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The influence of rebate programs on the demand for water heaters: The case of New South Wales[☆]

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ABSTRACT

This paper examines the role of Australian hot water system rebate programs in shifting the existing stock of electric water heaters toward more climate friendly versions using two unique data sets from New South Wales homeowners. The first data set is based on a survey of households who recently purchased a water heater before and after the rebate programs were in place. The other is based on a set of stated preference questions asked of households soon to face a replacement decision. While the former allows us to look at recent responses, the latter enables us to forecast future demand. We find that the programs significantly increase shares of solar/heat pump systems. The programs, however, appear less effective in reducing the stock of electric heaters for households with access to natural gas. This pattern is consistent in both datasets. Results from the discrete choice experiments suggest considerable heterogeneity with respect to household preferences toward different types of water heaters and the discount rates they hold. The effective cost of reducing carbon emissions via incentives for water heater replacement is considered from the counterfactual perspective of no government incentives.

1. Introduction

In 2005, Australia's per capita greenhouse gas emissions were among the highest in the world and the highest in the OECD. These high emissions are mainly driven by Australia's reliance on coal for electricity generation (Garnaut, 2009). To promote energy efficiency improvement, the Australian Federal and state governments have established a wide range of programs for all sectors. This paper focuses on water heater rebate programs aimed to reduce emissions from the New South Wales (NSW) residential sector.

Water heating is the largest single source of greenhouse gas emissions from the average Australian home.[1] For NSW, which includes the Sydney metropolitan area, electric water heaters account for more than a third of household energy use.[2] Switching one electric water heater to a climate-friendly version such as gas, solar or heat pump can reduce carbon emissions by 2.5–3.0 tons per year. While the share of gas water heaters has gradually increased, shares of solar and heat pump remained relatively small. Their high upfront costs have been seen as the key barrier. To overcome this barrier, the Federal and NSW governments initiated their own rebate programs in 2007. These two programs, combined together, could help households who replace their existing electric water heater with a climate-friendly one covering a large part of the upfront cost.

This paper aims to assess the effect of these programs in shifting the existing stock of electric heaters toward more climate-friendly versions. We designed a survey that allows us to conduct ex-post and ex-ante evaluation of the programs. Such evaluation involves distinguishing households who would have replaced their electric heater in the absence of incentives from those induced by the programs. This has been difficult in the past due to limited information available from typical appliance holdings or rebate take-up surveys.

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[1] http://www.climatechange.gov.au/government/programs-and-rebates/solar-hot-water.aspx.

[2] http://www.environment.nsw.gov.au/rebates (2007).

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Our study collected both actual water heater holdings and stated preference (SP) data employing a discrete choice experiment (DCE). The actual choice data came from households who recently purchased a water heater before and after the program was in place. Their replacement time and previous types of water heaters are key information, not available elsewhere, enabling us to evaluate the effect of the programs ex-post. Our SP sample was specifically targeted households who have not replaced their water heaters in the past ten years. Hence, they are soon to be in the market and are more relevant for future policies than those who just replaced their heater. We ex-ante evaluate the rebate programs by using the estimates from a discrete choice model to simulate households' responses under different scenarios.

Understanding and adequate modeling on how government incentives influence appliance choice is a necessary step to evaluate the effectiveness of policies aimed at households. Two important ingredients for such analysis are the estimates of the number of replacements induced by the program and energy savings per replacement. Our study contributes to the former.

Our results suggest that households who do not have access to natural gas are more responsive to the rebate program. Without incentive, these households are more likely to replace their electric heater with another electric heater. For those with access to natural gas, many of them would have chosen to replace their electric heater with a gas heater even if the rebate programs had not been in place. These findings are consistent in both ex-post and ex-ante evaluation.

From actual purchase data, we also find that the rebate programs appear to work largely on households that deliberately set out to replace their water heater rather than on households that replaced their water heater on an emergency/urgent basis. In addition, with our richer DCE data, we examine several flexible discrete choice models successfully applied in other fields. Application of the new mixture-of-normals mixed logit model results in two latent classes/segments with some random variation in taste parameters within each class. It outperforms other models for our datasets. Even conditional on non-emergency replacement, there is considerable heterogeneity with respect to household preferences toward different types of water heaters and the discount rates they hold.

The next two sections review the previous studies in this area and discuss the nature of the NSW water heater market. Section 4 describes data collection. Results from actual purchase data and stated choice experiments are reported in Sections 5 and 6, respectively. Section 7 discusses policy implications. The last section provides some concluding remarks.

2. Previous studies

While there has been a growing interest in how households adopt new energy-efficient appliances in the past two decades, the economics of energy-using durables is dated back to Hausman (1979). In this model, in the long-run consumers evaluate utility derived from each appliance and choose the appliance that gives the highest utility. They may trade-off a higher initial upfront cost with a lower operation cost. In the short run, holding their appliance stock fixed, consumers may adjust their usage in response to change in operating costs. Most empirical studies can focus on either the short-run or long-run decision due to data limitation. Our paper focuses on the long-run (purchase) decision.

Utility that household n derives from an appliance j (U_{nj}) is typically characterized by the appliance' upfront cost and annual running cost:

$$U_{nj} = \alpha_{jn} + \delta_{\mathrm{n}} \text{upfront cost}_{nj} + \gamma_{\mathrm{n}} \text{run cost}_{nj} + \varepsilon_{nj} \quad \text{for } n = 1, \ldots, N; j = 1, \ldots, J. \tag{1}$$

α_{jn} denotes the alternative specific constant (ASC), reflecting the value household n places on appliance j, not associated with its costs (e.g., some households may feel that a gas heater is safer than an electric heater). δ_{n} and γ_{n} are marginal (dis)utility household n places on appliance j's upfront cost and running cost, respectively. The ratio of these two parameters is often used to derive implicit discount rates, a measure of the temporal tradeoff that people are willing to pay for more energy efficiency.[3] ε_{nj} is the idiosyncratic (random) component.

How researchers specify distributions of the coefficients and ε_{nj} lead to different choice models. The multinomial logit model (MNL, McFadden, 1974) assumes that consumers have homogeneous taste for observed product attributes and ε_{nj} is iid. These assumptions, while easing estimation, imply very restrictive substitution patterns and rule out persistent heterogeneity in taste. A number of alternative models that overcome these limitations have been proposed. Popular choices include latent class (Kamakura and Russell, 1989) and mixed logit (McFadden and Train, 2000). We will discuss these models and some new developments in Section 6. Early studies (Dubin, 1986; Dubin and McFadden, 1984; Hausman, 1979) using the US data from utility suppliers estimated implicit discount rates of 20% for air-conditioners, 20–27% for space heating systems and 9.6% for water heaters. Most data on appliances, however, comes from government surveys that only contain information on current appliance holdings and household characteristics. This forces researchers to estimate a simpler probabilistic model, i.e.,

$$U_{nj} = \alpha_j^0 + \Sigma_k \alpha_j^k Z_n^k + \varepsilon_{nj} \qquad \text{for } j = 1, \ldots, J. \tag{2}$$

This is a special case of Eq. (1) where α_{jn} is specified to vary with observed demographic, dwelling or spatial factors, $\{Z_n^k\}$. Studies along this line include Fiebig and Woodland (1994) using Australian an appliance holding survey; Goto et al. (2011) studying water heater choices in Japan; and Michelsen and Medlener (2012) looking at space heating choices of German homeowners who received government grants. These studies generally found that dwelling characteristics (new home; accessibility to gas network) are key determinants of appliance choices. Household sizes, income and education play a minor role and are often insignificant predictors. Michelsen and Medlener (2012) included attitudinal (rating scale) questions about product attributes and found that these variables are important, especially for new homes.[4]

While appliance holdings data give us a good picture of actual market shares, the absence of information on upfront costs, running costs and choice sets makes it impossible to estimate a discount rate or simulate how households would respond to changes in features of incentive programs. Stated preference (SP) survey data has proven a successful alternative. Respondents are presented with a sequence of hypothetical choice scenarios and are asked to state their most preferred choice. Revelt and Train (1998) are the first authors using SP data to estimate the impact of rebates and loans on consumers' refrigerator choice. They found considerable heterogeneity among consumers and estimated a mean discount rate of 39% using a mixed logit model.

