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Market failures and willingness to accept the smart energy transition: Experimental evidence from the UK*

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Abstract

To facilitate the sustainable energy transition, governments and innovators are encouraging households to adopt smart technologies that allow for increased flexibility in energy grids. The UK's ambitious smart metering policy has indisputably failed to achieve its objective of equipping all dwellings with smart meters. This research uses a novel experiment to elicit the willingness to accept of 2,430 nationally representative UK households for smart meter installation. Randomized information treatments allow for assessment of the impact on adoption and willingness to accept of oft-cited market failures, namely information asymmetries and 'learning-by-using' externalities. We explore treatment effects and identify non-additional policy expenditures for a range of potential subsidy programs.

Keywords: Energy technology adoption, non-market valuation, learning by using, information asymmetry, field experiment

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1 Introduction

Economists researching the intersection between consumer behavior and energy systems are increasingly recognizing the importance of technology adoption behaviors in achieving environmental policy and energy systems-level goals. Indeed, while some policies target households' recurring energy-wasting habits, other more persistent policies target infrequent one-off behaviors or decisions.[1] For instance, economists have studied the impact of energy and fuel efficiency of energy consuming durables on purchasing decisions, finding mixed evidence regarding consumer attentiveness (Allcott and Taubinsky, 2015; Fowlie et al., 2015; Houde and Myers, 2019).

New technologies may particularly suffer from low take-up rates due to consumers' unfamiliarity with the technology's use and the associated private or social benefits (Foster and Rosenzweig, 2010). The literature on the energy efficiency gap highlights such disincentives for early adoption and costs of asymmetric information (Jaffe and Stavins, 1994a; Gillingham and Palmer, 2014), though supportive evidence is scant. Crucially, whether and how a government should intervene depends on the drivers of low adoption, and whether such adoption levels are inefficient (Jaffe and Stavins, 1994b).

This research contributes experimental evidence regarding the import of oft-cited market failures by studying the case of a relatively new technology—the smart electricity meter—in the context of an unprecedented UK-wide government-led public participation campaign. The smart meter, an internet-connected two-way communication device, boasts purported producer and consumer benefits stemming from its ability to measure site-specific energy consumption in real time. On the producer side, the benefits of widespread adoption are clear. For instance, real-time information enables immediate detection of distribution-level outages, expands the suite of tools for efficient matching of energy supply with demand over time and space, improves predictions regarding requisite energy capacity at various times of the day and year, eliminates the need for manual meter readings, and provides an opportunity to incentivize demand shifts to minimize system-level costs (Borenstein et al., 2002; Joskow, 2012; Harding and Sexton, 2017).

On the consumer side, the benefits are less clear. First, while smart meters equip consumers with information necessary to match energy-consuming behaviors to actual usage, evidence is mixed regarding the propensity of households to engage with the information to successfully reduce costs (Faruqui et al., 2010; National Audit Office, 2018). Second, costs—such as time off work to accommodate installers, and learning about the new technology—are certain and borne upfront, while a greater proportion of the benefits—such as system-level savings pass-through or energy bill savings from investments, shifting habits, or anticipated rate plan offerings—are uncertain and accrue in the future.[2] Third,

[1] To illustrate the significance of such one-off decisions, the UK Government estimated the potential energy savings from fully transitioning the stock of UK home appliances—in this case, dishwashers, washing machines, and televisions—to those with the minimum-viable EU standards, claiming a dramatic savings of 2930 GWh (about 3% of total residential energy consumption) per year by 2030 (BEIS, 2014).

[2] Recent evidence using smart meter data has demonstrated a 'timing premium' corresponding to a 40% value increase relative to previous estimates for investments in efficient residential air conditioners (Boomhower and Davis, 2020), highlighting the value of smart metering for our understanding of energy system dynamics and for consumers' ability to internalize the benefits of energy efficiency investments and behaviors, particularly under varying energy rates (Novan and Smith, 2018; Martin and Rivers, 2018). Indeed, one potential benefit of smart metering is the deployment of time-of-use (TOU) tariffs that create incentives for load shifting; when this research was undertaken, only two small suppliers were offering TOU tariffs (National Audit Office, 2018). According to Ofgem, as of October 2020, less than 0.2% of customer accounts were on TOU tariffs.

while a smart meter allows for monthly bill payments commensurate with actual usage, consumers may prefer to pay a fixed monthly fee for simplicity, budgeting, and consumption smoothing purposes, or may have no interest in the additional information.[3]

Yet, widespread smart energy technology adoption holds promise to considerably improve environmental outcomes through increased energy production efficiency—reducing overall energy production and greenhouse gas emissions—and flexibility—lowering the risk of blackouts and facilitating the integration of higher proportions of renewable energy into a given system's energy portfolio. Results of extensive cost-benefit analyses from 2012 to 2019 have consistently suggested that the environmental and financial savings far outweigh the costs of rapid transition to a smart energy system in the UK (UK CBA, 2019).[4] Having instated the Smart Meter Implementation Programme (SMIP) in 2013, providing the legal framework to install 48 million smart electricity and gas meters in UK households by 2020, the UK Government has failed to achieve this smart energy transition, with only 17.3 million meters operating by the end of Q1 2020 due in large part to consumer reticence and resistance (BEIS Report, Q1 2020). Indeed, wide-reaching energy policies that depend on consumer adoption frequently underdeliver (e.g., the Weatherization Assistance Program in the US, the Green New Deal in the UK). In this case, how can a social planner understand and quantify the extent of acceptance or resistance to the technology in question, and subsequently encourage adoption among reluctant or ambivalent consumers?

We develop an incentive compatible online experiment to elicit a large and representative panel of UK households' willingness to accept compensation (WTA) for smart meter installation following exposure to various treatments designed to overcome two prevalent market failures in energy technology adoption: imperfect information and learning-by-using externalities. [5] We elicit two primary outcome variables conditional on treatment received, namely (i) whether the household is willing to adopt without compensation, and (ii) the subsidy level necessary for non-adopting households to become willing to adopt, using the Becker-DeGroot-Marschak (BDM) method. From these responses, we measure the significance of private information, social information, and learning-by-using externalities in determining willingness to adopt and infer adoption rates at multiple subsidy levels.

The results suggest that £10, £50, and £75 subsidies would induce additional adoption of 4, 24, and 34 percentage points from a baseline of 22% adoption without a subsidy. Pairing these subsidies with a social benefits information campaign enhances these effects by 4.2, 4.9, and 6.6 percentage points ($p<0.05$), respectively, effectively doubling the impact of the £10 incentive and contributing an additional 20% of the impact of the £50 and £75 incentives. Our evidence suggests that neither a private benefits campaign (mirroring

[3]Evidence shows that consumers respond more to average rather than marginal pricing due to burdensome cognitive effort (Ito, 2014), and they increase energy use when enrolled in automatic bill payment, indicating that they do not take an active interest in their energy use (Sexton, 2015).

