3 What is the optimal incentive level to promote a switch to an efficient system?

A key objective of the HEEUP program was to understand the optimal incentive level that would enable a low-income home owner to upgrade to a more efficient hot water system. Two approaches were used to better understand the optimal incentive level:

1 Program delivery experience
2 A discrete choice experiment

PROGRAM DELIVERY EXPERIENCE

Summary of results

- Upgrades to solar and heat pump systems could be achieved in 65% of households with the following subsidy mix:
  - $2,300 to $2,900 for upgrades to solar (with a householder contribution around between $1,900 and $2,000)
  - $2,000 to $2,300 for upgrades to heat pumps (with a householder contribution between $1,600 and $1,800)
- Conversion rates from a home visit to an installation were higher when the subsidy was higher and the out-of-pocket expense lower.
- Higher subsidies and more choice coincided with more energy efficient systems being installed.

Introduction

Changes made to the format of the subsidy and the amount of the subsidy (affecting the out-of-pocket cost to the household) during the program provided a basis for a preliminary assessment of the households' response to different subsidy levels.

Data and methodology

Owner-occupier home visits were analysed to assess the proportion of home visits that translated to an upgrade, and the installation mix, in each program period. The HEEUP administrative data used in this analysis was collected by BSL HEEUP staff and includes:

- Number of standard owner-occupier home visits
- Type and date of hot water systems installed
- Subsidy amounts and out-of-pocket cost to the household –Subsidy provided by the BSL or the HESS program and recorded by HEEUP staff. The out -of-pocket cost refers to the cost to the household (up-front or with a loan) after all subsidies and discounts.

The data was assessed in the light of changes in program offer – changes to hot water system types on offer, the subsidy amounts and the format of the subsidy.

Results

The pattern of subsidies and fixed costs for hot water upgrades is shown in Table 13.

During the HESS phase, householders contributed a fixed $1,200 for solar or instant gas systems (the three on offer) which represented between 63% and 76% percent of the total cost depending on the upgrade type. They received a variable subsidy ranging from a median $2,078 for instant gas to $3,792 for electric boosted solar.

During BSL phase 1, they received a fixed subsidy of $2,000 for solar gas systems and contributed a median out-of-pocket cost of $2,426, representing between 10% and 45% of the total cost.

In BSL phase 2, the size of the subsidy also varied by installation type, from $150 for gas storage, to $2,500 for solar systems. The household median contribution by installation type ranged from $1,370 up to $1,892, representing between 10% and 57% of the total cost.

The last stage (BSL 3) reverted to a variable subsidy and a maximum fixed price per installation type that varied from $1,400 (gas storage) to $2,000 (solar or instant gas). Overall households contributed between 23% and 59% of installation costs.

Table 13: Installation types by subsidy period - percentage

Subsidy period and hot water systems on offer	Scheme rules – cost to household	Scheme rules – subsidy type and amount	Number of installs	% installs by type	Actual median cost paid by hh	Actual median subsidy	HH cost % of total price (after veet & stc)
HESS program subsidy 1/4/14 to 31/6/14	**Fixed amount. No less than:**	**Variable**	***42***				
Solar gas boosted	$1,200	Variable	21	50%	$1,200	$3,571	25%
Solar electric boost.	$1,200	Variable	17	10%	$1,200	$3,792	24%
Instantaneous gas	$1,200	Variable	4	40%	$1,200	$2,078	37%
BSL 1: Fixed subsidy 1/7/14 to 28/2/15	**Variable amount**	**Fixed amount**	***40***				
Solar gas boosted	Variable	$2,000	21	53%	2,426	$2,000	55%
Solar electric boost.	Variable	$2,000	0	0		N/A	

Instantaneous gas	Variable	$350	8	20%	1,894.5	$350	84%
Gas storage	Variable	$150	11	28%	1,340	$150	90%
BSL 2: Fixed subsidy 1/3/15 to 31/5/15	**Variable amount**	**Fixed amount**	***65***				
Solar gas boosted	Variable	$2,500	32	49%	$1,892	$2,500	43%
Solar electric boost.	Variable	$2,500	0	0%	0	N/A	N/A
Heat pump	Variable	$2,000	10	15%	$1,595	$2,068	44%
Instantaneous gas	Variable	$500	17	26%	$1,859	$500	79%
Gas storage	Variable	$150	6	3%	$1,370	$150	90%
BSL 3: Floating subsidy 1/6/15 to 18/12/15	**Max. cost to house hold**	**Variable**	***377***				
Solar gas boosted	$2,000	Variable	154	41%	$2,000	$2886	41%
Solar electric boost.	$2,000	Variable	23	6%	$1,890	$2309	45%
Heat pump	$1,800	Variable	101	27%	$1,800	$2334	44%
Instantaneous gas	$2,000	Variable	60	16%	$2,000	$800	71%
Gas storage	$1,400	Variable	39	10%	$1,200	$350	77%

Conversion rates: from home visit to hot water installation

Figure 14 shows home visits that led to an installation and those that did not. Both the total number of home visits and the installations that resulted from those home visits fluctuated per month. The changes largely reflected the timing and focus of recruitment or the varying subsidy levels. Most installations occurred soon after the home visit. It is apparent that the HESS period (April to June 2014) had very high conversion rates from home visit to installation; however, it had relatively low installation numbers. By contrast January and February 2015 had 100 or more home visits, but only 23 and 28 installations resulting from these home visits.

Figure 15 shows the proportion of households who received a home visit in a given month and subsequently installed a hot water system. It is important to note that there were some changes in recruitment in the different periods, especially in the final BSL subsidy period.

Figure 14: Number of installs and home visits per month (standard HEEUP only)