A number of recent SP studies (e.g., Banfi et al., 2008; Scarpa and Willis, 2010; Willis et al., 2011) have looked at whether consumers are willing to pay the premium for moving to renewable energy necessary to meet specific greenhouse gas emission reduction targets. Scarpa and Willis (2010) used a mixed logit model to look at the deployment of different micro-generation technologies for households in the UK. Shen and Saijo (2009) looked at the role of energy efficiency labels on demand of air conditioners and refrigerators in China using a latent class model. Alberini et al. (2013) studied retrofit choices of Swiss homeowners not having recently renovated their homes.

Another related literature focuses on evaluating cost-effectiveness of energy policies. Such evaluation requires estimates of (i) number of

[3] The ratio γ/δ represents the willingness to pay to save \$1 per year. Assuming the durability of q years, this ratio can be converted to discount rate (r) by solving $\text{wtp} = (1 + \text{r})^{-1} + (1 + \text{r})^{-1} + \ldots + (1 + \text{r})^{-\text{q}}$.

[4] See also Davis (2010) who looked at appliance choices of homeowner vs. renter.

Table 1
Distribution of water heaters by types for NSW households.
Source: Australian Bureau of Statistics (2008) for 1999–2008, Fiebig and Woodland (1994) for 1989.

NSW	1989	1999	2002	2005	2008
Electricity	79.0	75.9	79.0	63.8	58.0
Peak			33.1	17.3	10.9
Off-peak			45.9	46.5	47.1
Gas	16.0	20.8	23.4	25.2	25.5
Solar		2.7	2.4	1	5
Other		0.9	0.5	0.6	0.3
Did not know		0.8	2.2	8.6	12.1

replacements being induced by the program; and (ii) energy saving per replacement.[5] A major problem with (i) is how to identify "free-riders"– consumers who would have installed a more energy-efficient appliance in the absence of incentives. Joskow and Marron (1992) found a significant share of free-riders based on US data provided by utilities. Grosche et al. (2009) found a similar result using a discrete choice model to simulate share of German households who would free-ride a retrofit incentive program.[6]

There is also a concern that the ex-ante engineering estimates on energy-saving may overestimate the actual savings due to the "rebound effect". This refers to a situation where consumers use their newly replaced appliance more extensively due to its cheaper operating costs. The rebound effect estimates vary across appliances. Davis et al. (2012) reported that the rebound effect is important for air-conditioners but not important for refrigerators. For water heaters, there are few estimates from old sources (Sorrell et al., 2009). These estimates range from 0 to 38%.

Our study contributes to the adoption stage. We collected both actual water heater holdings and stated preference data to take advantage of each approach. Our SP sample was specifically targeted households with old water heaters and hence soon to be in the market. We also use our SP data to simulate households' response to different rebate levels. With the rebate set to zero, households who continue to switch from electric to climate-friendly water heaters would be whom Grosche et al. (2009) called "free-riders". In addition, our study contributes to understanding household water heater demand in the Australian context. Existing Australian studies (Bartels et al., 2006; Fiebig and Woodland, 1994) used data prior to 2000 and did not look at renewable energy-based water heaters.[7]

3. Background of New South Wales water heater market

In NSW, electric water heaters were originally installed in a large majority of homes. There has been a clear trend of moving away from peak electric to off-peak electric and gas systems since the 1980s (Fiebig and Woodland, 1994). Table 1 shows the distribution of water heater holdings by NSW households between 1989 and 2008. The share of gas heaters has gradually increased — likely due to the expansion of the gas network in NSW. The share of solar was still less than 3% in 2005. Two other types which recently have become more widely installed but not listed as separate categories here are the instantaneous gas system and heat pump.[8]

High upfront costs of the two renewable energy alternatives (solar and heat pump) have been seen as the key barrier for households to switch to these heaters. The upfront costs of traditional storage heaters are approximately $900–$1800 (all monetary amounts in Australian dollars). Instantaneous gas systems cost slightly higher at $1500–$2500. Solar and heat pumps are about three times more expensive than traditional electric systems, costing from $3500 to $6500 depending on their sizes installation complexity.

More recently there have been government efforts to encourage households to switch from electric systems to a more climate-friendly version. Since 2001 households who installed a solar or heat pump to replace an electric water heater were qualified for Renewable Energy Certificates (RECs). Each REC represents 1 MWh of electricity displaced by a solar or heat pump water heater. The REC program covers the entire period that we examine so we take it as the baseline rebate level.

The major change in the rebate program came with a set of large financial incentives. First, the Australian Government Solar Rebate program started in July 2007, where households who replaced an electric hot water system with a solar or a heat pump system would receive a rebate for $1000. Initially, only families with annual income below $100,000 were eligible. In February 2009, the program stopped means testing and increased the amount of the rebate to $1600. The amount of rebate was dropped back to $1000 in September 2009.[9]

Second, and to much greater publicity, the NSW government initiated a rebate program in October 2007 which was originally announced to end on June 30, 2009 but later extended to June, 2011. Eligible criteria for the NSW program were much less restricted and could be combined with the Federal government rebate. Subject to some eligibility requirements aimed at preventing new construction using the program, households who replaced their electric systems with a heat pump or solar system received a rebate between $600 and $1200.[10] Those replacing their electric systems with a gas system received $300. Because it is effectively impossible to sort the effects of all of these different programs, we will consider the aggregate impact of the NSW and new Federal policy initiatives and take October 2007 as their start date with the policy continuing through the end of 2009, when our survey went into the field.[11]

4. Data

We collected data through a very large web-based panel belonging to a major survey research company. During December 2009 and January 2010, 9400 total invitations were sent to the panelists who were NSW homeowners. The respondents were first asked about the type of their current water heater, the age of that water heater, and whether they purchased that water heater for their home or if it was built-in. For those who had purchased a water heater, the year of purchase and other information about that system and their previous system was elicited. For those who had not purchased a water heater since moving into their home, the respondent was asked to estimate the age of their hot water system. If the respondent could not do this, we approximated the age of the system by the year in which they moved into their dwelling.

[5] See Gillingham et al. (2006), Linares and Labandeira (2010) and Allcott and Greenstone (2012) for comprehensive reviews on energy-efficiency policies including welfare analysis.

[6] This study was built on Grosche and Vance (2009). Both used the same revealed preference data where the authors estimated upfront costs and energy savings using engineering calculations for possible alternatives.

[7] See also Gillingham (2009) for a New Zealand study using aggregate sales data of solar water heaters.

[8] These systems were rare in the past. The government projects that for new homes built between 2006 and 2020, the share of gas systems will be 70% with instantaneous gas more popular than storage gas. Shares of solar and heat pump systems are predicted to increase to 15% and 5%, respectively (Australian DEWHA, 2008).

[9] The number of available rebates is limited at 225,000 households. Eligible criteria include: owners or tenants (with owner permission); solar or heat pump systems with at least 20 RECs and a 5-year warranty; and the dwelling must be the principal place of residence. Starting in February 2010 (after our data collection period), rebates are $1000 for solar and $600 for heat pumps.

[10] The rebate provided is based on the amount of greenhouse gas emissions saved, determined by the REC's of heaters ($600 for 20–27 RECs, $800 for 28–35 RECs, $1000 for 36–43 RECs and $1200 for 44 + RECs).

[11] The 2007 Federal program started three months earlier than the NSW program but was less publicized. It was also initially targeted at the low income household segment that has a much higher propensity to rent. To the extent that there was a substantial increase in solar/heat pumps caused by the 2007 Federal program before the 2007 NSW program went into effect, we will underestimate the effect of the set of rebate incentives that differed from the original baseline 2001 Federal incentive program.

Table 2
Distribution of water heaters by types for NSW households in 2009–2010.
Source: Authors' own survey conducted during December 2009–January 2010. Respondents are homeowners living in a housing unit. Those who do not know their water heater types are excluded.

	Estimate age of the hot water system		
	10 or more years (1999 or earlier) %	6–9 years (2000–2003) %	5 years or less (2004 or later) %
Peak electricity	18.6	19.9	14.5
Off-peak electricity	39.2	35.3	26.5
Off-peak 1	22.9	18.8	15.1
Off-peak 2	16.3	16.6	11.5
Gas	37.6	38.5	37.9
Mains gas storage	26.6	24.2	17.5
Mains gas instantaneous	9.0	14.3	20.2
Solar	5.0	4.5	12.4
Heat pump	0.2	0.2	7.0
LPG	1.4	1.5	1.8
Total	925	863	1534

From the 9400 invitations, 3322 respondents were interested in participating in the survey (giving a response rate of 35%). Table 2 reports the distribution of water heater holdings by the (estimated) age of the water heater from this sample. The Peak (standard) electricity means that power supply is available 24 h. Off-peak "1" is the cheapest electricity and provides power on that meter only for limited hours (e.g., 10 pm–7 am). Off-peak "2" connects to both continuous and off-peak electricity supply at a price lower than peak power but higher than off-peak "1" power. The share of electric based systems has been declined among newer systems in favor of gas. Within gas systems, instantaneous gas has gained popularity. Solar and heat pump shares have strikingly increased in the last 5 years.