[4]Past UK cost-benefit analyses of smart meter rollout do not take into account a number of non-monetary costs. Several relevant actors—including the UK's National Audit Office, the media, and interest groups—have expressed concerns relating to data security and privacy, consumer vulnerability, and consumer resistance and ambivalence, among others (Sovacool et al., 2017). Indeed, the literature suggests consumer resistance may arise along a number of dimensions, such as privacy (McKenna et al., 2012), financial costs (Balta-Ozkan et al., 2013), hidden costs (Gillingham and Palmer, 2014; Fowlie et al., 2015), or general disengagement with or distrust in utilities (Central Market Authority, 2016).

[5]We partnered with the UK electricity and gas regulator (Ofgem) to enroll respondents in their utility's smart meter installation program should they opt to receive one. Of households who agree to adopt, 14% provide all information necessary for us to enroll them. We are unconcerned that the observed conversion rate diminishes incentive compatibility for several reasons outlined in detail in Section 2.2.3.

the policy approach to date) nor a campaign focused on societal learning and resultant technological improvements influences adoption rates.[6]

Our research contributes to several relevant literatures, in particular those on non-market valuation, the energy efficiency gap, optimal subsidy design, and households' acceptance of publicly beneficial smart technologies. Methodologically, our work has parallels with Allcott and Taubinsky (2013), who combine a randomized information treatment with a choice experiment to elicit demand for energy-efficient light bulbs in the US, and Berry et al. (2020), who combine randomized anchoring and strategic decision-making prompts in a BDM willingness-to-pay (WTP) valuation for clean water technology adoption in Ghana. The primary methodological novelties of this research include the use of BDM to elicit WTA, and the application of the latter methodology—i.e., randomized treatments combined with BDM valuation—in a developed country and real-world policy context. Our research shares contextual similarities with List et al. (2018), who conduct a natural field experiment on smart meter adoption incentives in the UK.[7]

Furthermore, we generalize the work of Boomhower and Davis (2014) by quantifying the cost of inframarginal participants across the entire potential subsidy distribution, providing a more thorough consideration of the optimal level of subsidy required. Expanding upon their work, we also introduce the concept of *non-additional subsidy payouts*, the policy costs that exceed the willingness to accept compensation of subsidy recipients, as an important consideration for policymakers seeking to encourage energy technology adoption. Critically, non-additional subsidy payouts associated with inframarginal consumers dominate the cost of any subsidy program in our context, ranging from 53% to 83% of total costs.

Finally, we add to a growing literature on the public acceptability of smart grid infrastructure and related technologies widely accepted as necessary to enable many countries' sustainable energy transitions (Fell et al., 2015; Spence et al., 2015; Bigerna et al. 2016; Sovacool et al., 2017; Chen et al., 2020). While the focus of this research is smart meter adoption in the UK, resistance to metering infrastructure rollout has occurred across Europe, in countries such as Portugal (Chawla et al., 2020), France (Chamaret et al., 2020), and Ireland (Quinn et al., 2016). The wider context of our research is in examining consumer resistance to state interventions promoting adoption of new technologies that may improve societal welfare on aggregate but hold uncertain costs and benefits for the individual. Consumer acceptance and adoption behaviors are becoming increasingly critical in the decarbonization of global energy consumption through, for example, electrification and adoption of smart technologies, utility's green tariff and demand response programs, and low-carbon heating systems (Scott and Powells, 2020). The methods we have developed and applied in this research can be used to assess non-market costs and policy or program (cost) effectiveness for a wide range of such policy interventions.

The remainder of this paper is structured as follows. The next section provides details of the experimental and valuation methodologies deployed. The third section details the data collection process and provides summary statistics for the data collected. The fourth section outlines our empirical strategy and results. The fifth section explores policy and welfare implications. The final section concludes.

[6]This result is in contrast to Bollinger et al. (2020) who find that self-interested messaging outperforms pro-social messaging in the adoption of solar panels.

[7]While List et al. (2018) trialed incentives of £5 and £10 with one large UK utility, our use of a BDM mechanism allows for estimation of impacts for a wide range of potential incentives and their interactions with treatment exposure for customers of the 11 largest utilities in the UK.

2 Methodology

Our research aim is to quantify the importance of several identified market failures that serve as rational barriers to adoption of welfare-enhancing energy technology in the home (Gillingham and Palmer, 2014). Of the five proposed barriers, three may hold relevance in the case of smart meter adoption, namely imperfect information, learning by using, and regulatory policies that fail to match energy prices to their true marginal (social) cost.[8] Given constraints on varying the latter, we designed three interventions that target potential information asymmetries regarding expected personal and social benefits of smart meter adoption as well as information regarding accumulated positive 'learning-by-using' externalities.[9] We did so using a survey experiment to capture adoption behavior and willingness to accept compensation for non-adopters, as described below.

2.1 Conceptual Framework

Eliciting precise willingness to accept (WTA) using the BDM method permits construction of a demand curve for the good in question. Given we estimated WTA rather than willingness-to-pay, the prices in our demand curve are negative.[10] In line with Boomhower and Davis (2014; 'BD' hereafter), we conduct a cost efficiency and welfare analysis for several discrete subsidy values. We define *non-additional subsidy payouts* to be the additional amount the government would have to pay relative to the next lowest subsidy value considered. Whereas BD observe marginal adoption behavior at two discontinuities—i.e. two subsidy values tied to assigned eligibility thresholds for the purchase of energy-efficient refrigerators and air conditioners in Mexico—our methodology elicits WTA for smart meters at each point along the demand curve, allowing us to empirically estimate the latter. Figure 1 provides a graphical illustration.

[Figure 1 here]

[8]Note that a fourth market failure—(misperceived) principal-agent issues—may also play a role here if tenants do not realize that they do not need their landlords' permission to adopt a smart meter in their rental property. This issues does not appear to be significant, as only seven of the 791 respondents cited landlord/tenant issues when asked to provide information on factors influencing their choice of WTA. Moreover, such split incentives have been shown to lead to relatively small inefficiencies in residential energy contexts (Gillingham et al., 2012). The fifth market failure identified in Gillingham and Palmer (2014)—credit and liquidity constraints—does not apply here, though a somewhat similar study using BDM to assess the WTP for energy efficient cookstoves in Ghana finds that alleviating credit constraints doubles WTP in their context (Berkouwer and Dean, 2019).

[9]There are a number of social-psychological theories that highlight the importance of self-interest (e.g., Technology Acceptance Model, Theory of Reasoned Action) or of concern for society and/or the environment (e.g., Norm Activation Model) in determining technology adoption. Ease of use and ability to achieve a personal goal—such as saving money on energy bills—characterize the former, while the latter posits that personal norms and moral obligation drive decisions to adopt. While our social information intervention can be seen as targeting the latter, the private information and learning-by-using treatments may be seen as compatible with the former. Structural equation modeling using attitudinal surveys have demonstrated both to be important to smart meter adoption in Europe (Toft et al., 2014); empirical and experimental research have demonstrated the importance of prosocial motivation in reducing residential energy use (Asensio and Delmas, 2015; Pratt and Erickson, 2020).