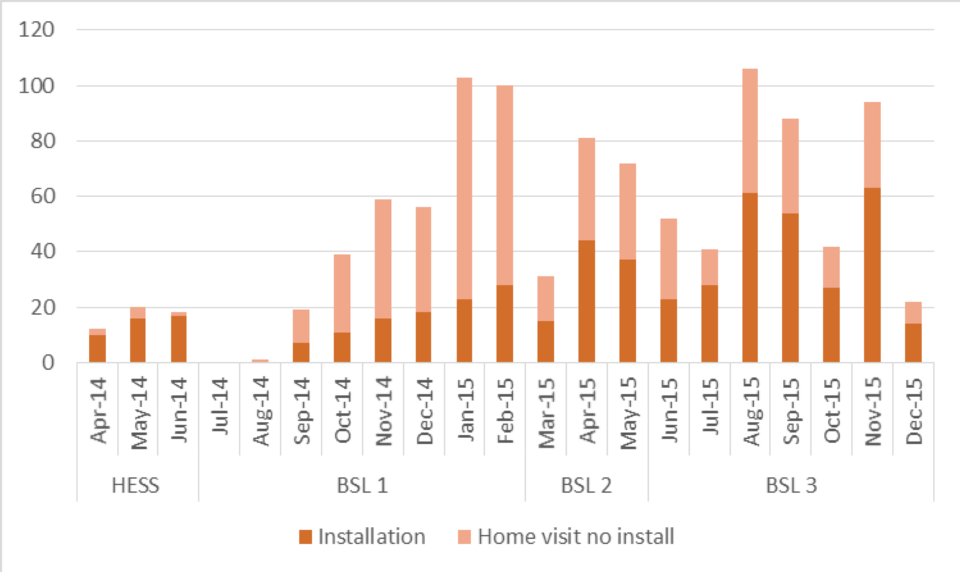
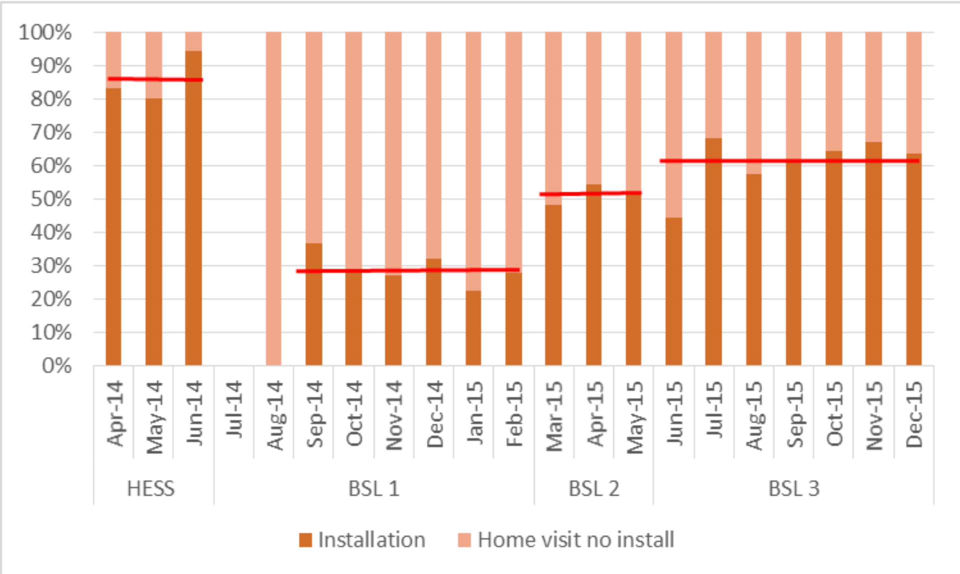


Figure 15: Installs as a percentage of home visits per month (standard HEEUP only)



Note: July and August 2014 had little activity and were not included in the calculation for BSL 1s

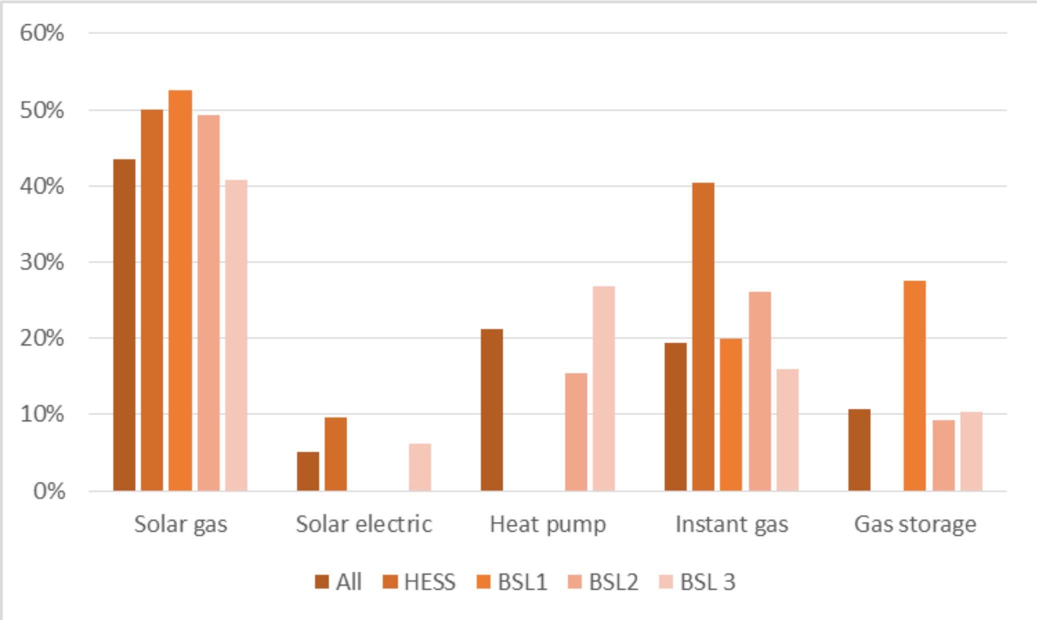
Figure 15 shows the average observed rates of conversion for each period:

- HESS program period – fixed up-front cost of $1,200 and a floating subsidy– 86% conversion from home visit to installation
- BSL 1 fixed subsidy period, floating up-front payment – 29% conversion from home visit to installation
- BSL 2 fixed subsidy period, floating up-front payment – 51% conversion from home visit to installation
- BSL floating subsidy, fixed upfront payment – 61% conversion from home visit to installation

Installation mix during different installation periods

The installation mix during the different subsidy periods is presented in Table 13, Figure 16 and Figure 17. Heat pumps, which were not available during the HESS period and much of BSL 1, became a larger proportion of the upgrades as the program progressed. Instant gas systems also decreased as gas storage systems were introduced and the out-of-pocket expense increased following the closure of the HESS program.

Figure 16: Installation types during subsidy periods (standard HEEUP)