We designed our survey so that we can conduct ex-post evaluation based on recent purchase and ex-ante evaluation based on the views of those likely to soon be in the market. Given water heater durability of 10 to 20 years, those who just made a replacement are unlikely to do so again in the next several years. Respondents who purchased the system in 2004 or afterward (a subsample of the last column of Table 2) were asked about their recent purchase.[12] We call this group the revealed preference (RP) respondents. Respondents with an old water heater (left column of Table 2) were assigned to answer a choice experiment survey. This group is called stated preference (SP) respondents. For both groups, the analysis is done separately for those with and without gas access because they face very different choice sets.

The sample we use consists of 912 RP respondents (408 with gas access and 504 without gas access) and 901 SP respondents (547 with gas access and 354 without gas access). RP respondents were asked about their just-installed water heater as well as their previous water heater, which determines eligibility for rebates. The choices of water heaters installed prior to 2004 in the RP and SP samples appear fairly similar. Those with gas access are less likely to own an electric system, 47% for RP and 39% for SP, with the lower fraction for the SP group consistent with a temporal shift toward gas water heaters. Not surprisingly, for both groups those without gas access are likely to own an electric heater (94% for RP and 91% for SP). Demographic characteristics of RP and SP samples are similar in most aspects. One exception is that the RP sample with gas access who replaced their water heater after October 2007 had somewhat higher income and education levels (see the web appendix Table A1).

5. Evidence from actual purchases

There are two typical approaches to evaluate the effect of a policy change. One is to estimate probability of selecting a climate-friendly water heater as a function of upfront cost, running cost, rebate and other attributes — like Eq. (1). The other is a difference-in-difference approach.

The first approach is not feasible for our RP sample. Exploratory work suggests that most respondents cannot easily recall what choices were available when they purchased. Many people know the type of their water heater but not the model. This makes it difficult to accurately impute upfront costs and choice set each household faced. A myriad of different tariff schedules offered by many retail electricity suppliers also make it complicated to estimate running costs.

Now consider the reduced form difference-in-difference. Our treatment group is NSW households with electric water heaters who would be eligible for rebates. We need a control group who do not have access to the rebates but are otherwise identical. Typical controls such as households with electric systems in other states are inappropriate in our case. NSW gas coverage is much lower than other states and gas prices are relatively higher.[13] In addition, other similar states while facing the same Federal rebate scheme offered rebate policies of their own.

We consider two other possible control groups: NSW households who owned nonelectric heaters and NSW households who owned electric heaters but faced a replacement decision right before the policy was in place (replacing their heater between 2004 and September 2007). Both raise some potential problems. The former suffers from the fact that households with nonelectric heaters (mostly gas) are less likely to go back to electric with or without the policy in place. Using their probability of choosing electric heaters as a counterfactual would underestimate the effect of the policy in shifting people away from electric systems. Using the latter group, on the other hand, may overestimate the effect of rebate policy if other factors (e.g., solar information campaign) changed their trend simultaneously with the policy.

In our view, the second group is more appropriate as the three years before and after October 2007 are similar in most respects. Available information including interviews with retailers, suggests that relative costs of all types of heaters had been fairly stable. Electricity and gas prices had steadily increased over time. Environmental attitudes also appeared to be fairly stable.[14] We later discuss the results using the alternative control.

We group water heaters by fuel types: electric (both peak and off-peak tariffs); gas (storage and instantaneous), and renewable technology (solar and heat pump) due to sample size considerations.[15] Due to the cross-sectional nature of the RP data set, we estimate standard logit model of Eq. (2) and do not attempt to estimate random coefficient models here.[16]

[12] RP respondents who installed water heaters in new homes are excluded from the analysis because of eligibility limitations as were seven respondents who picked LPG gas due to sample size considerations. We also screened out owners who reside in apartments, flats/units as they are less likely to be able to install solar water heaters or heat pumps. We further excluded a small number of households with eight or more people due to the presumption that their temporal demand characteristics for hot water were likely to be different from other households. We also limited the analysis sample to respondents who indicated that they were responsible for the household energy bill.

[13] Due to budget limitations, we deem it more appropriate to limit our sample to NSW rather than obtain a nation-wide sample with too few observations from each state to serve as an adequate control.

[14] NSW was controlled by the Labor Party during the entire time period while at the national level, the Labor Party which put more emphasis on climate change than the Liberal-National coalition, took power in December 2007. Real per capita income grew fairly steadily over the time period with Australia experiencing somewhat less of a boom and a much smaller drop due to the financial crisis than most industrialized countries. To the extent consumers felt more financially constrained in late 2008 and 2009, we will tend to underestimate the impact of the programs.

[15] The fraction of the sample with solar and heat pump systems pre-2007 is small and of these almost all are solar.

[16] We estimate a multinomial logit model for households who face three choices (the gas access sample) and a binary logit for households who face two choices (the no gas access sample). The details of the calculation of the estimates presented in Tables 3–5 are provided in the web appendix.

Table 3
Estimated policy effects from RP data for households with gas access.

	Before policy	After policy	Change in shares
Prob. of switching from electric to electric	0.28**	0.19**	−0.09
	(0.04)	(0.04)	(0.06)
Prob. of switching from electric to gas	0.69**	0.55**	−0.14**
	(0.04)	(0.06)	(0.07)
Prob. of switching from electric to solar/heat pump	0.03**	0.26**	0.23**
	(0.01)	(0.05)	(0.05)
	Before policy 2004–2005	2006–Sep 2007	Change in shares
Prob. of switching from electric to electric	0.39**	0.22**	−0.17*
	(0.08)	(0.05)	(0.09)
Prob. of switching from electric to gas	0.61**	0.74**	0.13
	(0.08)	(0.05)	(0.09)
Prob. of switching from electric to solar/heat pump	0.00	0.04*	0.04*
		(0.02)	(0.02)
Effects of policy on			Difference of changes in shares
Prob. of switching from electric to electric			0.08
			(0.10)
Prob. of switching from electric to gas			−0.27**
			(0.11)
Prob. of switching from electric to solar/heat pump			0.19**
			(0.06)

Note: The estimates are from the model without demographic variables. Standard errors (reported in parentheses) are calculated by using the delta method. ** and * indicate statistical significance at 1% and 5%, respectively.

It is useful to look at the average choice probabilities for each group at each time period without demographic variables first. Table 3 presents the result for gas access households. This model includes only alternative specific constants, time dummies and their interactions. The top three rows under the header "Before policy" indicate that before October 2007 on average the probability that households would replace their old electric system with a new electric system is 28%. The probability that they would switch to gas is 69%. Only 3% would switch to a solar or a heat pump. The next column, "After policy" refers to the period where rebate policies were in place. The probability of choosing solar or heat pump increases to 26%. This +23% increase comes from the reduction in both shares of electricity (−9%) and gas (−14%).

Table 4
Estimated policy effects from RP data for households with no gas access.

	Before policy	After policy	Change in shares
Prob. of switching from electric to electric	0.90**	0.40**	−0.50**
	(0.02)	(0.03)	(0.04)
Prob. of switching from electric to solar/heat pump	0.10**	0.60**	0.50**
	(0.02)	(0.03)	(0.04)
	Before policy 2004–2005	2006–Sep 2007	Change in shares
Prob. of switching from electric to electric	0.94**	0.87**	−0.07*
	(0.03)	(0.03)	(0.04)
Prob. of switching from electric to solar/heat pump	0.06**	0.13**	0.07*
	(0.03)	(0.03)	(0.04)
Effects of policy on			Difference of changes in shares
Prob. of switching from electric to electric			−0.43**
			(0.06)
Prob. of switching from electric to solar/heat pump			0.43**
			(0.06)

Note: The estimates are from the model without demographic variables. Standard errors (reported in parentheses) are calculated by using the delta method. ** and * indicate statistical significance at 1% and 5%, respectively.