[10]We provide a discussion of the relevant costs and benefits in Section 1. As outlined in Section 3.1 we focus our analysis on those households who do not have nor have been offered a smart meter. Individuals who place a positive value on smart meter adoption are likely to have already adopted, but will also be included amongst those participants willing to adopt without compensation.

The figure shows a demand curve in the negative price space with a supply curve initially at $p = 0$. The offer of a subsidy shifts the 'price' of adoption from p_0 to p_s, thereby increasing demand for the technology from q_0 to q_s. The non-shaded area therefore represents the amount of money a social planner pays in excess of what would be necessary under perfect price discrimination. We develop a methodology below that allows us to quantify this non-additional subsidy payout by empirically revealing the demand curve and considering a continuous range of possible subsidy values.

2.2 Experimental Design

We designed a survey experiment using Qualtrics survey software in which eligible household energy decision-makers receive an offer to adopt a smart meter following treatment exposure. Those who declined subsequently performed a WTA elicitation exercise to determine the subsidy value at which they would be willing to adopt. The exercise is incentive compatible in that we told respondents they would receive a payout equal to our randomly selected subsidy offer if our offer exceeded their stated WTA in return for their agreement to receive a smart meter. Individuals who provided sufficient electricity account information then received a versatile digital gift card for the offered subsidy amount, and we shared their details with the UK's energy regulator (Ofgem), who liaised with the smart metering teams of participants' energy suppliers to sign them up for installation. Figure 2 provides an overview of the survey layout, and the remainder of this subsection provides details and design considerations with respect to the most important elements of the survey experiment.

[Figure 2 here]

2.2.1 Treatments and Smart Meter Offer

Early in the survey, participants received basic information regarding smart meters (see Figure 3) prior to treatment exposure for two reasons: (i) to verify that they did not already have and had not yet been offered a smart meter (as part of the eligibility criteria), and (ii) to ensure they shared a base level of understanding regarding the good in question.

[Figure 3 here]

Once we confirmed eligibility, the participant viewed one of four randomly selected[11] information conditions for a minimum of fifteen seconds: (i) extraneous information on the structure of the energy system (Control); (ii) information on the private benefits of smart meter adoption (Treatment 1)[12]; (iii) information on the social benefits of smart meter

[11] Due to lack of pre-experimental data on participants, we did not stratify the randomization but instead used the Qualtrics *Randomizer* tool to randomly assign individuals who take the survey to receive one of the above four conditions. When we reached 2000 responses we then adjusted the (treatment) quotas to achieve balance across observable characteristics in our treatment assignments as well as national representativeness in our sample to the best of our ability (see Table A1).

[12] Our information regarding private benefits is modeled off of that which had been used in the SMIP rollout at the time of our study, focusing on the purported household-level monetary savings resulting from the Department for Business, Energy, and Industrial Strategy's modeling. While the private benefits depend heavily on consumer attentiveness, investments, and bill switching, these conditions were rarely included in Smart Energy

adoption (Treatment 2); and (iv) information on accumulated learning from the first six years of the UK's smart meter rollout, to which the technology and the energy system have adapted substantially (Treatment 3). We complemented the latter treatment with a dynamic norm to demonstrate that the technology is well past the 'early adoption' stage. The four conditions are presented in Figure 4.

[Figure 4 here]

Immediately following treatment exposure, we asked participants whether they would like to adopt a smart meter.[13] Those who said "yes" subsequently provided us with sociodemographic and attitudinal information, and then were asked to supply the account information necessary for us to sign them up to receive a smart meter through Ofgem. Critically, these participants were unaware and had no reason to believe that having said "no" to the initial smart meter installation offer would have led to an opportunity to receive an adoption incentive. Those who declined to have a smart meter installed at this stage continue on to a WTA elicitation exercise to gauge whether they may be inclined to receive a smart meter under a plausible subsidy scheme.

2.2.2 WTA Elicitation

Valuation methods. Environmental economists have designed a range of tools to recover the total valuation of non-market goods (or goods with non-market attributes; Carson et al., 2001). Due to issues surrounding hypothetical bias (Cummings et al., 1995, 1997) and consequentiality (Cummings and Taylor, 1998; Landry and List, 2007), we immediately narrow our focus toward two incentive compatible value elicitation methods. One simple method—'take-it-or-leave-it' (TIOLI)—asks respondents whether they will buy or sell a good or service at a given price, where the researchers generally vary the price to back out an implicit demand curve. TIOLI boasts an obvious benefit of comprehensibility. Its resemblance to familiar and routine market exchanges that consumers make in their daily lives all but ensures that researchers will elicit a true and unbiased response from their subjects. Yet, unless followed up with several (theoretically infinite) subsequent questions, the method suffers from imprecision: we do not obtain an exact data point for a given respondent to reflect his/her true WTA using the TIOLI method.

To overcome the issue of relatively limited information provided by each respondent, which demands a very large sample size to infer a demand curve, the Becker-DeGroot-Marschak (BDM) method directly elicits an exact WTA—i.e. a single 'selling price'—using a second-price auction against an unknown bidder, thereby circumventing the requisite iterative process of the TIOLI method. In accordance with the theory set out in Becker et al. (1964), surveyors can elicit a true and exact WTA from a respondent by offering

GB's marketing. Hence, our intervention allows for comparison of the status quo strategy with no strategy at all (Control), as well as with strategies focused on messaging around social benefits and learning-by-using externalities. Having a smart meter installed did not default customers into dynamic or time-of-use tariffs; customers remained on the same energy tariff, but gained the ability to monitor their energy use with the mandatory in-home display provided at the time of installation.

[13] Unlike Allcott and Taubinsky (2015), we did not elicit WTA prior to (in addition to following) treatment for two reasons: (i) our first outcome variable of interest is whether the individual adopts a smart meter without compensation and those who do so have a non-positive WTA, and (ii) we conjectured that eliciting the outcome variable on either side of treatment exposure may lead to (enhanced) experimenter effects. Therefore, our analysis will be restricted to a between-subject treatment comparison.

to pay an unknown (and, in our case, double blind) amount b—the researchers' 'buying price'—in the event that the latter exceeds the former. Given the unknown value of b, a rational seller (i.e. survey respondent) cognitively engages in an iterative TIOLI process, assessing their willingness to accept b in exchange for the good or service for every possible value that b could take, thereby ultimately identifying and stating their true selling price.

As highlighted in Berry et al. (2020), TIOLI can be quite impractical if there is a wide range of prices over which the researcher aims to understand WTA. From an ex ante research perspective, consumers' willingness to accept compensation for installing a smart meter is highly uncertain and the private costs associated with installation vary immensely across individuals, so the variance of true WTAs is potentially substantial. Moreover, it is possible that there is an interaction effect between WTA and treatment exposure. In other words, if a researcher is interested in the impact of various treatments on WTA and only one or two prices are offered as part of a TIOLI exercise, then the researcher can only identify the treatment effect at the offered TIOLI price levels. Therefore, without the assumption of a constant treatment effect, TIOLI could preclude identification of a treatment effect when one indeed exists for price points excluded from the TIOLI exercise. Finally, if compensation received could be a predictor of subsequent behaviors—e.g., in our case, actual smart meter installation, which we explore in section 2.2.3—then BDM offers the variation in compensation necessary to tease out such an effect.

