Technology adoption, consumer inattention and heuristic decision-making: evidence from a UK district heating scheme

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Abstract

This paper contributes to the debate on the energy efficiency paradox according to which consumers fail to adopt cost-effective, energy efficient technologies over less efficient technologies and therefore fail to reduce energy consumption. Both traditional and behavioural theories are used to investigate the decision-making process of residential consumers with empirical evidence based upon a specially designed quasi-experimental survey of 784 households on the decision to connect to a district-heating system, a more energy efficient alternative to individual heating systems. The results suggest an internal discount rate of around 36 per cent for homeowners, a signal that consumers undervalue future energy costs. We also find the household's decision to be negatively affected by years of payback up to around 7-8 years. Our findings suggest that neglecting consumer inattention and heuristics can lead to biases which cast doubt on the existence of the energy efficiency paradox. We believe that these results help to explain why some consumers are unlikely to invest in energy efficient technology, particularly those on low incomes.

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1 Introduction

Following the Paris Agreement on Climate Change, which entered into force in November 2016, Governments across the world have been implementing policies to reduce energy consumption and greenhouse gas emission with mixed success. The European Union's (EU) and the United Kingdom's (UK) Government have been particularly active in promoting policies for increased environmental sustainability, underpinned by the 2030 emission reduction targets of 40% (European Commission, 2013) and 57% below 1990s levels (Climate Change Committee, 2017). Improving energy efficiency in the residential sector (which produces around 13% of total direct greenhouse gas emissions) is one of the areas of policy intervention which have witnessed limited success (CCC, 2016b). In the UK residential consumers' uptake of cost reducing technologies has slowed down particularly since 2012 (CCC, 2016b), partly as a result of cuts in subsidies for renewable technologies. This could be interpreted as evidence of the so-called 'energy efficiency paradox' (see Gillingham and Palmer (2013) and Gerarden et al.(2015) for recent reviews).

According to the energy efficiency paradox consumers' failure to adopt cost-effective, energy-efficient technologies over more inefficient ones is arguably a phenomenon which hinders society's efforts to reduce energy consumption and CO_2 emissions (Jaffe and Stavins, 1994). This paper contributes to the literature on this perceived paradox by investigating the decision making process leading to the adoption of energy efficient technologies (Battisti 1998, Kesidou and Demirel 2012, Menanteau and Lefebvre, 2000, Stoneman and Battisti 2000). The novel contribution of the paper consists of extending the traditional neoclassical approach through the inclusion of more recent behavioural concepts such as heuristics and inattention.

Hausman (1979)'s seminal paper emphasised the tendency for consumers to purchase low-cost technologies and reject the more expensive yet efficient alternatives which can deliver a profitable stream of discounted net savings. He argued that consumers' reluctance to adopt energy efficient technologies is internally consistent with the traditional neoclassical economic theory, according to which consumers discount the future financial benefits from the use of the technology too heavily making adoption less attractive. The literature has indeed confirmed this (Jaffe at al 2004) and a stream of research has since developed looking at intertemporal decision making and at the different nature of the discount rate, e.g.

hyperbolic discounting (Pearce et al. 2003, Frederick et al., 2002; Laibson, 1997, Hepburn et al., 2010) or social discount rate, typically applied to public policy interventions (Groom et al., 2005; Stern, 2007).

More recently, economists have offered behavioural theories to explain the energy efficiency paradox, describing consumer choices as systematically deviating from the rational behaviour depicted in the neoclassical theory of consumption. They argue that consumers often simplify complex tasks for example by using simpler 'heuristic' estimates of the expected savings. Accordingly, simple 'rules-of-thumb' or quick-fire tactics used to help navigate complex decision-making scenarios (Kahneman and Tversky, 1974; Kahneman, 2011), might lead to the choice of inefficient technologies over profitable alternatives (Allcott, 2011; Attari et al., 2010). Behavioural theory has also identified 'inattention' as another deviation from the neoclassical assumptions of decision based on full information: due to lack of interest and systematic bias in beliefs. Jointly they make the cost of becoming fully informed about the costs of adoption and the characteristics of the technology so high that consumers overlook energy efficient technologies (Davis and Metcalf, 2015, Sallee, 2014, Reis, 2006).

In order to explore the validity of both the neoclassical arguments and the relevance of behavioural concepts, such as heuristics and inattention, in the adoption decision, we have carried out an ad-hoc and novel quasi-experimental survey, with the inclusion of a contrastive vignette experiment, to assess the factors affecting the decision to adopt an energy efficient technology, district heating (DH), by residential consumers in Birmingham, the second largest city in the UK. DH is a technology that was prevalent in the early 1900s and has exhibited a revival in the 1970s, especially in high rising social housing establishments, and in recent decades (Citizens Advice, 2016): around 200,000 residences were connected to one of 2,000 networks in the UK in 2015 (DECC, 2015). We have chosen this technology because of its great emission reduction potential, as up to 20% of heat demand could be met by DH schemes in order to meet emission targets (CCC, 2016).

The empirical approach taken in this paper adds to the experimental economics and policy literature by proposing a method which evaluates the impact of behavioural biases on consumers' preferences towards impure public goods. The presence of ancillary additional private benefits and externalities to the provision of a mixed rather than pure public good, such as reductions in environmental pollution, does play a key role in achieving environmental targets and in the successful implementation of environmental policies (Cornes and Sandler, 1984, Finus and Rubbelke, 2013 and Kotchen, 2006). Our findings significantly contribute to the understanding the factors which affect households' decisions to adopt an environmentally friendly technology and provide important policy insights on how to stimulate the adoption of sustainable technologies that are key to the generation of public returns to environmental policies.

The remainder of this paper is organised as follows: in the next section the paper reviews the key literature on the energy efficiency paradox, inattention and heuristics. Section 3 outlines the data and experimental design followed by the empirical strategy in Section 4. The analysis is presented in Section 5 before providing concluding remarks and the implications for policy in Section 6.

2 Literature on the energy efficiency paradox

Discounting lies at the heart of policy and intertemporal decision-making. Discount rates serve the central purpose of transforming future costs into present terms in cost-benefit analyses (Weitzman, 2001). They also describe different forms of consumers' preferences over time, including procrastination (Fischer, 1999) and addiction (O'Donoghue and Rabin, 1999). The energy efficiency paradox (EEP) states that consumers behave *as if* they applied high discount rates[1] when confronting the trade-off between the upfront acquisition costs and the costs of operating the technology (Jaffe et al., 1994).

Hausman's (1979) seminal paper in this area concluded that consumers' reluctance to adopt energy efficient technologies could be considered internally consistent, in line with the neoclassical economic theory of rational consumer behaviour based on cost minimising and utility maximising considerations with full information. Similar rational models were presented by McFadden (1984) and Goett (1978) who sought to create models of consumer

[1] High internal discount rates are consistent with theories of intertemporal decision-making which are variants of the neo-classical assumption that decisions are underpinned by exponential discounting (Samuelson, 1937). Hyperbolic discounting in particular implies that discount rates are relatively high for decisions made over short time horizons and diminish for those made over long time horizons (see, e.g., Frederick et al., 2002; Laibson, 1997). Reversals of (or time-inconsistent) preferences are not only consistent with the systematic undervaluing of energy efficiency, but also underpin behaviour related to resource depletion, addiction, procrastination and low saving rates (Hepburn et al., 2010).

decision making which involve comparing acquisition costs with the long run operating costs of the technology, thus enabling the estimation of the internal discount rate, a key parameter which translates future returns from the use of the technology into present values (Gillingham et al., 2009).