The second panel compares household behaviors before the policy change. We split households who installed a water heater before October 2007 into two periods. We can see that during this earlier period, the share of electric water heaters had already been reduced by 17%. Shares of gas and solar/heat pumps had increased by 13% and 4%, respectively. To take account of this time trend, we take the difference in behaviors of these two groups. As a result, the policy is estimated to increase the probability of switching to a solar or heat pump by 19%. However, this increase comes from drawing households away from gas heaters and implies no significant reduction in the share of electric heaters.

Table 4 is an analog analysis for households without gas access. Comparing before and after October 2007, the probability of choosing a solar or heat pump strikingly increases from 10% to 60%. Even after taking account of the time trend, the effect of the policy on the probability of choosing a solar or heat pump is large at 43% and statistically significant.

To explore whether the effects are heterogeneous, we consider several factors. To proxy financial constraints and accessibility to information about available rebates, we include income and education. To account for the households' expected savings, water usage is included. Although we do not know the tariffs each household faces, we asked them their expectations about electricity and gas prices. We also include whether the replacement is done on an emergency basis, i.e., their water heater breaks down and requires urgent replacement. In this situation, households have less time to study all available options. They may be more likely to stay with the same type of system they have as they fear that switching to a new technology will take longer to get hot water restored. This urgent factor has not been included in previous studies.

Table 5 reports the results from a model where we include all these factors and their interactions with time dummies. Because the logit coefficients are not directly interpretable, we compute choice probabilities

Table 5
Estimated policy effects from RP data for different demographic groups.

Effects of policy on	Gas access			No gas access
	Prob. of switching from electric to			Prob. of switching from electric to
	Electric	Gas	Solar/heat pump	Solar/heat pump
A. Mean characteristics	0.09	−0.25*	0.16**	.41**
	(.13)	(.13)	(.06)	(.08)
B. Emergency	0.13	−0.21	0.09	0.25**
	(.18)	(0.19)	(.05)	(.06)
Non-emergency	0.05	−.28*	.22**	0.49**
	(.11)	(.15)	(.08)	(.20)
C. Income below 60 k	0.33	−.53*	0.20	0.65**
	(.25)	(.30)	(.14)	(.07)
Income 60–100 k	0.09	−0.22	0.13*	0.41**
	(.16)	(.18)	(.07)	(.13)
Income 100 k or more	−0.02	−0.11	0.13*	0.09
	(.21)	(.23)	(.08)	(.16)
Prefer not to report income	0.08	−0.32	0.24*	0.08
	(.16)	(.24)	(.14)	(.27)
D. Small usage	0.01	−0.14	0.13	0.31**
	(.20)	(.23)	(.09)	(.12)
Medium usage	0.28*	−.44**	.15**	0.38**
	(.15)	(.16)	(.06)	(.11)
Large usage	−0.24	0.11	0.13	0.62**
	(.24)	(.30)	(.16)	(.10)
E. Non-college education	0.06	−0.18	0.12*	0.46**
	(.14)	(.16)	(.06)	(.08)
College education	0.15	−0.36	0.21**	0.30**
	(.20)	(.22)	(.09)	(.01)
F. Expect electricity price	0.01	0.17	0.16**	0.34**
to increase 25%+	(.15)	(.16)	(.08)	(.10)
Do not expect electricity price	0.24	−.39*	0.14*	0.52**
to increase more than 10%	(.20)	(.22)	(.07)	(.09)

Note: The standard errors (reported in parentheses) are calculated by using the delta method. ** and * indicate statistical significance at 1% and 5%, respectively.

for various groups at different periods and take the differences in choice probabilities. This is similar to the two previous tables, but demographic-specific. Time-specific probability estimates are omitted to conserve space.

Panel A reports the effect of policy evaluated at the mean characteristics. Controlling for other characteristics, the policy is estimated to increase the probabilities of choosing solar/heat pump by 16% and 41% for households with and without gas access, respectively. Panel B compares the case of emergency vs. non-emergency replacements, holding other factors at their means. For gas access households, the policy only appears effective for those replacing water heaters in a non-emergency basis, increasing the probability of choosing a solar or heat pump system by 22%. The effect for households whose replacement was done on an emergency basis is only 9% and statistically insignificant.[17] For households without gas access, policy effect estimates are much larger at 49% and 25% for nonemergency and emergency cases, respectively.

Panel C presents the estimates of the rebate policy on various income groups. The effects appear stronger for low income households with no gas access. In our dataset only a few low income households chose a solar/heat pump before the rebate programs were in place, suggesting that the program differentially helps the low income group. Panels D, E and F report the effects of policies evaluated at different water usage levels, education, and expectation on fuel prices. Households with no gas access with large water usage were more responsive to the programs. Low education households of this sample also appear more responsive. In contrast, the effect is stronger for the high education group for the sample with gas access. Note that some model coefficients using the gas access sample may be statistically insignificant because sample sizes for some cells are small.

We also have information of households who previously owned a non-electric system (almost exclusively gas) which can be served as an alternative control. There is no significant change in their behavior between "before" and "after" policies. This group's probability of choosing a new gas system was 91% during the 2004–September 2007 period and 95% during the October 2007–2009 period. This is consistent with that nothing changed with electric water heaters in the second time period to make them look more attractive than gas. There was also no large scale shift to solar/heat pumps by households with gas water heaters, which implies that solar/heat pumps did not gain cost advantages relative to gas and that households were not moved by an information campaign to buy solar/heat pumps independent of the rebate incentives.

In this section, we have ex-post evaluated the rebate program using recent purchase data. We now turn to an ex-ante analysis of SP respondents who are most likely to be in the water heater market in the near-term future. The DCE allows us to control the features of the options that respondents see and to extend those options outside the range of those available in the past. Its panel structure also facilitates modeling household preference heterogeneity.

6. Evidence from discrete choice experiments

Reliable stated preference data requires the scenarios presented to be plausible and choices seen to be relevant.[18] To encourage respondents to think about a plausible water heater purchase situation, we first asked them: *"Would you consider replacing your hot water system within the next couple years before it breaks down?"* If they selected 'likely', they were then asked to choose between different water heaters as if they were purchasing the system now. For respondents selecting 'unlikely', they were asked to consider a non-immediate replacement situation *"where your current hot water signaled some problems (e.g., discolored water due to rusty tank) and the plumber has suggested you to buy a new one instead of fixing it."*

Gas accessibility and water usage are used to narrow down the relevant choice set. Gas heaters are obviously irrelevant for those without gas access. Hot water usage determines the size of the heater needed. Respondents were asked to self-select themselves into three usage levels: small, medium or large. The web appendix provides more information about the development of our SP survey. Choice scenarios of respondents with gas access consist of 7 water heater options: three electric options (peak, off-peak "1", off-peak "2"), two gas options (storage and instantaneous), solar, and heat pump. Respondents without gas access have 5 options.

Displayed options differ by upfront costs, rebate amounts and annual running costs. Upfront costs were varied in a plausible range according to type and size of heaters in the market. Running costs were varied to cover a range of available estimates. The mail-in rebate is the money customers pay at the time of purchase and later receive back in the mail in about two months, which mimics existing programs. Electric systems never have a rebate.

Other system attributes could have been included such as special tariffs for solar, but this was not done to keep the choice task as straightforward as possible.[19] Based on our development work, an important feature was the water heater's warranty (and implicit durability). We kept this factor constant across all systems by telling respondents that all systems last about 15 years and came with a 10-year warranty. Each respondent was asked to complete 16 choice scenarios. The upfront cost before rebate is displayed as the sum of net upfront cost and the rebate. Respondents are given detailed information about all systems and shown a pictorial representation before starting the choice tasks. Fig. 1 shows an example of a choice scenario.

6.1. SP model formulation

Our empirical model extends Eq. (1) by decomposing the upfront cost term into two components: net upfront cost (cost_after_rebate) and a dummy for rebate (dmailin_rebate). The utility of household n derived from water heater j in scenario t is given by:

$$U_{njt} = \alpha_{jn} + \delta_{1n}\text{cost}_{\text{after}}\text{rebate}_{njt} + \delta_{2n}\text{dmailin}_{\text{rebate}\,njt} + \gamma_n \text{runcost}_{njt} + \varepsilon_{njt} \quad \text{for } n = 1, \ldots, N;\, j = 1, \ldots, J;\, t = 1, \ldots, 16. \tag{3}$$

This specification is similar to Revelt and Train (1998) and Bartels et al. (2006) where the rebate amount is incorporated in the net upfront cost term. The rebate dummy captures the perception about the mail-in rebate process holding their out-of-pocket expense constant. Its coefficient should be negative for respondents who have financial constraints or dislike mail-in-rebates, but it could be positive if the rebate signals that the product is "environmental friendly" or "on-sale".

