EVALUATION OF THE HOME POWER SAVINGS PROGRAM – PHASE 1

FINAL REPORT

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EXECUTIVE SUMMARY

The NSW Office of Environment and Heritage (OEH) commissioned the Institute for Sustainable Futures (ISF) to undertake a statistical evaluation of electricity savings from the Home Power Savings Program (HPSP). Savings in gas or other fuel usage were not examined.

The program targets low-income households in NSW, in both government and non-government accommodation. It involves a visit to the household by an energy advisor who provides a Personal Power Savings Action Plan. In addition, eligible households could be provided with various items from a Power Savings Kit (PSK) at no cost.

ISF used two separate techniques for the electricity saving analysis, regression and matched pairs mean comparison, and the results from both techniques are reported where applicable. Full technical descriptions of the two methodologies can be found in Appendix C.

This Phase 1 report follows on from the Pilot report which reported on the overall savings from the initial matched pairs analysis based on a more limited data set. Savings due to individual measures were not considered.

Data for 26,457 participating households was provided by the OEH, of which 12,145 were government or social housing tenants and 14,312 were owner-occupiers or private renters. Not all participating households could be included in the analysis due to data limitations, such as lack of meter data. Ausgrid, Essential Energy and Endeavour Energy provided meter data for 23,634 of the households. They also provided consumption data for four million non-participating households from which controls were sourced for use in the matched pair analysis. Information on the data provided is provided in Appendix B.

If households were metered separately for peak and off-peak energy use, these data were combined to create a total consumption for that household, and all analysis was based on the total consumption. This was done to eliminate the tariff biasing the results, as houses are much more likely to have off peak than units.

Steep rises in electricity prices in recent years have probably eroded the degree of savings from the HPSP. This is discussed in more detail in Section 3.

The average electricity saving across all participating households was estimated to be about 0.6kWh per household per day, which is about 4% of the average household consumption.

However, for households that received the full Power Savings Kit, the average electricity saving was about 1kWh per household per day, or 7.3% of the average household consumption based on the regression savings estimate method.

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1 THE HPSP PROGRAM

The HPSP commenced in June 2010 and is ongoing. Figure 1.1 shows the uptake of the program by households in the three energy providers' areas.

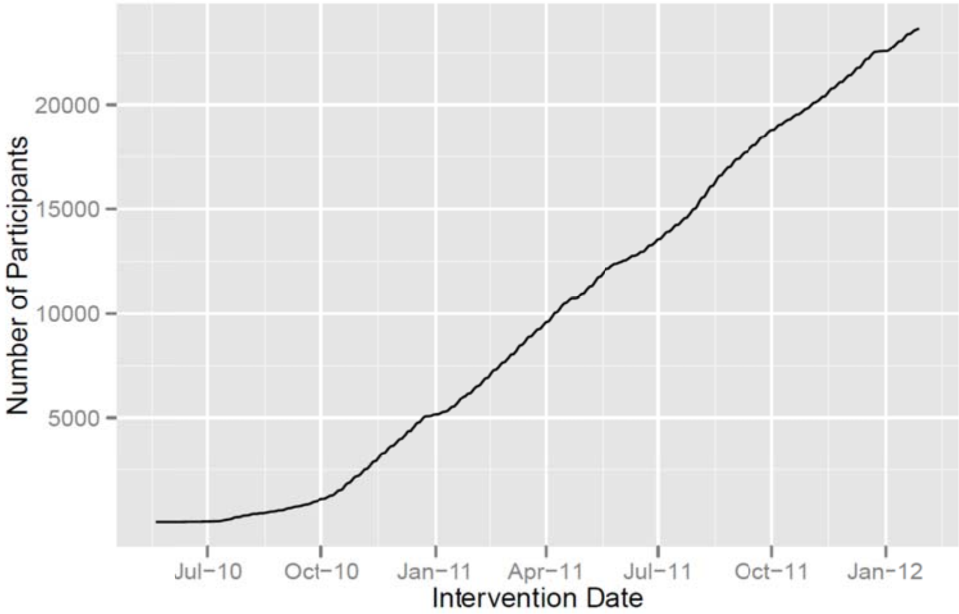

Figure 1-1 Uptake of the HPSP by households

The HPSP involves a visit to a low income household by an energy advisor who provides a Personal Power Savings Action Plan. In addition, eligible households could be provided with any combination of the following items from a Power Savings Kit at no cost:

- low flow showerhead
- up to 4 energy efficient light bulbs
- a stand-by saver power board
- shower timer
- tap aerator
- draught-proof strips for around the door
- door snakes.

Not all households received all these items, as some households already had them, refused them, were not offered them, or could not have them installed for some other reason. Only about 14% received a showerhead as many homes already had them or possibly didn't have a suitable water heater.

In most cases, items requiring installation were installed by the assessor, but in some cases they were left behind for the householder to install.

Household tenure was classified into three groups:

- Owner-occupier
- Private renter

- Renting government or social housing

Most government and social housing households did not receive a showerhead as these had been provided as part of previous low income household water efficiency programs. Of the 10731 government and social housing participants, only 617 (≈5%) got a shower head compared to about 14% of all households.

2 REGRESSION AND MATCHED PAIRS ANALYSES

Two different analytical approaches were used to estimate the savings from the HPSP, regression and matched pairs mean comparison (MP MC). The original intention was to just use matched pairs as a verification of the overall savings found from the regression analysis. However, a variety of distinct runs were in fact performed for the MPMC analysis.

2.1 MPMC APPROACH

The MPMC procedure is conceptually simple but computationally intensive, and is specifically designed for estimating energy and/or water savings using only billing data[1]. The core logic is:

- Each participant household is 'paired' with a non-participant household that has a similar consumption pattern prior to the start of the HPSP.
- Since each paired non-participant household had a similar consumption pattern to its paired participant household, it serves to indicate what the participant household's consumption *would have been* had it not participated in the program.
- Since we have an estimate of what each participant household would have consumed, and we observe what each participant household did consume, taking the difference of these gives us an estimate of the savings attributable to participation.

The MPMC approach implicitly controls for factors such as weather, changes in appliance ownership and other trends. ISF has undertaken extensive validation of the method and has confirmed that it can be used to obtain an unbiased estimate of savings (see Appendix D).

A total of 13,655 households were used for the analysis.

The runs examined were:

- Savings from all Participants
- Savings from receiving all items in the Power Savings Kit[2]
- Savings from receiving all items except a water efficient showerhead
- Savings by housing provider (Public/social housing versus owned/private rental)
- Savings by property type (units versus houses)

[1] Where detailed demographic and other data is available about both the participant and non-participant households (such as dwelling type, household income and structure, appliance ownership, and so on), a regression model may be more appropriate, and provide more detailed results.
2 Ignoring aerators, due to small number of households receiving these items.

- Savings by electricity provider (Ausgrid, Endeavour, Essential)

2.2 REGRESSION APPROACH

Regression is probably the most widely used approach to analysing energy efficiency programs (Vines & Sathaye 1999, Bartels and Fiebig 2000, Isaacs et al 2006). It differs from matched pairs in that non-program influences such as climate and household-specific differences are generally controlled for directly, whereas in matched pairs, they are implicitly controlled for. A regression model also allows savings from individual program components to be estimated more naturally than with matched pairs.

A total of 23,529 households were used in the regression model.

The regression analysis considered the following Program elements:

- Savings from all Participants
- Savings per person from receiving a water efficient showerhead
- Saving from efficient lights
- Savings from the power board
- Savings from behaviour change

2.3 SUMMARY OF KEY RESULTS

Note on significance of results: Unless otherwise stated, all results in this report are significant at 95% confidence or greater.

Table 2.1 shows two key saving estimates for HPSP program components from regression and matched pairs. A household was considered to have received all items in the Power Savings Kit if it got everything except for a tap aerator, as very few tap aerators were provided.

Table 2-1 Key HPSP saving results from regression and matched pairs

	Regression kWh/hh/day	%	Matched pairs kWh/hh/day	%
Average savings across all households	0.57	3.8	0.6	4
Average savings from households that received all items	1.1	7.3	0.9	6

No two techniques are likely to produce identical results, as they will rely on different underlying mathematical assumptions. Nevertheless, the estimates of savings from the two techniques agree fairly closely. Looking at the combined results from both techniques suggests that, regardless of which is used to analyse the data, the saving achieved by a household receiving all PSK items is around 1 kWh/day, and the average across all households is about 0.6 kWh/day.

3 PATTERNS OF USE IN PARTICIPANT AND CONTROL GROUPS

There are a number of background factors that should be taken into account when considering the results of the HPSP.

3.1 ELECTRICITY CONSUMPTION TRENDS

Average electricity consumption of participant households is lower than the average for all households in NSW. Participant households consumed about 5,500kWh per year compared to the average for all NSW households of about 7,000kWh. This is to be expected as there is a well-established link between income levels and energy consumption (IPART 2006; Rickwood 2009). This reduces the savings potential of programs targeting low income households.

Electricity consumption has also been trending down over the past several years. This is a pattern found in many parts of Australia. In its household expenditure survey for the Sydney metropolitan, Blue Mountains and Illawarra areas, IPART found that average household demand for electricity fell by around a total of six per cent over the four years between 2005-06 and 2009-10 (IPART 2010a). Surveys for the intervening years are not available to determine any annual trend.

As the Figure 3-1 shows, electricity consumption has dropped by 5 to 10% since 2008 in both the network average of the all the households and the HPSP participant households. The savings estimates for the HPSP in this report have been adjusted to allow for this reduction.

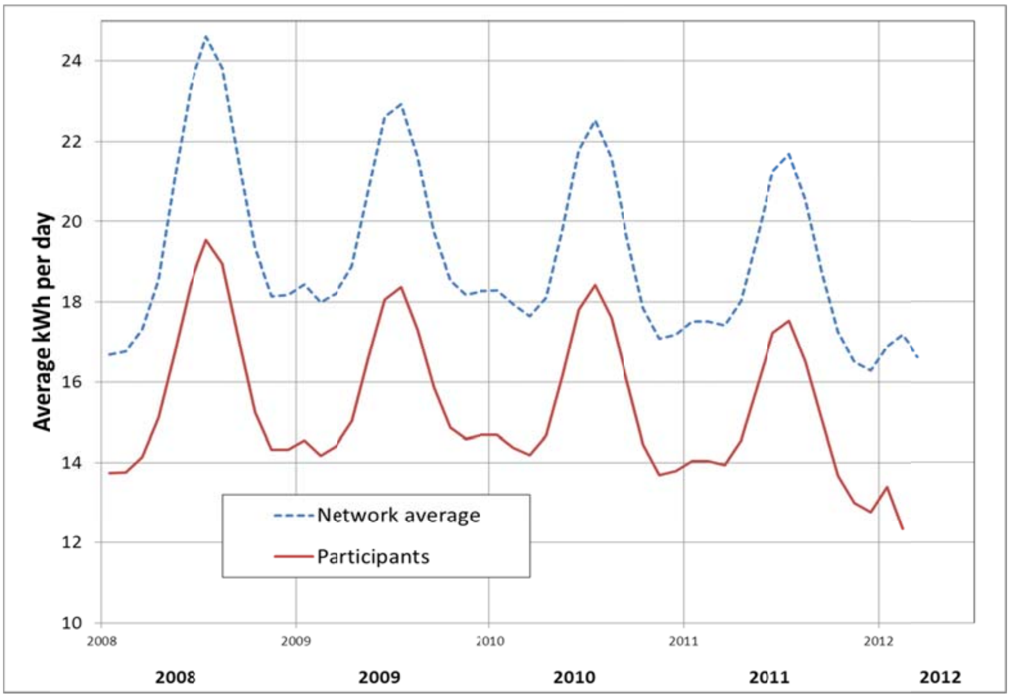

Figure 3-1 Trend in participant and network average electricity consumption over time

This drop in electricity consumption has probably been partly due to efficiency improvements. These efficiency improvements have been spurred by rapidly rising electricity prices over the past several years. It is possible that concern about the impact of the introduction of the carbon tax on increasing electricity prices has also had an effect, as there has been considerable coverage and speculation in the media about the prospect of future steep price rises.

Figure 3-2 shows the rise in average NSW residential electricity prices over the past 11 years. The consumption charge accounts for about 85 – 90% of a typical household's electricity bill. Prices in NSW will rise by an average of approximately 18% in 2012-2013 (IPART 2012)

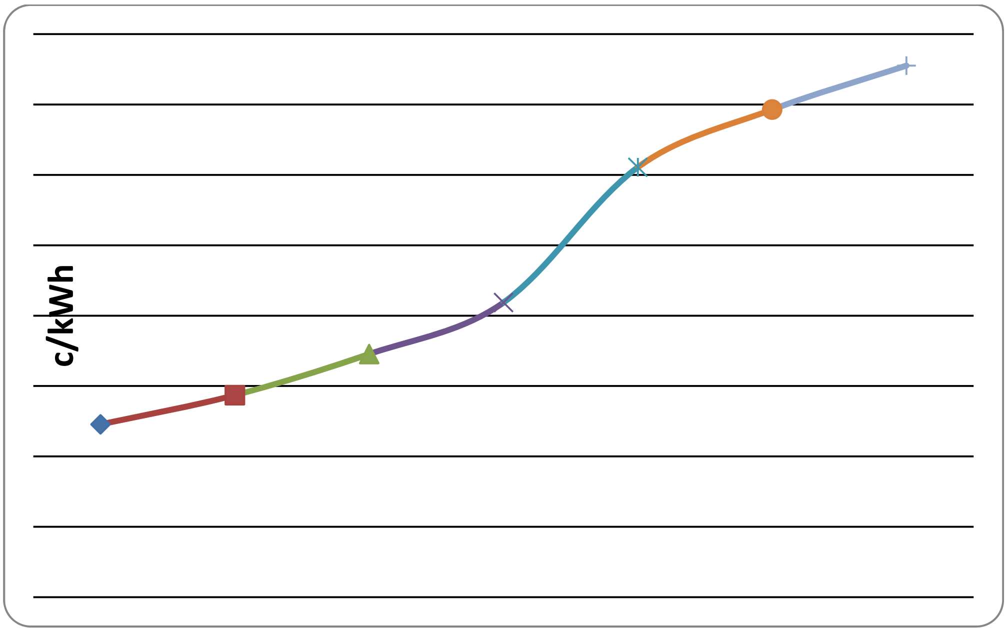

Figure 3-2 Average NSW residential electricity price

Source: KPMG spreadsheet available at www.aemo.com.au/Electricity/Planning/Electricity-Statement-of-Opportunities

The drop in consumption over time will mean that there is some degree of convergence between the usage in the participant and control households. There is also some indication that lower income households will have a less elastic response to price rises (Uniting Care, undated). These effects could have the effect of reducing the savings of participants relative to the controls over the life of the HPSP program.

3.2 THE TAKE-BACK EFFECT

A further influence when considering the results from the program is the rebound or take-back effect. This is where households 'take back' some of the potential energy saving benefits from an intervention in the form of an increased level of service. Although estimates of take back vary, it is an accepted factor in retrofit programs. The degree of take-back is usually larger in low income households as they are likely to already be taking a reduction in service level to save money and will therefore often take more of the benefit as an increased service level (Milne & Boardman, 2000). It is highly likely that the participant households have taken some benefits from the HPSP that are not readily assessed by a quantitative analysis that uses only consumption data.

4 ELECTRICITY SAVINGS FROM HPSP

This section presents a summary of the results of the regression and matched pair analyses for various components of the HPSP. Full details of the analyses can be found in Appendix A.

4.1 OVERALL HPSP SAVING

A total of 13,655 participant households were used to calculate the overall saving from the HPSP using matched pairs. The overall saving per household was found to be 0.57kWh/day from the regression analysis and 0.6 ±0.09 kWh/day from the matched pair analysis. This means there is effectively no difference between the two results for this component. A 0.6kWh/day saving equates to about a 4% average reduction per participant household.

Table 4-1 Average saving across all participating households

	Regression kWh/hh/day	%	Matched pairs kWh/hh/day	%
All households	0.57	3.8	0.6	4

However, this masks the significance of individual program components as not all households received all the available items on offer. Only about 14% of households had a water efficient shower provided as part of HPSP, but showerheads would probably be the biggest energy saving program measure for most households.

4.2 HOUSEHOLDS THAT RECEIVED ALL ITEMS

The estimated saving for the households that received all items is very close from both the matched pair and regression analysis, at 0.9 ± 0.26 kWh/day and 1.1 kWh/day respectively, indicating an average saving of about 1 kWh/household/day, or about 6.5%. A total of 1689 participant households were used for the matched pair estimate.

Table 4-2 Average saving for households receiving all PSK items

	Regression kWh/hh/day	%	Matched pairs kWh/hh/day	%
Households that received all items	1.1	7.3	0.9	6

4.3 HOUSEHOLDS THAT RECEIVED A SHOWEHEAD

The total saving achieved from a showerhead is highly dependent on the number of people living in the house. Showers account for around 60-70% of all household hot water use in the average home, and hot water is on average about 40% of a typical household's energy use. Therefore the number of people showering will have a significant impact on energy use. For this reason the estimate has been made per person.

Table 4-3 Average saving for households that received a showerhead

	Regression kWh/person/day	%	Matched pairs kWh/person/day	%
Households that received a showerhead	0.34	2.3	Not estimated	

This estimate is essentially only for owners-occupiers and private renters, as many fewer public or social housing households were provided with a showerhead. Of the 10,731 public or social housing participants, only 600 (≈5%) were given a shower head compared to about 3,000 private households.

Previous analysis of water saving programs undertaken by the ISF has found that efficient showers save in the range of 3.5kL to 5.5kL of water per person per year (Sarac et al 2002, Fyfe et al 2009). If it is assumed that the cold water is 18 degrees (the average annual figure for Sydney) and the hot water is 65 degrees, then approximately half of the water saved will be hot water. This will in the range of 1.75kL to 2.75kL of hot water based on the savings above. Using a simple engineering calculation, this equates to an energy saving of between 0.26kWh and 0.42kWh per day of hot water energy saved per person for a household with a standard electric water heater. The regression estimate is about the midpoint of this range.