This approach forms the cornerstone of the energy efficiency paradox literature and the mainstream literature has indeed supported the neoclassical argument demonstrating how consumers often discount future financial benefits too heavily. Gillingham et al. (2009)'s literature survey reveals that the estimated discount rate ranges between 25% to more than 100%, depending on the technology. While these values are generally greater than the market rate of return, their calculation incorporates standard neo-classical assumptions of consumer behaviour and is therefore able to theoretically justify why the paradox might exist under optimising behaviour (Loewenstein and Thaler, 1989; Jaffe and Stavins, 1994). Despite its importance, the presence of an energy efficiency paradox in the decision to adopt a technology by UK households has never been investigated, with the exception of Cohen et al. (2015). Hence we posit that for the adoption of energy efficient technologies in the UK the discount rate significantly deviates from the market rate of interest:

Hypothesis 1a: *Consumers discount the financial benefits accrued from the use of energy efficient technologies too heavily, i.e. their internal discount rates are significantly higher than the market rate of interest (classical energy efficiency paradox).*

We would also expect that, if present, relatively high discount rates would underestimate the future stream of benefits associated to the use of the energy efficient technology leading to a low adoption rate:

Hypothesis 1b: *The adoption of energy efficient technology is negatively affected by the consumer's estimate of the discounted future stream of financial benefits associated with its use (traditional economic approach to consumer behaviour).*

In the past decade behavioural theories have been developed to describe why choices can deviate from the traditional 'rationality' assumption based on full information about the characteristics, costs of adoption and performance of the technology. Allcott (2011) for example finds that around 40% of consumers do not consider fuel costs in their calculations when deciding to purchase an automobile but look at factors such as shape, colour, age, size, etc. This decision making approach has been shown to be adopted in the markets for appliances (Davis and Metcalf, 2016; Newell and Siikamäki, 2014), automobiles (Sallee, 2014) and lightbulbs (Allcott and Taubinsky, 2015). Evidence would also suggest that, when undertaking a task, inattention is likely to increase with effort (Gabaix and Laibson, 2006), competing stimuli and/or shrouded information (Della Vigna, 2009). Hence, as attention is scarce and collecting information is costly, decisions will not be taken under full information. An alternative explanation to the lack of full information in decision making is that search and information acquisition is undertaken if and only if its benefits are perceived to outweigh the costs (Reis, 2006). Hence, some consumers might decide to remain inattentive and overlook energy efficient technologies if the expected discounted savings do not justify the effort of becoming fully informed (Sallee, 2014), or indeed if energy costs are very low and competitive (which is not the case in the UK) and/or in the absence of taxation on energy consumption, the cost of adopting efficient behaviours is higher than the expected future benefits whatever discount rate is used. As suggested by the literature on switching, consumers often have a negative attitude towards changing supplier, e.g. electricity, telephone, insurance, irrespective of the size of the financial benefits associated with it (Gamble et al. 2009 and Deller et al. 2017). Such inattention-based consumer inertia often leads to stick with providers or default tariffs that are least beneficial (Sitzia et al. 2015). In a context similar to ours, i.e. energy related decision making based on financial considerations, Hortacsu et al. (2017) provide evidence on the decision to switch energy supplier in the US, a country with relative low energy cost. Their analysis leads to the conclusion that inattention bias is an important driver of the decision not to seek alternative suppliers, based on the understanding that inattention "represents factors such as psychic search costs and not having information, or being willing to gather information, about alternatives".' Hence, we posit that:

Hypothesis 2: *The adoption of an energy efficient technology is negatively affected by the consumers' lack of complete information about the true characteristics, returns and performance of the technology (inattention approach).*

An alternative behavioural approach to the traditional energy efficiency paradox is cognitive bias, known also as *heuristics*, which refers to the use of simplifying methods of performance measurement used when deciding among different alternatives. Kempton and Montgomery

(1984) provide valuable insights into how consumers use rules-of-thumb when purchasing efficient technologies, such as relying on annual energy bills instead of the amount of energy consumed or using the payback period rather than the net present value. Numerous laboratory experiments have confirmed that consumers often simplify complex tasks, thus making decisions which are inconsistent with those expected of rational utility-maximising consumers with full information (Kahnemann and Tversky, 1974; Kahnemann, 2011). Experimental studies in the automobile sector have for example shown how consumers are confused by changes in fuel efficiency, since on average consumers perceive gas consumption as decreasing linearly (instead of non-linearly) with miles-per-gallon (MPG) (Allcott, 2011). Similarly, Attari et al. (2010) suggest that consumers to some extent overestimate the potential savings associated with low-energy intensive activities and substantially underestimate the energy savings associate with durable appliances.

Taken together these studies suggest that simplified measures are likely to be used and to induce bias in the judgment. Most of the studies cited above are located in the US, which could potentially question the generality of inattention in other contexts. Inattention could be symptomatic of specific government policy, natural resource availability or general financial and economic conditions in which the consumers find themselves and therefore could be site specific. Hence, we control for location effects, energy costs, socio-economic characteristics and housing attributes in order to posit that, ceteris paribus, heuristic measures affect the consumers' likelihood to install a technology, or more precisely:

Hypothesis 3: *Consumer behaviour falls in line with simplified measures of returns and they negatively affect the likelihood of adoption of an energy efficient technology (heuristic approach).*

Finally, our inattention and heuristic measures could be a significant source of unobserved heterogeneity which, if not explicitly accounted for, could inflate the classical estimates of the internal discount rate. Existing studies have highlighted the potential relationship between inattention and heuristics and the likelihood of technology adoption, but they do not directly investigate the extent to which they affect the makeup and magnitude of the EEP. Hence in this paper we explore for the first time how the direct effect of inattention and heuristic influence, if at all, consumers' decision making.

3 Survey data and experimental design

This study uses the case of District Heating (DH) schemes, an alternative energy efficient technology which supplies heat and electricity typically from centralised Combined Heat and Power (CHP) plants to a wide range of buildings. CHP is efficient due to the process of recycling waste heat recovered from electricity generation, producing hot water and steam to transport through a network of underground insulated pipes (BEIS, 2017a). DH has been identified as a cost-effective approach to reducing CO_2 emissions in cities worldwide (UNEP, 2015). The associated carbon savings and efficiency gains vary however with several key variables, including heat density, fuel supply mix, generation mode, building types, and regulatory model (CCC, 2017; Munksgaard et al., 2005; Rezaie and Rosen, 2012; Routledge and Williams, 2012).

In order to test the validity of the three theories of consumer behaviour discussed above, a telephone experimental survey was carried out across residential customers in Birmingham in order to investigate how likely they were to connect to a local DH scheme should it become available in the near future[2]. An independent marketing company utilised proportionate sampling with simple random sampling and used Random Digit Dialling (RDD) within each area code to contact survey participants from a frame of households listed and unlisted in the telephone directory. The screening process restricted the sample to adults who are at least partially responsible for the household's bills and thereby most likely to be involved in the household's investment decisions. Between May and June 2014, a random sample of 784 households stratified proportionately by postcode, where each household is selected with equal probability[3], was collected.

The experimental survey used contrastive vignette technique (CVT) to investigate consumers' attitudes towards installing energy efficient technologies. CVT is an indirect-structured method of attitude elicitation which exploits between-group variation to evaluate the effect on the participants' response of a systematic change in the elements within a

[2] Birmingham's DH scheme does not currently supply private residential consumers but extension to residential consumers is being considered, not least because of its high heat (and population) density, access to low-carbon, local energy sources (e.g. biomass, CHP) and political appetite (Birmingham City Council, 2013).
[3] A Chi^2 test of equal proportions of the sample and population postcodes cannot be rejected at the 1 or 5% level (p-value=0.06). Hence sampling weights are equivalent to a simple random 'self-weighted' sample.

scenario (Alexander and Becker, 1978). One of the advantages of CVT is that it emulates a scenario in which a real-life decision is made; CVT is particularly appealing when a decision cannot be observed, such as the decision to participate in a DH scheme (Wason, et al., 2002). A single vignette describing the capital costs and environmental benefits of DH was allocated to each participant, while randomly varying the values of DH costs in order to determine the effect of capital costs, prices and profitability of investment (Table 1). The experiment randomly allocates one of two scenarios: (1) a fully functional boiler and one that needs replacing[4]. Furthermore, for each cost element the: (2) interface cost (equivalent to a replacement boiler), (3) average annual bill[5] and (4) maintenance cost was randomised. Therefore, costs 2, 3 and 4 varied across three respective levels, creating 27 distinct vignettes. To alleviate bias, the order in which the investment costs and benefits were allocated to the participants was randomised (Cues 2 and 3).

