

An unconditional means model (empty model) that included only the intercepts and the random effect for the highest level variable of the nested structure – in this case each household – was run first. The interclass correlation coefficient, the proportion of variance in the dependent variable that lies between groups (O'Dwyer and Parker 2014), was 0.656 ($p<0.001$) for the log of pcc, meaning that 65.6% of the variation in water consumption can be attributed to between-household variations. Therefore, the variation between households should be taken into account in the model by allowing intercepts to vary. The empty model also allowed the assessment of the need for a multilevel model. A baseline model that only includes the intercept was structured. Then, the fit of the unconditional means model (where intercepts are allowed to vary over households) is compared to that of the baseline model using Analysis of Variance (ANOVA). ANOVA for models comparison (Quick 2010) produced a Likelihood ratio of 2603 ($p<.001$), confirming that the varying intercepts of the empty model improved the model's fit.

The first variables to be entered in the model were the weather-related level-1 variables (Table 2). The natural logarithm of the number of days of more than 1 mm rain per month (Log.raindays) and the hours of sunshine per month (Log.Sunshine) were selected, as they appeared to have a more significant effect on water consumption than the other weather related variables (data on Maximum and Mean Temperature were also available for this time period). Also, it was possible for both of them to be used in the model, as the relationship between them appeared to be weak, with a correlation coefficient of 0.31. At level-2, the dummy variable for the water efficiency program implementation (intervention), Acorn class (Acorn) and the number of residents per household (occupants), were included in the model. The interactions between variables were also explored. The heterogeneity of slopes for Log.raindays was not significant. Thus, Log.raindays was entered in the model only as a fixed effect.

RESULTS

Table 2. Multilevel model results

	Unconditional Means Model	Level-1 fixed	Level-2 fixed	Level-2 fixed (incl. interactions)	Full model (incl. Random Slopes)
Intercept	4.682	4.681	4.91	4.911	4.909
Log.raindays	-	-0.0233*	-0.025**	-0.024*	-0.023*
Log.Sunshine	-	0.0335**	0.041***	0.015	0.013
Intervention	-	-	-0.072***	-0.076***	-0.075***
Acorn class	-	-	-0.074**	-0.074**	-0.073**
occupants	-	-	-0.079**	-0.106**	-0.106**
Interaction: Intervention-occupants	-	-	-	0.052***	0.052***
Interaction: Log.Sunshine-Intervention	-	-	-	0.056**	0.059**
Interaction: Log.Sunshine-occupants	-	-	-	-0.032***	-0.032**

*p<0.1, **p<0.05, ***p<0.001 Notes: water use observations = 2682; households = 66; observations per household = 41 on average. Weather datasets were obtained via the Met Office (www.metoffice.gov.uk/climate/uk/summaries)

Pcc increased with the hours of sunshine and decreased with days of rain of more than 1 mm, as expected. A 10% increase in daily sunshine is associated with a 0.41% increase in consumption, while a 10% increase in days with rain of more than 1 mm can lead to a 0.25% decrease in consumption. At the household level, water use was negatively correlated with the dummy variable for the water efficiency program, Acorn class and the number of occupants.

We can conclude that after the program launch there was a 6.95% decrease in consumption (*1-exp(-0.072)*), which can be attributed to the water efficiency program. Using the *intervals ( )* function of the *nlme* package in R, 95% confidence intervals were obtained for the intervention variable: [-0.092,-0.0525]. Taking into account the transformation of pcc to its natural logarithm, we can conclude that the water efficiency program resulted in a consumption decrease of between 5.1–8.8%.

As for the consumption of separate Acorn classes, the full model shows that moving from Acorn class 1 to Acorn class 5, pcc decreases by 7.1%. In other words, an average resident of an Acorn class 1 household consumes 7.1% more water than that of an average Acorn class 5 household. In the case of the number of people in the household, the full model demonstrates that an average occupant of a household of five members consumes 7.6% less water than an average occupant who lives on their own.