We consider several alternative models. To understand the differences across choices of models, it is useful to write Eq. (3) in a more concise form:

$$U_{njt} = \beta_n X_{\text{njt}} + \varepsilon_{njt} \qquad \text{for } n = 1, \ldots, N;\, j = 1, \ldots, J;\, t = 1, \ldots, 16 \tag{3$'$}$$

where β_n denotes all coefficients on observed product attributes including the alternative specific constant and X_{njt} collects all the terms of observed attributes.

MNL assumes $\beta_n = \beta$ for all n and that ε_{njt} is iid extreme value. The mixed logit model (MIXL) extends MNL to allow for random coefficients

[17] The probabilities of choosing electric in an emergency case are always higher than a non-emergency case.

[18] Louviere et al. (2000) and Carson and Hanemann (2005) provide overviews of SP surveys.

[19] Choice tasks that impose too much cognitive burden to respondents might lead to less reliable answers.

	Electric Off-peak 2	Electric Peak	Electric Off peak 1	Gas Storage	Gas Instantaneous	Solar	Heat Pump
Upfront cost	1500	1100	1500	1500	2100	4500	3300
Amount of mail-in rebate	-	-		-	300	-	800
Net cost	**1500**	**1100**	**1500**	**1500**	**1800**	**4500**	**2500**
Annual running costs ($/year)	**500**	**800**	**425**	**325**	**275**	**130**	**160**
Which heater is your most Preferred option?	□	□	□	□	□	□	□

Fig. 1. An example of choice scenario (for a respondent with gas access, medium water usage).

on observed attributes, but continues to assume that ε_{njt} is iid extreme value. The MIXL model is often written as:

$$U_{njt} = (\beta + \eta_n)X_{njt} + \varepsilon_{njt} \qquad \text{for } n = 1, \ldots, N; j = 1, \ldots, J; t = 1, \ldots, 16 \tag{4}$$

where β is the vector of mean marginal utilities in the population and η_n is the household n specific deviation from the mean. In most applications, MIXL assumes that β_n is distributed as multivariate normal in the population, $\beta_n \sim MVN(\beta,\Sigma)$. In the special case that the mixing distribution is discrete we obtain the latent class (LC) model. Here, β_n differs across segments but are the same for all consumers within the segment.

We also consider two relatively new models, the generalized multinomial logit "G-MNL" (Fiebig et al., 2010) and the mixture of normals logit model (see e.g., Keane and Wasi, 2012; Train, 2008). These two models were found to outperform MIXL and LC. G-MNL nests MIXL with the scale heterogeneity model by replacing β_n in (3′) with

$$\beta_n = \sigma_n\beta + \gamma\eta_n + (1-\gamma)\sigma_n\eta_n.$$

σ_n scales the whole β vector up and down. If $\sigma_n = 1$ for all n, G-MNL approaches MIXL in Eq. (4).[20] If trace $(\eta_n) = 0$, then G-MNL approaches the scale heterogeneity model with $\beta_n = \sigma_n\beta$, assuming that consumers are homogeneous in taste but some are more random than others in making a choice. Since β_n is unobserved, the *unconditional* choice probabilities of G-MNL are obtained by integrating over all possible values of β_n:

$$prob\left(\left\{y_{njt}\right\}_{t=1}^{T}\right) = \int \left[\prod_t \prod_j \left(e^{\beta_n x_{njt}} / \sum_i e^{\beta_n x_{nit}}\right)^{y_{njt}}\right] f(\beta_n) d\beta_n \tag{6}$$

where $y_{njt} = 1$ if person n chooses j on occasion t, and 0 otherwise.

The mixture of normals logit or "mixed mixed" logit model (MM-MNL) generalizes MIXL by specifying the mixing distribution in MIXL to be a discrete *mixture*-of-multivariate normals. That is, $\beta_n \sim MVN(\beta_s,\Sigma_s)$ with probability $w_{n,s}$ for each class $s = 1,\ldots,S$. If $w_{n,s} \to 0$ for all but one class, MM-MNL becomes the MIXL model in Eq. (4). MM-MNL also nests LC by setting $\Sigma_s \to 0\ \forall\ s$. Choice probabilities for MM-MNL are given by:

$$prob\left(\left\{y_{njt}\right\}_{t=1}^{T}\right) = \sum_{s=1}^{S} w_{n,s}\left\{\int \left[\prod_t \prod_j \left(e^{\beta_{n|s} x_{njt}} / \sum_k e^{\beta_{n|s} x_{nkt}}\right)^{y_{njt}}\right] f\left(\beta_{n|s}\right) d\beta_{n|s}\right\} \tag{7}$$

where $f(\beta_{n|s})$ refers to $MVN(\beta_s,\Sigma_s)$.

The choice probabilities of MNL and LC have a closed form expression and can be estimated by maximum likelihood. For Eqs. (6) and (7), we use maximum simulated likelihood. To improve estimation accuracy, all variables are scaled (downward) to have similar ranges and to ensure that our estimates were not at local maxima, we try a range of initial values.[21]

6.2. Discrete choice experiment results

We have estimated several versions of LC, MIXL, G-MNL and MM-MNL. Due to space limitation, we present the two best models selected by Bayesian Information Criterion (BIC) and the baseline MNL. G-MNL and MM-MNL outperform MIXL and LC for both gas access and no gas access samples. MIXL and LC results are available in the online appendix.

Column 1 of Table 6 reports the estimates from the MNL model for the gas access sample. The two cost variables have negative coefficients as expected. The coefficient of the rebate dummy is positive but not statistically different from zero.[22] The average WTP for $1 saved annually is $-3.99 * 10/-8.62 = 4.62$. Assuming the durability of 15 years, this implies a discount rate of 20%. Column 2 presents the result from the G-MNL model using the full covariance matrix version. The average WTP for $1 saved annually from this model is $6.55, implying a discount

[20] In practice, σ_n is assumed to follow the lognormal distribution, $\ln(\sigma_n) \sim N(-\tau^2/2, \tau^2)$. If $\tau = 0, \sigma_n = 1$ for all n and γ is not identified. γ is the parameter allowing η_n to be scaled up by σ_n ($\gamma = 0$) or to vary independently ($\gamma = 1$).

[21] Keane and Wasi (2012) provide a discussion of estimation issues. Note that all models considered here are estimated in terms of utility function parameters as our primary focus is to predict choice probabilities (forecast demand). If one was more interested in latent willingness to pay, the model could be formulated to directly estimate the parameters of the willingness to pay distribution (see e.g., Scarpa et al., 2008).

[22] This means that on average utility derived from paying $(X-R) upfront and utility derived from paying $X upfront and getting $R back later are not significantly different. Another way to test whether utility attached to rebate is different from that attached to upfront cost is to replace the net upfront cost and rebate dummy variables with upfront cost and rebate amount. For MNL, we found that the coefficient attached to rebate is slightly higher than that of upfront cost (8.86 vs. −8.61 for gas access sample and 7.37 vs. −7.13 for no gas access sample). However, the two coefficients are not statistically different at $p < .10$ and the likelihoods of these alternatives are almost identical to the ones presented. For models with unobserved heterogeneity, the version with a rebate dummy yields a better fit.

Table 6
Estimates from selected choice models (SP data).