[4] The scenarios are introduced to control for the impact of sunk investment costs (endowment effects) on the decision.

[5] The values simulate a 'low' (£550), 'medium' (£700) and 'high' (£800) yearly heating bill scenario and are representative of a competitive DH scheme (Which?, 2015).

Table 1: Experimental attributes and cues

Heating system scenario (1)	Fully functional	Needs replacing	
Price levels	*Low*	*Medium*	*High*
Average yearly bill (2)	£550	£700	£800
Interface cost (3)	£1500	£1750	£2000
Maintenance cost (4)	Free	£60	£100

Cues	
1	We would like to give you some information on district heating, but first please imagine that the scenario where your current heating system **(1).**
2	District heating is able to transport central and water heating through a network of insulated pipes from a local energy source to households in Birmingham. An interface unit connects each house to the network replacing the current heat generator whilst providing the user control over the amount of heat needed. It would offer an environmentally friendly and sustainable alternative to your current heating system.
3	Please imagine a scenario where the yearly bill for heating would be of about **(2)** for a household with average use, interface would cost (**3**) and annual maintenance costs are **(4)**.

In the UK a DH heat interface unit (HIU) – which gives the household access to heat and hot water from the district heating system – costs around £2000 including installation (Committee on Climate Change, 2015; DECC, 2015); this case forms the high-end benchmark and would be competitive against a standard gas-boiler replacement with an A-rated level of efficiency (Energy Savings Trust, 2016). The medium-price of £1750 is competitive with a slightly cheaper gas-boiler with around 90% efficiency (uSwitch, 2016) and lower bound HIU unit cost applied in CCC (2015). The low-price scenario is based on a £250 government subsidy, similar to the discount offered in a traditional boiler scrappage scheme (Which?, 2015) and the price quoted for non-bulk schemes by DECC(2015). Finally, the maintenance costs vary between £100 and 0 with a medium costs of £60 (Which?, 2012).

The capital and maintenance costs are modelled such that they are comparable with current DH and gas-boiler markets[6].

Overall, the random allocation of the costs worked well, as each cost element has been assigned to a nearly equal proportion of the sampled households, as is evident in Table 2.

Table 2: Summary statistics for experimental variables

Variable	N	Mean	S.D.	Min	Max
Yearly bill					
£550	784	0.33	0.47	0	1
£700	784	0.31	0.46	0	1
£800	784	0.36	0.48	0	1
Annual maintenance					
Free	784	0.31	0.46	0	1
£60	784	0.36	0.48	0	1
£100	784	0.33	0.47	0	1
Installation costs					
£1500	784	0.34	0.47	0	1
£1750	784	0.34	0.47	0	1
£2000	784	0.32	0.47	0	1

The households' attitudes towards participating in a DH system are measured on a 5-point Likert scale. Nearly half of respondents indicated, on the basis of the cost information provided, they were likely to adopt the technology, whereas less than 8% chose 'definitely likely'. In contrast around 18% of the respondents indicated that they were definitely unlikely to connect while 17% were unlikely. Fewer than 8% of respondents were unsure about their participation in a DH scheme. Hence, there is an overwhelming preference towards connecting to DH in this sample. The experimental survey also contained a number of traditional household socio-economic characteristics including information on demographics, housing, income and energy use that we use as control variables.

[6] It is assumed that the network infrastructure and meter replacement costs are borne by the district heating provider and recouped through the household's energy bills. Nevertheless it is important to acknowledge that pricing mechanisms applied by the network providers can vary across countries (e.g. some Scandinavian district heat systems operate on a not-for-profit basis) and depending on whether each property has a HIU or a unit is shared between multiple properties (AECOM, 2017).

Many of the sample statistics for the social and economic variables which are expected to influence the household's decision to connect to a DH scheme are close to the population statistics collected in the UK Census (ONS, 2011a; ONS, 2011b) for Birmingham and, to a lesser extent, England (see Table A1, Appendix1). Although they refer to two different time periods, we find that the main differences between the sample and the Birmingham population are the median income and the proportion of single and elderly households. The findings therefore may overestimate the likelihood of investing in energy efficient technologies as married or co-habiting households are more likely to adopt it, while low-income and the elderly are less likely to do so (Ameli and Brandt, 2014). Hence the overall direction of bias in terms of representativeness is unclear.

4 Methodology

Classical theory of residential household's decision-making

The *classical theory of residential household's decision-making* suggests that the lifetime-cost (LTC) of installing DH technology is the key driver when deciding whether to adopt the suggested technology. In particular, Hypothesis 1 states that high discount rates would underestimate the stream of costs associated to the use of the energy efficient technology. To calculate the household specific discount rate, we follow Hausman (1979) and model the consumer's choice via the present value of *LTC* of capital calculated on the basis of the annual costs AC_i including average bill *(DH-BILL)* and upfront interface costs UC_i of DH[7] *(INTERFACE)* provided to the survey participants[8]:

$$LTC_i = UC_i + AC_i \, \frac{(1-(1+\rho)^{-\tau})}{\rho} \qquad (1)$$

Where the annual cost is discounted at the rate $\frac{(1-(1+\rho)^{-\tau})}{\rho}$ with an internal discount rate ρ and lifetime durability τ of the HIU. The latent utility function U is specified as follows:

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[7] DH maintenance costs are consistently found to be insignificant and removed in favour of a more parsimonious framework using the full-specification (LR-test: Chi^2=0.62, p-value=0.43).
[8] The typical assumptions in the literature are made herein: annual costs do not rise in real terms; the decision to connect is irreversible; and the heating system does not depreciate.

$$U_{ci}=\beta_1 UC_i+\beta_2 AC_i+\varepsilon_i \qquad (2)$$

Where ε_i is the independent and identically distributed error component containing the unobserved factors related to the preferences for heating systems for $i=1,\dots,784$ households, and assumed to follow a standard normal cumulative distribution function Φ.

The internal discount rate ρ, though unobserved, can be determined using the point at which the consumer is indifferent between a marginal change in the annual and upfront costs of DH, i.e. following traditional economic theory the marginal rate of substitution (MRS). This is done by rearranging Equation (2) with $\beta_1 UC_i$ on the LHS, dividing throughout by β_1 and taking the partial derivative with respect to AC_i, given the ratio between annual and upfront costs is the marginal rate of substitution β_1/β_2, one arrives at Equation (3):

$$MRS=\frac{\beta_1}{\beta_2}=\left[\frac{(1-(1+\rho)^{-\tau})}{\rho}\right]^{-1}=DR \qquad (3)$$

Based on the estimated coefficients β_1 and β_2 it is possible to derive the MRS by setting it equal to the discount rate DR and solving for the average internal discount rate given a fixed lifetime durability of the HIU which we assume, in line with the literature, to be equal to 15 (Davies and Woods, 2009)[9].

Coefficients β_1 and β_2 are hypothesised to be less than zero, since it is anticipated that a marginal increase in either the upfront costs or energy costs will decrease the probability of adoption. According to theory, in the absence of market or internal inefficiencies in the consumers' decisions, the implied discount rate ρ in (3), will be close to the market rate of interest. However, a discount rate exceeding the market rate of interest would imply that households excessively weigh the cost of energy efficiency relative to the upfront costs.

[9] We also experimented with using 20 and 25 years obtaining very similar results

Hence, for Hypothesis 1 to hold we would expect the estimated consumer's discount rate ρ to be larger than the market rate of interest.

Behavioural theory of consumers' inattention

To test whether the adoption of energy efficient technologies is negatively affected by consumers' inattention (Hypothesis 2), we include two proxy vectors of variables.

The first measure of inattention, is a vector of variables founded on research which indicates that consumers chose not to search for information if the benefits do not outweigh the costs of both adoption and information acquisition (Allcott, 2011; Palmer and Walls, 2015). Building on this line of research, the households' attentiveness has been measured in our survey by asking the following question: 'What is the minimum you would need to save per year before you would consider connecting to district heating, assuming zero upfront costs?' The households selected answers within a specified range or stated a specific amount as their expected savings.