Participating households were provided with a showerhead if they had gas, heat pump or solar water heating. Thus the estimated HPSP saving from regression analysis will be slightly lower than for households with electric water heaters because it is across all households, including those with non-electric systems.

It may also be that low income households use less hot water than the average. However, there are no savings data available specific to low income households.

4.4 HOUSEHOLDS THAT RECEIVED ALL ITEMS EXCEPT A SHOWERHEAD

The estimated saving for the 11,118 households that received all items except a showerhead were used for the matched pair analysis. The regression saving estimate is 0.45 kWh/hh/day, and from matched pairs 0.52 ± 0.09 kWh/hh/day.

Table 4-4 Average saving for households that received all items except a showerhead

	Regression kWh/hh/day	%	Matched pairs kWh/hh/day	%
Households that received all items except showerhead	0.45	3.0	0.52	3.5

4.5 HOUSEHOLDS THAT RECEIVED EFFICIENT LIGHT GLOBES

The savings available from lighting replacement programs have been significantly reduced in recent years due to the national phase out of the least efficient incandescent globes that commenced in November 2009. It would be expected that the most intensively used incandescent lamps in a home, which had a life expectancy of 1,000 to 2,000 hours, would have been replaced by more efficient lamps within 12 to 18 months of the phase out starting.

Assuming a lamp is used for four hours per day, replacing a 60W incandescent lamp with a 15W CFL will save about 0.18kWh/day ([60-15]*4/1000). Lamps used for less than four hours per day will save less.

Table 4-5 Average saving for households that received efficient lights

	Regression kWh/hh/day	%	Matched pairs kWh/hh/day	%
Saving from efficient lights	0.35	2.3	Not estimated	

The savings from lighting are much less sensitive to the number of occupants as most lighting energy use is in living areas, and these tend to be used for the same number of hours per day irrespective of the number of people living in the house.

4.6 HOUSEHOLDS THAT RECEIVED A POWERBOARD

Although standby consumption in a typical household accounts for about 10% of electricity consumption, savings from a single power board are unlikely to be very high on average.

Table 4-6 Average saving for households that received power board

	Regression kWh/hh/day	%	Matched pairs kWh/hh/day	%
Saving from a power board	-0.02*	-	Not estimated	

*Not statistically different from zero at the 95% confidence level

Most of the large standby users in a home are things that people are unable or unwilling to turn off, such as DVD recorders that are set to perform timed recording, cordless phones, Wi-Fi modems, security systems or Pay TV set top boxes. Standby consumption of individual appliances has generally been dropping over recent years, and more appliances, such as TVs and phone chargers, are becoming Energy Star® compliant. The issue is more the increasing number of appliances in homes that have standby consumption. Therefore, turning off a few appliances will not necessarily have a significant impact on standby consumption.

Little is known about standby consumption in low income households. However, one of the larger standby users in homes is home office equipment, and about 40% of the participant households did not have a computer compared to the Australian average of about 20%. This too could reduce the savings potential in these households[3].

4.7 BEHAVIOUR CHANGE

As the behaviour responses of households are not directly observed (except through their electricity use), it was not possible to analyse savings due to 'behaviour change' directly. Instead, it is assumed that any savings not directly explainable by specific kit items (showerhead, lights, etc.) are caused by changes in behaviour as a result of the audit.

Average savings from behaviour change were estimated at 0.16 kWh per household per day, but this result is not statistically different from 0 at 95% confidence level. A low saving from behaviour change is unsurprising. Although the potential savings from behaviour change are large, it usually requires active engagement to achieve them. Issuing people just with advice rarely results in significant savings. It is essential that advice is followed up by subsequent interventions to engage households and keep them engaged.

Table 4-7 Average saving from behavior change

	Regression kWh/hh/day	%	Matched pairs kWh/hh/day	%
Saving for behaviour change	0.16*	1	Not estimated	

*Not statistically different from zero at the 95% confidence level

4.8 HOUSING TYPE

[3] http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/1370.0~2010~Chapter~Home%20computers%20%284.8.3%29 (Accessed 27 June 2012)

The saving by housing type was estimated using matched pairs only. There were 4356 participants in units and 9369 participants in houses used in the MPMC approach.

A participant was assumed to live in a unit if the property type was:

- Studio apartment (60m^2)
- 2 bed unit (60-100m^2)
- Large unit (150-200m^2)
- Small terrace house/3-4 bed unit (100-150m^2)

A participant was assumed to live in a house if the property type was:

- Average 2-3 bed house (200-250m^2)
- Detached 4 bed house (250-400m^2)
- Large 5+ bed house (>400m^2)

Houses have a higher average daily consumption than units, 16.5 kWh/day and 11.2 kWh/day respectively, largely due to higher occupancy levels, and therefore a greater saving potential. However, units saved slightly more in percentage terms than houses.

The saving from participants in units is 0.47 ± 0.12 kWh/hh/d, whereas the saving from participants in houses is 0.66 ± 0.11 kWh/hh/d.

Note that this observed saving difference is due at least in part (and possibly in full) to differences in demographics between houses and units. For example, household size (i.e. number of occupants) is smaller in units than in houses and incomes are lower, and this may explain part (or all) of the observed difference rather than any independent effect from dwelling structure. ISF was unable to detect any independent effect from dwelling type in the regression models trialled, so this further suggests that savings are not strongly affected by dwelling type alone, but rather by other factors associated with dwelling type (such as household size).

Table 4-8 Average daily usage and saving by housing type

	Houses kWh/hh/day	% saving	Units kWh/hh/day	% saving
Average daily electricity use	16.5		11.2	
Saving by housing type	0.66	4.0	0.47	4.2

4.9 HOUSING TENURE

The saving by housing tenure was estimated using matched pairs only. There were 7053 government and social housing households and 4356 private housing households used in the MPMC approach.

Three types of tenure were available from the data:

- owner occupiers
- rent from a private landlord
- rent from a public or social housing provider

The saving from private housing (owner occupier or renting privately) is 0.73±0.13 kWh/hh/day, whereas the saving from government and social housing is 0.45±0.12 kWh/hh/day.

Part of this difference between tenures is due to the fact that most government and social housing participants did not receive a showerhead whereas a higher percentage of private housing participants did. If private households that received a showerhead are eliminated from the analysis, then the saving for this group drops to 0.65 kWh/hh/day.

Table 4-9 Average saving by housing tenure

	Private housing	% saving	Government / social housing	% saving
All households	0.73	4.9	0.45	3
Private households that did not receive a showerhead	0.65	4.2		

Another factor is that whereas only around 16% of private household participants live in units, about 84% of public and social housing participants live in units, as shown in Figure 4.1. As shown in the previous section, the saving in houses is larger than units, 0.66 kWh/day for houses compared to 0.47 kWh/day for units so the savings will be greater in private than in public housing.

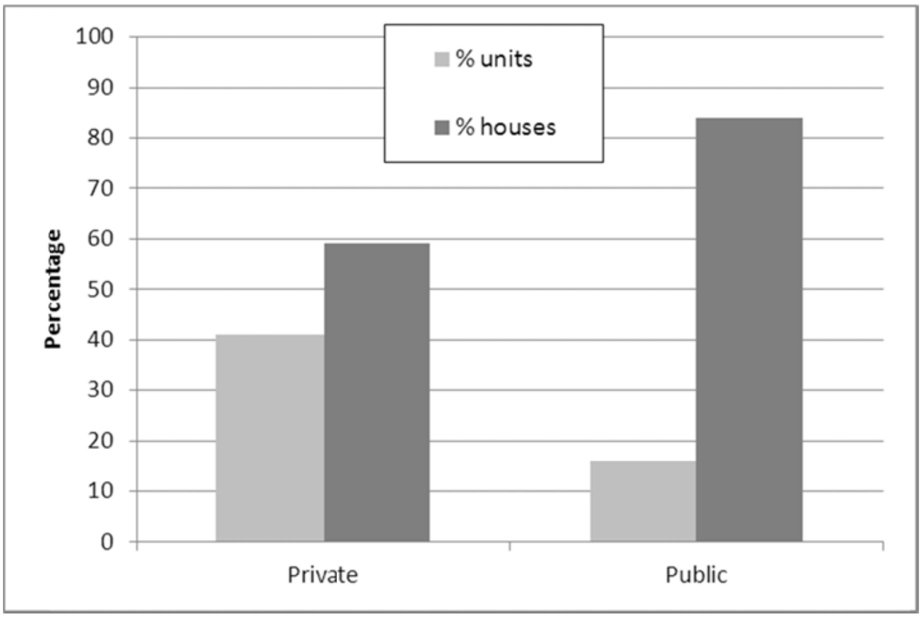

Figure 4-1 Percentage of households in units and houses

4.10 ENERGY PROVIDER

The saving by energy provider was estimated using matched pairs only. The number of households used in the matched pairs analysis for each energy provider was:

- Ausgrid: 7237
- Endeavour: 3214
- Essential: 2823

The table shows the average savings in each of the energy providers' network areas

Table 4-10 Average savings by energy provider

Provider	Saving
Ausgrid	0.55 ± 0.12 kWh/hh/d
Endeavour	0.44 ± 0.16 kWh/hh/d
Essential	0.78 ± 0.21 kWh/hh/d

None of the savings by network area are statistically significantly different from the overall saving of 0.6 kWh/hh/d, but the difference between Essential and Endeavour is significant. The savings by provider can be in part explained by household differences in their areas.

Essential Energy participants' higher level of savings could be due to the fact that they have:

- Only 20% of households in units compared to the overall participant group's 28%
- Only 33% of households in social housing compared to the participant group's 46%

Since it is known from above results that houses save more than units and private housing participants save more than social housing participants, Essential's households higher savings value could be expected.

The relatively low energy savings from Endeavour customers appears odd, particularly given Endeavour has a strong base in Western Sydney. However, by examining the participants' metadata, we see that the percentage of units is similar to the participant population (26% compared to 28%) but the percentage of participants in social housing is considerably higher (58% compared to 46%).

4.11 DECAY OVER TIME

For the purposes of the following discussion, it is important to stress again that ISF estimates *net savings* attributable to the HPSP. Thus, if participating households 'save' energy by receiving efficient light bulbs, but non-participating households are independently replacing light bulbs at the same rate and achieving the same saving, we would report zero net savings.

With this in mind, we expect that for any efficiency program, savings will 'decay' over time, as non-participating households 'catch-up' to participating households. We would expect, for instance, that non-participating households will be replacing their inefficient light bulbs with efficient compact fluorescents, and that over time, this will erode the savings from the light bulbs distributed by the Home Power Savings Program.

While we *expect* savings to decay over time, ISF is unable to observe any such decay. See, for example, Figure 4-2 below, showing savings (in green) relatively constant over time[4].

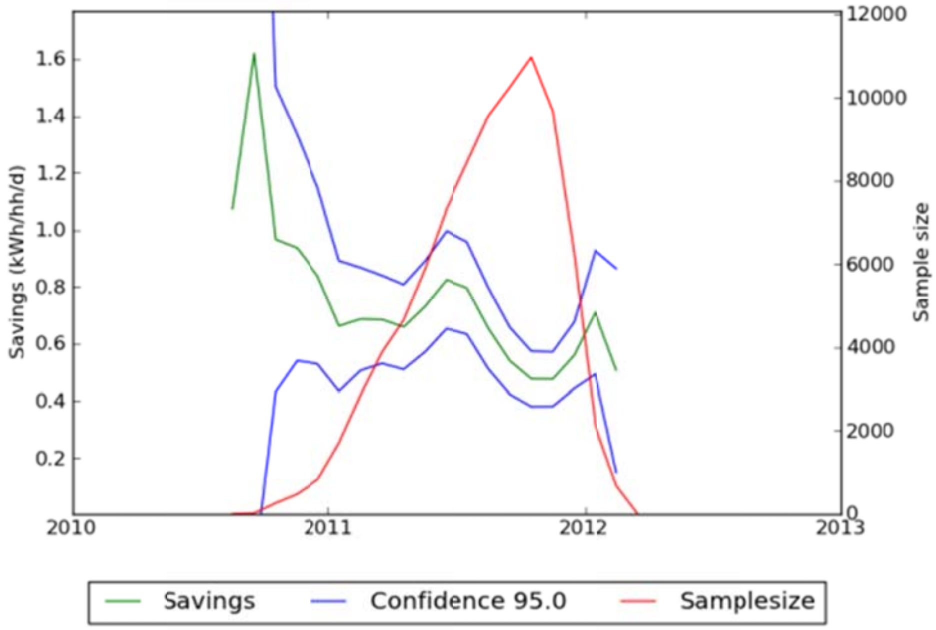

Figure 4-2 Savings over time from the HPSP. The green line shows estimates savings by calendar month, and the blue lines show the 95% confidence interval for each month. The red line (right-hand scale) shows the number of HPSP participants in the pair-matching analysis.

No statistically significant decay or increase over time in any of the savings could be found in the data. In other words, it seems plausible that savings from the program remain relatively constant over the timeframe of this analysis. In the longer term, some decay would be expected as the control households adopt the same structural efficiency measures as the participants. However, over the timeframe of this analysis this is unlikely to be significant.

4.12 SEASONALITY

Although we would expect to see some seasonal variation in savings, especially for showerheads, no significant seasonal effects could be detected in the available data.

[4] More formally, fitting a linear model to savings-by-month, we were unable to reject the null hypothesis that there is no decay.

4.13 BILL SAVINGS

The prices used to calculate electricity bill savings are the regulated tariffs for Energy Australia for 2011/12 and 2012/13 (including GST) and are summarised below.

2011/12 Tariffs

All Time tariff	
First 1,750 kWh per quarter (19kWh/day)	22.66 c/kWh
Remaining usage per quarter	32.01 c/kWh

Off peak 1	9.02 c/kWh

2012/13 Tariffs

All Time tariff	
First 1,000 kWh per quarter (11kWh/day)	26.84 c/kWh
Next 1,000 kWh per quarter	28.05 c/kWh

Off peak 1	11.11 c/kWh

The table shows the calculated annual electricity bill savings for three different savings scenarios using 2011/12 and 2012/13.

a) a house on the All Time tariff saving 4.5%;
b) a house on the All Time tariff saving 6.5%; and
c) a house saving 6.5% but with the Off Peak tariff for their electric hot water system.

The calculations assume the average participant consumption of 15 kWh per day. It is also assumed that for the 2011/12 prices they will not exceed 1750 kWh in any quarter (19kWh/day) and pay the consequently higher block tariff. For the 2012/13 prices it is assumed that they will exceed the 1,000 kWh in all quarters (11kWh/day) as is shown in Figure 3.1.

Hot water savings for the off peak calculations are based on the average participant household occupancy of 1.9 people and an electricity use saving of 0.34kWh per person per day.

Table 4-11 Typical electricity bill savings

Electricity prices used	4% overall saving General tariff	6.5% saving from all items General tariff	6.5% saving from all items Off Peak hot water tariff
2011/12	$50	$81	$48
2012/13	$60	$97	$58

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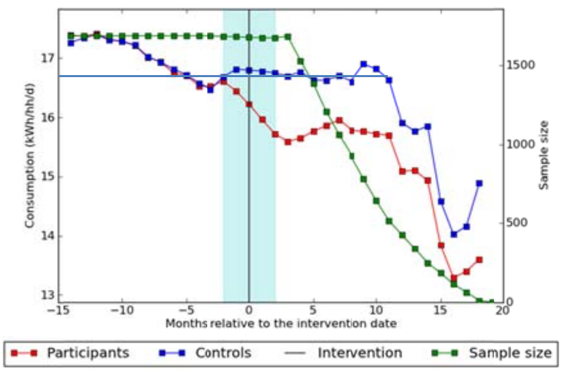
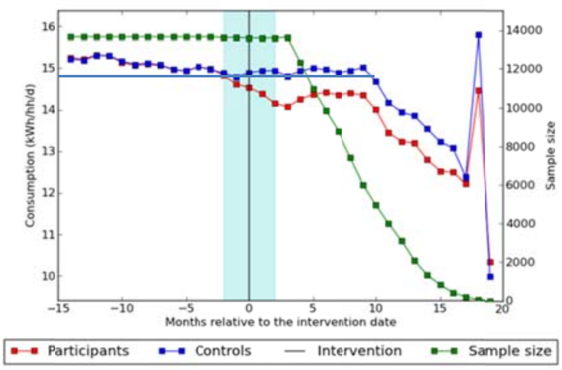
6 APPENDIX A: DETAILED RESULTS

This Appendix presents the findings of the regression and MPMC analyses in more detail.

For the MPMC method, percentage savings for participants are calculated as the difference between the average post intervention consumption of the participants and that of the corresponding control group cohort. For example, the overall percentage saving for the participant households that received all items is based on the average daily consumption in the 12 months post intervention of their control group cohort, which is 16.7kWh. However, when looking at the savings from households that didn't receive a showerhead, then only that cohort from the control group is used and these have a post intervention consumption of 14.8 kWh/day. This is shown in Figure 6-1.



A: Households that received all PSK items



B: Households that received all items except a showerhead

Figure 6-1 Illustrating the difference in post intervention daily consumption of controls for different cohorts

6.1 REGRESSION ESTIMATES

Table 6-1 Regression estimated savings

Savings category	Estimated average savings kWh/hh/day	%
All households.	0.57	3.8
Households that received all PSK items	1.1	7.3
Households that received a showerhead	0.34 kWh/person/day	
Households that received all items except showerhead	0.45	3.0

Households that received efficient lights	0.35	2.3
Households that received a power board	-0.02	-
Behaviour change	0.16	1.1

Regression coefficient	Estimate (negative values indicate savings)	Notes
δ: estimate of savings attributable to 'behaviour change'	-0.16 kWh/hh/day (95% confidence interval: -0.59 to 0.08)	Not statistically different from 0 at 95% confidence level.
η: estimate of savings attributable to the provision or installation of efficient lights	-0.35 kWh/hh/day (95% confidence interval: -0.52 to 0.19)	Significant at 95% confidence level. We could not detect a difference between lights installed or lights left behind. Although savings from lighting is likely to be seasonal (higher in winter), we did not have sufficient data to detect such an effect, so this estimate is the average saving across all months.
ζ: estimate of savings *per occupant* attributable to showerhead.	-0.34 kWh *per person* per day. (95% confidence interval: -0.38 to -0.29).	As with lights, we were expecting that installed showerheads would result in higher savings than showerheads left behind, but we could not detect any such effect, so this term covers both installed and left behind showerheads. Is it very likely that savings from the showerhead *are* seasonal, but we are unable to detect this with the data available.
θ: estimate of savings from provision of a standby saving power board	0.02 kWh/hh/day (95% confidence interval: -0.19 to 0.22)	Not statistically different from zero (i.e. we estimate little to no savings from power-board). ISF did trial more complex regression equations that included the number of appliances and/or house size when assessing the impact of the power-board, but none of these equations yielded results better than the simpler model used.
α (not of policy interest)	Not of policy interest	Intercept term. Included in model to help estimate other coefficients but not of policy interest.
β (not of policy interest)	Not of policy interest	Term relating variation in participant consumption to variation in average non-participant consumption. Included in model but not of direct

		policy interest.
γ_i (not of policy interest)	(per-household random effect)	This term is specific to each household, and acts to control for household-specific factors. Including it helps with the estimation of other parameters, but by itself it is not of policy interest.
$\kappa_{t,m}$ (not of policy interest)	Not of policy interest (per-month fixed effect)	Helps to control for seasonal/monthly differences between participant and control consumption.