	Gas access							No gas access						
	[1]	[2]		[3]				[4]	[5]		[6]			
	MNL	G-MNL[a]		MM-MNL[b]				MNL	G-MNL[a]		MM-MNL[b]			
				Class 1		Class 2					Class 1		Class 2	
		Mean	Stdev	Mean	Stdev	Mean	Stdev		Mean	Stdev	Mean	Stdev	Mean	Stdev
(Omitted electric off-peak2)														
Electric peak	0.44**	−0.98**	2.22**	−1.13**	1.47**	−1.35**	2.4**	−0.04	−0.70**	2.53**	−1.84**	3.85**	−1.63**	1.98**
	(0.10)	(0.19)	(0.22)	(0.26)	(0.21)	(0.28)	(0.18)	(0.11)	(0.24)	(0.25)	(0.68)	(0.60)	(0.35)	(0.22)
Electric off-peak 1	0.41**	0.20	2.85**	−0.02	1.81**	−1.07**	3.87**	0.61**	−1.04**	3.36**	0.62*	1.97**	0.31	3.24**
	(0.08)	(0.17)	(0.15)	(0.21)	(0.17)	(0.18)	(0.27)	(0.08)	(0.23)	(0.24)	(0.33)	(0.31)	(0.23)	(0.26)
Gas storage	1.38**	3.2**	3.54**	1.69**	1.08**	0.9**	5.28**							
	(0.08)	(0.18)	(0.15)	(0.16)	(0.09)	(0.28)	(0.38)							
Gas instantaneous	1.73**	3.72**	5.02**	2.26**	0.62**	1.03**	9.87**							
	(0.08)	(0.20)	(0.16)	(0.17)	(0.08)	(0.31)	(0.66)							
Solar	2.5**	4.31**	3.85**	2.76**	1.28**	1.23**	8.39**	1.84**	2.63**	4.41**	3.9**	1.55**	3.33**	7.29**
	(0.10)	(0.21)	(0.15)	(0.19)	(0.08)	(0.37)	(0.49)	(0.12)	(0.26)	(0.25)	(0.41)	(0.13)	(0.44)	(0.39)
Heat pump	1.69**	2.42**	4.73**	1.56**	2.09**	−1.71**	1.06**	1.23**	1.42**	3.26**	3.1**	0.26	−1.21**	5.4**
	(0.10)	(0.24)	(0.16)	(0.20)	(0.10)	(0.34)	(0.22)	(0.12)	(0.28)	(0.21)	(0.40)	(0.26)	(0.52)	(0.42)
Cost-after-rebate/10000	−8.62**	−27.13**	12.53**	−27.3**	14.66**	−16.93**	12.9**	−7.13**	−40.51**	23.7**	−29.48**	11.95**	−15.86**	19.16**
	(0.18)	(0.82)	(0.64)	(0.80)	(0.55)	(1.01)	(1.04)	(0.21)	(2.95)	(2.05)	(1.45)	(0.90)	(1.22)	(1.21)
1 if mail-in rebate	0.002	0.01	0.61**	0.01	0.07	−0.28*	1.33**	0.05	0.05	1.23**	−0.05	0.98**	0.34	0.62**
	(0.03)	(0.06)	(0.07)	(0.06)	(0.10)	(0.16)	(0.11)	(0.05)	(0.15)	(0.19)	(0.14)	(0.17)	(0.22)	(0.30)
Annual running cost/1000	−3.99**	−17.76**	9.21**	−22.02**	15.42**	−9.35**	6.94**	−4.6**	−36.54**	20.04**	−27.45**	19.82**	−4.96**	2.53**
	(0.20)	(0.65)	(0.45)	(0.76)	(0.49)	(0.74)	(0.47)	(0.29)	(2.83)	(1.61)	(1.80)	(1.29)	(0.94)	(0.35)
Class prob.				0.66**		0.34**					0.58**		0.42**	
				(0.02)		(0.02)					(0.03)		(0.03)	
τ		0.75**							1.24**					
		(0.03)							(0.07)					
γ^*		−0.81**							−1.84**					
		(0.04)							(0.02)					
No. of parameters	9	56		37				7	37		29			
Log Likelihood	−12861	−7177		−7142				−6250	**−3414**		−3441			
AIC	25740	14465		**14359**				12514	**6902**		6941			
BIC	25804	14861		**14620**				12560	7148		**7133**			
CAIC	25813	14917		**14657**				12567	7185		**7162**			

Note: ** and * indicate statistical significance at 1% and 5%, respectively. The bold figures indicate the preferred model by information criteria listed in each row.
[a] Estimates from correlated coefficient specification.
[b] Estimates from a mixture-of-two-independent-normals.

rate of 12.8%. While the mean estimate of the rebate dummy coefficient is .01, their standard deviation is statistically significant at .61. This suggests that respondents' perception on rebates is quite heterogeneous. Some derive utility from rebates while others dislike rebates, holding their net cost constant.

Column 3 reports the estimates from MM-MNL, the preferred model. This is a version with a mixture of two independent normals.[23] This model's log likelihood is slightly better than the G-MNL model and it also uses a much smaller number of parameters. There are noticeable differences between the mean estimates of the two segments. The first segment, representing 66% of population, derives positive marginal utility from heat pump while the second derives disutility from heat pump. Their average WTP for $1 saved annually are $8.07 and $5.52, which can be converted to discount rates of 9% and 16%, respectively. The second segment also consists of respondents who possess a negative attitude toward rebates.

For the respondents with no gas access, the ranking of models is quite similar except that G-MNL achieves a somewhat better likelihood than MM-MNL. However, G-MNL is again dominated by MM-MNL based on BIC and CAIC due to the latter's use of fewer parameters (see columns 5–6). It is interesting that this sample also splits into two segments with opposite perceptions toward heat pumps. The estimates of average WTP to save for $1 annual running cost from MM-MNL's two segments are at $9.31 and $3.13, respectively.

To further examine the distribution of taste heterogeneity, we adopt an "approximate Bayesian" approach (see Allenby and Rossi, 1998; Train, 2003 for details). The MM-MNL's estimated heterogeneity distribution is taken as the prior. The posterior means of the individual-specific coefficients are then calculated conditional on each respondent's choices.

The posterior distributions which represent preferences for each type of water heaters are plotted in Fig. 2. These are kernel density estimates using a normal kernel. The distributions from both gas access sample (Panel A) and no gas access sample (Panel B) are widely dispersed and depart substantially from normality. Most respondents (80–90%) derive disutility from a peak electric system. More than 70% of respondents derive positive marginal utility from two gas options and solar—with a small fraction who extremely prefer instantaneous gas or solar heaters. The distributions for heat pump coefficients are clearly bi-modal.

If the posterior distribution for MNL was plotted, it would put all mass on a point. MNL estimates also imply that *all* households are indifferent between instantaneous gas and a heat pump. Both coefficients are around 1.7. In contrast, MM-MNL indicates that more respondents have negative perception toward a heat pump (20% dislike gas vs. 46% dislike heat pump).

[23] Geweke and Keane (1999) show that a mixture of two or three components of normal usually approximate highly non-normal distributions quite well in practice. We also tried to extend MM-MNL by parameterizing, w_{ns}, the segment probability, as a function of demographic variables, or allowing the means of each component to be shifted by the demographic variable. The latter approach achieves better likelihoods, but the base models are still preferred by BIC for both samples. This suggests that water heater choices in our data are largely explained by unobserved rather than observed heterogeneity. The MM-MNL models with full covariance matrix for each segment (rather than only standard deviations) also achieve better likelihood but were inferior from the perspective of the BIC criterion.