The contextual features of the service we aim to value more closely reflect those that favor BDM rather than TIOLI. Specifically, the range of individuals' true WTA is likely wide, and lack of a well-established market for provision of this service means that individuals will have little prior experience of prices to anchor their valuations. Moreover, we are indeed interested in heterogeneous treatment effects, so BDM provides us with the nuance necessary to tease out these effects with a reasonable sample size. Finally, Berry et al. find that their BDM and TIOLI demand models predict out-of-sample TIOLI decisions with similar accuracy. We therefore performed a BDM exercise to elicit WTA for individuals who could demonstrate comprehension via a 'test of understanding' (see Appendix A.1.2), and presented a TIOLI offer of £10 to those who did not pass this test.[14]

Design considerations. Apart from BDM's lower comprehensibility relative to TIOLI, some methodological difficulties are worth noting. Foremost, and particularly in the case of missing or unfamiliar markets, the appropriate buying price range is both difficult to identify and could even influence survey responses if mentioned explicitly. Simultaneously, without such a range to anchor respondents' selling prices, the surveyor risks extracting valuations that are perhaps unreasonable or infeasible to pay out.[15]

[14] We selected the TIOLI offer of £10 to replicate the findings of List et al. (2018), the only field experiment to our knowledge to have incentivized adoption of smart meters in the UK, which we discuss in section 2.2.3.

[15] To understand the implications of various solutions to this issue for the valuation of a familiar commodity—here, subjects were endowed with a voucher for gasoline—Bohm et al. (1997) conducted an experiment in which they compared mean selling prices elicited using the BDM to those in a real market setting. In addition to sensitivity of responses to varying levels of the upper bound of the buying price, they found that an upper bound on the buying price equal to either the actual market price of the good or an unspecified value described as 'the maximum price we believe any real buyer would be willing to pay' leads to valuations no different from the experimental market price; when this text is omitted, or when the upper bound is set above the market price, the selling price significantly exceeds the market price. In valuing travel mugs, Mazar et al. (2014) also demonstrated that valuations elicited using BDM can be influenced by the distribution of prices offered. Similarly, Vassilopoulos et al. (2018) identified an anchoring effect of the buying price range when selling mugs,

In the absence of a market price on which to anchor our subjects—or on which subjects' prior experience may anchor their valuations in the absence of a researcher-induced anchor—we designed a pilot survey to determine whether an anchoring effect existed in our BDM context.[16] Specifically, in delimiting the potential buying price, we tested three designs—a £50 maximum, a £100 maximum, and an unstated maximum—under the control condition. We found that making the range explicit significantly suppressed valuations and concentrated them near the maximum of the range.[17]

We therefore elected to leave the maximum of the range open-ended while using subtle cheap talk and anchoring techniques to channel WTA toward values well within the underlying offer range of (£0, £100].[18] With regard to the former technique, we explained in our instructions that energy companies have provided incentives of £5, £10, and £50 as an example.[19] To anchor, we ensured that all examples in the 'test of understanding' for both bids and offers fell in the range of (£0, £100], and that these values were randomized to ensure we did not anchor on specific values. This procedure generated a uniform distribution of offer values the details of which can be found in Appendix A.4

Additionally, as with all stated valuation research, misleading responses can significantly influence mean valuations. As noted in Boyle (2017), there are three types of misleading responses, all of which are difficult to detect and pose issues for stated valuation research. First, protest responses—generally $0 responses for willingness-to-pay studies and very high responses for willingness to accept studies—represent a reaction against the contingent valuation mechanism itself. Left unaddressed, such responses tend to bias the mean valuation downward for the former and upward for the latter. Comprehension represents a second issue; if respondents do not fully grasp the valuation mechanism, responses may not be meaningful or accurate. While this issue introduces a type of measurement error, it does not necessarily introduce bias in a particular direction.

Third, strategic responses aim to influence the underlying policy that is being valued in a particular direction, and can introduce bias in either direction if strategic respondents overwhelmingly tend to (dis-)favor the policy. Given that Boyle (2017) does not discuss the 'willingness to accept' framework explicitly, we add a second type of strategic behavior that could arise in our context. Specifically, participants may try to 'game the system', in our case by taking the survey multiple times and trying to guess at a value that would

and Sugden et al. (2013) found an anchoring effect of both the buying and selling price range for several goods whose market value is £5.

[16] The technology for which they must state a WTA—the smart meter—has been widely promoted by the UK Government and therefore respondents may perceive compensation as a type of subsidy for providing a public good. While various supplier incentives have been trialed with small customer samples in the UK, most energy decision-makers will be unaware of these offers, and offers may have varied both within and across suppliers. Moreover, most of these trials are commercially sensitive, so the incentives offered remain unknown; a published trial performed in partnership with British Gas reveals that £5 and £10 incentives have been trialed at the low end (List et al., 2018), though we are anecdotally aware of some suppliers having offered up to £50 incentives.

[17] This question was experimentally tested during the pilot phase. Results are available on request.

[18] Note that due to budget constraints we lowered the offer range to £0-£50 halfway through the trial period.

[19] Survey text: "Given your answer to the [smart meter offer] question, we'd like to see what it might take to change your mind about getting a smart meter. Think of it this way — if someone said they would pay you to have a smart meter installed in your home, how much money would you ask for? This research project is about answering this question. In the past, various energy companies in the UK have offered a range of incentives for customers to adopt smart meters (for example, £5 or £10 in club card points, or £50 off your next bill, and so on). It appears that some customers will sign up to get a smart meter only if given the right incentive. We're interested in learning what that 'right incentive' might be for you, if any."

give them money in return for installing a smart meter. We identified all survey response duplicates (of which there were 109) by name, IP address, and the email address they provided, and removed these responses from the data.

We aimed to attenuate the above concerns and measure biases via two channels: in-depth comprehension tests as well as both closed- and open-ended questions regarding the respondents' rationales for their selections. First, the test of understanding—which followed extensive BDM instructions (see Appendix A.1.1)—involved a set of three questions with randomly determined 'bid prices' (i.e. WTA values) and 'offers' for which the respondent must determine the outcome (i.e., whether and how much money would be transferred to the respondent in return for his/her signing up to receive a smart meter). The participant was tasked to correctly identify the answers to all three questions on the screen (see Appendix A.1.2), and if they missed one or more they could make a second and a third attempt. If there were any errors on the third attempt, they were provided a TIOLI offer and did not participate in the BDM exercise (see Figure 2). We also captured a weak measure of comprehensibility directly following the instructions in which we asked the respondent to indicate whether they felt they understood the instructions.