6.2 MPMC ESTIMATES

Table 16 shows the estimated savings from the MPMC analysis. Each of these is discussed in more detail in the following sections.

Table 6-2 Matched pair estimated savings

Saving category	Estimated saving kWh/hh/day
Average savings (all households, all networks)	0.60 ± 0.09
Average savings for households that received all items.	0.90 ± 0.26
Average savings for households that received all items except a showerhead.	0.52 ± 0.09
Savings for privately owned / rented housing	0.73 ± 0.13
Savings for Government / social housing	0.45 ± 0.12
Average savings for Ausgrid's network area	0.55 ± 0.12
Average savings for Endeavour's network area	0.44 ± 0.16
Average savings for Essential's network area	0.78 ± 0.21

There is a feature in Figures 6.3 to 6.15 where the controls consumption appears to decline by approximately 2 kWh/hh/d about 10 months after the intervention on the relative scale. The reason for this can be explained by the understanding that for each month the characteristics of the participants' changes as indicated in Figure 6.2.

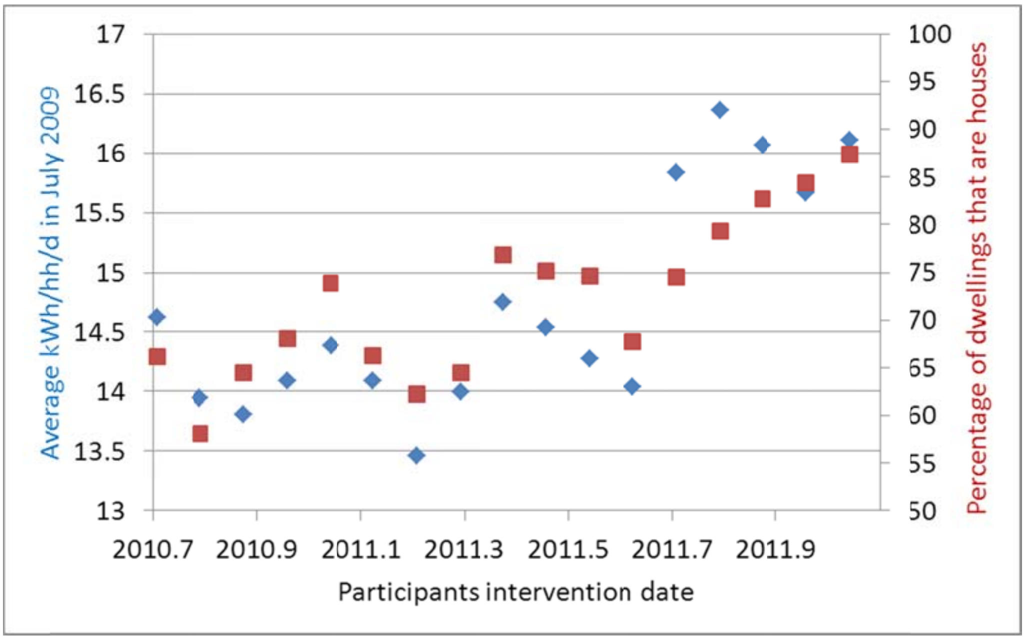


Figure 6-2 Participant housing type by intervention month

As shown in Figure 6-2, households in detached dwellings were disproportionally signed up later in the HPSP program. The average consumption of late-comers to the program was also higher[5]. Put another way – different 'cohorts' were signed up at different times, and these cohorts had different characteristics. This explains some of the peculiarities in the analysis. For instance, we see in Figure 6-1 that the average consumption of households in the program for 12 months or longer is lower than the average consumption of households in the program for less than a year. This is in part caused by the fact that low-consumption households signed up to the program earlier, as shown in the figure above.

6.2.1 OVERALL SAVING FROM ALL PARTICIPANTS

The overall saving estimate across households and over time is 0.60±0.09 kWh/hh/d. This translates to a percentage savings of 4.0 ± 0.6%. ISF's analysis suggests that households in the HPSP program use around 0.6 kW less than comparable households not in the program on a daily basis, with a 95% confidence interval of 0.51 – 0.69 kWh. This compares to an estimate of 0.91 kWh ± 0.60 kWh in ISF's interim report (Fyfe et al., 2011), which was based on just 200 participants from Essential Energy's network area.

The savings estimate is shown in Figure 6-3. There is a 5 month[6] period which is excluded from the analysis due to billing data covering both the pre and post intervention period. The saving by calendar month is shown in Figure 6.4. The number of households dropped throughout the MPMC process is shown in Table 6.3. As shown we drop just under 10,000 of

[5] This is unsurprising as participants in houses consume more energy than those in units (Section 4.9).

[6] Two months either side of the intervention month plus the intervention month

the 23,000 participants, however more than 9,000 of these dropped participants are due to insufficient pre or post data.

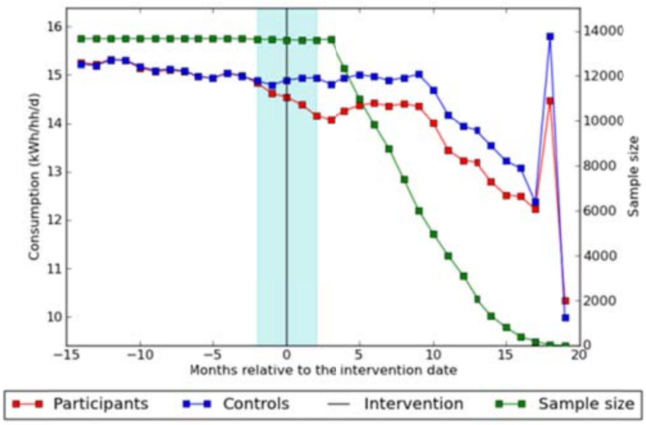


Figure 6-3: Average consumption data for participants and matched non-participants relative to the HPSP intervention month.

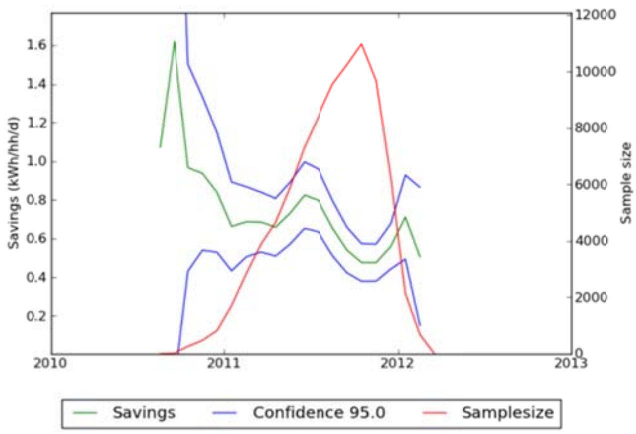


Figure 6-4: Electricity savings and sample size plotted by calendar month.

Table 6-3 Participants lost in the filtering process from all participants

Number of Participants	All
Initial clean participants	23,634
Insufficient pre-period data	3,874
Insufficient post-period data	5,392
Statistical outliers	7
Failed matching period spur test	98
Failed after period spur test	32
No match found	107
Failed quadrant, correlation and variance ratio tests	469
Participants used to estimate savings	**13,655**

6.2.2 SAVING FROM ALL ITEMS

The saving from participants who received all items[7] is 0.90±0.26 kWh/hh/d (5.4±1.6%)**.** The saving estimate for the participant cohorts are shown in Figure 6-5. The savings by calendar month is shown in Figure 6-6.

There are 1689 participant who received all items that were successfully used in the MPMC approach. The number of households dropped in the MPMC process is presented in Table 6.4.

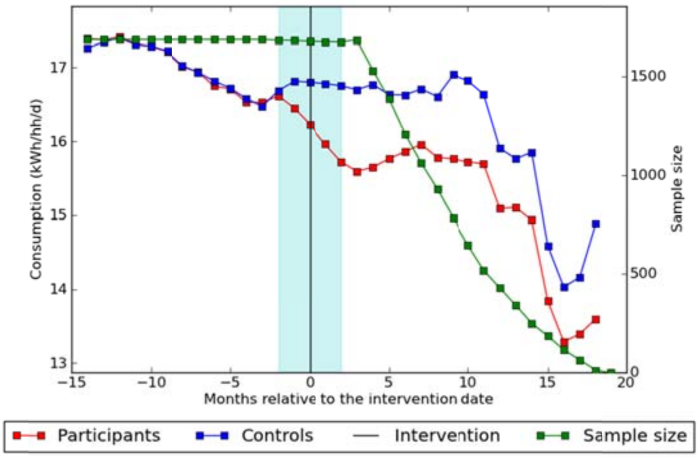


Figure 6-5: Average consumption data for Participants who received all items and matched non-participants relative to the HPSP intervention month, by items received.

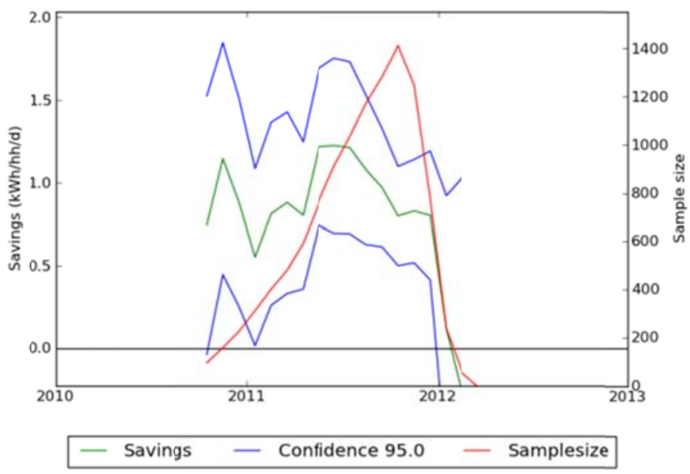


Figure 6-6 Participants Electricity savings and sample size plotted by calendar month who received all items

[7] Ignoring aerators, due to small number of households receiving these items.

Table 6-4 Participants lost in the filtering process by cohort

Number of Participants	All items
Initial clean participants	3217
Insufficient pre-period data	505
Insufficient post-period data	942
Statistical outliers	2
Failed matching period spur test	8
Failed after period spur test	2
No match found	
Failed quadrant, correlation and variance ratio tests	69
Participants used to estimate savings	**1689**

6.2.3 SAVING FOR ALL ITEMS EXCEPT FOR A WATER EFFICIENT SHOWERHEAD

The saving from participants who received all items except a water efficient shower head is 0.52 ±0.09 kWh/hh/d (5.4±1.6%)**.** The savings estimates for the participant cohorts are shown in Figure 6.7. The savings by calendar month is shown in Figure 6-8.

There are 11118 participants who received all items except a shower head that were successfully used in the MPMC approach. The number of households dropped in the MPMC process is presented in Table 6-5.

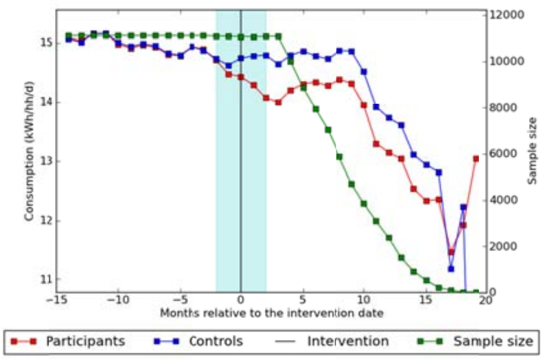


Figure 6-7 Average consumption data for participants who received all items except shower head and matched non-participants relative to the HPSP intervention month.

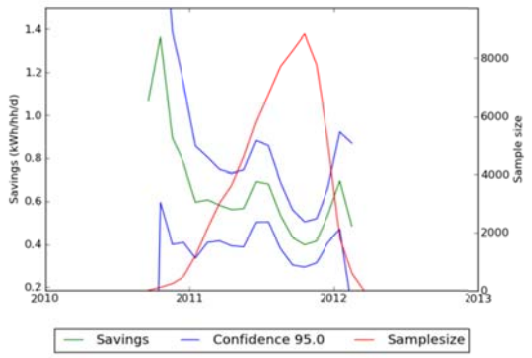


Figure 6-8 Participants Electricity savings and sample size plotted by calendar month

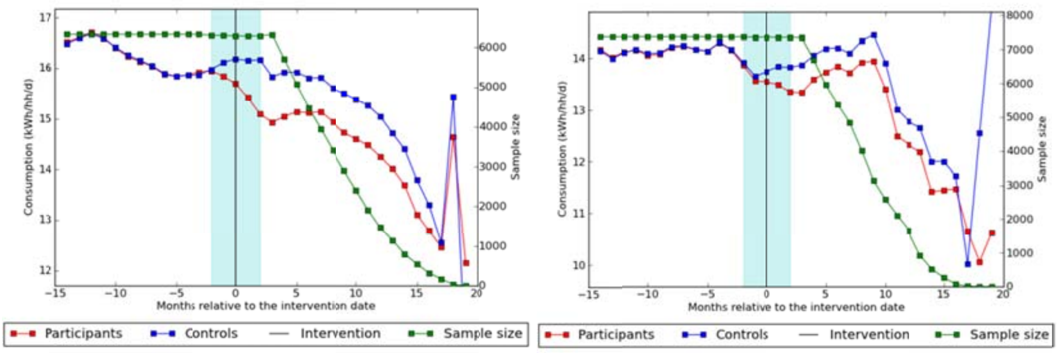
Table 6-5 Participants lost in the filtering process by cohort

Number of Participants	All items except Shower head
Initial clean participants	19041
Insufficient pre-period data	3167
Insufficient post-period data	4205
Statistical outliers	5
Failed matching period spur test	83
Failed after period spur test	28
No match found	72
Failed quadrant, correlation and variance ratio tests	363
Participants used to estimate savings	**11118**

6.2.4 SAVING BY HOUSING TENURE (SOCIAL HOUSING VERSUS OWNED/PRIVATELY RENTED)

The savings from private housing (owner occupier or renting privately) is 0.73±0.13 kWh/hh/d, whereas savings from Government housing is 0.45±0.12 kWh/hh/d. These savings correspond to 4.6±0.8% for private housing and 3.2±0.8%. The savings estimates for private housing and Government housing are shown in Figure 6.9. The savings by calendar month are shown in Figure 6.10.

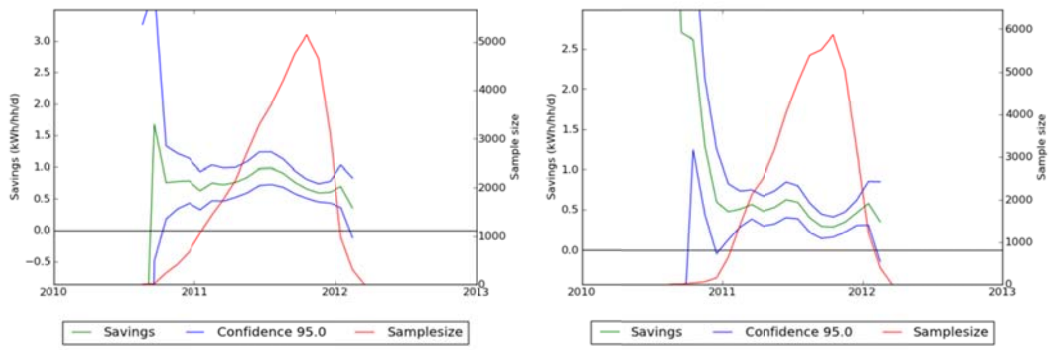
There were 6336 private housing and 7369 government/social housing participants used in the MPMC approach; the weighted average savings for all participants therefore is 0.58 in line with the overall savings above. The number of households dropped in the MPMC process is presented in Table 6.6. The number of households removed by the MPMC resulted in more participants from private housing being removed than from government housing. This resulted in the percentage of participants in social housing changing from 45% before the MPMC process to 54% after the MPMC process. Since government/social housing participants save less than private housing participants, it is likely that the overall savings from the total participant group is higher than the savings determined from the MPMC valid participants as the subset used is not a true reflection of total participant set.



A) Private Housing

B) Government/social Housing

Figure 6-9 Average consumption data for participants and matched non-participants relative to the HPSP intervention month, by private or social housing.



A) Private Housing

B) Government/social Housing

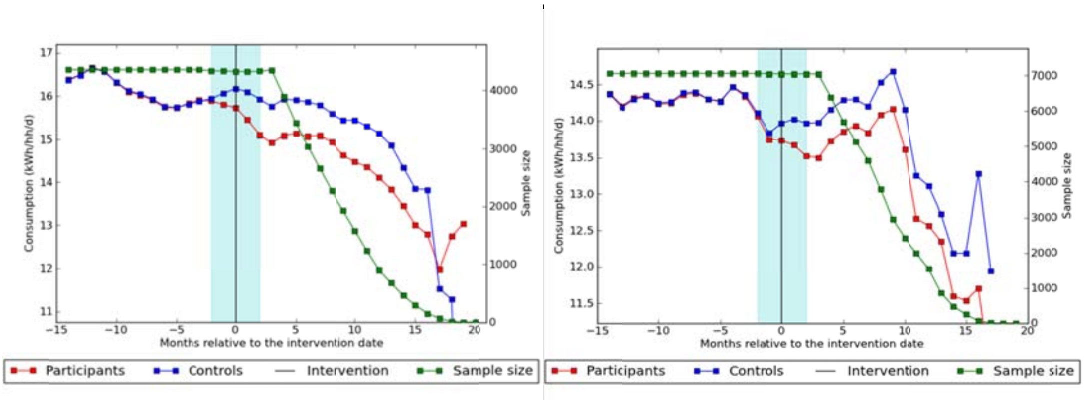
Figure 6-10 Electricity savings and sample size plotted by calendar month, by private or social housing.