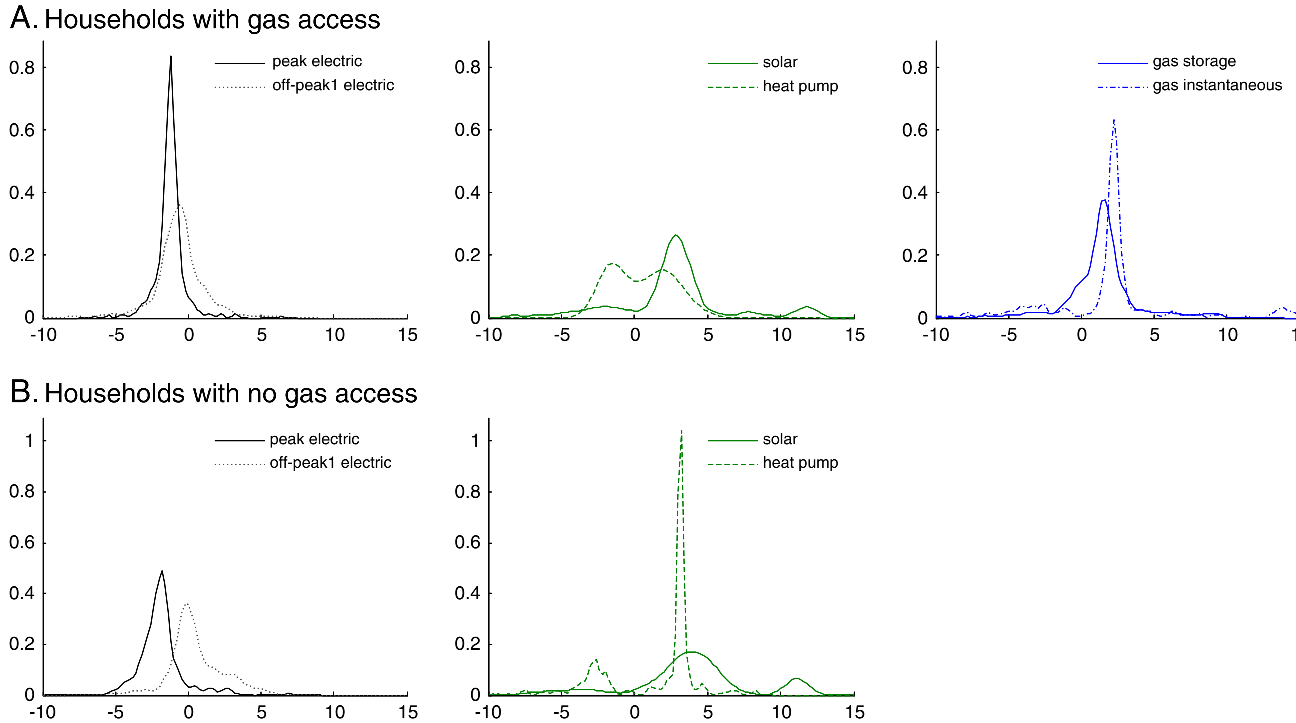

Fig. 2. Posterior distribution of individual-level coefficients. Note: Each kernel density estimate uses a normal kernel with an optimal bandwidth (h). The formula used is $h = \sigma(4/3N)^{1/5}$ where σ is the standard deviation and N is the number of observations.

Table 7
Distribution of estimated discount rates from SP sample.

Implied individual discount rates	Gas access Freq (%)	No gas access Freq (%)
Less than 2%	29	31
2–10%	22	23
10–20%	24	18
20–40%	16	10
Higher than 40%	9	18
Median discount rate	9.4%	8.5%

We also calculate the posterior distributions of individual-specific implied discount rates. The respondents are very heterogeneous with respect to the discount rate they hold (see Table 7). While 51–54% of respondents have a discount rate below 10%, 25–28% of respondents possess a discount rate higher than 20%. Some respondents, however, may have borrowing constraints that can alter the strict interpretation of the discount rate in terms of a money-time tradeoff.[24] The median discount rates for those with and without gas access are 9.4% and 8.5%, respectively.

7. Policy implications

Models estimated using our SP data can be used to simulate household response under different scenarios. In evaluating the effects of programs intended to reduce carbon emissions, one needs to estimate the number of replacement *induced by the program*. The simulated market shares for the no rebate situation allow us to estimate the fraction of "free-riders" who would have purchased non-electric heaters in the absence of rebates. Analysis using RP data (Tables 3–5) suggests that this fraction of households is not trivial. We now look at the SP data using MM-MNL estimates and show how it can be used to calculate the cost of reducing carbon.

The top panel of Fig. 3 shows predicted shares under various scenarios. First, let's focus on the top-right and top-middle figures which present simulated shares for respondents who previously owned an electric heater with and without gas access, respectively. The first bars show the simulated shares for the "no rebate" situation.[25] Here, in the absence of incentive, only 26% of households with gas access would replace their electric heater with another electric heater (62% switch to gas and 12% switch to a solar or a heat pump). For households without gas access, however, 68% would still choose another electric heater.

To see how these figures compare to RP data, we plot the observed shares from RP data during the 2004–Sep 2007 period where no rebate was in place in the bottom panel. The shares calculated from all observations and conditional on nonemergency replacement are shown.[26] The simulated shares from SP data are quite consistent with RP data except that the shares of solar and heat pump in SP are larger than RP data.[27] One explanation is that RP comes from the earlier period when some respondents may have been unaware of the availability of solar/heat pump systems. SP respondents were framed to think about their next replacement (likely 2012–2013).

Next we consider the scenario which mimics the NSW and Federal programs in effect during the period that our data was collected. This Scenario I assumes that a $300 rebate is available for gas and rebates

[24] While the respondents were asked to assume that all water heaters last for 15 years, there may be some heterogeneity in expected lifetimes. Such heterogeneity, while less likely in SP than RP data, can mimic heterogeneity in discount rates.

[25] The rebate level is set to zero. Upfront costs and running costs are chosen based on water heaters available in the market during 2007–2009. The upfront costs are $900–1800 for electric heaters, $1200–2400 for gas heaters, and for $4000–$6500 for solar/heat pump (see the web appendix Table C2 for details).

[26] RP data conditional on nonemergency replacement should be more comparable with SP data, but this reduces the number of observations.

[27] Breaking types down into further details, we see that SP consistently predict that the majority of households with gas access choose a gas instantaneous system. Those with no gas access tend to choose an electric off-peak system.

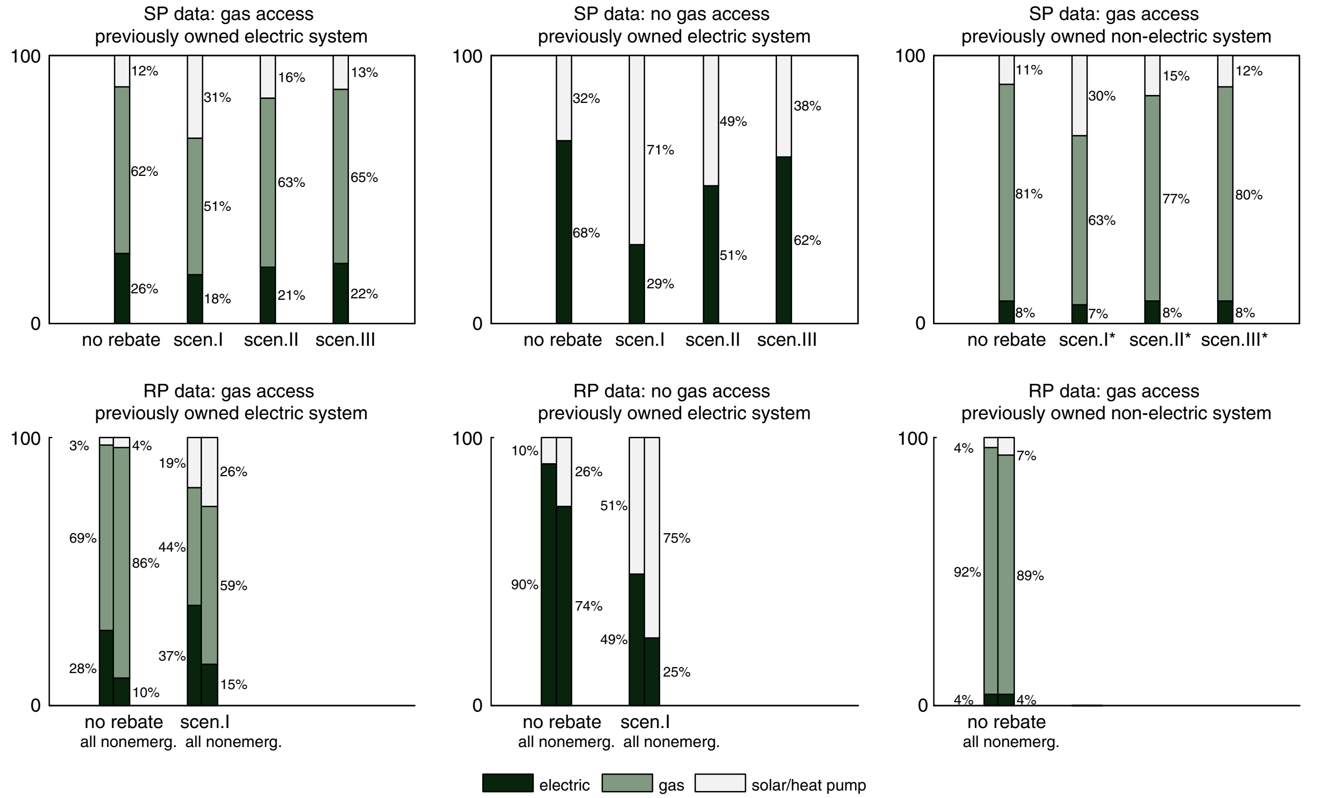

Fig. 3. Simulated and observed shares from SP and RP data under different scenarios. Note: For RP sample, "no rebate" for those who previously owned electric system refers to the period of 2004–September 2007. For those who previously owned non-electric system, "no rebate" refers to the entire period of study (2004–2010). For SP data, scen. I refers to a scenario which mimics the actual rebate programs taking place in 2007 (with \$300 for gas, covers 50% of upfront cost of solar/heat pump). Scen. II and III assume that the rebate for gas is kept at \$300; rebates for solar/heat pump cover 25% and 10% of their upfront cost, respectively. Scen. I*, II*, and III* for SP sample who previously own non-electric system are analogous to Scen. I, II, and III except that there is no rebate for gas.

covers 50% of the upfront cost of solar and heat pump systems (about \$2000–\$3000). The predicted responses are plotted in the second bars. To assess the effect of the policy, we have to look at how these shares change from the "no rebate" scenario. As a result, we find that for households with gas access, the share of electric and gas heaters would reduce by 8% and 11%, respectively. The share of solar/heat pump would increase by 19%. Households with no access to natural gas, while still possessing more electric heaters, are more responsive to the rebate policy (38% reduction in the share of electric heaters).