After testing down, we recoded the categories such that the second inattention variable *(IN_{2i})* is equal 1 if the minimum needed is less than £300, 2 if greater than £300 and 3 if the participant responded 'unsure'. Around 35% of households were uncertain about the minimum savings they would require to install DH (Table 3). The coefficient for the second category *(HIGH UNOBSERVED COSTS)* is anticipated to exert a negative impact upon the decision to adopt DH, as greater required savings would imply higher unobserved costs and lower utility, reducing the likelihood of adoption. In line with Hypothesis 2, it is expected that the coefficient associated with the third category *(INATTENTIVE COSTS)* will be negative as an inattentive household will be less willing to participate in DH schemes than someone who is interested in seeking a positive level of savings.

Table 3: The 'minimum needed to connect to district heating'

Minimum needed		
1=Less than £300	326	41.6
2=£300 or more *(HIGH UNOBSERVED COSTS)*	186	23.7
3=Not sure *(INATTENTIVE COSTS)*	272	34.7
Total	784	100

During the survey the participants indicated by which method they would prefer to receive additional information regarding DH. The choice of information method was aggregated into three groups: 1) direct search methods, which require little effort to receive information, including post, email, face-to-face consultation or a telephone call *(DIRECT INFO)*; 2) indirect search methods, which require at least some costly search activities, including information made available online and a community information day *(INDIRECT INFO)*; and 3) zero search activity i.e. lack of interest in engaging in any information acquisition about the DH technology *(INATTENTIVE INFO).*

Heuristic approach

Hypothesis 3 concerns the heuristic approach and suggests that consumers may behave *as if* they emploied simplified measures of profitability. Thus, an increase in the number of years of payback would decrease the probability of connecting to DH. Equation 4 utilises the payback period *(HEURISTIC$_i$)* to reflect the households' perceived risk calculated on the basis of current costs and expected annual savings (Kempton and Montgomory, 1984). The payback period is defined as follows:

$$Payback_i = \frac{UC_i}{S_i} = \frac{UC_i^{DH}}{AC_i^{CH} - AC_i^{DH}} \tag{4}$$

Where UC_i denotes the upfront cost of a HIU, S_i represents the expected annual savings, calculated by the taking difference between annual costs *(AC_i)* accrued by installing the district heating heat interface unit (HIU) and keeping the current heating system *(CH)*. It is important to note that the former refers to the values randomly presented to the households during the survey whereas the latter represents the households reported energy bills and the maintenance costs of their current heating system.

One potential issue related to the calculation of payback period arises due to the fact that around 100 households did not report their energy bills. Following Palmer and Walls (2015), this response is used to control for inattention towards energy consumption by including an indicator variable equal to 1 if the household reported their energy bill *and* maintenance costs, and 0 otherwise *(DONTKNOW COSTS)*. An estimate of the expected savings was used to calculate the payback for the households who could report their annual energy bills.

It is also important to consider negative savings. Obtaining individual energy consumption levels for each household prior to the survey was infeasible. To circumvent this problem the vignette randomly allocated an estimated DH annual heating bill based on average energy use. As a result 431 households could potentially save money by keeping their current heating system. This was controlled for by including an indicator variable equal to 1 if savings are below zero and 0 otherwise *(NEG-SAVINGS)*. The payback variable has been log transformed to control for right skew and potential outliers and categorised into quartiles (ranging from low *(PBK-Q1)* to high *(PBK-Q4)* to pick up any non-linearity between the households' decision to participate in a DH scheme and the payback period.

To further explore how the relationship between income and energy expenditure might affect the uptake of energy efficient technology (Ameli and Brandt, 2014, Michelsen and Madlener, 2012) we created four indicators of relative income and energy costs which depend on whether income or costs are below or above the 60% percentile. They range from low-income-high-cost (LIHC)) to high income low costs (HILC), to control for the relative impact of poverty and energy affordability on the investment decision (Hills, 2012). The Low-Income-High-Cost (LIHC) group is expected to be the least likely to participate in a DH scheme due to financial constraints, although this technology would help them reduce the burden of high energy bills. On the other hand, those in the high income group tend to be less subject to liquidity constraints, more educated and more likely to gather information and hence to adopt new technologies.

Estimating equation

Empirically the paper proceeds by estimating the likelihood of connecting to DH using an ordered probit model. The household's choice towards participating in DH is:

$$D_i \Rightarrow j = \begin{cases} 1 = \text{Definitely Unlikely} \\ 2 = \text{Unlikely} \\ 3 = \text{Not Sure} \\ 4 = \text{Likely} \\ 5 = \text{Definitely Likely} \end{cases}$$

The probability (P) of choosing category j is determined by the households' underlying utility. Their decision is ranked between a series of thresholds $-\infty<\alpha_1<\ldots<\alpha_4<+\infty$, located along the real line of the continuous utility function, which corresponds to the strength of preference j towards participating in DH (e.g. α_1 represents the cut-off point between categories 1 and 2). The probability of decision j for the full specification is defined using the standard approach:

$$P(D_i = j) = \Phi\,(\alpha_j - CLASSICAL_i{}' \beta - INATTENTION_i{}' \delta - HEURISTIC_i{}' \xi - X'_i \gamma) -$$

$$\Phi\,(\alpha_{j-1} - CLASSICAL_i{}' \beta - INATTENTION_i{}' \delta - HEURISTIC_i{}' \xi - X'_i \gamma) \qquad (5)$$

Whereby *CLASSICAL*, *INATTENTION* and *HEURISTIC* are the variables used to capture the three potential drivers of the efficiency paradox, X_i is a vector containing socio-economic and housing characteristics, while β, δ, ξ and γ are the respective vectors of coefficients.

The coefficients and thresholds α are estimated in accordance with maximising the following log-likelihood function[10]:

$$lnL = \sum_{i=1}^{784} \sum_{j=1}^{5} I_j (D_i = j) P(D_i = j)$$

Where I_j is an indicator function equal to 1 if category $D_i = j$ is chosen by households i and equal to 0 otherwise, while $P(D_i = j)$ is the probability of category D_i conditional on the indicator function. Using this approach it is possible to estimate ρ while controlling both for inattention variables and a heuristic measure of profitability. All specifications include socio-economic, demographic and housing variables which have been highlighted in the literature

[10] The marginal effects are calculated in general by: $\frac{\partial P(D_i = j)}{\partial X_i} = \gamma[\Phi'(\alpha_j - X_i'\gamma) - \Phi(\alpha_{j-1} - X_i'\gamma)]$.

as important determinants of household investment in energy efficient technologies. Table A2 in Appendix 1 reports a summary of the variables definitions.

To account for the fact that tenants have limited agency regarding the purchase and installation of heating technologies and landlords have weaker incentives to purchase such technologies on their behalf (Gillingham et al., 2012), we use the variable *TENANT*, which is set equal to 1 if the household does not own their home and 0 otherwise. We allow TENANT to interact with the key decision variables. However, the likelihood ratio tests suggest the interactions with *TENANT* are jointly significant only for the *CLASSICAL* variables (LR $Chi^2(2)=5.75$, $p=0.056$) therefore we report only the results for these interactions.

The variables expected to have a positive influence on technology adoption include: homeownership (Gillingham et al., 2012) and education (Michelsen and Madlener, 2012). In contrast, variables expected to exert a negative influence include age, particularly over 60 years (Ameli and Brandt, 2014), marital status, structural imperfections in the property and economic inactivity. Intra-regional effects could be positive or negative depending on the local socio-economic conditions (Davis, 2010; Michelsen and Madlener, 2012; Mills and Schleich, 2012).

Lastly, an indicator variable is included to control for the household's prior knowledge of DH technology. The effect on adoption could be positive or negative depending on their perception of DH technology and of the ability to switch to alternative heating providers. The latter may be particularly relevant if a customer is concerned about being locked-in to a high-cost long-term contract[11]. Furthermore, this indicator is interacted with the installation costs of DH to capture the effect of the respondents' perception of the upfront costs of adoption.