Table 6-6 Participants lost in the filtering process from private and social housing

Number of Participants	Private Houses	Government /social Housing
Initial clean participants	12897	10730
Insufficient pre-period data	2019	1854
Insufficient post-period data	4187	1204
Statistical outliers	3	4
Failed matching period spur test	46	17
Failed after period spur test	13	52
No match found	54	0
Failed quadrant, correlation and variance ratio tests	239	230
Participants used to estimate savings	**6336**	**7369**

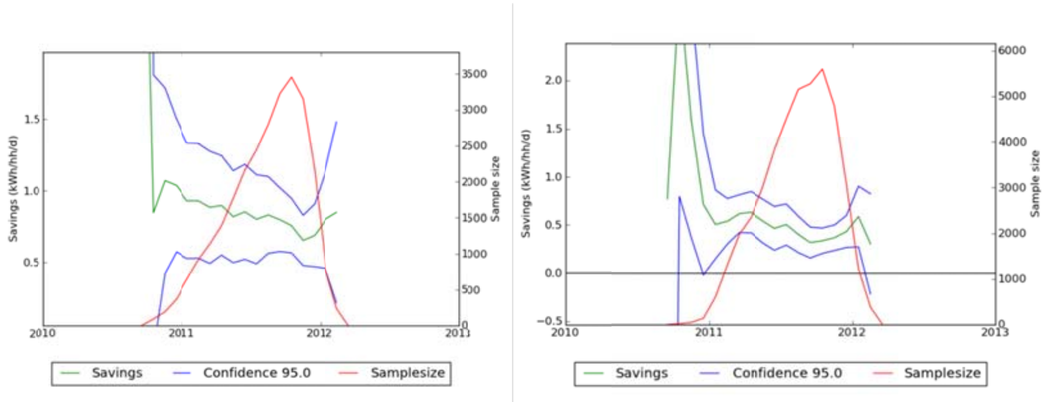
Government and social housing households that received all items except a shower head saved: 0.44 ± 0.12 kWh/hh/d (3.1 ± 0.9%), all other households that received all items except a showerhead saved: 0.73 ± 0.16 kWh/hh/d (4.9 ± 1.0%). The savings in a relative scale are shown in Figure 6.11, and savings over time are presented in Figure 6.12.

There were 7053 government and social housing households and 4356 private housing households, used in the MPMC approach (see Table 6.7). The weighted average of the savings equates to 0.55 kWh/hh/d, which is similar to the savings of all households that received everything except a showerhead (0.52 ± 0.09 kWh/hh/d).



A) Private Housing **B) Government/social Housing**

Figure 6-11 Average consumption data for participants who got everything except a shower head and matched non-participants relative to the HPSP intervention month, by private or government housing.



A) Private Housing **B) Government/social Housing**

Figure 6-12 Electricity savings and sample size plotted by calendar month, for participants who got everything except a shower head by private or government/social housing.

Table 6-7 Participants who got everything except a showerhead lost in the filtering process from by Private and Government housing

Number of Participants	Private Houses	Government /social Housing

Initial clean participants	8928	10113
Insufficient pre-period data	1402	1765
Insufficient post-period data	3060	1145
Statistical outliers	1	4
Failed matching period spur test	35	48
Failed after period spur test	10	20
No match found	0	0
Failed quadrant, correlation and variance ratio tests	64	78
Participants used to estimate savings	**4356**	**7053**

6.2.5 SAVINGS BY ELECTRICITY PROVIDER (AUSGRID, ENDEAVOUR, ESSENTIAL)

The savings from participants by provider are:

- Ausgrid: 0.55 ± 0.12 kWh/hh/d or 3.9 ± 0.9 %
- Endeavour: 0.44 ± 0.16 kWh/hh/d or 2.8 ± 1.1 %
- Essential: 0.78 ± 0.21 kWh/hh/d or 4.9 ± 1.3 %

The savings by provider show some interesting results. At first glance the results are surprising, however Essential Energy participants:

1. have 20% of households in units compared to the overall participant group of 28%
2. have 33% of households in government/social housing compared to the overall group of 46%

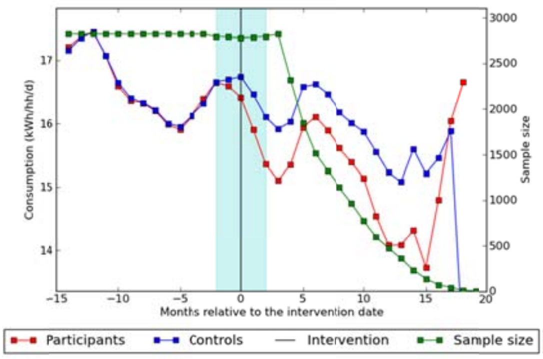
Since it is known from above results that houses save more than units and private housing participants save more than government/social housing participants Essentials high savings value is expected.

In a similar fashion the relatively low energy savings from Endeavour customers appears initially unusual (particularly given Endeavour has a strong base in Western Sydney) however by examining the participants metadata, we see that the percentage of units is similar to the participant population (26% compared to 28%) but the percentage of participants in government/social housing is considerably higher (58% compared to 46%).

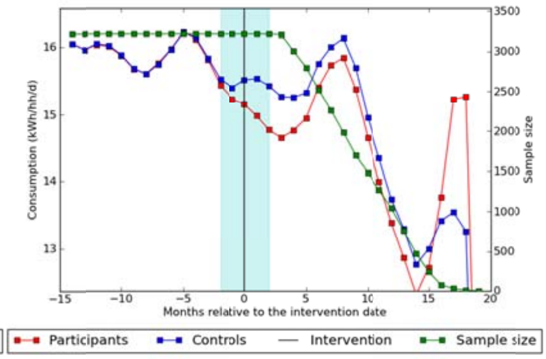
The number of successful participants used in the MPMC approach by provider was:

- Ausgrid: 7237
- Endeavour: 3214
- Essential: 2823

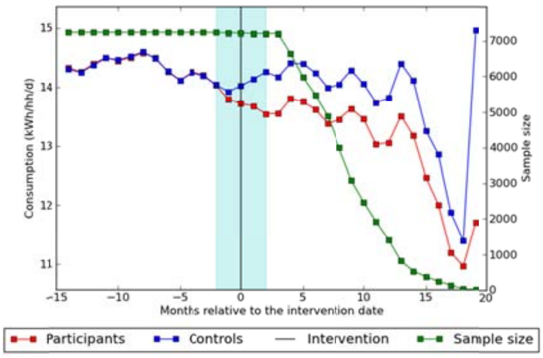
The weighted average savings for all participants is 0.57 in line with the overall savings above. The number of households dropped in the MPMC process is presented in Table 6.8.



A) Essential Energy

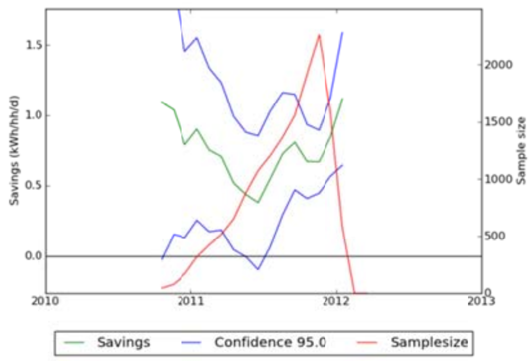


B) Endeavour Energy

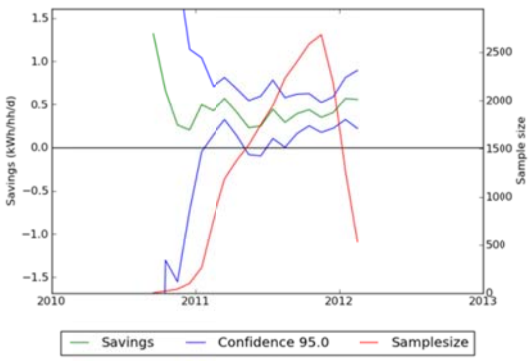


C) Ausgrid

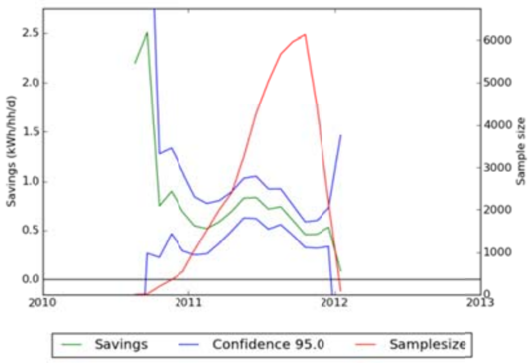
Figure 6-13 Average consumption data for participants and matched non-participants relative to the HPSP intervention month, by electricity provider.



A) Essential Energy



B) Endeavour Energy



C) Ausgrid

Figure 6-14 Electricity savings and sample size plotted by calendar month, by electricity provider.

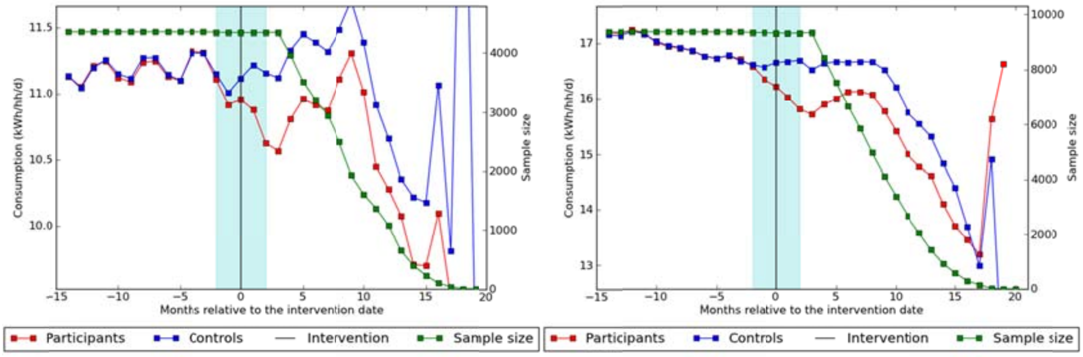
Table 6-8 Participants lost in the filtering process from by electricity provider

Number of Participants	Essential customers	Endeavour customers	Ausgrid Customers
Initial clean participants	6377	6516	10737
Insufficient pre-period data	2064	1825	313
Insufficient post-period data	1342	1410	2921
Statistical outliers	1	0	6
Failed matching period spur test	2	5	87
Failed after period spur test	7	2	14
No match found	0	0	23
Failed quadrant, correlation and variance ratio tests	138	60	136
Participants used to estimate savings	**2823**	**3214**	**7237**

6.2.6 SAVINGS BY HOUSING TYPE (UNITS VERSUS HOUSES)

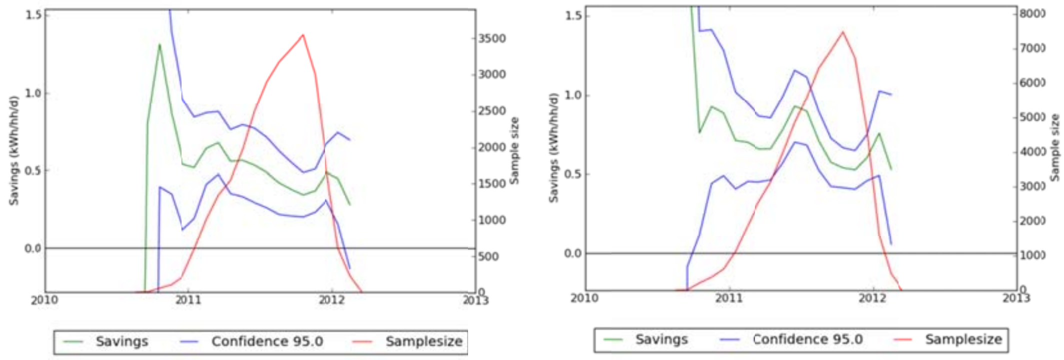
The savings from participants in units is 0.47 ± 0.12 kWh/hh/d, whereas savings from participants in houses is 0.66 ± 0.11 kWh/hh/d. These savings correspond to 4.2±1.1% for participants in units and 4.0±0.7% from participants in houses. The savings estimates for houses and units are shown in Figure 6-15 and the savings by calendar month is presented in Figure 6.16.

There are 4356 participants in units and 9369 participants in houses that were successfully used in the MPMC approach. The weighted average savings for all participants is 0.59 in line with the overall savings above. The number of households dropped in the MPMC process is presented in Table 6-9.



A) Units B) Houses

Figure 6-15 Average consumption data for participants and matched non-participants relative to the HPSP intervention month, by housing type.



A) Units B) Houses

Figure 6-16 Electricity savings and sample size plotted by calendar month, by housing type.

Table 6-9 Participants lost in the filtering process from by house type

Number of Participants	Units	Houses
Initial clean participants	6684	16943
Insufficient pre-period data	1076	4329
Insufficient post-period data	1062	2797
Statistical outliers	2	5
Failed matching period spur test	55	43
Failed after period spur test	11	20
No match found	0	64
Failed quadrant, correlation and variance ratio tests	122	316
Participants used to estimate savings	**4356**	**9369**

6.2.7 DISTRIBUTION OF (CONTROL-PARTICIPANT) DIFFERENCES

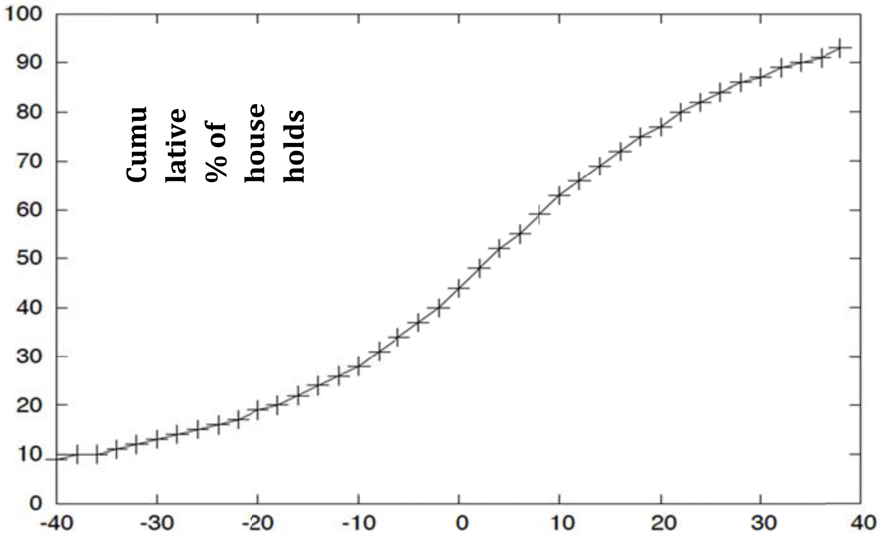


Figure 6-17 % change in participant energy use (relative to control)

Figure 6.17 shows the cumulative distribution of the differences in consumption between control/participant pairs in the pair-matching analysis. As previously described, the average saving per household was 4% with a standard deviation of 32.7%. While the mean of the distribution of control/participant pair differences is a valid estimate of the average net savings achieved by HPSP participants, it is not valid to use the difference in consumption between an individual household and its control to draw inferences about the savings attributable to that individual household. For instance, if the control household installs air-conditioning and increases consumption, this results in an artificial 'saving' (because the participant household has reduced consumption relative to its control). Conversely, if members of the control household were to leave the house, control consumption would drop and the paired participant household may well have use more than its control (i.e. there would be a negative saving). We can see that because of situations like those described above, the difference between a participant and control does not give a good estimate of savings at the individual household level. Pair matching relies on the fact that across a large number of households, idiosyncratic variations in consumption cancel each other out. Thus, the mean savings across all households is a reliable indicator of average savings, but individual household-by-household savings figures are much too noisy to be relied upon. ***It is not valid, for instance, to look at Figure 6.17 and conclude that ~ 20 % of households saved more than 20%.***

7 APPENDIX B – DATA PROVIDED BY OEH AND ENERGY COMPANIES

Two main sets of primary data have been used in the analysis of the HPSP participants:

1) OEH provided a list of households that participated in the HPSP and have signed a consent form to allow their electricity consumption data to be accessed for the purposes of evaluation. The list also contains the date of consent for each household and this is assumed to be the intervention date (i.e. the date where participation in the HPSP started). Savings attributed to the program are assumed to commence from the intervention date onwards.
2) Billing data was provided by Ausgrid, Essential Energy and Endeavour Energy.

As noted earlier, the analysis in this report is based on total household consumption. If households were metered separately for peak and off-peak energy use, these were combined to create a total consumption for that household which was used for the analysis.

Endeavour Energy, Essential Energy and Ausgrid provided consumption data for participant and non-participant households. Endeavour Energy and Essential Energy records were binned (i.e. monthly consumption was inferred from quarterly meter reads, as explained in Section 9.3). Ausgrid provided pre-binned monthly data directly to ISF.

Endeavour, Essential and Ausgrid together provided billing data for 4 million non-participant households and over 23,000 participant households. Given the large number of non-participant households relative to the number of participant households, ISF reduced the size of the non-participant set to 200,000 (or more) households. Figure 7.1 shows that the controls subsets selected are genuinely random and do not alter the underlying distribution of the full control set.