Second, we asked two specific questions regarding individuals' rationale for having denied a smart meter and selected a particular WTA value.[20] The first question was a multiple-response multiple choice question in which respondents checked any box that aligned with their reasoning for declining the smart meter offer. Responses included (i) 'privacy/security concerns', (ii) 'too much hassle', (iii) 'health concerns', (iv) 'I do not think I will save energy/money', (v) 'I do not trust my energy supplier'; and (vi) 'Other (please specify)'. The open-ended question simply asked the respondent just following their input of WTA (i.e. on the same screen) to 'Please let us know why you've chosen this amount.' The question is optional, though 38% of individuals provided a response. Finally, an open-ended question at the end of the survey allows respondents to provide any additional comments or feedback on the survey, and some provided information related to the above from which we can glean further information. An additional 32% of individuals provided information related to their choice of WTA.

2.2.3 Incentive compatibility

To avoid hypothetical bias and maximize incentive compatibility, we collaborated with the UK electricity and natural gas regulator, Ofgem, so that we could actually enroll respondents to receive a smart meter if they were promised one in the survey. We made clear to respondents that all decisions were incentive compatible in this way.[21] Individuals who expressed that they would like a smart meter (with or without compensation from the BDM or TIOLI exercises) were subsequently asked to provide their electricity account details so that we could pass them along to their respective suppliers. This step required extensive information in order to ensure that each of the 11 utilities could identify the individual in their respective customer databases. Specifically, to receive the meter, individuals had to

[20] Fowlie et al. (2015) demonstrated evidence of non-monetary costs for energy-efficient home upgrades. We explore such costs to provide evidence on the relative importance of various barriers in Appendix A.4 and A.6.

[21] Prior to explaining the BDM exercise, we state, "To make things realistic, we'll use our research funding to give you a chance to state your price and actually be paid in exchange for signing up to get a smart meter installed." We then provide a detailed explanation of the BDM process and administer a test of understanding. Just before the respondent states their WTA, we emphasize,"Please remember that we will use our research funds to pay all participants whose bid price is less than our offer."

provide their first and last names, postcode, email address, electricity account number, and Meter Point Administration Number (or MPAN), which features on most electricity bills and can be found on one's meter.[22] Those who agreed to get the smart meter via the BDM or TIOLI mechanism who also provided complete account information received Tango Gift Card e-vouchers redeemable at a large number of global and UK-specific (online) retailers, restaurants, ride-share services, and the like.

Of those who indicated willingness to adopt a smart meter, 14% followed through and provided the research team with sufficiently complete information to sign them up, including 62/368 (16.8%) affirmative smart meter offer respondents, 29/246 (11.8%) BDM 'winners', and 2/46 (4.3%) affirmative TIOLI respondents. Despite our efforts to stress the non-hypothetical nature of the exercise to participants, one might have concerns that the BDM methodology we use is only incentive compatible when respondents commit to the offer. Given the low conversion rate, there is a possibility that participants are understating their true WTA.

While we cannot entirely rule out this possibility, we maintain that the exercise is incentive compatible for several reasons. First and foremost, individuals committed to their responses prior to being informed that they would need to provide both their MPAN and electricity account numbers, a 'hassle cost' that is not characteristic of the regular sign-up process and that we therefore did not wish to capture in participants' valuations. Second, we find no differences across the sample of individuals who did not provide complete information and those who did across a number of relevant dimensions, including the difference between our offer and the respondent's WTA (£26.64 vs. £25.89, t-test, p=0.86) and the offer itself (£57.5 vs £59.3, t-test, p=0.73).[23] Treatment received and survey duration also do not have a significant impact on account information provision (see Table A7).

Third, to further rule out hypothetical bias or strategic behavior, we thoroughly investigate participants' motivations through their stated reasons for choosing their WTA values. Examining open-ended responses we categorize 53 "detailed" reasons which are further aggregated into 14 overarching categories (details in Appendix A.4.2). We then undertake sensitivity analysis removing suspected miscomprehension, strategic behavior, and anchoring, and despite a reduction in sample size the results remain intact (and, in fact, are even more statistically significant).

In short, we attribute the observed follow-through rate in no small part to the large amount of inconvenient or unfamiliar (i.e. electricity account number and MPAN) information, in addition to personally identifiable information, necessary to adopt the meter through the research. Conventionally, households sign up for a smart meter directly through their energy supplier, who provide several convenient and secure channels for opting in (e.g., email links and phone calls) with a simple click of a button or affirmative verbal response.

[22]Individuals could provide this information directly in the survey or could opt to receive a follow-up email with the same short form, which we asked them to fill within two weeks. Unfortunately we do not observe whether the individuals who did not provide information neglected to do so due to the amount of information required or due to indifference toward receiving the meter, and we do not observe whether they instead asked their supplier for a smart meter directly.

[23]A comparison of full distributions strongly supports this finding; see Appendix A.4.3.

2.3 Empirical Strategy

We consider two primary outcome variables of interest. The first is a binary measure that captures whether participants state that they are willing to adopt a smart meter without compensation after having viewed the randomized information provided. We estimate a linear probability model using OLS regression, which we specify as follows:

$$Adopt_i = \beta T_i + \gamma X_i + \epsilon \tag{1}$$

where T_i is the treatment group assignment of individual i, X_i is a vector of observable individual characteristics, and ϵ is a random error term. As outlined previously, the BDM works by allowing individuals who do not wish to adopt a smart meter without compensation to select a value that they would be willing to accept as compensation for having a smart meter installed in their homes, and their WTA can take on any positive value.

We perform a distributional analysis in line with the recommendation of Angrist and Pischke (2008) that considers the treatment effects at various subsidy values defined at relevant mass points in our data (see Figure 6). That is, in light of the selection bias that arises in the 'conditional-on-positive' effect of a two-part model, we define our dependent variable not as a continuous left-censored dependent variable WTA_i, but rather as a binary participation variable at various possible subsidy levels c:

$$[WTA_i \leq c] = \beta T_i + \gamma X_i + \epsilon \tag{2}$$

where T_i , X_i, and ϵ are as defined above.[24]

3 Data

3.1 Composition of sample

The study sample comprises adult (18+) UK residents whose characteristics reflect those of the national population, screening to ensure that respondents neither have smart meters installed in their homes nor have been offered smart meters by their energy provider. The panel was recruited via Qualtrics Research Services.[25] Sample quotas for gender, age, education, and region were set to match those of the UK population at large.

Our sample consists of 2,430 household electricity decision-makers.[26] The sample differs from the population only to the extent that they have agreed to take part in survey

[24] Note that we do not use a Tobit model, as indicated in our pre-registry, due to concerns over selection bias.

[25] Respondents are sourced from a variety of methods including the following: ads and promotions across various digital networks, search, word of mouth and membership referrals, social networks, online and mobile games, affiliate marketing, banner ads, offerwalls, television and radio ads, and offline recruitment with mail campaigns. Typically, respondents can choose to join a panel through a double opt-in process. Upon registration, they enter some basic data about themselves, including demographic information, hobbies, interests, etc. Based on this information they will be invited to take part in certain surveys. At the time of enrollment, it is made clear that the panel is for research-only purposes and that this is not part of a sales process. Survey invitations provide only basic links and information that is non-leading. Panelists are rewarded for taking part in surveys according to a structured incentive scheme, with the incentive amount offered for a survey determined by the length of survey and nature of the sample. Panelists have the option to unsubscribe at any time.