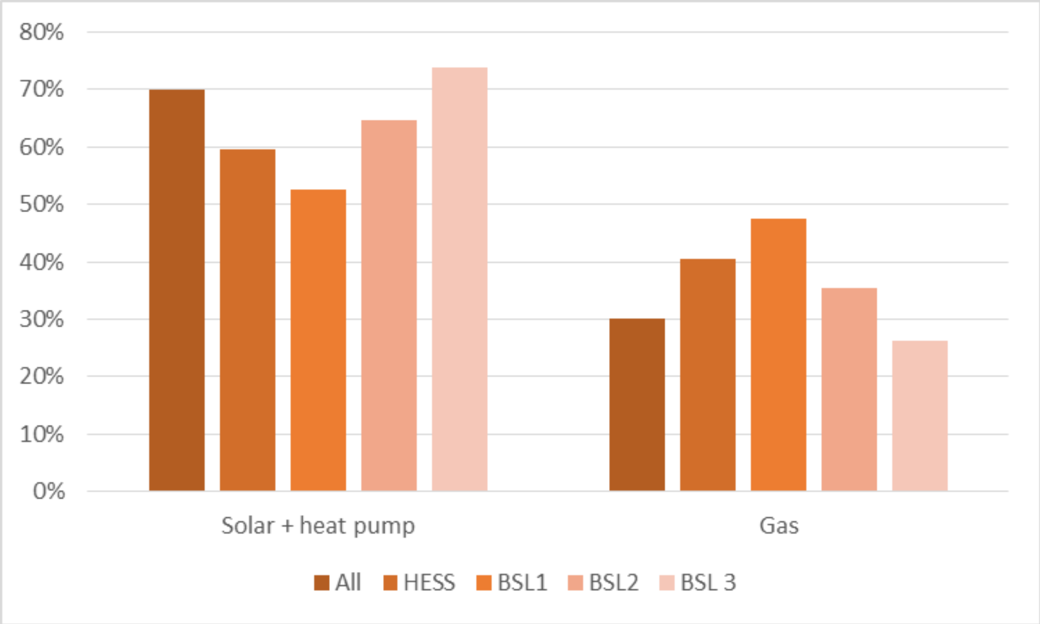


N: All: 524; HESS: 42; BSL 1: 40; BSL 2: 65; BSL 3: 377

When grouped together (Figure 17) the more energy efficient, and expensive, systems – solar or heat pump – reached a maximum of 74% of the installation mix during the final BSL subsidy period, which had a maximum out-of-pocket expense of $2,000 for solar and $1,800 for heat pump. The efficient systems were 60% during the HESS period (when households only had to pay $1,200 for solar) and were at their lowest during the BSL 1 subsidy period, when households received a maximum $2,000 subsidy and heat pumps were not yet included into the program. Gas systems were highest during the HESS subsidy and BSL 1, with instant gas driving the uptake during HESS and gas storage during BSL 1.

Along with a change in subsidy, the final BSL subsidy period also coincided with new recruitment strategies which specifically targeted households who were interested in solar or heat pump installations.

Figure 17: Solar & heat pump vs instant and storage gas, different subsidy periods



n=524

Discussion

The analysis suggests relationships between the level of subsidy, the conversion of home visits to hot water installations and the types of hot water services installed.

Conversion rates were higher when the subsidy was higher and the out-of-pocket expense was lower

As would be expected, a higher subsidy and lower out-of-pocket cost to the household led to a higher conversion rate from home visit to installation. This was most notable during the HESS program period when the installed cost of a solar or instant gas system was only $1,200 and the conversion rate was 86% (though with low installation numbers). Similarly in BSL phase 3 the conversion from home visit to installation was 61%. During this period the out-of-pocket cost was fixed at below $2,000 for solar and below $1,800 for heat pump. The median subsidy for solar gas was $2,886 and for solar electric and heat pump just over $2,300.

Higher conversion rates mean the home visits are better value for effort.

Higher subsidies and more choice coincided with more efficient systems being installed

The mix of systems installed fluctuated with the different systems on offer and with different subsidy levels. The proportion of solar or heat pumps installed was lowest when the subsidy was lowest in the BSL 1 period. The HESS period with the highest subsidy and lowest out-of-pocket expense to the household coincided with a 60% installation rate of the most efficient system offered at that time. Both BSL 2 and BSL 3 had higher rates of installations of efficient systems, even though they had lower subsidy levels than HESS.

The addition of heat pumps to the systems offered increased the uptake of efficient systems, without requiring a subsidy of the level provided in HESS.

Taken together these results suggest that:

1. Upgrades to solar and heat pump could be achieved in 65% of households with the following subsidy mix:
    - $2,300 to $2,900 for upgrades to solar (with a householder contribution between $1,900 and $2,000)
    - $2,000 to $2,300 for upgrades to heat pumps (with a householder contribution between $1,600 and $1,800)

    These subsidies would need to be on top of any existing subsidies in the market such as VEET or STC.
2. The subsidy level needs to be high enough to stimulate the preferred purchases in the target group, but not so high as to be too costly to fund.
3. Lower subsidies mean that more home visits are required to achieve the same number of installations. One approach to maximise the value of the home visits could be to limit them to those households who demonstrate a need for advice. While this would not necessarily impact on the conversion rate it would reduce the overall costs of the program.

Further research

While this analysis provides some initial insights into the optimal level of subsidy, further research could address important limitations that occurred because of a lack of data on:

- the financial characteristics of the households. The reflective practice process identified possible differences in liquidity (cash in the bank) between the households in the HESS phase and those in other program phases.
- the households that expressed interest but dropped out prior to the home visit
- the different intake and recruitment processes used during HEEUP.

DISCRETE CHOICE EXPERIMENT, RESULTS AND ANALYSIS FOR HEEUP

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Summary of results

This study first explored household preferences for hot water service replacement and then produced a flexible tool to estimate the levels of subsidy that would be most likely to encourage take-up of more energy-efficient systems.

A stated choice experiment was conducted to provide information about household demand for hot water systems at various net costs. The experiment was conducted through a survey of over 500 homeowner households with concession cards in the Melbourne area. Participants were presented with choices between different types of generic hot water systems with varying upfront cost and running costs; and then with choices between systems using different technologies, with corresponding upfront and running costs. The cost estimates were adjusted according to the participant's household size, to make them realistic.

The generic choice set showed that:

1. An extra dollar of annual running cost has about 6.7 times the impact of an extra dollar of upfront cost on people's choice.
2. A subsidy has more effect than a comparable reduction in upfront cost.

The response to running cost did not correspond to the person's financial literacy.

The technology choice set, with the scenario that their current hot water system is within two years of its rated life, showed that:

1. People preferred to retain their existing system rather than to install a new system, except for solar and gas.
2. A subsidy had no more effect than a reduced market cost on people's preference: evidently this choice was based on the technology.
3. The annual running cost had more influence on people's preference than in the generic choice set.

The project's core objective was to produce evidence for determining the best subsidies. The decision-support tool that was developed uses three types of input:

- estimates of demand (from the experiment)
- estimates of household hot water costs (initially from HEEUP households)
- budget constraints (funds available for subsidy and for recruiting households)

An important decision in using the tool is identifying the desired objective.

If the purpose is to minimise average running cost for eligible households, then the best option is to provide very high subsidies for solar gas systems, and minimal subsidies for other technologies. However if the objective is to maximise household utility, the maximum subsidies should be similar for all technologies and around $2,000, leaving the choice to the consumer. It may be desirable to balance these two objectives; in any case, the mix of subsidies should be at a level to attract enough recruits.

Introduction

A stated choice experiment was conducted to provide information about household demand for hot water systems at various net costs. The experiment was conducted through a survey of over 500 homeowner households with concession cards in the Melbourne area. A decision-support tool was developed in Excel, based on the analysis of the experimental results. The tool combines three types of input: (1) estimates of demand from the experiment, (2) data on the estimated costs of various hot water systems to a sample of real households and (3) user-defined constraints such as available budget and recruitment costs. Using these inputs, the tool provides an estimate of the impacts of various subsidies for various energy-saving hot water technologies in the Home Energy Efficiency Upgrade Program (HEEUP) program. The report details the objectives, design, conduct, and analysis of the experiment, as well as the development and use of the subsidy decision-support tool. The operation of the tool is described in section 5 (particularly subsection 5.3); readers interested only in the practicalities may wish to skip there directly.

Overview of objectives and methods

The HEEUP program administered by the Brotherhood of St Laurence (BSL) provides subsidies to eligible households for the purchase of more energy-efficient hot water systems. BSL specified that the program objective is to reduce energy bills for eligible households as much as possible. The level of these subsidies must be selected with care to meet this program objective cost-effectively. If the subsidies are set too low, then uptake will be low and recruitment costs high. If the subsidies are set too high, then the budget would cover fewer household system upgrades than desired.