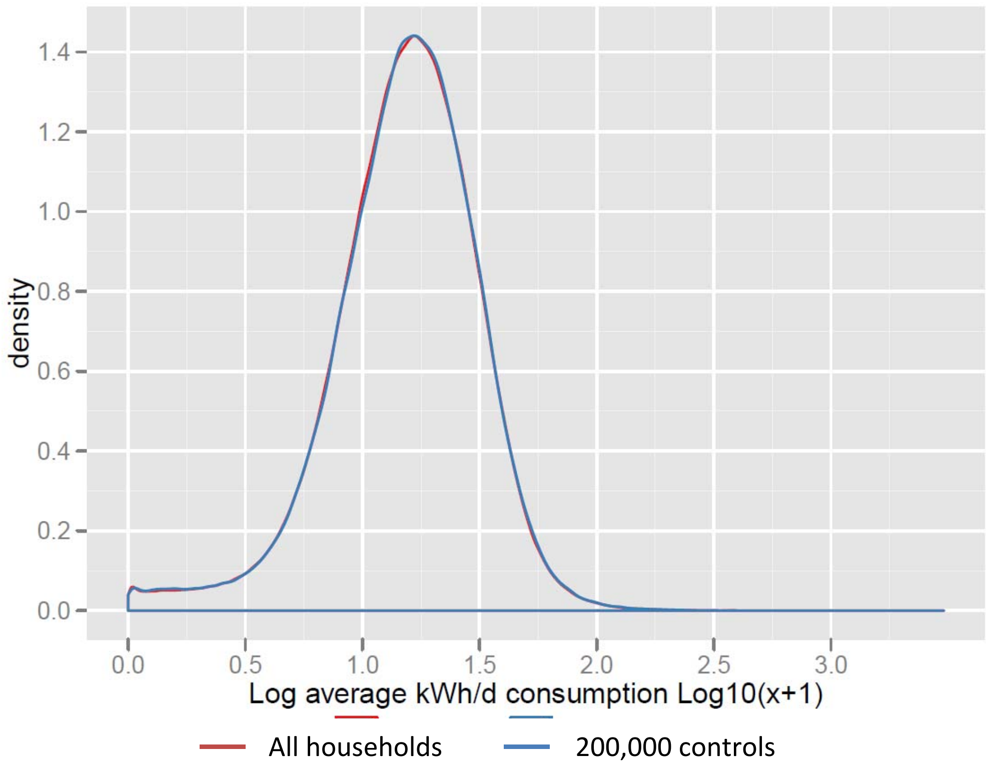


Figure 7-1 The histograms of the various control groups. They overlap so closely that they are indistinguishable.

Data was provided by the distributors in slightly different formats. Essential Energy and Endeavour Energy provided raw billing data (i.e. household billing records), and Ausgrid provided monthly consumption for each household (determined by Ausgrid's own internal analysis of billing data).

The data set supplied by Essential Energy comprised of two tables. The first table contains electricity consumption data for the HPSP participants identified in the list from OEH. Consumption data on all residential tariffs are included in the data and the local government area (LGA) of each property is also given. The second table takes the same form as the first, but contains data for ALL non-participating properties in the Essential Energy database. The key difference between this table and the participants table, however, is that instead of NMI, households are identified by a new identifier code that is designed to prevent occupants being identified. This de-identification ensures that the data is anonymous and that customer consumption data effectively remains private.

The Ausgrid data consisted of two data tables. The first table contained binned electricity consumption data for the HPSP participants identified by the NMI code. The data table also states the number of days used in the binning of the data. The second table provided by Ausgrid contained the binned consumption for all non-participating properties and the number of days used, however instead of a NMI a generic id was provided by Ausgrid to prevent occupants being identified. As with the Essential Energy data, this de-identification ensures that the data is anonymous. A key difference between the Ausgrid and Essential Energy datasets is that there is no way of knowing the LGA area of the Ausgrid non-participants.

8 APPENDIX C: REGRESSION METHODOLOGY

A mixed (random & fixed effects[8]) regression model was used to analyse the data on HPSP participants. A number of different model structures were trialled, and the model used for the final analysis was chosen based on two main criteria:

1) The model had to make intuitive sense. In other words, model structure and coefficients had to have a plausible link to real-world behaviour. It makes little intuitive sense, for instance, to have a model where a 'hasPool' dummy variable is interacted with a variable describing the number of efficient lights installed.
2) Simpler models were preferred to more complex models unless the more complex model performed significantly better than the simpler model.

The model structure used for the final analysis was:

$$\begin{aligned}\mathrm{Consump}_{i,t} = \quad & \alpha + \beta\ \mathrm{avgConsump}_t + \gamma_i + \\ & \sum_{m=1}^{12} \kappa_m \mathrm{monthDummy}_{m,t} + \\ & \delta\ \mathrm{inProg}_{i,t} + \eta\ \mathrm{gotLights}_{i,t} + \\ & \zeta \times \mathrm{numOccupants}_i \times \mathrm{gotShowerhead}_{i,t} + \\ & \theta\ \mathrm{gotStandby}_{i,t}\end{aligned}$$

where:

- $\mathrm{Consump}_{i,t}$ is the consumption (in kWh per day) of household *i* in month *t*.
- $\alpha,\beta,\gamma_i,\delta,\eta,\zeta,\theta,\kappa$ are the parameters to be estimated (all are fixed effects apart from γ_i, which is a random effect).
- α is a common intercept term shared by all households
- β $\mathrm{avgConsump}_t$ is a term that allows the average consumption of non-participant households to help explain the consumption of participant households. This is useful because non-participant households are affected by many of the same factors as participant households, and including non-participant consumption in the model is a better way of controlling for these factors than attempting to control for them explicitly.
- γ_i is a separate intercept term (random effect) for each household. This term helps to control for household-specific factors.
- $\kappa_{m,t}$ is a coefficient for each month *m*, with $\mathrm{monthDummy}_t$ being 1 if it is month *m* at time *t*, and 0 otherwise. In other words, if it is January at time *t*, then $\mathrm{monthDummy}_1$

[8] See Demidenko, E (2004). Mixed models: Theory and Applications. John Wiley and Sons for a basic introduction to mixed regression models

would have the value 1; but if it was February at time *t*, then monthDummy_2 would have the value 1, and so on.

- $\text{inProg}_{i,t}$ is 1 if household *i* is in the HPSP at time *t*, 0 otherwise. The coefficient in this term (δ) is intended to capture behaviour-change savings from the program. That is, savings over and above those explainable by structural changes (such as changing of lights and showerheads).
- $\text{gotLights}_{i,t}$ is 1 if household *i* received efficient lights from the HPSP at or before time *t*, 0 otherwise. The coefficient in this term (η) estimates savings attributable directly to efficient lights installed or left by the HPSP.
- numOccupants_i is the number of occupants in the household.
- $\text{gotShowerhead}_{i,t}$ is 1 if household *i* received an efficient showerhead at or before time *t*, 0 otherwise.
- The coefficient ζ is an estimate of the savings per occupant attributable to the showerhead.
- $\text{gotStandby}_{i,t}$ is 1 if household *i* received efficient lights from the HPSP at or before time *t*, 0 otherwise. The coefficient in this term (θ) estimates savings attributable directly to efficient lights installed or left by the HPSP.

ISF trialled a large number of more complex regression equations to try and determine other important factors affecting savings. None of these complex models produced more plausible estimates, and many resulting in counter-intuitive estimates, or exhibited other behaviour that suggested they were not well specified. A few examples of terms included in more complex models were:

- ISF allowed standby savings to be linked to the number of appliances, or the number of people in the household.
- ISF allowed savings from efficient lights to vary depending on the number of occupants in each household, but such models did not perform better than the model used.
- ISF allowed savings from showerheads to vary by month, but these monthly estimates showed no clear pattern (i.e. savings were not consistently higher in winter than in summer, as we would expect)

Based on ISF trials of different regression model structures, it was clear that some estimates are quite sensitive to regression model structure/assumptions, while others are not. In particular, estimates of savings from behaviour change, were quite sensitive to model structure (they are not significantly different from zero in the model used for the final analysis). Estimates of savings from lights and showerhead were much more stable.

Regression coefficient	Estimate (negative values indicate savings)	Notes
δ: estimate of savings attributable to 'behaviour change'	-0.16 kWh/hh/day (95% confidence interval: -0.59 to 0.08)	Not statistically different from 0 at 95% confidence level.
η: estimate of savings	-0.35 kWh/hh/day	Significant at 95% confidence level. We could not detect a difference

attributable to the provision or installation of efficient lights	(95% confidence interval: -0.52 to 0.19)	between lights installed or lights left behind. Although savings from lighting is likely to be seasonal (higher in winter), we did not have sufficient data to detect such an effect, so this estimate is the average saving across all months.
ζ: estimate of savings *per occupant* attributable to showerhead.	-0.34 kWh *per person* per day. (95% confidence interval: -0.38 to -0.29).	As with lights, we were expecting that installed showerheads would result in higher savings than showerheads left behind, but we could not detect any such effect, so this term covers both installed and left behind showerheads. Is it very likely that savings from the showerhead *are* seasonal, but we are unable to detect this with the data available.
θ: estimate of savings from provision of a standby saving power board	0.02 kWh/hh/day (95% confidence interval: -0.19 to 0.22)	Not statistically different from zero (i.e. we estimate little to no savings from power-board). ISF did trial more complex regression equations that included the number of appliances and/or house size when assessing the impact of the power-board, but none of these equations yielded results better than the simpler model used.
α (not of policy interest)	Not of policy interest	Intercept term. Included in model to help estimate other coefficients but not of policy interest.
β (not of policy interest)	Not of policy interest	Term relating variation in participant consumption to variation in average non-participant consumption. Included in model but not of direct policy interest.
γ_i (not of policy interest)	(per-household random effect)	This term is specific to each household, and acts to control for household-specific factors. Including it helps with the estimation of other parameters, but by itself it is not of policy interest.
$\kappa_{t,m}$ (not of policy interest)	Not of policy interest (per-month fixed effect)	Helps to control for seasonal/monthly differences between participant and control consumption.

9 APPENDIX D: MPMC METHODOLOGY

The MPMC method was originally developed specifically for evaluating water efficiency programs using billing (metered consumption) data when there is limited information about participating households and is described in Fyfe et al. (2010). It is designed to control for external factors that cause household consumption to vary over time and would otherwise bias estimates of savings associated with an efficiency program. Specifically, a household that has participated in an efficiency program (a participant) is matched to a household that has not participated in any programs (a control). The participant and control are matched according to their corresponding usage patterns prior to the participant's involvement in the program. This study is applying this approach to evaluating energy savings from a dedicated energy efficiency program.

The MPMC analysis assumes that if two households have a near identical usage pattern prior to one of them being involved in an efficiency program, then they can be considered to have similar demographics and dwelling characteristics (e.g. number of occupants, income, appliances, heating and cooling needs etc.), and would respond to external factors that influence demand (such as climate and changes in prices) in a similar manner. Hence, the departure in the participant's electricity consumption from the corresponding control's consumption pattern following their involvement in a program is assumed to be the effect of the program. In reality, this assumption is not entirely valid as participants are typically self-selecting, which immediately sets them apart from the broader population of electricity users.

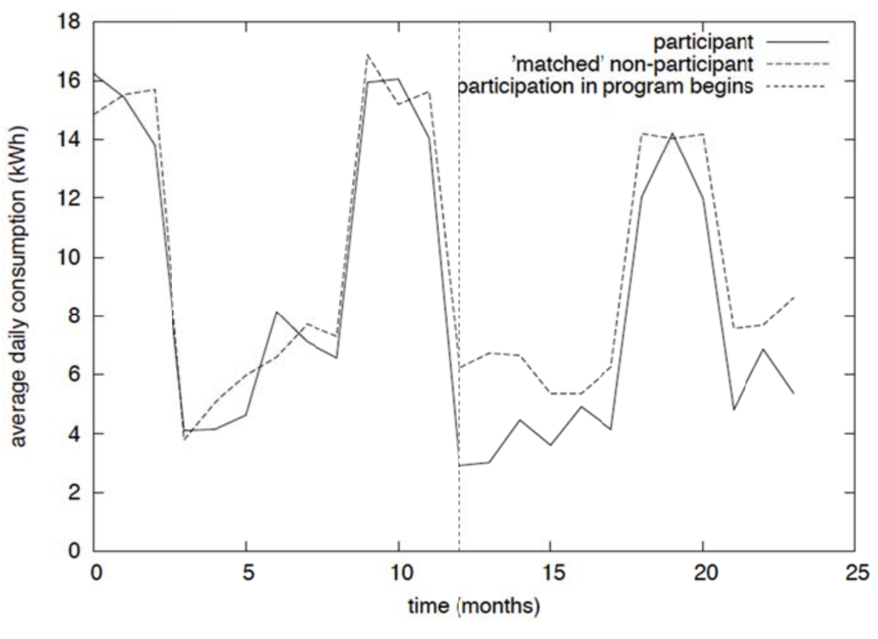


Figure 9-1 An illustration of the pair-matching process

Ideally, participant and control households would be randomly selected before the program is initiated. This would constitute a statistically robust test of the program's effectiveness based on an 'experimental design' that satisfies the assumption that all households in the analysis are randomly sampled from the same parent population. Often for water or electricity efficiency programs, however, such an approach is not practical as the program is made available to all customers in the service area and participation is voluntary (thus self-selecting) and indeed encouraged to maximise net savings. Consequently, the identification of those who do not participate in the program as a basis for comparison occurs retrospectively. In the MPMC methodology, randomised sampling is effectively substituted with a statistically-driven process of carefully constructing a non-participant control group that seeks to ensure that the characteristics of participant and control groups are similar. The non-participants selected in this process are more accurately referred to as a comparison group rather than control group; however, the term 'control' is often loosely applied to these kinds of analyses. Herein the term ‘control’ is used to describe a *non-participant household that have been matched to participant household* in the MPMC process.

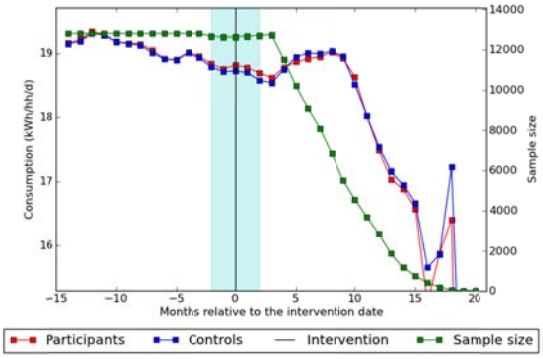
Under the assumptions that 1) short-term electricity use dynamics are relatively constant, and 2) participation in efficiency program does not substantially change a household’s other electricity use habits, the control group is established by identifying a matching non-participating household for each participating household using a least squares analysis of consumption in the period immediately before the participant’s involvement in the program. By identifying controls on a household-by-household basis, the process generates a control group of the same size as the participant group and allows savings to be calculated on an individual household level. This in turn reduces the test of statistical significance of savings to a simple repeated measures t-test. Moreover, the control group can be considered more reliable in controlling for the influence of external factors.

Electricity consumption of the paired households is then compared before and after the ‘intervention’ (date of engagement with the program), with the divergence in consumption during the post-intervention period representing the electricity savings resulting from the program. While this divergence may in reality be caused by other factors that could cause consumption to rise or fall, the overall effects should theoretically average out in a sufficiently large sample, leaving an observed change related to the efficiency program in question. It is also worth noting that while self-selection is an inherent bias to this analysis that may make extrapolating savings outside a particular participant sample problematic, the MPMC approach does, nonetheless, present a powerful means of estimating actual savings for ex-post evaluation.

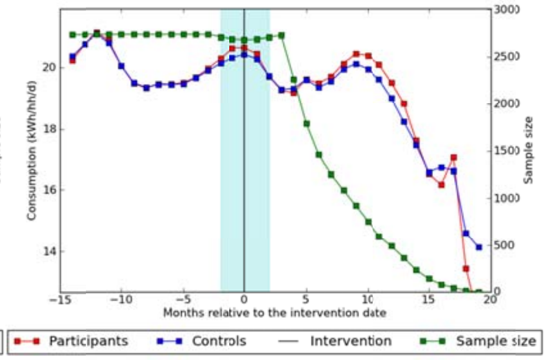
9.1 VALIDATION OF MPMC APPROACH FOR OEH DATA

To help validate the matched pairs approach, ISF randomly selected *non-participant* households and tagged them as participating in the program. ISF then used the MPMC method to estimate program savings on these households. Since both non-participant and ‘fake’ participant households are not in the program, the savings estimate produced should not be statistically different from zero.

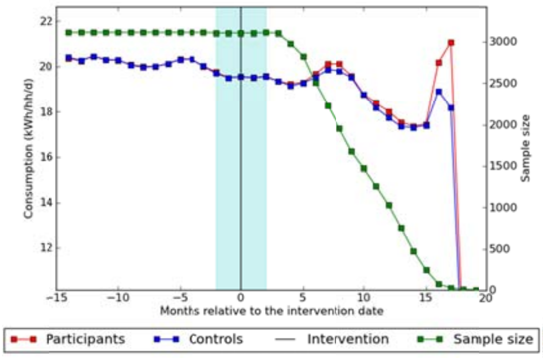
The savings estimates for the validation runs are shown in Figure 9-2. The savings estimates for the three validation runs are statistically not significant.