[26] We provide additional information on sample size calculations in Appendix A.2. Of this sample, 608 were exposed to Control, 608 to Treatment 1, 609 to Treatment 2, and 605 to Treatment 3.

research as part of a panel. Columns 1-5 of Table A1 provide a comparison of our sample to the national population. It is broadly representative along observable dimensions including gender, age, education, income, and region, with a few caveats: younger (18-24) and older (55 and above) age categories are slightly under-represented in our sample, while degree holders and individuals with A-levels and GCSEs are over-represented. One education category, "Other vocational qualification / Foreign qualification", is significantly under-represented (though balanced across treatments).[27] Region of residence is broadly representative across ten categories of Government Office region, including Scotland and Wales. While not forming part of the quota, we also present a comparison of income. Higher income households (above £45k per year) are slightly over-represented, while some lower income categories (£16-19k per year) are under-represented.

Columns 6-8 of Table A1 report p-values for tests of the difference in the mean of each variable for all control-treatment pairs. Given random assignment of treatment we observe that all groups are largely balanced. We observe a slight imbalance for some of our regional variables, notably London (14% of Control sample, 11% of Treatment 2 sample, p<0.05). An F-test for joint orthogonality of all variables, also reported in Table A1, results in an insignificant p-value. Taken together, the results suggest that the pattern of observed differences is likely due to sampling variation in the random assignment of treatment. However, for robustness we include baseline control variables in our main specifications.

3.2 BDM Comprehension and WTA Data Quality

Of the 2,430 respondents, 2,062 indicated that they did not want a free smart meter when asked and therefore were exposed to the BDM valuation exercise. After providing extensive instructions, we asked whether respondents felt confident they understood the exercise, and 93.15% of the 2,058 responses answered in the affirmative (five did not respond). Even so, 41.0% (n=846) of the 2,062 respondents who did not want a smart meter without compensation passed the test of understanding without failing, while 20.5% (n=423) and 3.7% (n=76) passed after failing on the first and second attempts, respectively, for an overall success rate of 65.2%. The final 34.8% (n=718) did not pass any of the three attempts and were then asked the TIOLI question, to which 42 individuals (5.96% of TIOLI respondents) responded in the affirmative and 13 did not provide a response.[28] Finally, three individuals who passed the comprehension test neglected to provide a WTA. Table 2 summarizes.

[Table 2 here]

Given that 35% of individuals who declined the smart meter offer failed the comprehension test, it is important to understand for whom we are measuring WTA. Table 3 reports the results of a linear probability model where we regress self-reported BDM understanding

[27] The disparity is possibly due to a lower number of non-UK nationals participating in the survey, but also potentially attributable to some confusion among participants in answering this question, which would also partly explain the over-representation on other education categories.

[28] Individuals who reported being confident that they understood the exercise prior to the test of understanding were significantly more likely to pass the test. A χ^2-test of two binary indicators of self-reported understanding and passing the test is significant (p=0.000, χ^2=90.9), and a basic regression of the number of failed test-of-understanding rounds on the self-reported understanding indicator shows that self-reported comprehension lowers the number of failed rounds by 1.1 (p=0.000). Still, 32.0% of those who self-report understanding the exercise ultimately fail, compared to 71.6% of those who self-report a lack of comprehension.

and comprehension test failure on treatment and several socio-demographic characteristics, namely gender, welfare status, region, supplier, employment status, renting status, income, and education. The results suggest that education significantly increases self-reported understanding and decreases comprehension test failure, while being a recipient of welfare benefits and having a higher household income also significantly decrease comprehension test failure. We therefore likely over-represent more educated, higher-income, and welfare-receiving individuals in our BDM measure relative to the population as a whole. Given that higher income generally translates to lower marginal utility of income, we expect this over-representation to lead to, if anything, an underestimate of adoption rates for the subsidy values considered.

[Table 3 here]

4 Econometric Results

4.1 Adoption without compensation

We first investigate the likelihood that respondents adopt a smart meter without compensation following exposure to their assigned information treatment. Mean adoption levels are similar across groups with participants in Treatment 2 having the highest adoption rate of 16% (compared to 15% in Control, 14.7% in Treatment 1, and 15.2% in Treatment 3).

The output of the linear probability model following equation (1) (see Table 4, column 2) shows that none of the treatments had a meaningful effect on smart meter adoption relative to the control group. These results suggest that individuals who currently adopt smart meters are either already well informed about the benefits we convey in the treatments (and their salience is unimportant in decision making), or that they are interested in adopting the technology regardless of these benefits.

[Table 4 here]

4.2 Subsidized adoption

Among those who did not wish to adopt a meter without compensation and passed the BDM comprehension test, the range of WTA values elicited is highly skewed, as demonstrated by the summary statistics in Figure 5. The interquartile range lies between £50-£150 for all groups, though the social benefit group has a marginally lower median than learning-by-using, and both are lower than private benefit and control.

A prominent feature of the data is the bunching of WTA values at certain points in the distribution. When analyzing the data we must account for this feature and for the variance in the relative ranking of mean and median by treatment depending on where we constrain the maximum.[29]

[Figure 5 here]

[29] See Table A2 in the Appendix for summary statistics for various WTA ranges.

Our approach therefore focuses on specific subsidy values that represent mass points of the WTA distribution. The subsidy values examined here (i.e. the c values) were identified ex-post based on the high frequency of their selection by respondents of the WTA exercise and the relevant percentage of respondents who fall under each respective category (approximately 27%, 32%, 47%, 75%, and 85%, for c=10, 25, 50, 75, 100, and 200, respectively). In other words, about half of individuals reported a WTA of less than or equal to £50, and therefore presumably would agree to adopt a smart meter if offered a £50 subsidy (a quarter for a £10 subsidy, a third for a £25 subsidy, etc.). Figure 6 presents the selected mass points graphically.

[Figure 6 here]

For this portion of the analysis, we exclude individuals who did not pass the BDM comprehension test and also did not accept the TIOLI offer, since we do not have sufficient information on these individuals to understand whether they would have accepted the subsidies we consider here. We include all individuals who indicated interest in obtaining a smart meter without compensation as well as individuals who accepted the TIOLI offer, since all of these individuals indicated a WTA valuation of less than or equal to £10, the minimum subsidy considered in this analysis.

Table 5 displays the results from the linear probability model following equation (2). The results indicate that neither information on private benefits nor on accumulated learning have consistent positive or negative causal effects on uptake under various subsidy values. However, information on the social benefits of smart grid infrastructure appear to influence decisions in a consistently positive direction. While failure to comprehend the BDM mechanism attenuated our sample size for this exercise by about a third (diminishing our power to detect effects), it nevertheless appears that the social benefits intervention played a role in boosting adoption rates, and with statistical significance for subsidy values of £10 (β=4.2 percentage points, p=0.013), £50 (β=4.9 percentage points, p=0.015), and £75 (β=6.6 percentage points, p=0.026). The coefficients remain positive (though not significant) for the other subsidy values considered.