The demand relationship between subsidy levels and household adoption of various technologies needs to be estimated to analyse these trade-offs. To do so, we apply the widely used method of stated preference in a discrete choice experiment format. In this approach, a sample of households is provided a series of hypothetical choices between water systems with various initial costs, subsidy levels, and running costs. Using data on the most-preferred choices, researchers can estimate the demand relationship between subsidy level and adoption rate. We use widely accepted best-practice experimental design to limit any difference between the stated choices of households and the real choices they would make if actually offered the choices.[12]

The results of the choice experiment provide estimates of demand for various hot water system upgrades (or no upgrade) as the subsidy level, installation cost, and running cost of the systems vary. In the experiment, these elements can be varied somewhat arbitrarily to get information about choices under a wide range of conditions. However, to estimate actual demand as a function of subsidies in a real setting, of course one must first plug in realistic estimates of installation costs and running costs for these technologies.[13] Given this information, a decision support tool is provided to recommend subsidies that are predicted to best achieve the program objective of minimising household energy bills, subject to program budget and recruitment costs.

Survey design

The survey instrument is the core component of a stated preference study. In addition to our personal research experience with stated preference surveys, we used evidence from four sources to refine the survey design: prior research on energy efficiency, a focus group, BSL participant data, and pilot data.

Prior studies

Wasi and Carson (2013) examine hot water system purchases in an Australian context. They use a discrete choice experiment to study how consumers respond to upfront costs, running costs and a government subsidy for a variety of hot water systems. We draw on the lessons of this study to guide our design. For example, we are able to use their results to optimise the statistical efficiency of our DCE. This determines the combination of hypothetical scenarios that the respondents see in the survey. The hypothetical scenarios are called ‘choice sets’, and we combine two features of recent research. We also expand on their survey in several important ways. For example, we provide a generic choice that highlights upfront costs and running costs similar to Newell and Siikamäki (2014), as well as a scenario that includes specific types of hot water systems as in Wasi and Carson (2013). Respondents answer five choice sets of the generic choice and five choice sets for the technology-specific choice. Choice sets vary by the values chosen to learn how consumers’ preferences vary between different features of the hot water purchase decision. An example choice set for the generic choice is displayed in Figure 1, and an example of the technology specific choice is shown in Figure 2. For the technology-specific choice we also provide a fact sheet

[12] Carlsson and Martinsson (2001) test the degree to which such hypothetical and real choices might differ in one choice experiment and find no evidence for differences. Murphy et al. (2005) present a meta-analysis of hypothetical bias that finds no significant impact for private goods in a choice experiment context, such as this. Nevertheless, there is always some risk that hypothetical answers will differ from real choices.

[13] For the decision-support tool, we use estimates of these costs from a sample of houses that have received on-site visits; however, these estimates can be changed by the end-user as appropriate.

describing features of each system. Similar to Wasi and Carson (2013) we condition the scenarios on the household size in order to make the scenarios as realistic as possible.

An important feature in choosing a hot water system is trading off between upfront costs and running costs. Most high-efficiency systems that have lower running costs are more expensive. Economists have found that many consumers do not appear to make an investment in energy efficiency that would essentially pay for itself over the lifetime of the product. For example, Allcott and Taubinsky (2013) find that consumers do not purchase compact fluorescent light bulbs even though they will be cheaper in the long run compared to incandescent light bulbs. This anomaly is termed the energy efficiency gap, and we design our survey to better understand to what extent this gap may exist in the context of the HEEUP. Most importantly, we gather information about financial literacy Lusardi & Mitchell 2014) and numeracy that may impact the ability to make a complicated decision such as purchasing a hot water system. Second, we collect information on individual rate of time preferences (discount rates) through a task that asks respondents to choose between receiving some money in one month or more money in seven months. Third, we elicit preferences for risk through a task where respondents choose between various uncertain outcomes, which may be relevant in understanding whether households will replace a system before it completely fails. These three tasks may help explain the energy efficiency gap, and identify different types of consumers that underinvest in energy efficiency.

Figure 18: Generic choice

Choice Experiment Set 1

	New system A	New system B	New system C
Upfront cost	1450	4650	950
Rebate amount	0	50	0
Upfront cost after rebate	1450	4600	950
Annual running cost	640	110	710
Preferred option	○	○	○

Figure 19: Technology-specific choice

You can click the **"Hot Water Systems Information"** to learn more about the specific systems.

Choice Experiment Set 6

	Keep Current System (2 years away from rated service life)	Electric storage	Gas Storage	Gas Instantaneous	Solar + electric	Solar + gas	Heat pump
Upfront cost	0	900	1300	1550	4500	3900	2800
Rebate amount	0	0	0	50	560	470	260
Upfront cost after rebate	0	900	1300	1500	3940	3430	2540
Annual running cost	510	570	520	490	180	350	450
Most preferred option							
Second-most preferred option							

Focus group

After designing the initial survey we conducted a focus group to test and get feedback on the draft survey instrument. The focus group comprised nine individuals, mostly concession card holders, recruited by Taverner Market Research. The session was conducted by Dr Brent and was video-recorded. A primary aim was getting general feedback about the wording and clarity of the questions. In addition, we created choice sets to determine whether respondents were making 'mistakes' with respect to choosing between upfront costs and running costs. If costs are the only decision factor (as they should be in the generic choice) then a respondent should select the option that minimises the lifetime net present cost, defined as the upfront cost plus discounted future running costs. We found that respondents often did not select the option that minimised the net present costs. There were several general decision rules mentioned by the focus group:

- payback period: determining how many years it would take to pay back higher upfront costs through reduced running costs
- environmental concerns: even in the generic choice higher running costs were associated with more energy use and more environmental damage
- information content of the subsidy: since the subsidy program was funded by the government and run by a non-profit the hot water systems with a subsidy were thought to be higher quality

Respondents also provided testimonies of their own experiences buying hot water systems. One theme was that the layout of the home meant some hot water systems would have very expensive installation costs if they require significant plumbing and/or electrical work. Additionally, respondents said that choosing an expensive energy efficient hot water system would come at the expense of other investments such as double-glazed windows. Lastly, we tried to understand whether the subsidy program could induce consumers to update their hot water system before it failed. Some respondents indicated that they would be willing to update their system if it was close to the end of the rated service life though it wasn't showing any signs of failure. Respondents also indicated that the survey was mentally taxing since it involved complex calculations to determine the best system.

We updated the survey in response to the focus group in several ways. First we included a button that calculates the payback period relative to the cheapest option. We randomise whether the respondent has access to the button, to determine whether the additional information changes the respondents' choices, and particularly whether it increases the likelihood of selecting the system with the lowest net present costs. We also changed some of the language that the respondents found unclear, such as framing the risk task in the context of investments in hot water systems.