The interaction of the intervention with the number of occupants was positive and highly significant (0.052, p<0.001). This finding translates into the fact that the negative effect of device installation (-0.072, p<0.001) became less negative with increasing number of people in the household. In simpler words, it shows that in households with more occupants, the water efficiency program was less effective, as the pcc decrease that was caused by the device installation became smaller. The interaction of the intervention with log.Sunshine was positive and significant (0.059, p<0.05). This finding shows that in periods of increased sunshine, the effect of the intervention became less negative. This notion translates to the fact that the water efficiency program appeared to be less effective in reducing consumption during periods of sunny weather. Finally, the interaction term of log.Sunshine and occupants was negative and significant (-0.032, $p<0.05$). The negative effect of occupants (-0.079, $p<0.05$) became less negative with increasing log.Sunshine (which has a positive effect on pcc), indicating that during periods of sunny weather, a person would consume much more water than usual if he/she lived alone than if he/she lived together with more people. Variance inflation factors (VIFs) of the independent variables were calculated. All VIFs were under 2.4; thus it can be assumed that there is no multicollinearity problem in the dataset.

Results comparison between before-after means comparison and multilevel model

The multilevel model demonstrated that there was a mean 5.1–8.8% pcc decrease, attributable to the water efficiency program. A simple before-after test for the sample of participating households was also conducted using participants' pcc data only (not shown here). Six months before the program take-up period and the same six months of the following year were used for the comparison for each household. Bootstrapped 95% confidence intervals were obtained for the consumption change using the *boot.ci()* function from *boot* package in R, showing an average decrease of between 7.98–27.12%. Bootstrapping is a computationally intensive technique which enables inferences without making strong distributional assumptions, it rather uses Monte Carlo resampling to estimate a distribution (Wright et al. 2011). As evident, there is a large difference between the consumption decrease ranges that the two techniques provide, with the multilevel model providing a much more precise estimate and much narrower confidence intervals.

DISCUSSION

In our study, a 10% increase in daily sunshine was associated with a 0.41% increase in consumption ($p<0.001$), while a 10% increase in days with rain of more than 5mm was shown to lead to a 0.25% decrease in consumption ($p<0.05$). These results are in line with past American and Australian research, which in its larger extent found climate variables to be significant but of low magnitude (Gato et al. 2007, Mieno and Braden 2011). Pcc in Acorn class 1 properties was 7.1% higher than in class 5 ones ($p<0.05$). The most likely explanation for this is that richer homes usually contain more water amenities, both indoors and outdoors and that due to their affluence, they might be less concerned about their water bills. This finding is also supported by relevant research which shows that suburban affluent homes in the UK and Phoenix, Arizona respectively, use more water than the rest household types (Harlan et al. 2009). The effect of household size on pcc was also tested in the present study. It was shown that people living alone consume 7.6% ($p<0.05$) more water daily than those who live in a five-member home. Many researchers suggest that pcc decreases with an increase in household size, due to economies of scale with many residents in a house, where food preparation, dish washing, gardening and other activities take place despite the household size and are capitalized on a shared living environment (Polebitski and Palmer 2010). An interesting finding was that during periods of sunny weather, a person would consume much more water than usual if he/she lives alone. A possible explanation for this is summer outdoor use. Water quantity used for irrigation is larger during sunny weather, due to evapotranspiration and decreased frequency of rain events and garden watering is going to take place regardless of how many people live in a household. Past American research (Bao 2013) suggests that there is a relationship between a household's consumption sensitivity to weather and household size, although this relationship appears to be weak in most instances. Finally, it was illustrated that in households with more occupants, the efficiency program was less effective, as the pcc decrease that was caused by the devices installation became smaller. This result agrees with the previous UK study by Gilg and Barr (2006).

In contrast to price-related policies, technological changes such as retrofit programs and other non-price demand management policies have gained less attention, as Millock and Nauges (2010) recognise, mainly because of the lack of adequate data. Even in the cases when researchers have explored the effect of technological changes on water demand, they usually rely on engineering assumptions of the expected demand reductions (Kenney et al. 2008).

CONCLUSIONS

This study further contributes to the existing literature, as disseminating knowledge obtained through implemented water efficiency programs internationally is crucial for the establishment of a robust evaluation framework that will move existing evaluation practices forward. Based on the results of the multilevel model, the water efficiency program was successful in decreasing per capita water consumption of the households that took part by approximately 7%. Moreover, it was illustrated that Acorn class can be used effectively in water efficiency evaluation studies as a proxy for household income and property size when these data are not readily available and that powerful analysis can be conducted for the evaluation of efficiency programs using multilevel models, even without a control sample of households. Based on robust multilevel modelling results, it is highly recommended that future efficiency programs are targeted to small households, where the potential to save more water is larger.

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