[Table 5 here]

4.3 Robustness, heterogeneity, and barriers to adoption

Section A.4 of the Appendix presents an overview of all robustness checks undertaken: (i) we run alternative estimations both including and excluding the TIOLI sample; (ii) we assess the WTA data quality for anchoring, miscomprehension, and strategic behavior; (iii) we compare our primary results to those from a binary logistic regression model; (iv) we present a justification for our standard error clustering adjustment and conduct sensitivity analyses by undertaking a wild bootstrap estimation to account for the low number of clusters (11). In addition, we report wild bootstrap p-values in our primary estimation results, presented in Table 5.

Appendix A.5 provides a heterogeneity analysis, based on the exploratory hypotheses proposed in our project pre-registration. We do not find evidence to support hypotheses that participants respond more favorably to certain treatments depending on their income, interest and knowledge of environmental issues or revealed interest in technology. We do find evidence that Treatment 3 (Learning) and Treatment 2 (Social Benefit) increase the likelihood of risk-averse individuals adopting smart meters for all considered subsidy levels.

We also elicit information on subjective barriers to adoption, which we use to provide evidence on the society-wide barriers inhibiting participants from adopting. Participants noted a range of barriers, the most frequently cited of which were hassle costs, privacy or security concerns, and belief that the device will not lead to savings. Section A.6 of the Appendix provides a detailed discussion.

5 Policy Implications

Figure 7 presents cumulative demand curves for smart meters based on the elicited WTA (or negative price) of our sample participants. We include all households who would have adopted a smart meter without compensation as having a price of £0 and all of those who accepted our TIOLI offer as having a price of -£10. We present a demand curve for those participants whose WTA was £1000 or less and a second demand curve constrained at £200 or less. For our sample a subsidy of £200 would result in 1490 additional households adopting or about 85% of the total for whom we have WTA information. An inflection point in the demand curve suggests that subsidies beyond £200 may not result in substantially more demand. As demonstrated in Table A7 of Appendix A.7, where we provide separate demand curves for each of the control and treated groups, the demand curve for Treatment 3 shifts right of the others for WTA values greater than £200, indicating that the learning-by-using treatment may have led to more protest responses. The shift to the right of the demand curve for Treatment 2 becomes visible at lower WTA values, in line with our econometric results.

[Figure 7 here]

We additionally conduct a cost efficiency and welfare analysis for the subsidy values under consideration to better grasp the policy implications of our data. We define marginal non-additional subsidy payouts to be the additional amount the government would have to pay for non-additional households' participation relative to either the next lowest subsidy value considered (in discrete analysis) or relative to households' stated willingness to accept (in continuous analysis). For example, under a £25 subsidy in our discrete analysis, individuals who accept a meter without compensation nonetheless each receive £25 from the government, and individuals who do not accept a meter without compensation but do accept for a £10 subsidy each receive a non-additional subsidy payout of £15. For the continuous analysis, the marginal non-additional subsidy payout is the difference between the subsidy value and all non-additional participants' WTA. In the UK, where the alternative is no subsidy (i.e. £0), the total non-additional subsidy payout is then the summation of all such marginal values, equivalent to the shaded area above the static demand curve shown in Figure 1.[30]

[30] As noted in Langer and Lemoine (2018), an efficient subsidy schedule would allow for the social planner to intertemporally price discriminate, providing low subsidies to first movers with relatively low willingness-to-pay in early periods and increasing the subsidy over time until the efficient level of adoption is attained. However, consumer anticipation of future subsidies may lead some consumers to wait for the higher subsidy to be instated, expanding the pool of inframarginal consumers beyond those who receive a higher subsidy than is necessary to induce adoption in a given period to include those who postpone adoption to receive a higher subsidy. Evidence

We observe willingness to accept for smart meters at each point along the demand curve.[31] To first provide comparable discrete analysis to that of Boomhower and Davis (2014) ("BD"), we focus on the selected mass points within the plausible subsidy range of (£0, £200], as considered in our main regression analyses.

[Table 6 here]

Using similar back-of-the-envelope calculations to those undertaken in BD, we demonstrate in Table 6 (column 11) that non-additional subsidy payouts dominate the total program cost of any subsidy program, ranging from 53%-83% of total program costs for the subsidy values considered.[32] Of course, the larger is the subsidy value, the higher the government transfer to any participating household, so the total non-additional subsidy payouts increase substantially as the subsidy value increases. For instance in the case of £10, £50, and £100 subsidy offers, the total non-additional subsidy payouts for our sample of 2,430 come out to £3690, £23,590, and £67,515, respectively, when we account for the participation of individuals at these subsidy levels relative to the preceding subsidy level in the table (see column 1).[33]

Normalizing these costs indicates that these subsidy offers would lead to 'excess spending' of approximately £2, £14, and £39 per capita (see column 7). When we consider the efficiency costs of making these transfers, and using the presumed efficiency cost in Goulder et al. (1997) of $\eta = 1.3$ as in BD, the costs increase further (see columns 8-10). Finally, considering additionality for these three subsidy offers over a baseline of no subsidy (i.e. £0), the percentage of non-additional adopters—i.e., those who would have adopted without a subsidy as a percentage of total adopters, which declines with subsidy value by design if we assume elasticity of demand exceeds one—is 83%, 47%, and 29% (see column 4). Hence, a policymaker choosing from these eight possible subsidy values would trade off various considerations—including targeted adoption rates, (percent) non-additional subsidy payouts, program costs per capita, and additionality—to optimize her social welfare function.

Our WTA elicitation methodology allows us to improve upon the above insights into optimal subsidy provision, where the subsidy values considered affect the outputs of the analysis. Figure 8 capitalizes upon the continuous nature of our WTA elicitation to present the results from Table 6 for a continuous range of potential subsidies. For our sample, a local minimum in the proportion of total costs that are non-additional is observed at

of the former 'type' of inframarginal consumer is strong; for instance, using a regression discontinuity design, Boomhower and Davis (2014) find that 65% of subsidy recipients for refrigerator replacements in Mexico would have accepted the lower subsidy, indicating dramatic cost-ineffectiveness. Evidence of the latter is demonstrated in Langer and Lemoine (2018), who show that consumer foresight increases the requisite subsidy for early adopters, and that this effect has a positive interaction with anticipated technical change.

[31] We do not observe marginal adoption behavior for the TIOLI sample, since we only observe their binary adoption decision provided £0 and £10 subsidy values; we therefore focus this segment of our analysis on the sample for whom we have elicited a WTA valuation, including those who accepted a meter without compensation (i.e. WTA=£0) in the 'discrete' analysis; this subsample includes 1711 participants. Given there are no non-additional costs at a subsidy level of £0, meter adopters who do not require compensation are naturally excluded from the 'continuous analysis' below (i.e. Figure 8).

[32] Boomhower and Davis (2014) find that 69%-84% of total costs are associated with inframarginal participants in their context.