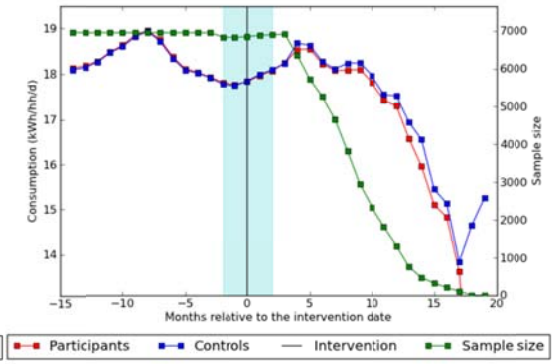
A) All Participants



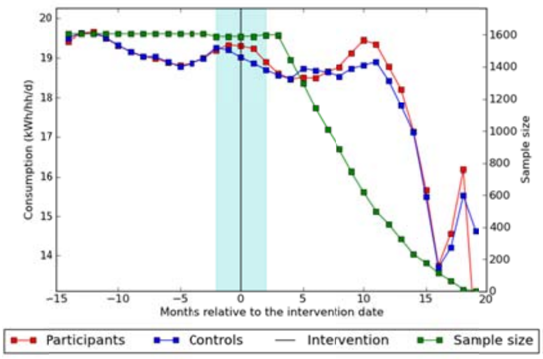
B) Essential Customers



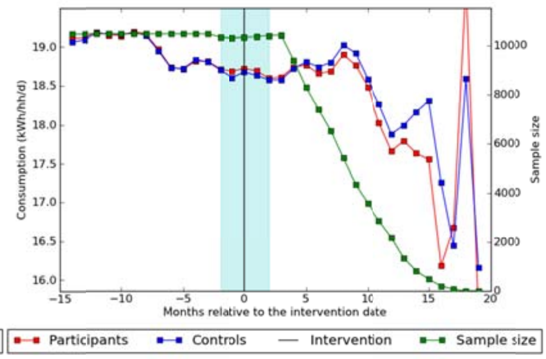
C) Endeavour customers



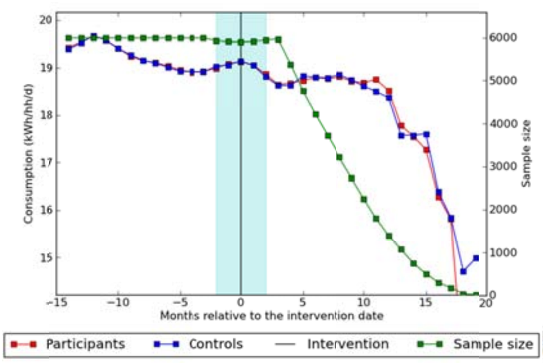
D) Ausgrid customers

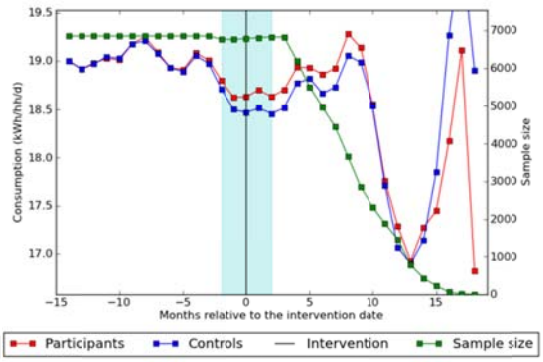


E) Participants who received all items except a shower head



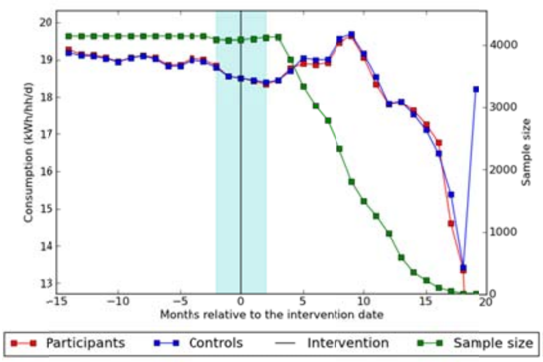
F) Participants who received all items

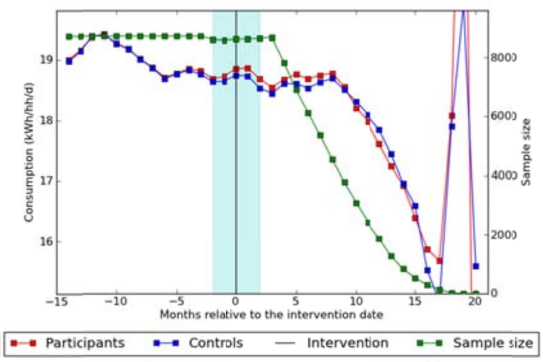




G) Participants in private housing

H) Participants in Government housing





I) Units

J) Houses

Figure 9-2 Average consumption data for a random set of non-participants and their matched controls relative to the HPSP intervention month

Table 9-1 Savings estimates for the four validation runs.

Participant Group	Savings
All Participants	0.03 ± 0.12
Endeavour Customers	0.00 ± 0.19
Essential Customers	-0.07 ± 0.28
Ausgrid Customers	0.08 ± 0.16
Participants in houses	-0.09 ± 0.14
Participants in units	0.01 ± 0.20
Participants in social housing	-0.14 ± 0.15
Participants in government housing	0.00 ± 0.17
Participants who got all items	-0.13 ± 0.32
Participant who got all items except for a shower head	0.04 ± 0.13

9.2 THE MPMC PROCESS

The MPMC analysis used in this study is implemented in the Python programming language, and comprises five stages, as shown in Figure 9.3. In the pre-processing stage, the participant and non-participant property billing records are binned to create monthly consumption records. The consumption records are then aligned to contiguous households (as opposed to properties) by examining the dates that houses changed ownership or tenancy. The data is then filtered to remove households that do not have sufficient data or contain outlier or spurious consumption data. The pair matching stage involves selecting the participants randomly and pairing the participant to a non-participant household (control).

Households were matched within their own network area (e.g. Endeavour customers were only paired with other Endeavour customers). This pairing is based on the least sum square error from comparing the participant's consumption in the 12 months prior to their audit with corresponding consumption from all valid non-participants from the same energy provider. Finally, the differences between the control and participants records before and after the participant has commenced a program are calculated to determine savings at an individual household level which are then used to estimate and test average savings.

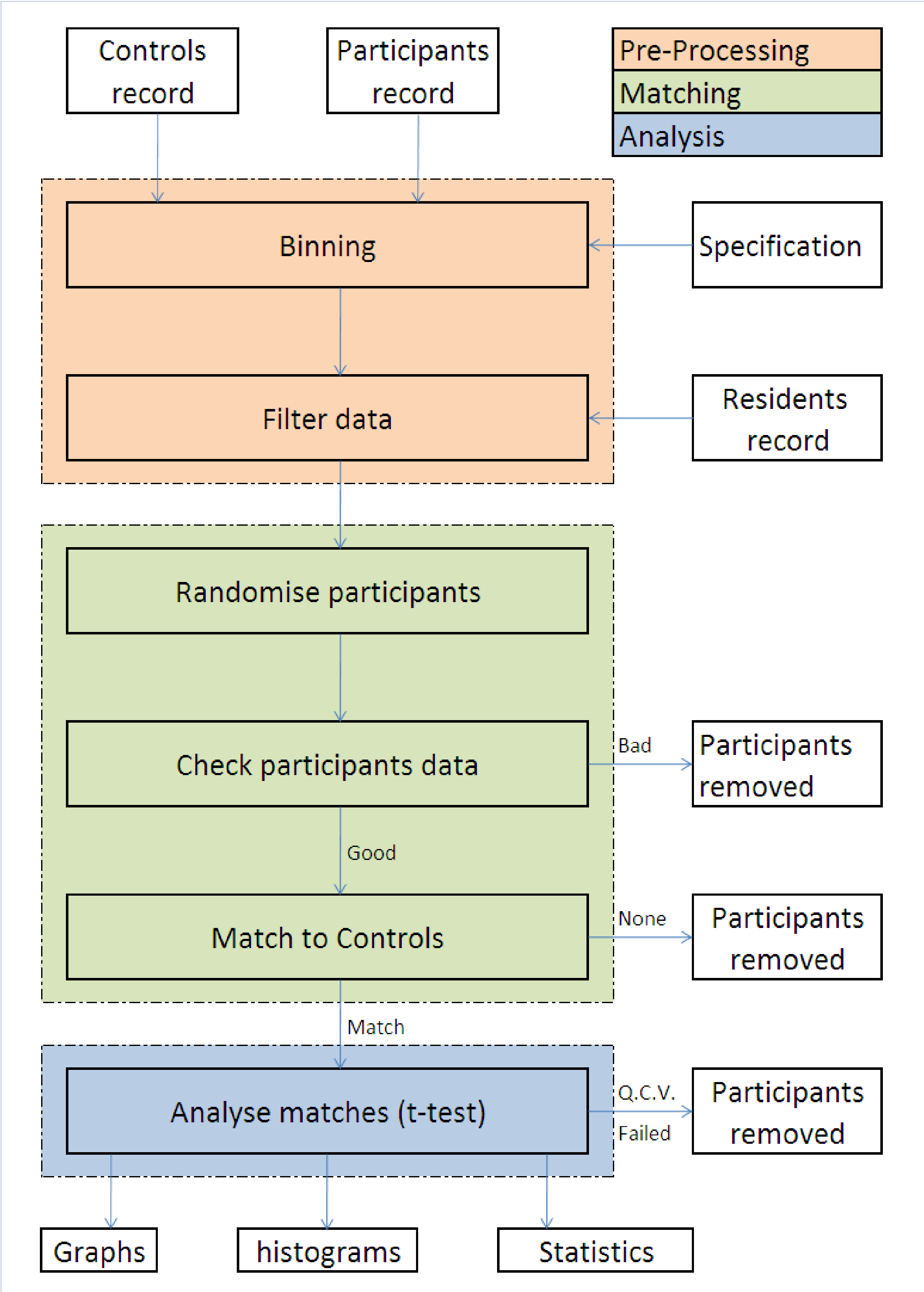


Figure 9-3 The MPMC analysis process as implemented in Python.

9.3 BINNING

Billing data collected at intervals greater than one month on a rolling meter read schedule need to be standardised to monthly figures in order to allow direct comparisons between different households. Standardisation involves a process termed 'binning', whereby quarterly consumption readings are apportioned into months on a simple linear pro rata basis. Essentially it converts gross quarterly consumption in kWh (per household) into monthly average day consumption values with units of kWh/d. The process, depicted in Figure 9-4, involves several steps. A given consumption read is first divided by the number of days in the meter read period to produce an average daily consumption for the period (which assumes that energy use is constant each day over the entire period). The daily consumption values are then grouped into months according to the number of days in the month covered by the bill to obtain weighted consumption for each month.

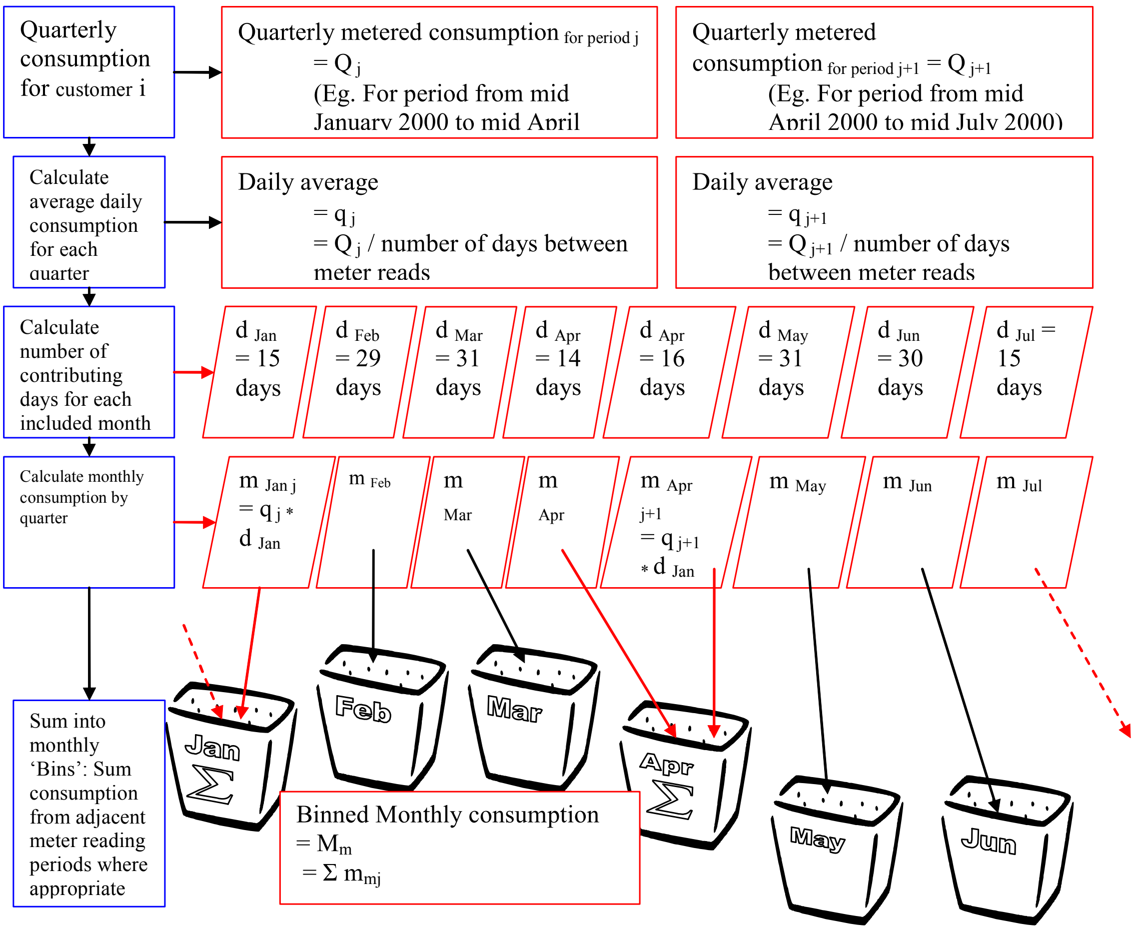


Figure 9-4 Illustration of apportioning demand into monthly bins of time

Binning introduces some unavoidable noise into the data, as consumption for any given month is in part determined by consumption from up to three months prior to and following that month. Binning also assumes that demand is constant over the given meter read period, which is often not the case (Moglia et al. 2009). More important to the purpose of evaluation studies such as this, however, is that monthly binned data is readily aligned and aggregated, which is necessary for the MPMC analysis used in this study, and provides an improved sense of seasonality in overall usage patterns.

With the presence of different tariffs within the electricity consumption data, binning could take one of three forms depending on how a given tariff was to be used in subsequent analyses. The three binning processes, single, union and intersection, are depicted in Figure 9-5 and are described below.

9.3.1 SINGLE TARIFF

The single tariff specification is used for and electricity billing data where only one type of electricity consumption is required for an analysis. It is also the default binning process for water or electricity billing data. It creates a monthly consumption figure if all days in the month are covered by billing data. Where a month is not completely covered by one or more meter reads, then a null entry is recorded for that month. 9.5 shows that months at the edge of the billing record for binning on the single tariff process are dropped where the bills do not cover the whole month.

9.3.2 UNION OF TARIFFS

The union of tariffs is applied where the consumption from two or more tariffs is to be summed. All property records are binned and the different types are then summed to create a total consumption value for each month. Since it is possible for the consumption in a given month to be associated with one tariff or multiple tariffs, all billed data is assigned to a given month, regardless of whether billing data covers all or only a part of that month, or how many tariffs are active in that month. In Figure 9-5, the raw data from tariff 1 and tariff 2 are pro-rated and summed to produce a total consumption figure for all billed months.

9.3.3 INTERSECTION OF TARIFFS

The intersection of tariffs is similar to the union, except that the output includes just one of the multiple tariffs rather than the sum of all the tariffs entered into the process. It is designed to capture the consumption on a particular tariff only when it is accompanied by consumption on other tariffs. The data on all the tariffs to be used in the intersection is binned but only the binned data associated with the tariff selected by the user is saved to the output file. The consumption on the selected tariff in a given month is only saved, however, where the household has consumption values for all other tariff types included in the intersection and the entire month is covered by all tariffs. In the example in Figure 9-5, two tariffs are used in two examples of the intersection binning process. The first example saves the consumption of tariff 1 only where there is corresponding consumption on tariff 2 and the entire month is covered by both tariffs. The second takes consumption on tariff 2 only in the presence of consumption on tariff 1.

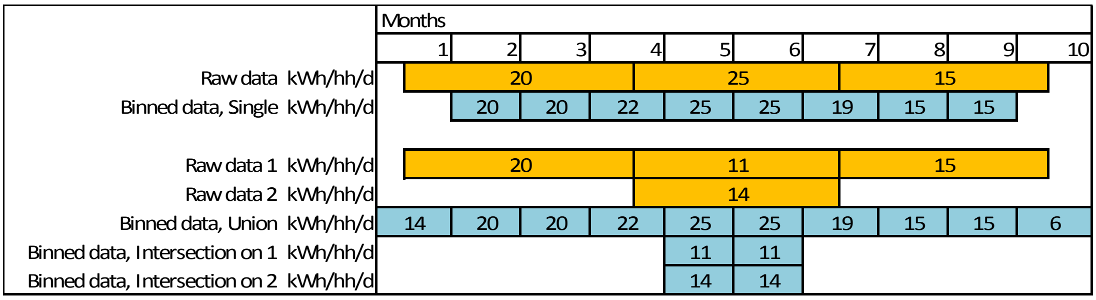


Figure 9-5 Example showing how the single, intersection and union binning processes are applied to quarterly consumption data.

9.4 ACCOUNTING FOR CHANGES IN PROPERTY OWNERSHIP AND TENANCY

A change in occupancy at a property can potentially radically change the energy footprint associated with the property. Hence when estimating savings at the individual property level (which is the case for the MPMC method), it is important that the consumption data being analysed for a particular property comes from a constant occupant or group of occupants.

Here it is important to distinguish between *properties* and *households*. The primary key used in the Essential Energy consumption data refers to the property (dwelling) as opposed to the household (occupants). Ideally, properties are split to account for occupancy changes, however due to this information being unknown for the Ausgrid controls, the ISF has implemented the analysis without accounting for changes in property ownership and tenancy.

9.5 DATA FILTERING

Following binning and adjusting for household changes, the matching process iterates through the participants to screen out unusable data before commencing with the pair matching. Data checks are first run to make sure that participant households have sufficient data to analyse. Then the data is screened to remove statistical outliers that may cause leverage bias. Finally a 'spur' test is applied that checks for spurious consumption figures within a household record.

9.5.1 DATA CHECKS

To test if the participant has the necessary data to perform matching on, its consumption record is split into the matching period and the post-audit period. The month that the audit/consent (intervention) date occurs in for a given household is denoted Month 0. As billing records occur quarterly, two months either side of the intervention month may contain billing data from both before and after the intervention date. Hence, the two months either side of the intervention date are excluded and the matching period is taken to be the twelve month period between months -14 to -3. Similarly the after period is taken to be the period from month 3 to the last month that exists in the record. A participant's record showing the intervention date, matching period and after period is shown in Figure 9.6.