Recall that from RP data conditional on nonemergency replacement, the estimated effects on shares of solar and heat pump are +22% and +49% for gas and no gas access households, respectively. The estimated effects from SP are somewhat smaller than RP and this may be driven by two factors that suggest the two estimates may bracket the impact of a current policy change. First, there is likely a selection effect—households that are the most sensitive to availability of incentives chose to take advantage of them when initially offered (becoming our RP sample), leaving the SP sample somewhat less sensitive. Second, the SP sample may have an incentive to indicate choices that are more sensitive to the magnitude of incentives than they would be in actual purchase decisions.

We also explore other policy scenarios where the rebates for solar and heat pump cover a smaller portion of their upfront cost (either 25% or 10%) and the rebate for gas is kept at \$300.[28] Under these two scenarios (the 3rd and 4th bars), households with gas access are more likely to replace their electric heater with a gas heater. Households with no access to natural gas are still responsive, with electric heaters being replaced at 17% and 6%, respectively. Another plausible option is that NSW allows households with a non-electric heater to be eligible for a rebate as in some other Australian states. This group is currently ineligible for the existing NSW and Federal rebate programs. With no incentive in place, both RP and SP data suggest that a majority of respondents (80+%) would stay with a gas system. If this group was eligible, the shares of solar/heat pump installed can be increased by about 20%. The results are shown in the right panel. This option, however, turns to be an expensive one as discussed below. Our results involving households who have a gas option are similar to Grosche et al.'s (2009) finding which suggests that more expensive retrofit options are likely to be adopted when more of the cost is covered by the government grant.

Our simulated market shares can be used in conjunction with the engineering estimates of the carbon emissions to estimate the cost in terms of the incentives paid per ton of carbon. Table 8 presents the emissions by types of water heater used by the NSW government. The carbon price, expected rebate amount paid to households divided by expected change in carbon emissions is:

$$\text{Carbon price (/ton)} = \frac{\sum_n \sum_{j=1}^{J} (prob_{n,j}|rebate) * rebate_j}{\sum_n \left(\sum_{j=1}^{J} \left(prob_{n,j}|no\ \ rebate \right) * carbon_{j,n} - \sum_{j=1}^{J} \left(prob_{n,j}|rebate \right) * carbon_{j,n} \right)}.$$

The numerator is the product of the probability that household n would choose heater type j and the rebate amount available for that heater aggregating over all types and households. The denominator is total carbon saved induced by the program aggregating over all households.

We focus on Scenario I, which mimics the actual rebate program during the study period. For households currently possessing an electric

[28] The 25% of upfront cost case is similar to the new rebate program that NSW put into effect starting in 2010 where all systems are only eligible for a \$300 rebate, but solar and heat pump systems are still eligible for Federal rebates. The 10% of upfront cost rebate is similar to the case where the Federal government stopped its rebate program.

Table 8
Greenhouse gas emissions per year by types of water heaters and household sizes. Source: Australian Greenhouse Office.

	Household size (number of people)		
	Small (1–2)	Medium (3–4)	Large (5+)
Electric off peak	2.8	4.2	5.8
Electric peak	2.7	4.2	6.1
Gas storage	1.0	1.4	1.9
Gas instant	0.8	1.2	1.8
Solar	0.4	0.9	1.7
Heat pump	0.7	1.1	1.6

water heater, the average costs of carbon reduction from SP data are $254 using a gas access sample and $105 per ton from a sample with no access to natural gas. The situation where we allow for those possessing a non-electric heater to be eligible yields substantially higher cost per ton of carbon reduction. This is not surprising as a gas heater emits only slightly more carbon than a solar or heat pump. We can perform similar calculations from RP data if we assume that these respondents faced that same price and rebate amount as those in our experiment (see Table 9).

These estimates are higher than many US studies ($47 per ton[29]) but close to the estimates of Davis et al. (2012) using Mexico data ($280–$500 per ton). A concern is that our estimates are also strikingly larger than the NSW Climate Change Fund estimate of $26 per ton.[30] NSW Department of Environment and Climate Change, 2010. Looking closely, however, we find that NSW estimates relied on two key different assumptions. First, they assume that without incentive all households would continue to install electric heaters. If we were to change our denominator based on this assumption, our carbon cost would reduce to $28 and $57 per ton (see Table 9, column 2). Another assumption is that the NSW estimate does not include the large 2007 subsidy of the Federal government. If we were to subtract the federal rebate from our numerator, our estimates would be $170 and $63 per ton.[31]

This exercise emphasizes that without assessing a counterfactual scenario, one could underestimate costs of a demand-side management program. It should also be noted that more accurate estimates of the carbon price are to use data on actual usage post-installation rather than the engineering estimates. This would enable the policy analysis to take into account the likely change in usage where arguments have been made that there will be an increase in usage due to lower marginal cost (rebound effect) and that there will be a decrease in usage due to consumers who switch adopting a greater conservation orientation.

8. Concluding remarks

In the past decade the Australian governments have established a wide range of financial incentives and regulations to cut greenhouse gas emissions. This paper focuses on the hot water system rebates targeted at the residential sector, and the role of increasing rebates in shifting the existing stock of electric water heaters toward more climate friendly versions. Surprisingly, little work looking at such programs has been done. Due to a lack of data, we designed a two-pronged approach survey. The first part collected information from households who recently installed water heaters. The second part used stated preference survey targeting at households who are likely to comprise the market for water heaters in the future. The former was used to evaluate the program *ex-post* while the latter was used to conduct *ex-ante* evaluation.

Our results suggest that the programs were successful at increasing the number of solar and heat pump installed. But to which extent the programs reduce the number of electric heaters is more ambiguous. For households without access to natural gas, the increase in solar/heat pump share implies a reciprocal reduction in the share of electric heaters. For households with access to natural gas, however, the majority would have switched from electric to gas rather than replaced their existing electric heater with another electric heater if the policy had not been in place. This pattern is consistent in both datasets. Two key policy implications here are that (1) a program that targets households without access to natural gas is clearly the most cost-effective; and (2) carbon costs can be largely underestimated if one assumes that an old electric heater would be replaced with another electric heater without an incentive.

In addition, from RP data, we find evidence that purchases under emergency situations are much less responsive to the government rebate programs. Consumers who urgently need a water heater may not be imperfectly informed and make inefficient investment. The first-best policy here is to improve the information set available to households who make purchases in emergency situations. Programs which educate or provide incentives for plumbers may also be useful. From SP data, even conditional on nonemergency replacement we find considerable consumer heterogeneity in preferences toward different types of water heaters and the discount rates they hold. This heterogeneity is likely to be important when considering cost effectiveness and welfare improvement of policy alternatives.

[29] U.S. Department of Energy (2011) using a conversion rate of .0007 ton per kWh.
[30] NSW Department of Environment and Climate Change, 2010
[31] Another different assumption that is going the opposite direction is that we use a 15 year life span for water heaters rather than the 10 years NSW assumes.

Table 9
Estimated carbon cost per ton under different assumptions.

	Account for free-riders & federal rebate	Account for federal rebate, but not free-riders	Account for free-riders but not federal rebate
SP data			
Gas access	$254	$28	$170
No gas access	$105	$57	$63
RP data			
Gas access	N/A	$18	N/A
No gas access	$91	$56	$53

Note: The estimates from RP data for gas access sample which account for free-riders are not available because in those situations, the estimates imply no carbon reduction on average.

Appendix A. Supplementary material

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2013.08.009.

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