5 Results

In this section, we investigate the significance of the neoclassical and behavioural theories in the decision to adopt an energy efficiency technology and estimate the internal discount rate.

[11] Compared to non-district heating networks, the district heating (median) price is lower but exhibits a larger variance (CCC, 2016; BEIS, 2017b). Therefore, while UK district heating prices are among the lowest in Europe (Werner, 2016) on average, some consumers may be paying relatively high prices (Which?, 2015; Citizens Advice, 2016).

These findings are then subject to several robustness checks to evaluate the impact of heuristics and inattention upon the neoclassical estimate of the discount rate behind the decision to adopt.

Table 4: Income and socio-economic variables

	Sample					
Variable	N	Mean	S.D.	Median	Min	Max
Income variables						
Annual income	645	22994	18396	18462	2830	201460
Annual energy costs						
Annual gas bill	683	711.79	431.25	611.56	0	3577.82
Maintenance costs	558	224.01	893.44	50	0	15000
Low-income-high-cost indicator						
LILC	784	0.12	0.33	0	0	1
LIHC	784	0.11	0.31	0	0	1
HILC	784	0.23	0.42	0	0	1
HIHC	784	0.22	0.41	0	0	1
UNDISCLOSED	784	0.33	0.47	0	0	1
Demographic variables						
NON-OWNER	784	0.65	0.48	0	0	1
DEGREE	784	0.30	0.46	0	0	1
ELDERLY	784	0.35	0.48	0	0	1
SINGLE	784	0.21	0.41	0	0	1
INACTIVE	784	0.36	0.48	0	0	1
DAMP	784	0.67	0.47	1	0	1
KNOWS-DH	784	0.15	0.36	0	0	1

Table 5 presents the marginal effects of the ordered probit model used to test hypotheses 1 to 3. For brevity, we focus on the interpretation of the analysis for the respondents who have said to be ‘likely’ to connect to a DH scheme response (Column 4). Column 4 shows that a £100 increase in the annual cost and interface cost for DH decreases, as would be expected, the probability of being likely to connect to DH by 4.6% and 2.6%, respectively. The effect of each coefficient and the joint effect are significant at the 5% level (LR test: Chi^2=8.70; p-value=0.0129). This would support the classical economic view that financial considerations are central to the adoption decision (Hypotheses 1a and 1b).

In line with Hypothesis 2, the marginal effects suggest that the adoption of energy efficient technologies is negatively affected by consumers' inattention *(INATTENTIVE INFO* and *INATTENTIVE COSTS)* and its intensity increases with the degree of inattention for both the information acquisition medium and the information acquisition cost approach. Firstly, the probability of adoption by consumers who are unable to quantify the amount of compensation needed to encourage their participation in a DH scheme is 48 percentage points lower than for those who would be interested given a reduction in bills equivalent to less than £300. And secondly, the probability of adoption for households who prefer not to receive any more information is 20 percentage points less than for households who would prefer to be contacted directly. Thus, the marginal effects suggest that the household's lack of interest in energy related matters represents a significant barrier which can prevent the uptake of energy efficient technologies.

As stipulated by Hypothesis 3, the number of years required to pay back the outlays for an energy efficient technology reduces the consumers' likelihood to install it. Furthermore, Columns 4 and 5 suggest a potential non-linear negative relationship between the payback period and the decision to connect. The probability of participating reaches a minimum around a payback of 4-5 years for those who are likely to participate, and a payback of 7-8 years for those who are definitely likely to connect. Akin to Anderson and Newell's (2002) research on the adoption of energy efficient technologies by firms, this paper also finds that households potentially ignore the payback information and become increasingly likely to connect after the minimum is breached, though they remain less likely to connect compared with a payback period of 0-2 years.

There are several socio-economic variables worth highlighting as significant drivers of the decision to connect. For instance, the existence of fuel poverty, as captured by low-income-high-costs, and living in a home with structural deficiencies are negatively related to being likely to participate in a DH scheme. As expected, households containing a resident with high educational qualifications and active in the labour market have a higher probability of participating in a DH scheme.

Table 5: Ordered probit marginal effects for the 'decision to connect' to district heating

	DU	U	NS	L	DL
Experimental Variables			Marginal Effects		
TENANT	-0.0196	-0.0130	-0.00297	0.0279	0.00773
	(0.0203)	(0.0132)	(0.00295)	(0.0286)	(0.00772)
DH-BILL	0.0319***	0.0216***	0.00509***	-0.0456***	-0.0131***
	(0.00862)	(0.00610)	(0.00165)	(0.0124)	(0.00377)
INTERFACE	0.00184	0.00125	0.000293	-0.00263	-0.000753
	(0.00422)	(0.00287)	(0.000675)	(0.00603)	(0.00173)
KNOWS-DH	0.0333	0.0207	0.00433	-0.0465	-0.0118
	(0.0244)	(0.0141)	(0.00273)	(0.0334)	(0.00766)
Heuristics (years of payback)					
PBK-LM	0.164***	0.111***	0.0261***	-0.234***	-0.0670***
	(0.0466)	(0.0329)	(0.00887)	(0.0672)	(0.0202)
PBK-MH	0.0320	0.118***	0.0571***	-0.0899	-0.117***
	(0.0486)	(0.0301)	(0.0152)	(0.0643)	(0.0296)
PBK-H	0.125***	0.0849***	0.0200**	-0.179***	-0.0512***
	(0.0465)	(0.0322)	(0.00830)	(0.0668)	(0.0196)
NEG-SAVINGS	0.157***	0.106***	0.0250***	-0.224***	-0.0642***
	(0.0376)	(0.0269)	(0.00753)	(0.0544)	(0.0167)
DK-ANNUAL COSTS	0.133***	0.0901***	0.0212***	-0.190***	-0.0544***
	(0.0423)	(0.0296)	(0.00777)	(0.0608)	(0.0182)
Inattention variables					
POSTAL INFO	0.0582**	0.0395**	0.00929**	-0.0832**	-0.0238**
	(0.0236)	(0.0163)	(0.00411)	(0.0338)	(0.00994)
INDIRECT INFO	0.140***	0.0949***	0.0223***	-0.200***	-0.0573***
	(0.0295)	(0.0214)	(0.00617)	(0.0427)	(0.0134)
INATTENTIVE INFO	0.338***	0.230***	0.0540***	-0.483***	-0.138***
	(0.0555)	(0.0410)	(0.0124)	(0.0786)	(0.0270)
HIGH UNOBSERVED COSTS	0.0468**	0.0318**	0.00746*	-0.0669**	-0.0192**
	(0.0223)	(0.0153)	(0.00383)	(0.0320)	(0.00933)
INATTENTIVE COSTS	0.140***	0.0951***	0.0224***	-0.200***	-0.0574***
	(0.0218)	(0.0167)	(0.00537)	(0.0319)	(0.0107)
Low income high cost indicator					
LIHC	0.0834**	0.0566**	0.0133**	-0.119**	-0.0341**
	(0.0365)	(0.0252)	(0.00632)	(0.0524)	(0.0153)
LILC	0.0174	0.0118	0.00277	-0.0248	-0.00712
	(0.0359)	(0.0244)	(0.00576)	(0.0513)	(0.0147)
HILC	0.0104	0.00707	0.00166	-0.0149	-0.00426
	(0.0304)	(0.0206)	(0.00486)	(0.0434)	(0.0124)
UNDISCLOSED	0.0340	0.0670***	0.0292***	-0.0687*	-0.0615***
	(0.0300)	(0.0188)	(0.00854)	(0.0404)	(0.0168)
Demographic characteristics					
ACTIVE	-0.0539**	-0.0366**	-0.00859**	0.0770**	0.0221**
	(0.0212)	(0.0146)	(0.00371)	(0.0304)	(0.00896)
SINGLE	0.0632***	0.0429***	0.0101**	-0.0904***	-0.0259***
	(0.0222)	(0.0156)	(0.00401)	(0.0319)	(0.00954)
ELDERLY	0.0325	0.0220	0.00518	-0.0464	-0.0133
	(0.0223)	(0.0153)	(0.00369)	(0.0320)	(0.00928)
DEGREE	-0.0418**	-0.0284**	-0.00667*	0.0597**	0.0171**
	(0.0202)	(0.0139)	(0.00345)	(0.0290)	(0.00844)
DAMP	0.0482**	0.0327**	0.00769**	-0.0689**	-0.0197**
	(0.0193)	(0.0134)	(0.00339)	(0.0277)	(0.00815)
Observations	784				
Pseudo R^2	0.136				
LR χ^2	289.34***				