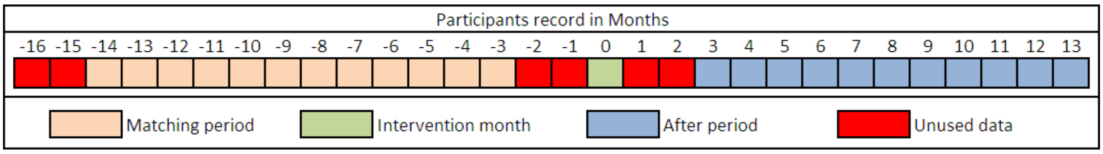


Figure 9-6 Partitioning of the participants data.

There are four checks that ensure that the participant data has the minimum data required for pair matching and analysis on the after period able to occur. The four checks ensure that:

- The participant consumption record commences before the twelve month matching period begins. That is, the first month of recorded data is at least 14 months before the intervention date.
- The participant consumption record has at least one month of after period data. That is, the last month of recorded data is >2.
- The twelve matching months all contain consumption data. That is, there are no gaps in the before period consumption data.
- The participant after period has at least 1 month of consumption data that is not a NULL value.

9.5.2 REMOVAL OF STATISTICAL OUTLIERS

Statistical analyses can be prone to leverage bias caused by unusually large data values or outliers whereby the relative magnitude of an unusually large consumer weighs heavily on the overall average savings estimate. In billed electricity consumption data, outliers are likely to come from erroneous entries from incorrectly recorded meter reads, misclassifications of properties (e.g. a commercial building classified as a residential dwelling), or uncontrolled usage such as a leaking water heater unit. To minimise the bias caused by outliers, two filters were applied to all binned consumption data.

First households with average consumption figures above a statistically-defined threshold were discarded from subsequent analyses. This threshold was calculated based upon the fundamental assumption that the average household consumption data followed a lognormal distribution. Figure 9-7 is a histogram of the log-transformed average (time-based) daily electricity consumption for all participant and non-participant households. When compared against a normal (Gaussian) distribution (black lines), this assumption appears to be reasonable.

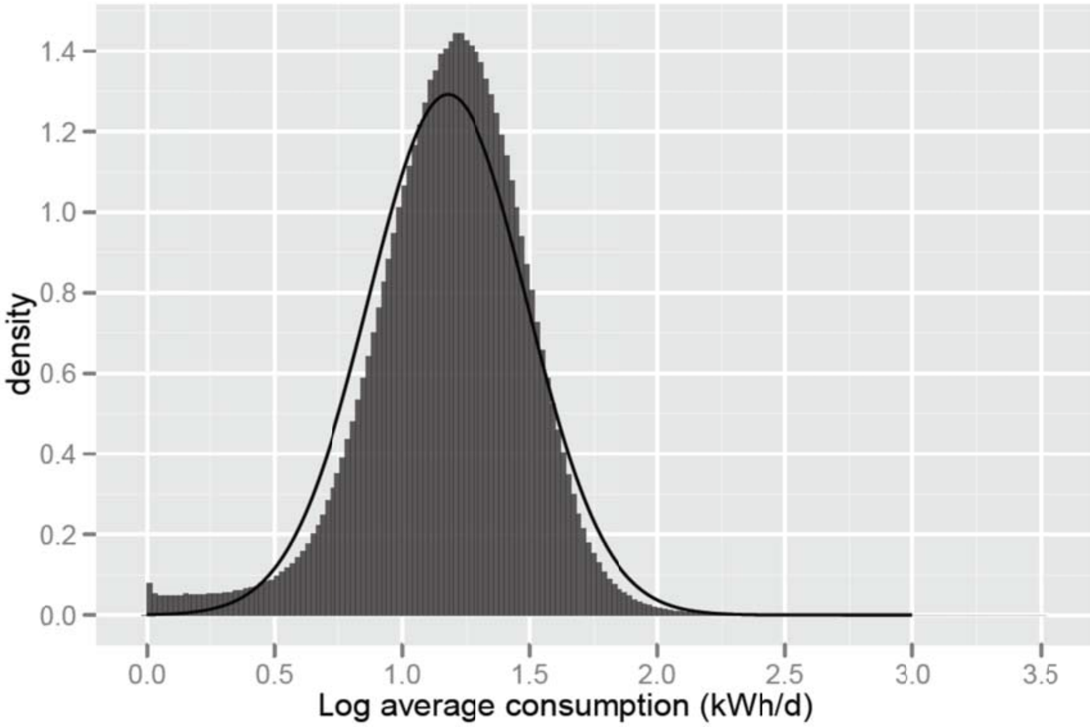


Figure 9-7 Histogram of log-transformed average household consumption

To calculate thresholds, average household consumption data from the participant group of interest was combined with average household consumption from all non-participant data and logarithmically transformed. The average and standard deviation of the logarithmically transformed data was calculated and the threshold set as:

$$\mu + 2.5\sigma$$

where

μ = the mean of the logarithmically transformed average households consumptions and

σ = the standard deviation of the logarithmically transformed data.

Since the log-transformed data may be considered normally distributed, this threshold should theoretically result in only the upper 0.6% of the data being filtered (Murdoch 1998). According to Chebychev's theorem, the worst case scenario for data loss, irrespective of the type of distribution, would be 16% (Freund 1992). Figure 9.8 shows the distributions of average consumption (not log-transformed) of all properties in the 150,000 random control subset and average consumption amongst HPSP participants. The threshold defined as per the above equation would remove properties that sit above the marked line (98.1 kWh/hh/d).

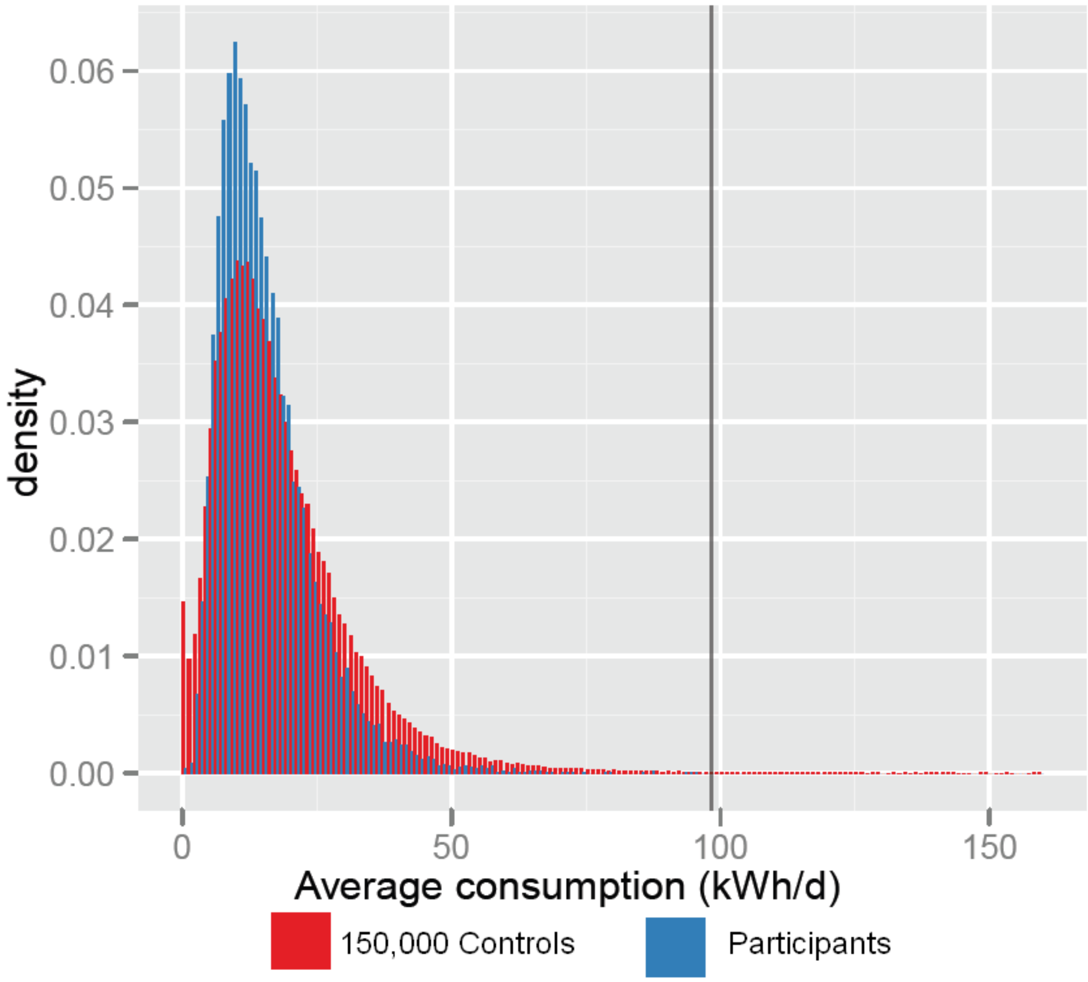


Figure 9-8 Histogram of average household electricity consumption for all properties and participants.

Second households with any month's consumption value above a statistically-defined threshold were discarded from subsequent analyses. This threshold was calculated based upon the fundamental assumption that the household's monthly consumption data followed a lognormal distribution. Figure 9.9 is a histogram of the log-transformed average (time-based) daily electricity consumption for all participant and the 150,000 control subset households. When compared against a normal (Gaussian) distribution (black lines), this assumption appears to be reasonable.

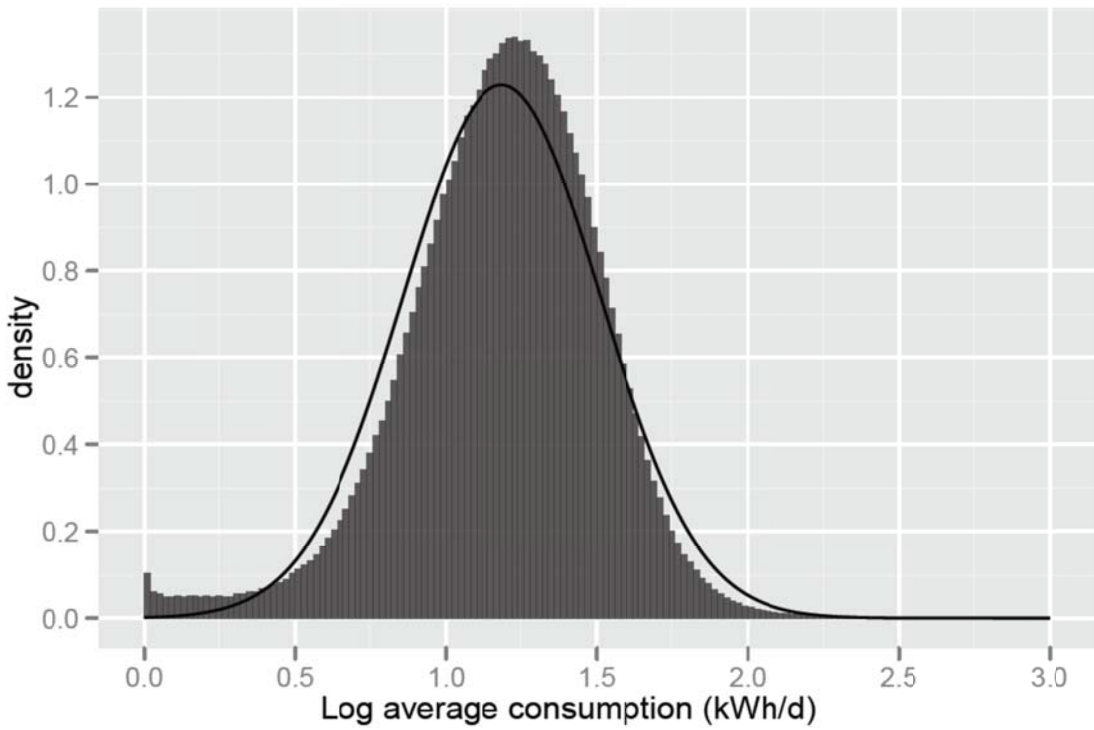


Figure 9-9 Histogram of log-transformed monthly household consumption

To calculate thresholds, monthly consumption data from the participant group of interest was combined with the 150,000 non-participant subset monthly consumption data and logarithmically transformed. The average and standard deviation of the logarithmically transformed data was calculated and the threshold set as:

$$\mu + 3.29\sigma$$

Where:

μ = the logarithmically transformed households consumptions for a given month and

σ = the standard deviation of the logarithmically transformed data.

Since the log-transformed data may be considered normally distributed, this threshold should theoretically result in only the upper 0.05% of the data being filtered (Murdoch 1998). According to Chebychev's theorem, the worst case scenario for data loss, irrespective of the type of distribution, would be 9% (Freund 1992). Figure 9.10 shows the distributions of average consumption (not log-transformed) of all properties in the 150,000 random control subset and average consumption amongst HPSP participants. The threshold defined as per the above equation would remove properties that sit above the marked line (177.1 kWh/hh/d).

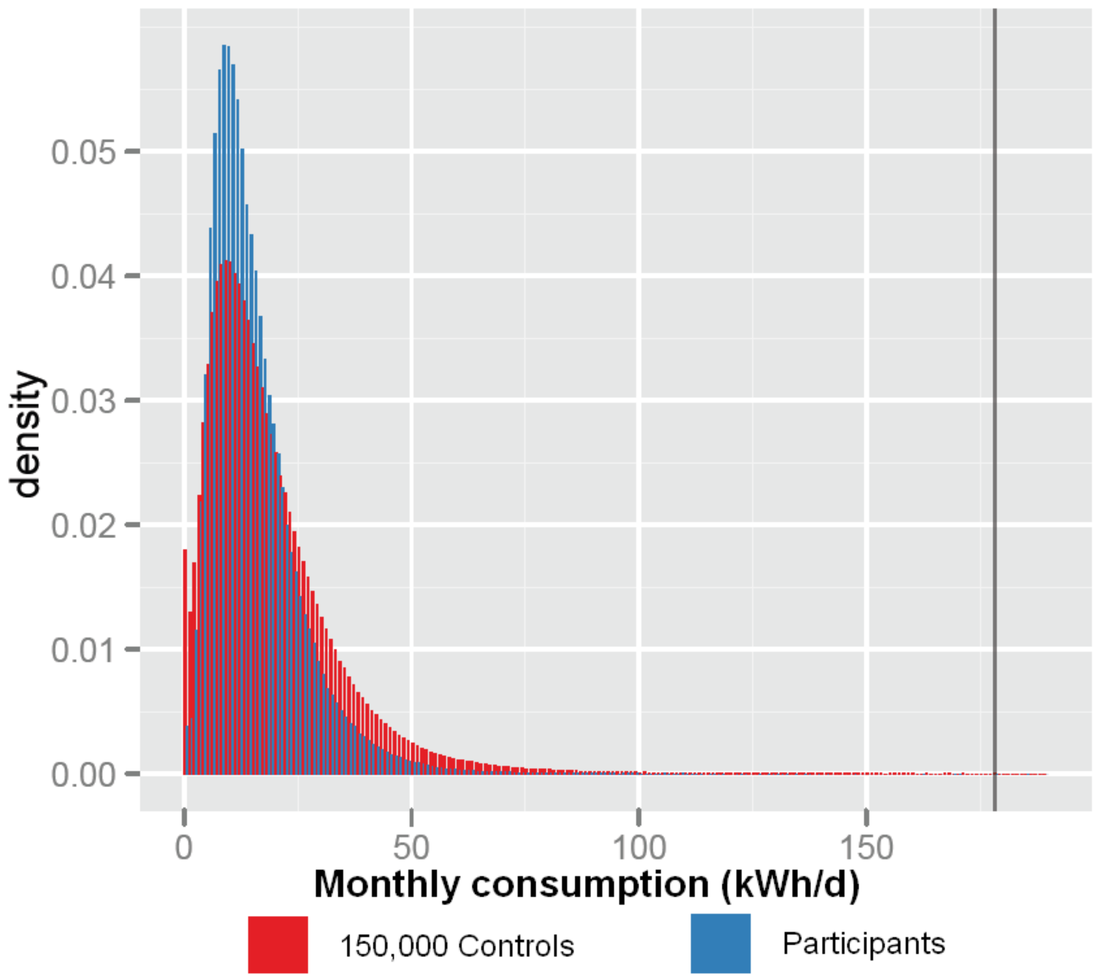


Figure 9-10 Histogram of monthly household electricity consumption for all properties and participants.

9.5.3 MATCHING PERIOD SPUR TEST

Each participant's matching period is checked to ensure that there are no spurious (unusually high or low) consumption figures over the 12 months. In other to pass the spur test, the difference between any two adjacent months in the participant's matching period cannot differ by more than one order of magnitude. Mathematically, if the months are M_i and M_j then

$0.1M_i < M_j < 10M_i$ and

$0.1M_j < M_i < 10M_j$

If any month in the before period fails the spur test, then the entire participant record is removed from the subsequent analyses.

9.6 PAIR MATCHING

Pair matching seeks to select, from all viable non-participants in the database, a household that has the closest consumption profile to each participant household that has made it through the data filtering. To do this, the Python script iterates through a randomised sorting of the participants. With each iteration, a 150,000 sample set of the non-participants is scanned for potential households that have the necessary data and applies a matching calculation to determine which of the viable non-participants is the closest match to the participant. The main steps of the process are detailed below.

9.6.1 RANDOMISE PARTICIPANTS

The order of the participants is first randomised prior to pair matching to minimise any potential bias that may result from an ordered list of participants. Bias may be introduced when, for example, participants are ordered by NMI as this will likely be reflect a geographical clustering, which may cause properties of a particular size and socio-economic status to be matched en bloc.

9.6.2 CHECKING NON-PARTICIPANTS

The non-participant consumption data are then checked to ensure each non-participant has the necessary data to be matched to the participant being matched, and that there are no spurious consumption figures in the matching period. The spur test applied to the non-participants is identical to the matching period test applied to non-participants. The necessary data checks are slightly different to those applied to the participants. They include:

- The non-participants consumption record commences before the twelve month matching period begins. That is, the first month of recorded data is 14 months before the intervention date (< month -13)
- The control consumption record has at least M month of after period data, where M is the minimum between 24 and the length of the participants after period.
- The twelve matching months all contain consumption data. That is, there are no gaps in the before period consumption data.
- The first M months must not contain a null consumption value.