BSL participant data

One of our goals in designing the survey instrument was to make it relevant to the HEEUP so that policy recommendations could be made based on the results. Therefore we analysed early participation data from the program. Our participation data is from 1 April 2014 to 12 March 2015; until 1 July 2014 HEEUP was run in conjunction with the Home Energy Saver Scheme (HESS), which offered larger rebates than the subsequent phase of HEEUP. We used two primary datasets. The first is the administrative data on participation including everyone who enquired about the program but eventually dropped out. The second dataset contains data collected during home visits by staff from the BSL, using options derived from the Hot Water Tool (HWT).The HWT was developed by the New South Wales government and takes inputs such as the number of occupants, type of appliances, and number of showers per week to estimate the running costs and upfront costs of a new hot water system. The BSL selects a subset of the sixteen options to show to the householder to help them decide which hot water system to purchase.

One key feature of the participation data is that of the roughly 1000 participants who had expressed interest in HEEUP (as of April and after HESS ended) 7% have completed installations with another 13% somewhere in the process that could lead to a successful installation. Presumably, the other 80% choose not to replace their system at this time (or at least not to replace it as part of this program), even though they had been considering the possibility. This suggests that it is important to understand the decision to replace an ageing hot water system even if it is still functioning. In order to address this question, in the technology-specific choice (Figure 2) we allow the respondents the option to keep their current system. We tell them that the current system has two years left on its rated service life, and that the subsidy may not be available next year. This is expected to replicate the decision process of many of the people who drop out after expressing interest. In this setting we ask for the top two choices, so that we are able to learn what system a respondent would choose if their first choice is to keep their current system.

The second feature that we consider is the lifetime cost estimates that we generate from upfront and running cost estimates from the Hot Water Tool. As described above we calculate the net present lifetime cost (NPLC) of a new system with the following formula that accounts for both upfront and running costs.

$$net\ present\ lifetime\ cost = upfront\ cost + \sum_{0}^{T} \frac{running\ cost}{(1+r)^t}$$

We assume a rated service life of 10 years (*T*=10) and a discount rate of 5% (*r* =0.05). Higher values for *T* and lower values of *r* will make more efficient systems like solar have lower NPLC. A discount rate of 5% is on the lower side of what is found in the economics literature. In the context of hot water systems Wasi & Carson (2013) find an average discount rate of 20% and (Newell & Siikamäki (2014) elicit average discount rates of 19%. Based on these assumptions we find that in the sample that received a home visit, even accounting for the BSL subsidies, gas systems had the lowest NPLC for 60% of the households and solar systems were the cheapest in terms of NPLC for the remaining 40%. These numbers are similar in the sample that eventually installed a new system through HEEUP. While 60% of the HEEUP installations post-HESS were solar + gas systems, this was the system with lowest NPLC for only 30% of the participating households. On average the NPLCs were approximately $800 higher for the installed model compared to the model with the lowest NPLC.

Pilot data

Running a pilot wave in a discrete choice experiment is advantageous for two reasons. The first reason is to identify areas of the survey that are unclear to the respondents and update accordingly. Second, getting pilot data allows the researcher to update the design of the discrete choice experiment based on the initial round of data, which can produce a more efficient design from a statistical perspective. There were not many changes that we made to the survey based on the pilot, but we did update the experimental design to improve statistical precision. It was helpful to understand two strains of comments from the pilot data. Many respondents stated that the survey was very interesting and challenged them to think in different ways from other surveys they completed. Another group of respondents stated that the maths made the choice sets quite difficult. This is important to consider in the context of actual purchase of hot water systems, which is even more complex than the choice experiment. Some comments from the pilot are listed below:

> ‘Very interesting exercise to try sensible, realistic comparisons’
>
> ‘Very thought provoking’
>
> ‘Unexpectedly mentally challenging!!!’
>
> ‘A fantastic and very different but very interesting survey, really enjoyed’

`'Very interesting, makes you think about long term costs'`

`'A bit tough on the grey matter!!'`

`'You have to be good at maths to work this out'`

`'Thanks, made my maths brain work hard'`

Final survey

The final survey was implemented by the Iview market research company with a sample of over 500 households that satisfied all the selection criteria: homeowners, concession-card holders and in the Melbourne area. These selection criteria, which reflected the original eligibility criteria for HEEUP, produced a sample predominantly of older adults. The instructions to the survey firm are included in Appendix G: Discrete choice experiment. The survey participants are part of an online panel that has agreed to be invited to participate in a variety of studies. The participants receive a small incentive for participation, with a cash equivalent value of a few dollars. The panel provider performs periodic checks on panel members' responses for quality assurance. In our sample, we gathered completion time data as a check on attentiveness. The survey instruction specified that we expected the questions to take no more than 20 minutes. Some 95 per cent of the sample took at least 12 minutes to complete the survey. The quickest 5 per cent of the sample were discarded as potentially non-attentive.

A key design feature is that the hot water system choice sets for each respondent are customised for the household size. This is important for maintaining plausibility and realism. For example, it would make little sense to provide a one-person household with a choice-set that contained typical annual running costs for a five-person household. The reasonable and relevant ranges for each household size were taken from the BSL participation data discussed in section 2.3. Each participant was asked to select their most preferred option in each of 10 choice sets, half of which specified technologies and half of which were generic. As noted before, Figure 1 and Figure 2 are examples of the main types of choice sets.

Sample characteristics and summary of survey responses

Age: The mean age is 67 years. Half of the sample is between 64 and 71 years of age.

Housing: 86% of the sample own a house. The remainder own flats, townhouses, or duplexes.

Language: 98% of the sample speak English at home; this high rate is not surprising given that the sample consists of people who sign up to participate in English-language surveys.

Sex: 51% of the sample is female.

Household size: 1 – 22%, 2 – 65%, 3 – 6%, 4 or more – 7%

Marital status:

Marital	Freq.	Percent	Cum.
De facto relationship	22	3.98	3.98
Divorced	61	11.03	15.01
Married	343	62.03	77.03
NA	55	9.95	86.98
Refused	8	1.45	88.43
Separated	7	1.27	89.69
Single	57	10.31	100.00

Employment: 71% retired, 10% part-time, 10% no response

Current hot water system:

Current hws	Freq.	Percent	Cum.
Don't know	15	2.71	2.71
Electric	98	17.72	20.43
Gas instant	148	26.76	47.20
Gas storage	221	39.96	87.16
Heat pump	5	0.90	88.07
Multiple	31	5.61	93.67
Other	4	0.72	94.39
Solar	31	5.61	100.00

Age of current hot water system:

Hws age	Freq.	Percent	Cum.
1-2 years	80	14.47	14.47
3-5 years	123	22.24	36.71
6-10 years	152	27.49	64.20
Don't know	37	6.69	70.89
More than 10 years	161	29.11	100.00

Considering replacing hot water system: 7.5% yes

Gas connection: 88% yes

Q13. What would be the four most important factors to you in choosing a new hot water system?