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Next, in Table 6, we report our estimates of the discount rate whose standard error is calculated using the 'delta method' for non-linear post-estimations. The fourth column reports the estimates of the model without behavioural controls which generates a discount rate of around 41%, providing support for Hypothesis 1a, that the households' discount rate is significantly higher than the market rate of interest. It also provides support for Hypothesis 1b, that the discount rate significantly affects the adoption decision (p-value=0.05). Both results still hold when we control for heuristics measures of the returns from adoption via the length of payback time (associated with a slightly higher discount rate of 51%, p-value= 0.07, see Column 2). This is due to the overestimation of the coefficient on annual costs in the classic model (see *DH-BILL and INTERFACE* in Table 5) by around 20%. Intuitively, behaviour that is driven by a simple payback period (UC/S) compared to the discounted calculation (UC/$\delta \cdot$S), would be consistent with an overestimate of the true time-value of money. Therefore, neglecting the heuristic behaviour produces an implied discount rate that is lower than would otherwise be expected without controlling for it.

In contrast, the discount rate falls to 27.8% when we control only for inattention but it is no longer significant (p-value= 0.115, see column 3). Similar results are obtained when we control for both inattention and heuristic decision making. The interest rate reduces to 36%, but again it is insignificant (p-value= 0.141, see column 1)[12]. In both cases, although insignificant, the discount rate is smaller than in the classic model. The significance of its component suggests that the upward bias works through the upfront costs as its coefficient falls by around 27% in absolute terms after controlling for inattention alone. This is plausible if inattention leads consumers to heavily discount energy costs relative to upfront costs.

Overall our results suggest that, consistent with the EEP, consumers' decision making discounts at rates that are higher than the market interest rate. We also find that leaving the behavioural drivers unaccounted for biases the discount rate away from zero, suggesting that they are major drivers of the bias in the calculations of the classic discount rate.

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[12] Despite the interest rate being insignificant in both model 1 and 3 (Table 6), the cost variables *(DH-BILL and INTERFACE)* are individually and jointly significant *(LR Chi2=7.17; p-value = 0.028)* suggesting overall economic significance of the full model, à la McCloskey (Ziliak and McCloskey, 2008).

The strength of these findings is investigated by assessing a series of diagnostic checks (Table 6). The full model (Column 1) is tested against the specifications in which the behavioural variables are sequentially excluded (Columns 2 to 4). The likelihood ratio (LR) test, Akaike Information Criterion (AIC) and Pseudo-R^2 indicate that the fully nested model best fits the data. In comparison, the Bayesian Information Criterion (BIC) indicates that the inattention model (Column 3) provides a better fit. Hence, one cannot out-and-out favour the full model (Column 1) over the rival specification (Column 3).

Indeed, alternative diagnostic tests shed little light on a 'preferred' model: upon estimating the generalised residuals (Gourieroux et al., 1987) and implementing the Jarque-Bera test (correcting for sample size) it is possible to conclude that the residuals follow a normal distribution for *all* models. An additional diagnostic check tests for the significance of the square of the estimated link function (e.g. Pregibon, 1979; Ramsey, 1969) and leads to the tentative conclusion that all models are correctly specified, due to low power of the test.

Finally, underpinning our analysis is the assumption that the coefficients are equal across all *J* categories of the ordered dependent variable, this is also known as the parallel assumption. As the LR-test reported above indicates that this assumption is violated (Chi^2=111.12, p-value=0.00), we have undertaken further tests which show that the parallel assumption does not hold only for a small number of variables. The partial parallel regression model allows a *specific* set of coefficients to vary, which makes it possible to test whether the deviation from the baseline group's proportionality for *J-2* categories equals zero i.e. $\gamma = 0$ (Peterson and Harell, 1990). An empirical backward stepwise approach[13] is implemented to identify the variables that violate the parallel assumption: *INATTENTIVE COSTS* and *UNDISCLOSED*[14]. After controlling for the deviation from parallel-lines γ for these variables[15], the implied discount rate only falls by around 3 percentage points compared to the results in Column 1 (Table 6).

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[13] Using Stata's 'stepwise' command setting the threshold α=0.10.

[14] The coefficient deviations γ are insignificant for the 3rd cut-off point, therefore an additional constraint that asserts the parallel assumption for this point is applied.

[15] Results are reported in in Table A5 in Appendix 2. All estimates for the control variables and cut-off points are presented in Table A4.

Table 6: Estimated coefficients and implied discount rates for the 'decision to connect' to district heating

	Ordered probit coefficients			
Model	(1)	(2)	(3)	(4)
$\beta_{INTERFACE}$ / $\beta_{DH\ BILL}$	0.367	0.521*	0.293	0.419**
	(0.250)	(0.290)	(0.186)	(0.211)
P-VALUE	0.141	0.073	0.115	0.047
IMPLIED DISCOUNT RATE	0.358	0.518	0.278	0.412
Experimental variables				
TENANT	-1.391	-2.156**	-1.498	-2.245**
	(0.986)	(0.963)	(0.980)	(0.958)
DH-BILL	-0.160**	-0.154**	-0.202***	-0.192***
	(0.0682)	(0.0663)	(0.0671)	(0.0652)
INTERFACE	-0.0590*	-0.0804**	-0.0593*	-0.0806**
	(0.0356)	(0.0349)	(0.0355)	(0.0347)
TENANTxDH-BILL	0.0442	0.0805	0.0705	0.103
	(0.0824)	(0.0805)	(0.0819)	(0.0800)
TENANTxINTERFACE	0.0642	0.0942**	0.0578	0.0884**
	(0.0424)	(0.0415)	(0.0421)	(0.0413)
Inattention variables				
POSTAL INFO	-0.304***		-0.305***	
	(0.109)		(0.108)	
INDIRECT INFO	-0.644***		-0.634***	
	(0.132)		(0.131)	
INATTENTIVE INFO	-1.691***		-1.657***	
	(0.243)		(0.241)	
HIGH UNOBSERVED COSTS	-0.210**		-0.169	
	(0.105)		(0.104)	
INATTENTIVE COSTS	-0.645***		-0.645***	
	(0.0994)		(0.0985)	
Heuristics (years of payback)				
PBK-LM	-0.703***	-0.691***		
	(0.206)	(0.201)		
PBK-MH	-0.538***	-0.498**		
	(0.203)	(0.200)		
PBK-H	-0.479**	-0.460**		
	(0.207)	(0.203)		
NEG-SAVINGS	-0.673***	-0.631***		
	(0.167)	(0.164)		
DONTKNOW COSTS	-0.595***	-0.618***		
	(0.198)	(0.193)		
Controls	Y	Y	Y	Y
Observations	784	784	784	784
Log-likelihood	-930.01	-992.10	-939.106	-1000.80
Pseudo R^2	0.127	0.070	0.119	0.061
LR χ^2	271.66***	147.49***	253.47***	130.08***
LR χ^2(Ho: m=1 vs. m=2,…,6)	-	124.17***	18.19***	141.57***
AIC	1920.025	2034.197	1928.212	2041.60
BIC	2059.957	2150.807	2044.822	2134.89
Df	30	25	25	20
Residual Pr(Skewness)	0.892	0.895	0.605	0.794
Residual Pr(Kurtosis)	0.264	0.521	0.399	0.307
Residual Normal (p-value)	0.892	0.805	0.612	0.573
Link test $x'\hat{\beta}^2$ (p-value)	0.396	0.878	0.229	0.963

Notes:, * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. See Table A.3 for controls and cut-off points.