9.6.3 MATCHING TO NON-PARTICIPANT CONTROLS

A control household is then selected from all the non-participant households that passed the data checks based on the smallest sum of squares result over the matching period. To avoid contaminating the matching period with post-intervention consumption data, a buffer around the intervention date is added, so the matching period is on the twelve month period from months -14 to -3 (where month 0 is the intervention month). Two matching calculations are possible ‘sum squares’ and ‘median matching’. The ‘sum squares’ is calculated using the participant and non-participant consumption data in the matching period according to the following equation:

$$E = \sqrt{(C_{-14} - P_{-14})^2 + (C_{-13} - P_{-13})^2 + \dots + (C_{-3} - P_{-3})^2}$$

Where
E = the error calculation
P = Monthly average day consumption of the participant,
C = Monthly average day consumption of corresponding non-participant, and

the subscript indicates the month relative to the intervention date of the participant, e.g. C_{-14} is the consumption for the month 14 months prior to the intervention date.

The 'median matching' is calculated on the participant and non-participants consumption record according to the following equation:

$$E = \left| Median\left(C_{-14} - P_{-14}, C_{-13} - P_{-13}, \ldots, C_{-3} - P_{-3}\right) \right|$$

Where
E = the error calculation
P = Monthly average day consumption of the participant,
C = Monthly average day consumption of corresponding non-participant, and

the subscript indicates the month relative to the intervention date of the participant, e.g. C_{-14} is the consumption for the month 14 months prior to the intervention date.

Median stands for the standard calculation of the median value of a list.

9.6.3.1 CONSTRAINING MATCHING TO ENERGY PROVIDER

The service boundary of Essential Energy and Ausgrid encompasses a very large area that spans a range of climate zones and demographics. Although the LGA data is known for Essential Energy participants and non-participants, the LGA data for Ausgrid non-participants are not known. For this reason, the matching is only restricted to a household from the same energy provider.

9.7 ANALYSIS

The final stage of the MPMC process is the actual analysis of savings using the data from the matched pairs. Before the savings are calculated, however, the veracity of the matching is checked by applying a number of statistical tests to each matched pair. Household savings are then calculated using the pairs that pass the matching validation to then be used in calculating monthly and global savings averages which are verified using the repeated measures t-test and the equivalent non-parametric Wilcoxon test.

9.7.1 VALIDATION OF MATCHED PAIRS

Each matched pair is validated using four tests to ensure their statistical integrity, namely:

- After period spur test;
- Quadrant test;
- Correlation test;
- Variance ratio test

A pair that fails the spur test or fails *all* three of the quadrant, correlation and variance ratio tests is discarded. Thus, pairs that are retained for the means comparison analysis are those which pass the spur test and one (or more) of the quadrant, correlation and variance ratio tests. The rationale behind each test is described below.

AFTER PERIOD SPUR TEST

The spur test examines both the control and participants after period data in the same way. A month's consumption value (denoted Q_i) in the after period is removed if the value is more than six times the mean of the match period consumption (denoted μ) or less than one tenth the size of the mean of the match period consumption. Mathematically this can be expressed as

$$0.1\mu < Q_i < 6\mu$$

If after passing through the spur test, all of the after period has been removed, then the participant is dropped from the analysis.

QUADRANT TEST

The quadrant test is used to test the strength of the matches between participants and users. The test places a statistical limit on the size of the root mean square error from the pair matching. The quadrant test calculates the least squares over the matching period and then takes the square root of the result (the root square error, RSE). Since there is no absolute measure of the strength of a RSE result, a test was developed that superimposes a normal distribution onto the RSE results from all the matched pairs. This defines a relative measure derived from the sample itself against which to identify lower-quality matches. The RSE calculation generates a skewed (log-normal) distribution of results with a lower bound of zero and a large tail to the right. The side of the distribution not skewed is mirrored at the geometric mean (GM) to define an acceptable upper limit. Thus poor matches were defined as those least squares results that sit outside the range:

$$RSE_{\min} \leq RSE_i \leq RSE_{GM} + (RSE_{GM} - RSE_{\min})$$

Where

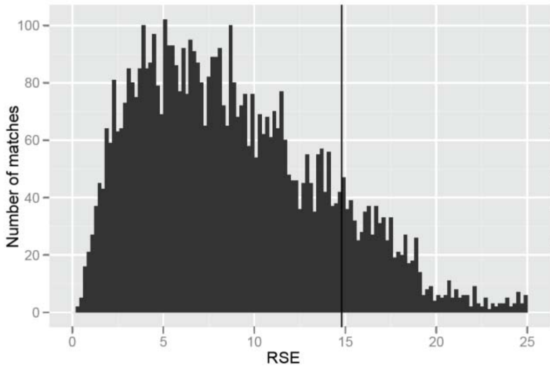
$RSE_{\min} = \text{Minimum of root square error results}$

$RSE_i = \text{Root sqare error result of the } i\text{th matched pair}$

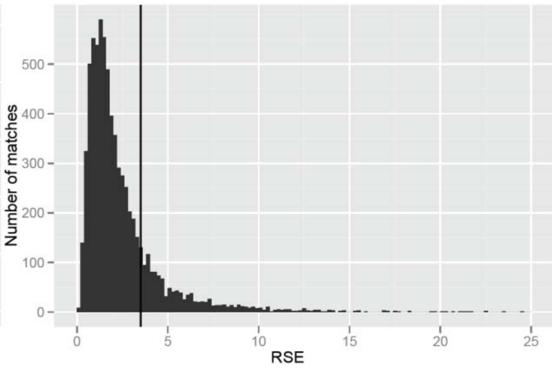
$RSE_{GM} = \text{Geometric mean of root square error results}$

When the minimum RSE is zero the upper bound becomes 2 times the RSE geometric mean. The application of the quadrant test is shown in Figure 9.11 A) 150,000 Controls, Median Matching B) 150,000 Controls, Sum Square

To capture those matches where the RSE is high *relative to* the consumption figures that it is calculated from, the quadrant test is also applied to the normalised RSE results (that is RSE divided by the mean consumption of the matched pair control). Properties with a RSE value that failed either of the quadrant tests were then subjected to the correlation test described below.



A) 150,000 Controls, Median Matching



B) 150,000 Controls, Sum Square

Figure 9-11 Quadrant test applied to the HPSP matched pairs root square errors

CORRELATION TEST

The Pearson correlation coefficient is a figure between -1 and +1 that indicates the closeness of the match between the participant and control profile. A value of +1 indicates perfect correlation. A negative value indicates negative correlation, that is, participant consumption increases in months when control consumption decreases, or vice versa. A higher positive correlation indicates greater confidence in the match, while a low or negative coefficient raises doubts about the quality of the match. For the purposes of this analysis, a minimum correlation of 0.96 was used to identify a satisfactory correlation and pairs with a coefficient of less than this value underwent further testing.

VARIANCE RATIO TEST

A low level of variance in a matched pair's consumption data would give a low positive correlation, even if the least squares match was of an acceptable quality. Hence the variance ratio test is used to provide further verification of match validity.

When combined with low correlation, a high variance ratio can indicate a poor match. If the variance of a participant's consumption is much larger than the consumption variance of its control, or vice versa, then the consumption ranges will be different and the match may be unacceptable. A variance ratio between 0.5 and 2 was used to define acceptable matches for cases where the correlation coefficient was smaller than 0.96.

9.7.2 SAVINGS CALCULATIONS

SAVINGS BY MONTH

Following the matching of participant-control pairs, the baseline for each pair is established by calculating the monthly differences in consumption before the program intervention. These baseline differences should be close to zero if participant-control pairs are closely matched. The same differences are also calculated for each month after the intervention. The differences between participant consumption and control consumption for each month in the period following the Program's inception are subtracted from the corresponding participant-control differences in the pre-intervention period (on a revolving basis where the post-period is greater than 12 months). To avoid cross-over between pre- and post-intervention consumption figures (refer to section 9.5.1), the two months either side of a household's intervention date are not included in this calculation. The mean of the differences of differences in each month represent the savings achieved by the program. The calculation is summarised in Table 9.2.

Table 9-2 Calculation of net monthly average per-household savings using matched pairs. Note the before period months are not ascribed to a year as the intervention date varies between households.

Pair ID	Monthly consumption (kWh/hh/d)					Monthly savings (kWh/hh/d)	
	Before Period		…	After Period (savings)		Mar-09	Apr-09
	Mar	Apr		Mar-09	Apr-09		
1	$\Delta(P1,C1)_{Jan05}$	$\Delta(P1,C1)_{Feb05}$	…	$\Delta(P1,C1)_{Jan06}$	$\Delta(P1,C1)_{Feb06}$	$\Delta(P1,C1)_{Jan05}$ - $\Delta(P1,C1)_{Jan06}$	$\Delta(P1,C1)_{Feb05}$ - $\Delta(P1,C1)_{Feb06}$
2	$\Delta(P2,C2)_{Jan05}$	$\Delta(P2,C2)_{Feb05}$	…	$\Delta(P2,C2)_{Jan06}$	$\Delta(P2,C2)_{Feb06}$	$\Delta(P2,C2)_{Jan05}$ - $\Delta(P2,C2)_{Jan06}$	$\Delta(P2,C2)_{Feb05}$ - $\Delta(P2,C2)_{Feb06}$
…	…	…	…	…	…	…	…
n	$\Delta(Pn,Cn)_{Jan05}$	$\Delta(Pn,Cn)_{Feb05}$	…	$\Delta(Pn,Cn)_{Jan06}$	$\Delta(Pn,Cn)_{Feb06}$	$\Delta(Pn,Cn)_{Jan05}$ - $\Delta(Pn,Cn)_{Jan06}$	$\Delta(Pn,Cn)_{Feb05}$ - $\Delta(Pn,Cn)_{Feb06}$
						Average Net Saving	**Average Net Saving**

ABSOLUTE AND RELATIVE TIME SCALES

The differencing described above is based on an absolute time scale and determines savings by calendar month as per Figure 9-12. In order to gain insight into the longevity of savings, a differencing technique was developed for a relative time scale such that a time series of savings is generated according the number of months following intervention. In this sense, intervention dates for all matched pairs are aligned as per Figure 9.13. As with the absolute time scale, the differences for each post-intervention month on the relative time scale are subtracted from the difference of corresponding pre-intervention month. The distinction however is that the savings are not ascribed to the calendar month but the position of that month relative to the month of the intervention. This allows us to gauge how savings vary as time elapses following engagement with the program.

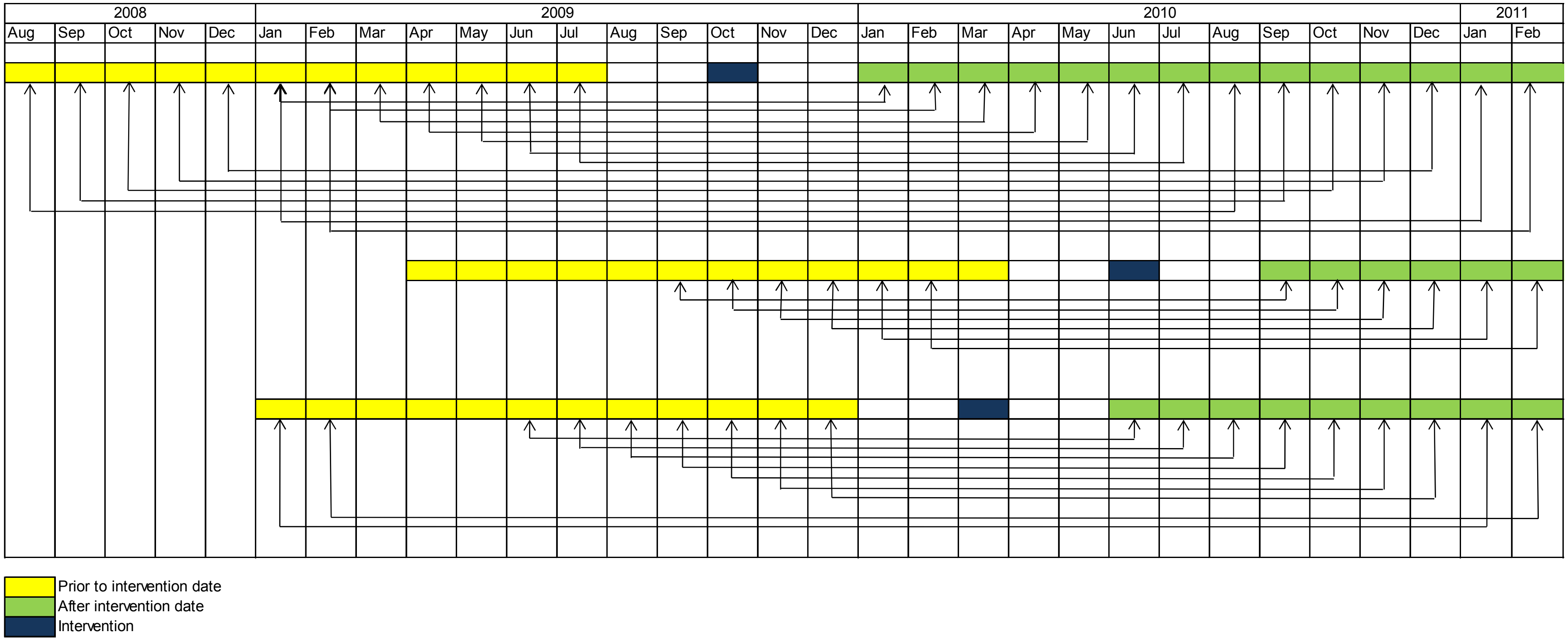


Figure 9-12 Household savings calculation on an absolute (calendar month) time scale.

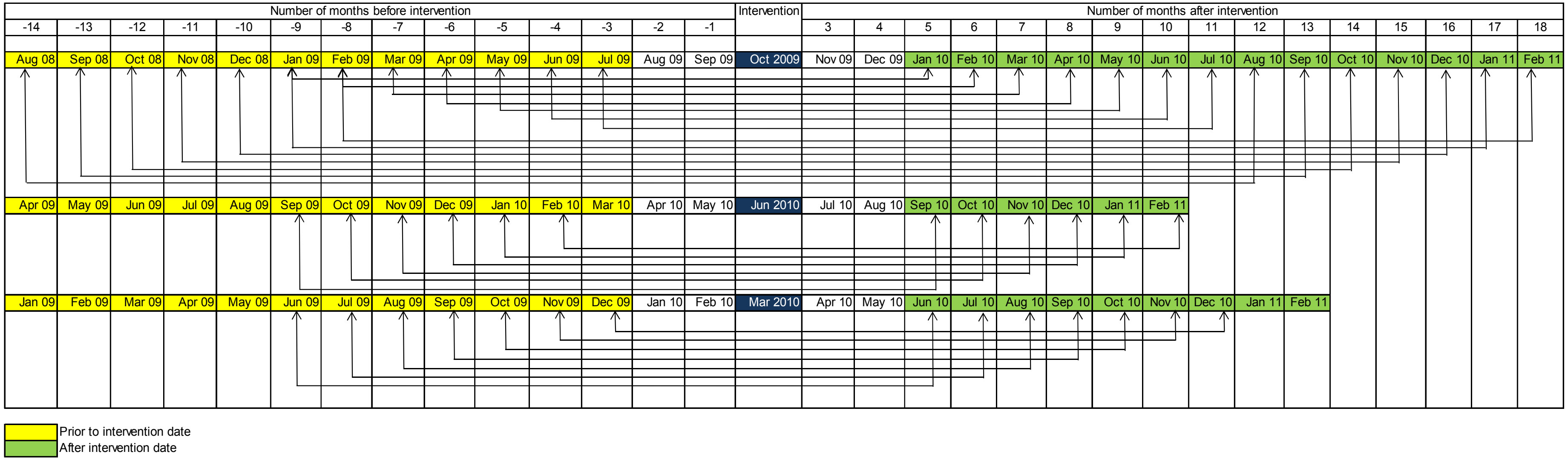


Figure 9-13 Household savings calculation on a time scale relative to the intervention date.

GLOBAL MEAN

In calculating a global mean (average over time and across participants), it is important to recognize that additional monthly consumption data for an individual household does not necessarily add new information, as month-by-month consumption/savings for a particular household may be highly correlated. Thus to calculate a global mean savings figure, we first calculate average savings *per household*, and take the mean of these averages (i.e. the mean of means) as the global estimate of average household savings. Calculating the mean in this manner also ensures that the uncertainty of the estimate is not understated by restricting the degrees of freedom used to the number of households, and not the number of data points. This also ensures that parametric confidence intervals will err on the conservative side, as the number of households is a lower bound estimate on the true degrees of freedom.

9.7.3 STATISTICS

The global and monthly mean savings are then tested to determine whether they are statistically significant using a standard paired (repeated measures) t-test. A t-test evaluates the *null hypothesis* (H_0) that the *expected values* (means) of two groups are equal. In this case, *each month* provides two groups of observations:

- the *differences* in energy consumption between (actual) controls and (future) participants **before** Program implementation (Δ_{BEFORE}); and
- the *differences* in energy consumption between (extrapolated) controls and (actual) participants (Δ_{AFTER}).

The alternative hypothesis (H_A) is that the opposite is true, i.e., that the groups are **not** equal. With a confidence of 95% the null hypothesis can be rejected if the result from the t-test (the so-called p-value) is below 0.05.

The null hypothesis (H_0) for our case can be formulated as follows:

> The *mean* difference in energy consumption between (actual) controls and (future) participants before Program implementation and the *mean* difference in energy consumption between (extrapolated) controls and (actual) participants are equal.

If the null hypothesis can be rejected, the difference between the groups is statistically significant at the 95%-confidence level. This means that the two means (their difference being the expected *net* savings for the month) are valid and can be used in the calculation of the average *monthly* savings of the particular program.

The repeated measures t-test is applied to both the monthly savings data and to the overall average. As an alternative to the parametric t-test, the non-parametric Wilcoxon signed rank test is also applied to the monthly and global averages. Other statistics including standard deviation, standard error, 95% confidence intervals, the Shapiro-Wilk and Kolmogorov-Smirnov tests for normality, and skewness and kurtosis are also produced to gauge the distribution of the savings data.