*Select exactly 4 answers [**PERCENT SELECTING IN SAMPLE INDICATED]***

1. **23%** Plumber's recommendation
2. **71%** Fuel type (electricity, gas, solar, heat pump)
3. **10%** Flow rate

4. **28%** Lifetime
5. **6%** Noise/quietness
6. **45%** Upfront cost
7. **13%** Simple installation process
8. **14%** Sitting position (e.g. indoor/outdoor, roof/ground)
9. **16%** Temperature control
10. **26%** Least chance of running out of water
11. **11%** Tank material (e.g. stainless steel)
12. **72%** Low running cost
13. **27%** Environmental friendliness
14. **28%** Warranty
15. **9%** Brand
16. **1%** Other (please specify) _________

Q14. Also, what would be the three least important factors in choosing a new hot water system? *(Remove top four choices)*

*Select exactly 3 answers [**PERCENT SELECTING IN SAMPLE INDICATED]***

1. **30%** Plumber's recommendation
2. **6%** Fuel type (electricity, gas, solar, heat pump)
3. **15%** Flow rate
4. **12%** Lifetime
5. **34%** Noise/quietness
6. **14%** Upfront cost
7. **26%** Simple installation process
8. **35%** Sitting position (e.g. indoor/outdoor, roof/ground)
9. **10%** Temperature control
10. **17%** Least chance of running out of water
11. **28%** Tank material (e.g. stainless steel)
12. **4%** Low running cost
13. **12%** Environmental friendliness
14. **8%** Warranty
15. **50%** Brand
16. **1%** Other (please specify) _________

Q20

Expected change in natural gas price over 10 years:

Gas price	Freq.	Percent	Cum.
Decrease by 5% or more	1	0.18	0.18
Don't know	70	12.66	12.84
Increase between 10-25%	217	39.24	52.08
Increase by less than 10%	102	18.44	70.52
Increase by more than 25%	136	24.59	95.12
No significant change	27	4.88	100.00

Q22. If you received a letter from a non-profit offering a rebate of up to $____ for a gas hot water system or up to $_____ for a solar hot water system would you call the listed number to find out more information?

1. **29%** Yes
2. **61%** No, I don't need a new hot water system
3. **10%** No, other reason, please specify_________

[If No #2 above] Q23. If you need to replace your system in the next __ years, would you call to find out more about the rebate?

1. **81%** Yes
2. **19%** No

NOTE: the dollar and year amounts in Q22 & Q23 did not significantly predict response

Discrete choice analysis

Generic choice sets

A typical generic choice set is displayed in Figure 1 of Section 2.1. Here, generic is taken to mean that the particular type of water heater is not specified, but only the (a) net cost, (b) subsidy, and (c) annual running cost. The directions specify that the current water heater must be replaced due to failure. Each choice set provides 3 options, one of which is not subsidised.

The choices were analysed using a conditional logistic regression, with explanatory variables being net (of subsidy) initial cost, annual running cost, and subsidy. The unit on each is $10,000. In addition, a 'dummy' variable indicating presence (not level) of subsidy is included. All variables are highly significant.[14] There are two key findings here. First, an extra dollar of annual running cost has about 6.7 times the impact on people's choice as an extra dollar of installation cost. This is a plausible figure, as the running cost will be borne annually over the life of the system (the rated life is specified as 10 years).

Second, a subsidy has greater impact than simply a dollar-for-dollar reduction in net upfront cost. In effect, $0.80 of additional subsidy has the same impact on purchase decisions as a $1.00 reduction in the market cost of a system. This may be consistent with respondents inferring that subsidised systems have higher quality in unspecified dimensions. Regression output is displayed in Table 14.

Table 14

Conditional (fixed-effects) logistic regression				Number of obs = 8295		
				Wald chi2(4) = 383.10		
				Prob > chi2 = 0.0000		
Log pseudolikelihood = -2767.4463				Pseudo R2 = 0.0890		
(Std. Err. adjusted for 553 clusters in id)						
		Robust				
Chosen	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Net10k	-7.02803	.3849137	-18.26	0.000	-7.782447	-6.273613
Run10k	-47.90285	3.098502	-15.46	0.000	-53.9758	-41.8299
Sub10k	1.733758	.2383739	7.27	0.000	1.266554	2.200962
Subdum	.2429807	.1068316	2.27	0.023	.0335946	.4523667

About half of the sample were presented with a calculation aid in the form of 'payback period' relative to the unsubsidised option. This treatment was provided to explore how sensitive respondents are to the framing of choices. This information treatment had very little economic or statistical effect on the estimated results.

The impact of financial literacy was tested by including an interaction between the respondent's literacy index and their responses to running costs. No significant effect was detected.

A more general random-parameters specification (mixed logit with normal terms) was also tested as a robustness check. As is typical, there is evidence of correlation between choice set decisions for individuals. However, as a predictor of average demand, the random parameters specification adds no significant value. This is evident from using a pseudo-likelihood approach that omits group structure, as if each choice were independent.[15]

Technology-specific choice sets

A typical generic choice set is displayed in Figure 2 of Section 2.1. Here, technology-based is taken to mean that the particular type of water heater is explicitly specified in

[15] Kelejian and Prucha (1999) present the theory of pseudo-likelihood estimation in discrete outcome models.

addition to the (a) net cost, (b) subsidy, and (c) annual running cost. The directions specify that the current water heater is within two years of the rated service life. However, keeping the current system at no immediate cost is an option. Each choice set provides 7 options: no new system, electric storage, gas storage, gas instant, solar with electric boost, solar with gas boost, and heat pump. The survey directions contained a link to a description of these technologies.

The choices were analysed using a conditional logistic regression, with explanatory variables being net (of subsidy) initial cost, annual running cost and subsidy. The annual running cost for no change is entered separately, because the scenario states that the unit will reach the end of its rated life in two years. The unit on each is in $10,000.

In addition, indicator variables for the type of technology are included. The default technology is no change, so the technology coefficient should be interpreted as relative to no change. Results from a conditional logistic regression are presented in Table 15.

Table 15 (Preliminary model)

```
Conditional (fixed-effects) logistic regression   Number of obs   =      19355
                                                  Wald chi2(11)   =     430.91
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -4612.7517                 Pseudo R2       =     0.1427
                                   (Std. Err. adjusted for 553 clusters in id)
```

Chosen1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
Electric	-1.465992	.2580195	-5.68	0.000	-1.971701	-.9602834
Gas storage	-.7843474	.2269523	-3.46	0.001	-1.229166	-.339529
Gas instant	-.3013716	.2571037	-1.17	0.241	-.8052856	.2025424
Solar+gas	-.3335984	.2917927	-1.14	0.253	-.9055016	.2383049
Solar+electr	.0413374	.2975617	0.14	0.890	-.5418728	.6245477
Heatpump	-1.909594	.3354738	-5.69	0.000	-2.567111	-1.252078
Net10k	-3.226535	.3703205	-8.71	0.000	-3.95235	-2.50072
Run10k	-30.43153	4.767202	-6.38	0.000	-39.77508	-21.08799
Runcur	-22.11087	4.2943	-5.15	0.000	-30.52754	-13.6942
Sub10k	.2065826	.3001683	0.69	0.491	-.3817365	.7949017
Subdum	.1568391	.1576509	0.99	0.320	-.152151	.4658292

Here, the first six variables are technology indicators. We observe from the negative signs a significant distaste for moving to new technologies, except solar and gas instant, relative to what might be expected from net upfront cost and annual running cost.