6 Discussion and conclusion

Residential heat demand poses a significant challenge to the United Kingdom's 2050 emission targets partly due to an energy inefficient housing stock and limited uptake of energy efficient technology. This paper aims to explore the reason for the slow uptake of energy efficient technologies by considering both traditional and behavioural theories used to explain the so-called energy efficiency paradox whereby consumers fail to adopt cost-effective, energy efficient technologies over comparatively less efficient technologies. Empirically, we use the evidence on the decision to connect to a district heating system, using a specifically designed quasi-experimental survey of residential consumers in Birmingham, the second largest city in the UK. The results of our analysis lead to four key conclusions about the decision making process undertaken by consumers when faced with the opportunity to invest in energy efficient technology.

First of all, in line with the neoclassical economic theory we find that the adoption decision of residential consumers is associated with internal rates of returns which are much higher than markets rates. Secondly, we find that this significantly and adversely affects the decision to adopt an energy efficient technology, providing evidence in support of the existence of the EEP. Central to this paper was also to test whether the size and significance of an estimated discount rate of around 40% could be explained by alternative theories of consumer behaviour. After controlling for behavioural factors, such as inattention and heuristic decision making, the estimated discount rate is significantly reduced. In particular we find evidence of both heuristics and inattention. More precisely, when considering heuristic decision making based on the expected returns, we find that the likelihood of adoption is negatively and significantly affected by an increase in the payback period, with the probability of being likely to connect to a district heating system reaching a minimum at around 4 to 5 years. These results are consistent with the possibility that the information derived from the payback period might become 'valueless' beyond a certain time horizon, in which case consumers may use other quick-fire tactics to guide their decision.

Overall the approach taken in this paper makes a step forward in helping to address the research gap identified first by Jaffe et al. (2004) and later reaffirmed by Schliech et al. (2016) that *"To observe that implicit discount rates are high, however, says nothing about the reason people make the decisions they make [...]"*. In this paper we have attempted to shed more light on the possible behavioural biases influencing how decisions are made. As claimed by Schliech et al. (2016) this is not only important to interpretation of the discount rate but also for policy design, not least because the type of inattention, either bounded rationality or rational inattention, would determine the efficacy of policy. For example, the impact of carbon tax would be muted in the former but not in the latter.

Besides behavioural considerations, it can be argued that the interest rate might indeed reflect the local or national market conditions (Jaffe et al. 2004). For instance, in our study the size of the discount rate may well reflect a region which contains consumers whose earnings fall below the national average and who are credit constrained. For these consumers the decision making process may have adjusted to the experience of high-cost/interest short-term credit, such as payday loans (Hirsch, 2013 and CMA, 2015). The experience of high premiums could have a dual impact, first, on the consumer's ability to smooth over income shortfalls and, second, on the consumer's expectations around the future prospect of being able to afford energy efficient goods and services. Empirical methods, and policy for that matter, could benefit by making a step towards recognising the disparate mechanisms underpinning consumer decision making as well as the impact of consumers' socio-economic backgrounds. We believe that this is a fertile ground for future research in this area.

Our findings are also relevant to the broader policy issue of consumer preferences for, and the supply of, impure public goods such as the reduction of environmental pollution. On the one hand, low-carbon, energy efficient goods exhibit several public characteristics, such as increasing energy supply security, reducing environmental degradation and pollution and creating innovation spill overs (Corradini et al., 2014; Ghisetti et al., 2015). On the other hand, the exclusivity of impure public goods brings about private gains associated with the adoption of energy saving and energy efficient technologies that range from the "warm glow" effect of the personal utility derived from the act of engaging, to the pecuniary private returns via savings and social signalling. As suggested by Cornes and Sandler (1984) and by Finus and Rubbelke (2013) among others, the presence of ancillary additional private benefits and the spillovers to the provision of a public good are complementary to achieving environmental targets.This paper has identified important behavioural biases that exert a negative effect on the attitudes towards impure public goods and this has important repercussion on the successful implementation of environmental policies. The underestimation of the size of the ancillary private benefits from the uptake of environmental technologies reduces not only the potential private benefits but also the societal benefit from energy efficient technologies, providing another useful insight for policy makers.

Of course, a potential limitation of this paper arises from the fact that the participants in the survey do not have to commit to making a real investment, a form of 'hypothetical bias' (Hensher, 2010), so that the participants may fail to translate their intentions into action, or 'incongruence' whereby plans are time-inconsistent (Pearce et al., 2003). Also, participants might not have been aware that deregulated district heating systems currently lock-in consumers, with lengthy contracts (up to 20 years), creating natural monopolies. As a result these systems have come under scrutiny by authorities in the UK (CMA, 2017) and Sweden (Söderholm and Wårell, 2011). Although these biases are alleviated in part by asking the participants to indicate their *strength of interest* in the energy efficient technology, the findings could be viewed as over optimistic about the decision to adopt DH. Despite these limitations, we believe that our results contribute to a deeper understanding of the interaction of economic and behavioural factors underlying a consumer's decision to invest in a technology with relatively high initial cost but long lasting economic benefits and expected durability.

To conclude, the results of our analysis indicate that both the classic perspective on the adoption of consumer technology, based on the implicit calculation of a discount rate, *and* the behavioural perspective, which considers the effect of inattention and heuristic decision-making, contribute to explaining the apparent reluctance to adopt energy efficient technologies by domestic consumers. For this reason policy interventions aimed at promoting higher levels of adoption may need to account for the different forms of consumer behaviour and develop appropriate measures to target different types of consumers.

Appendices

Appendix 1 Sample characteristics

Table A.1: Comparing the sample statistics against Birmingham and England

Variable	Sample			Birmingham, West Midlands and England		
	N	%	Median	Birmingham Median / %	England Median / %	West Midlands Median / %
*Income variables**						
Annual income	645		18462	25014	27500	
Annual Energy Costs†						
Annual gas bill	683		611.56		666.76	700.13
Demographic variables★						
ELDERLY	784	0.35		0.23	0.28	
SINGLE	784	0.21		0.42	0.34	
INACTIVE	784	0.36		0.36	0.30	
DEGREE	784	0.30		0.23	0.27	
TENANT	784	0.35		0.45	0.37	
Low-Income-High-Cost Indicator§						
LIHC	784	0.11			0.10	0.14
LILC	784	0.12			0.15	0.15
HIHC	784	0.22			0.40	0.41
HILC	784	0.23			0.35	0.29
UNDISCLOSED	784	0.33				

*Notes: *Source: ONS (2014); †Source: EHS (2014) ★Source: ONS (2011a; 2011b) §Source: EHS (2014)*

Table A.2 Variable definitions and labels

Variable name	Definition
CLASSICAL Vignette variables	
DH-BILL	Annual DH bill allocated to household (£100s).
INTERFACE	Upfront cost of DH HIU allocated to household (£100s).
INATTENTION variables	
1. Information acquisition and search method	
POSTAL INFO	Household prefers information to be sent by post.
INDIRECT INFO	Household prefers indirect information delivery.
INATTENTIVE INFO	Household prefers to remain inattentive at the time of the survey.
2. Inattentive to costs	
HIGH UNOBS COSTS	Household requires at least £300 reduction in annual energy bill to join a DH scheme (given upfront costs are zero).
INATTENTIVE COSTS	Household unsure/does not know reduction in annual energy bill required to join DH scheme (given upfront costs are zero).
HEURISTIC Variables	
Log (payback period)	
PBK Q2	Low-mid (2^{nd}) quartile of payback period.
PBK Q3	High-mid (3^{rd}) quartile of payback period.
PBK Q4	High (4^{th}) quartile of payback period.
NEG-SAVINGS	Current annual bill < district heating bill.
DONTKNOW COSTS	Household is unsure/does not know energy or maintenance costs.
CONTROL variables	
Low-Income-High Cost Indicator	
LIHC	Residual income < 60% of median income *and* annual energy expenditure > median.
LILC	Residual income < 60% of median income *and* annual energy expenditure <median.
HIHC	Residual income > 60% of median income *and* annual energy expenditure > median.
HILC	Residual income > 60% of median income *and* annual energy expenditure < median.
UNDISCLOSED	Household representative prefers not to disclose energy bills and/or annual income.
Demographic and housing variables	
INACTIVE	All household residents are unemployed, not sought work in the last 2 weeks and/or unavailable to work in the following 4 weeks.
SINGLE	Household representative's marital status is single.
ELDERLY	Household representative is aged over 60.
DEGREE	Highest educational attainment of the household is at least a degree qualification.
TENANT	Household does not own their property.
DAMP	At least one structural problem in the home e.g. damp, rot or leaky roof.
KNOWS-DH	Household representative has at least an 'average' understanding of DH schemes.