In contrast to the generic model, the subsidy terms are no longer significant by themselves. Of course, subsidies are still quite important through their impact on net upfront cost, but a dollar of subsidy has the same impact as a dollar reduction in the market cost of a system. This is consistent with respondents focusing on the technology choice as the primary indicator of quality, rather than focusing on existence of a subsidy.

We also observe a higher focus on the annual running cost as compared to the generic choice, with the ratio now about 9.5. Arguably, this is *too* much focus, as it would be consistent with an effectively zero discount rate if the systems last their rated 10-year life. As one would expect, the impact of the current system running cost (denoted runcur) is less than the replacement system. However, the ratio is higher than one would expect from discounting considerations. However, it is not implausible as a predictor of actual behaviour, which is our goal in this analysis.

These findings suggest that the model may be usefully simplified for predictive purposes by omitting the direct subsidy effects. Table 16 shows this simplified (and preferred) model.

Table 16 Simplified and preferred model

```
Conditional (fixed-effects) logistic regression   Number of obs   =      19355
                                                  Wald chi2(9)    =     436.65
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -4614.0334                 Pseudo R2       =     0.1424
                                    (Std. Err. adjusted for 553 clusters in id)
```

Chosen1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Electric	-1.42968	.2547836	-5.61	0.000	-1.929046	-.9303128
Gas storage	-.7095775	.2165917	-3.28	0.001	-1.134089	-.2850657
Gas instant	-.1216188	.2026653	-0.60	0.548	-.5188355	.2755979
Solar+gas	-.0938273	.2129212	-0.44	0.659	-.5111453	.3234906
Solar+electr	.2801706	.2292201	1.22	0.222	-.1690926	.7294338
Heatpump	-1.683753	.2636747	-6.39	0.000	-2.200546	-1.16696
Net10k	-3.333995	.3386235	-9.85	0.000	-3.997684	-2.670305
Run10k	-31.19573	4.743465	-6.58	0.000	-40.49275	-21.89871
Runcur	-22.29274	4.311943	-5.17	0.000	-30.744	-13.84149

As with the generic choice experiment, a random parameters generalisation was estimated as a robustness check (mixed logit with normal terms). The qualitative results are similar. Again, there is evidence of heterogeneity across households in the acceptable trade-offs. However, once again a pseudo-likelihood approach finds no evidence for improved prediction of average demand. Accordingly, we do not use the random-parameters approach in estimating demand for the decision tool.

Decision-support tool

The core objective of this project is to provide an evidence base for the determination of the best subsidies. To provide this evidence in a user-friendly format, we have produced a decision-support tool in Excel. The tool combines three types of input: (1) estimates of demand from the experiment, (2) data on the estimated costs of various hot water systems to a sample of real households and (3) user-defined constraints such as available budget and recruitment costs. It allows use of the Solver functionality in Excel to solve a constrained optimisation problem, though we recommend an experimental and iterative user-driven approach centred around the current subsidy scheme.

Methodology

One reasonable objective function is to minimise the expected sum of annual running cost of households eligible for HEEUP. We focus on this for clarity, but later address alternative objective functions (see Section 5.3 below). The primary constraint is the program budget. The variable costs in this budget are (a) expected subsidy requirements and (b) recruitment costs associated with in-home consultations.

To make the tool operational, we apply the optimisation procedure as if the sample of households who have participated in the program through BSL are representative (see 2.3).[16] To fix ideas, consider expected running costs for a single household. That household is offered a menu of new technologies (indexed by *j*) each with a differing subsidy level sub_j (possibly 0). One option is always to not participate in the subsidy program. The expected running cost for this household can be expressed symbolically as

$$\sum_j p_j(sub|\beta, z)\ run_j.$$

Here, *p* indicates the demand for technology *j* in terms of the probability that the household will choose each technology. The choice variables that we use to control demand are the subsidies *sub.* Demand also depends on the vector of characteristics *z*, which include running costs and market costs of the systems. The term β indicates that demand depends on the parameters statistically estimated from the experiment, as presented in Table 3.

[16] It is straightforward for the end-user to adjust the sample as new information arrives about the characteristics of eligible households.

To operationalise this, it is helpful to write out the full expression for the probabilities *p* implied by the form of the conditional logistic regression implemented in Section 4*:*

$$p_j \propto \exp\,(\alpha_j + \beta_{net}\, upfront_j - \beta_{net} sub_j + \beta_{run} run_j)$$

Here, α_j is the technology corresponding coefficient (e.g. solarg). β_{net} is the coefficient on net upfront costs, and β_{run} is the coefficient on the running cost. The subsidies are choice variables. The symbol ∝ indicates 'is proportional to', and so the exact values of the probabilities *p* can be determined by normalising the sum of the technology probabilities to sum to one for each household. In the decision tool, the various coefficients correspond to those displayed in Table 3.

The upfront costs and the running costs in the probability equations are data for the household options. The goal is to select a standard subsidy for any household. So we need to average the predicted demand over many representative households, because the running cost and installation cost data for households will vary.

In sum, the decision tool chooses subsidies to maximise the expected total annual running cost *savings* over *T* households, relative to current (no change) running costs of run_0.

$$T * \sum_{i=1}^{N} \frac{1}{N} * (run_{i0} - \sum_j p_{ij}(sub|\beta, z)\ run_{ij})$$

subject to the constraint

$$T * \sum_{i=1}^{N} \frac{1}{N} * \sum_j p_j(sub|\beta, z)\ sub_j\ + T * visit\_cost < budget$$

Here *visit_cost* reflects any marginal cost of providing a home consultation. This parameter, as well as the available budget, can be supplied by the analyst. Here, we take the target number of households visited *T* as a fixed parameter. However, it can be adjusted by the user to explore different options. The first summation and then division by N reflects the averaging of demand over data for N representative households.

Implementation

To operationalise this method, of course we need a sample of representative cost data. Of course, there are many households with different characteristics and costs. For this purpose, we use a sample for which BSL has conducted in-home consultations and run HWT estimates (see 2.3). The working hypothesis is that the characteristics of this sample are representative of the overall potential Melbourne base of eligible households. This is the most defensible default source of data for the model, in the sense that it assumes that future households that receive home consultations under the BSL scheme will be on average similar to the sample of past households. However, the data supplied can always be customised to reflect any improved information on that score.

Our initial data sample includes 230 observations from the HWT provided by BSL. In addition to options for new technologies, the tool specifies the closest approximation to the current technology. Of these 71% are ‘natural gas storage 4’, 19% are ‘electric off-peak’, and 9% are ‘natural gas instant 4’. Our 7 options in the choice experiment are taken to correspond to the HWT options of ‘current technology’, ‘electric storage off-peak’, ‘natural gas storage 6’, ‘natural gas instant 6’, ‘solar natural gas’, ‘solar electric off-peak tariff’, and ‘heat pump’.

Operation

The decision-support tool is implemented in Excel. The user must supply:

1) Data on a representative sample of hot water system costs at the household level. The tool currently uses output from the HWT on a sample who have received home consultations from BSL. The user may change these. These are coded in blue in the tool.

2) Coefficients for household preferences in the logit model. These are taken from Table 3 in this report, based on analysis of the discrete choice data. These are coded in green in the tool.

3) Key parameters. These include (a) total budget for subsidies and visits (currently input at $1.5 million), (b) cost for a home consultation (currently $150), and (c) target number of home consultations (currently 1000). In addition, the user may specify weights to put on household utility versus total energy bill savings, which are not the same as discussed later. These are coded in orange in the tool.

4) Key choice variables. These are (a) the subsidies by technology and (b) a minimum co-payment by the household by technology. These are both specified in units of $10,000. So, for example, the tool currently specifies $500 as the minimum co-payment. This is entered as 0.05. These choice variables are coded in yellow in the tool. There are extra columns just below that translate these back into ordinary dollars, so the user can easily ensure that the units are translated correctly.

5) Results of the tool calculations. These are coded in light red in the tool. These include (a) average current running cost, (b) average new running cost (post-HEEUP), (c) average subsidy, (d) expected recruits, (e) total cost of home visits and subsidies, (f) participation rate (home consultations converting to participation), and (g) predicted shares of technologies. Two additional outputs are the ‘average household utility’ and ‘weighted criterion’. These may be helpful in determining broader impact of the program on participants. These will be discussed more later.

Currently, the tool has illustrative choices for all inputs, and so it is fully operational. BSL users can update the data and parameter choices as appropriate and required.

The most basic mode of operation should be changing the subsidies (in yellow), and observing what happens to the result measures (in red).

With care, the Solver plug-in can be used to calculate optimal choices under various criteria. The ‘with care’ is especially important when minimum co-payments are positive. It is not recommended to choose these co-payments with Solver, because of corner cases. For example, if the minimum co-payment exceeds the actual cost of a system type, then no subsidy will ever be given (making a very high subsidy confusing but mathematically reasonable). Solver currently has an example loaded. All that is required is to go to Tools/Solver and hit ‘Solve’. However, it may be more informative and practical to start near the current scheme and experiment by hand with changes that seem institutionally plausible or promising.

Minimising running costs

Next, we discuss patterns in optimal choices from a variety of test runs. Our key finding is that the choice of objective function is extremely important. If the objective function is to minimise the average annual running cost, then a robust pattern is to set very high subsidies on solar gas, and very little (or no) subsidy for other technologies. This was surprising to us at first. However, on detailed inspection it appears to be correct. The intuition is that solar gas has the lowest running cost on average by a fair margin. When the objective is to minimise running cost, there is a strong logic to putting almost all weight on getting people to adopt that technology. Subsidising a less running-cost efficient technology in addition makes more people choose the less efficient technology; hence, there is a logic to having low or no subsidies for alternatives. The pattern of very high subsidies on solar gas is robust to many experimental variations. These include setting the technology coefficients to zero, increasing the net cost coefficient, and increasing minimum co-payments. While combinations can be found that do offer modest subsidies to other technologies, solar gas is robustly much higher. This may be somewhat unexpected, and that may be because the benefit to the consumer is intuitively a consideration as well. We discuss this point next.

Maximising utility

Note that very high solar gas subsidies are not necessarily the best outcome for HEEUP participants. That is because some participants would rather have a different technology, and will only adopt solar gas with the very high subsidies. From the point of view of such a person, they would often be better off with a reasonable but lower subsidy on a different technology (with higher running costs). The capital cost subsidy is a direct benefit to HEEUP participants, and so they do not care only about the running cost. If the total pool of subsidies is roughly fixed, one might wonder how this can be an issue. The calculations show that a policy that focuses exclusively on solar gas induces households to spend more on upfront costs (net of subsidies) than do more balanced subsidy policies. One alternative objective function that reflects this issue is to maximise household utility[17]. Underlying the logistic discrete choice model is a utility-based model

[17] In economics, utility is understood as the ability of a good or service to satisfy one or more needs or wants of a consumer. A hot water service, for example, might be assessed by a consumer in terms of its appearance, environmental impact, durability, etc, as well as its direct financial costs.

of consumer choice (McFadden 1986). The expected utility reflects both the costs and the probabilities of choosing various alternatives. This is also known in the literature as the 'inclusive value', and it has the form of the log of sum of the exponential terms underpinning the probabilities.

In experiments with the household utility as the objective function, a reasonably robust pattern is that the largest available subsidies for all technologies should be similar and on the order of $2,000 (though in practice they will differ due to binding co-pay constraints). While perhaps surprising at first, there is a reasonable economic logic to this pattern. The utility approach takes the consumer preferences as the key guiding principle. Offering similar maximum rebates leaves the best decision in the hands of the consumer, without steering this way or that overly much. Such steering is not needed if we take consumer preferences as well-informed and our core guide. Of course, one will not actually deliver a $2,000 subsidy on an item that costs less than that (co-pays cannot be negative at the least). But that is a separate constraint and does not limit what one might reasonably pay if the costs had been higher.

Balancing cost and utility

While there is logic in the previous outcomes, neither the cost-minimising nor utility-maximising results seem 'comfortable'. One intuitively expects an outcome between these, probably because one intuitively places weight on both objective functions. It is reasonably straightforward to create a criterion that balances the two, with weights determined by the user. The most important element is normalising the two objective functions to the same implicit scale. The tool implements this as the 'weighted criterion', based on the choice of user-selected weights that should sum to one. A weight of 0 on either term and 1 on the other boils down to using just one of the objective functions. As an illustration, we have experimented with weights of 0.5 on each.

Bottom line

Different choices of objective function lead to a different balance of subsidies between technologies. However, perhaps more important is getting the overall mix of subsidies to be at a level that brings in sufficient recruits to the program. That requires a balance of large enough subsidies to be attractive and keep recruiting and drop-out costs low, and small enough subsidies that many people can benefit. The tool provides estimates of program enrolment for any mix of subsidies. The recommended approach is one of experimentation around a general pattern of subsidies that makes sense to BSL. In doing so, one can gain information about how a general increase or decrease in the levels will affect outcomes including overall recruitment. As one would expect, the results are between the two extremes, with (conditional on the illustrative parameter choices) maximum subsidies of 0 for electric storage and heat pump, $900 for gas, $1300 for gas instant, $1400 for solar electric, and very large $3800 for solar gas. The overall pattern is the point here, not the exact figures, as those will be driven especially by available budget and target number of recruits.

Limitations

We have conducted this analysis in good faith using best practice techniques as we understand them, subject to time, budget and logistical limitations. However, it should be understood that this analysis is only a guide to overall patterns that may be expected. The analysis is based on stated preference responses to hypothetical choices. Accordingly, there will almost surely be some discrepancy between the choices that households would actually make, and those that they state they will make in a survey context. Further, the analysis is based on a sample of householders participating in an online market research panel, who appear to be eligible for HEEUP. These households may not be representative of average eligible households along various dimensions relevant to water heater investment. The parameters and the data implemented in the tool should be scrutinised by the BSL. The current choices are illustrative, based on the best albeit limited information we have at hand. They are intended to be fine-tuned. The insights of the analysis and the tool should be combined with practical experience, both past and future, by the HEEUP team. It should not and cannot be taken as an exact prediction of what will happen in various scenarios. In short, this is a research project, not a crystal ball. While we have done our best, the end user should apply judgement and experience in interpreting the results.