Appendix 2 Controls, diagnostic and specification checks

Table A.3: Estimated coefficients for the controls and cut-off points for Table 7

	Ordered probit coefficients					
	(1)	(2)	(3)	(4)	(5)	(6)
Experimental controls						
KNOWS-DH	-1.580	-1.810*	-1.735*	-1.938**	-0.129	-0.153
	(1.005)	(0.989)	(1.000)	(0.985)	(0.112)	(0.109)
KNOWS-DHxINTERFACE	0.0828	0.0957*	0.0907	0.102*		
	(0.0565)	(0.0555)	(0.0562)	(0.0553)		
Low income high cost indicator						
LIHC	-0.377**	-0.421***	-0.348**	-0.392**	-0.404**	-0.422***
	(0.166)	(0.162)	(0.165)	(0.162)	(0.165)	(0.161)
LILC	-0.0930	-0.222	-0.180	-0.303**	-0.119	-0.354**
	(0.164)	(0.159)	(0.156)	(0.152)	(0.163)	(0.151)
HILC	-0.0941	-0.126	-0.181	-0.206*	-0.0660	-0.206*
	(0.136)	(0.134)	(0.125)	(0.123)	(0.135)	(0.122)
UNDISCLOSED	-0.380***	-0.476***	-0.421***	-0.530***	-0.375***	-0.541***
	(0.124)	(0.120)	(0.113)	(0.110)	(0.123)	(0.110)
Demographic characteristics						
ACTIVE	0.232**	0.264***	0.243**	0.280***	0.206**	0.253***
	(0.101)	(0.0993)	(0.101)	(0.0987)	(0.101)	(0.0981)
SINGLE	-0.317***	-0.346***	-0.338***	-0.369***	-0.310***	-0.360***
	(0.104)	(0.101)	(0.102)	(0.100)	(0.103)	(0.0998)
ELDERLY	-0.185*	-0.298***	-0.196*	-0.308***	-0.175	-0.289***
	(0.109)	(0.105)	(0.108)	(0.105)	(0.108)	(0.104)
DEGREE	0.184*	0.193**	0.171*	0.183**	0.184**	0.180**
	(0.0941)	(0.0914)	(0.0935)	(0.0909)	(0.0937)	(0.0905)
DAMP	-0.191**	-0.202**	-0.207**	-0.220**	-0.202**	-0.239***
	(0.0898)	(0.0883)	(0.0893)	(0.0879)	(0.0892)	(0.0873)
CUT 1	-4.740***	-4.390***	-4.504***	-4.161***	-2.676***	-1.449***
	(0.860)	(0.838)	(0.852)	(0.829)	(0.241)	(0.174)
CUT 2	-4.094***	-3.811***	-3.867***	-3.590***	-2.036***	-0.886***
	(0.858)	(0.836)	(0.850)	(0.827)	(0.237)	(0.171)
CUT 3	-3.829***	-3.573***	-3.607***	-3.356***	-1.776***	-0.655***
	(0.857)	(0.835)	(0.849)	(0.826)	(0.235)	(0.170)
CUT 4	-1.913**	-1.789**	-1.718**	-1.597*	0.117	1.077***
	(0.850)	(0.830)	(0.842)	(0.822)	(0.227)	(0.173)

Notes: † *$p < 0.15$,* * *$p < 0.1$,* ** *$p < 0.05$,* *** *$p < 0.01$. Standard errors in parentheses.*

Table A.4: Estimated coefficients for the controls and cut-off points for Table 8

	Het. choice coefficients	Partial prop. coefficients
	(7)	(8)
Experimental controls		
KNOWS-DH	-1.387*	-1.568
	(0.801)	(1.009)
KNOWS-DHxINTERFACE	0.0720	0.0819
	(0.0450)	(0.0567)
Low income high cost indicator		
LIHC	-0.345**	-0.365**
	(0.150)	(0.167)
LILC	-0.0719	-0.0844
	(0.149)	(0.165)
HILC	-0.0431	-0.0788
	(0.126)	(0.137)
UNDISCLOSED	-0.329***	-0.209
	(0.106)	(0.134)
Demographic characteristics		
ACTIVE	0.223**	0.240**
	(0.0872)	(0.101)
SINGLE	-0.262***	-0.308***
	(0.0922)	(0.104)
ELDERLY	-0.134	-0.180*
	(0.0927)	(0.109)
DEGREE	0.173**	0.191**
	(0.0834)	(0.0946)
DAMP	-0.199**	-0.185**
	(0.0792)	(0.0901)
CUT 1	-4.252***	4.701***
	(0.747)	(0.860)
CUT 2	-3.684***	4.270***
	(0.741)	(0.859)
CUT 3	-3.454***	4.061***
	(0.738)	(0.859)
CUT 4	-1.733**	1.956**
	(0.728)	(0.850)

Notes: † *p < 0.15,* * *p < 0.1,* ** *p < 0.05,* *** *p < 0.01. Standard errors in parentheses.*

Table A.5 Estimated coefficients and implied discount rates for the 'decision to connect' to district heating using the behavioural specification, heterogeneous ordered probit and partial proportional ordered probit

	Het. choice coefficients		Partial prop. Coefficients
Model (m)	(5)		(6)
$\beta_{INTERFACE} / \beta_{DH\ BILL}$	0.334		0.389
	(0.219)		(0.250)
P-VALUE	0.129		0.120
IMPLIED DISCOUNT RATE	0.334		0.382
Experimental variables			
TENANT	-1.031		-1.476
	(0.852)		(0.987)
DH-BILL	-0.154***		-0.164**
	(0.0578)		(0.0684)
INTERFACE	-0.0514*		-0.0637*
	(0.0310)		(0.0357)
TENANTxDH-BILL	0.0503		0.0470
	(0.0367)		(0.0826)
TENANTxINTERFACE	0.0339		0.0682
	(0.0708)		(0.0425)
Inattention variables	Y		Y
Heuristics (years of payback)	Y		Y
Ln(σ):PBK-H	-0.418***		
	(0.132)		
Ln(σ):UNDISCLOSED	-0.191***		
	(0.073)		
Ln(σ):KNOWS-DHxINTERFACE	-0.010*		
	(0.006)		
γ_1: INATTENTIVE COSTS			-0.215**
			(0.096)
γ_1: UNDISCLOSED			-0.277***
			(0.095)
γ_2: INATTENTIVE COSTS			-0.314***
			(0.106)
γ_2: UNDISCLOSED			-0.326***
			(0.103)
Observations	784		784
Log-likelihood	-921.17		-919.66
Pseudo R^2	0.136		0.137
LR χ^2	289.34***		292.36***
LR χ^2(Ho: m=7,8 vs. m=1)	17.69***		20.70***
LR χ^2(Ho: m=7 vs. m=8)		3.02*	
AIC	1908.34		1907.32
BIC	2062.27		2065.91
Df	33		34
Residual Pr(Skewness)	0.832		
Residual Pr(Kurtosis)	0.502		
Residual Normal (p-value)	0.779		
Link test $x'\hat{\beta}^2$ (p-value)	0.708		

*Notes:, * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. See Table A.4 for controls and cut-off points.*

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