[33] Note that the subsidy values selected for the analysis will affect these numbers, since non-additional subsidy payouts are considered to be the difference between the subsidy offer at which one adopts and the subsidy offered.

a subsidy value of £100. While non-additional subsidy payouts dominate any potential subsidy scheme, this feature of the data suggests that—should a social planner decide to subsidize smart meter adoption—a £100 subsidy minimizes the percentage of spending that is non-additional. However, given the jump in the proportion of adopters at a subsidy value of £100, we also see an increase in the total cost per capita—calculated as the cost to society of non-additional participants multiplied by the number of adopters at each subsidy increment, normalized by the total number of adopters—at £100. This increase in the total cost coincides with a higher adoption rate, which also enters into the policymaker's social welfare function.

[Figure 8 here]

In short, the optimal subsidy will depend on the parameters of the social welfare function, so we cannot comment on the "correct" subsidy, and such is not our objective here. Rather, we aim to more broadly demonstrate the merits of our methodology for making such tradeoffs transparent to better inform a social planner's decision-making.

6 Discussion and Limitations

Encouraging private adoption of technologies and behaviors that have direct private costs and uncertain benefits is an objective that will continue to feature prominently in society's response to climate change and other environmental externalities, and in particular the energy transition. The adoption of smart meters presents an interesting case study due to their particular characteristics and the scale of the UK-wide government-led roll out and public participation campaign.

Based on the UK Government's own cost-benefit analysis, society could benefit from subsidizing each smart meter installation up to £212.[34] Our results suggest that a subsidy of £10 would increase demand for a smart meter about 5 percentage points from a baseline of 15%.[35] Excluding the sample of respondents for whom we do not elicit WTAs, we infer that offering £10, £25, and £50 would induce additional adoption of 4, 9, and 24 percentage points respectively from an updated baseline of 22% adoption, and that pairing these subsidies with a social information campaign can boost these numbers by an additional 2 to 5 percentage points.

However, non-additional subsidy payouts would dominate the cost of any subsidy program, ranging from 53%-83% of total costs. From the perspective of minimizing the percentage of policy expenditures that are non-additional, our data suggest a £100 subsidy could be optimal. It must be noted, however, that higher subsidy values will attract a greater proportion of marginal adopters, who may be increasingly less likely to engage with the meter in ways that improve energy flexibility and conservation, consistent with findings regarding energy efficiency upgrades in Allcott and Greenstone (2017), and may be more prone to making inefficient adoption decisions (Gilbert et al., 2020). Pairing

[34] This assertion assumes not only that the UK Government's CBA is optimal but also that there are no distortions induced by subsidization; a back-of-the-envelope calculation using Goulder et al. (1997)'s efficiency loss parameter, the government would be willing to subsidize up to £163.

[35] The subsidy increases uptake by 4.9 percentage points from a baseline of 15.2% adoption in the full sample (a 32% increase in adoption), and it increases adoption by 6 percentage points in the sample of respondents who answered the TIOLI question.

smart meters with technologies or energy plans that are facilitate cost savings—such as salient time-of-use plans (Jessoe and Rapson, 2014; Gilbert and Zivin, 2014), automated demand response technologies (Ivanov et al., 2013; Gillan, 2017), or technologies that provide appliance-specific information—could help to increase uptake as well as consumer and social benefits from adoption. Yet, low adoption inhibits such private sector offerings and innovation.

Our results hold relevant policy insights. We recommend that policymakers identify the appropriate evidence-based policy measure by carefully considering objectives relating to dynamic and non-additional policy costs and incentives, as well as ideal thresholds of system-wide adoption. With respect to increasing energy technology uptake, we recommend rigorous engagement with households in order to gain a deep understanding of the (extent of) drivers and barriers to adoption, and consider the use of financial incentives where appropriate. For instance, qualitative information from our sample of non-adopters suggests that hassle costs, concerns about privacy and security, and skepticism about the benefits of smart meters constitute major barriers to smart meter adoption despite widespread and costly ad campaigns touting their benefits.

Compounding these barriers are the positive network externalities of adoption and the dynamic nature of technological progress. That is, the longer a household postpones adoption, the more likely it is that the technology has progressed along desired dimensions (e.g., security, privacy, system interoperability). The social planner may therefore have dueling incentives: (i) to provide subsidies for early adoption to both capture low-WTA users at no or low cost (i.e. price discriminate) and address potential learning-by-using and network externalities, and (ii) to delay subsidy provision or increases to avoid subsidizing inframarginal consumers, where the very possibility of the latter in itself may induce households to postpone adoption even further (Langer and Lemoine, 2018). Indeed, qualitative evidence from our survey provides evidence of the latter phenomenon in that a significant number of individuals alluded to future technological progress to justify current non-adoption.

In the case of the UK's Smart Meter Implementation Programme, our research suggests that a broadened information campaign educating consumers about the society-wide benefits of household-level action could increase uptake of smart meters if appropriately paired with a reasonable subsidy scheme.

A potential limitation of this work is a concern over true incentive compatibility as, on average, only 14 percent of households who commit to adopting a smart meter actually convert on the agreement. This potential shortcoming is largely driven by the online nature of the experiment, which in turn was necessary to gather a large and representative sample. Given the scale of the policy objective, and the goal to understand relative treatment effects, we prioritized wide reach and representativeness while striving for incentive compatibility. The trade-off, of course, was that the extensive and personally identifiable information necessary to realize incentive compatibility likely led to low adoption follow-through, including collaboration with the UK energy regulator to enroll respondents and stressing the non-hypothetical nature of the exercise throughout. We do not observe significant differences between the stated and actual adopters across a number of key dimensions, and observe identical uptake to a contextually similar field experiment. While we cannot rule out that the WTA distribution and demand curve we elicit are a lower bound of the true WTA, we find no evidence of hypothetical bias.

7 Conclusion

Our research demonstrates a novel method to quantify resistance to the private adoption of a new and unfamiliar technology with uncertain costs and benefits. We focus on the smart electricity meter, though the methods we develop and apply can be used in a range of other circumstances to assess non-market costs and policy or program (cost) effectiveness.

We first assess the level of adoption that would occur without compensation, then devise a method to quantify the level of compensation required to encourage unwilling consumers to adopt. Combining this approach with randomized information treatments allows for an assessment of potential market failures inhibiting adoption. Treatment effects and non-additional policy expenditures are then explored for a range of potential subsidy programs.

In undertaking this research, we build on prior research by Jaffe and Stavins (1994a), Gillingham and Palmer (2014), and Fowlie et al. (2015) among others in identifying non-monetary costs and other barriers to adoption. Our use of a BDM valuation mechanism to elicit willingness to accept in a developed country and real-world policy context is novel. Further, our elicitation of the full demand curve in the negative price space allows us to generalize important work by Boomhower and Davis (2014) in estimating the non-additional costs of any potential subsidy scheme.

Given the increasing importance of consumer acceptance in the decarbonization of global energy consumption, we see great potential in developing and applying our methods to a number of contexts relevant to the emerging energy transition, for example in the electrification of heating, the adoption of novel smart technologies, and enrollment in demand response programs.

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8 Figures

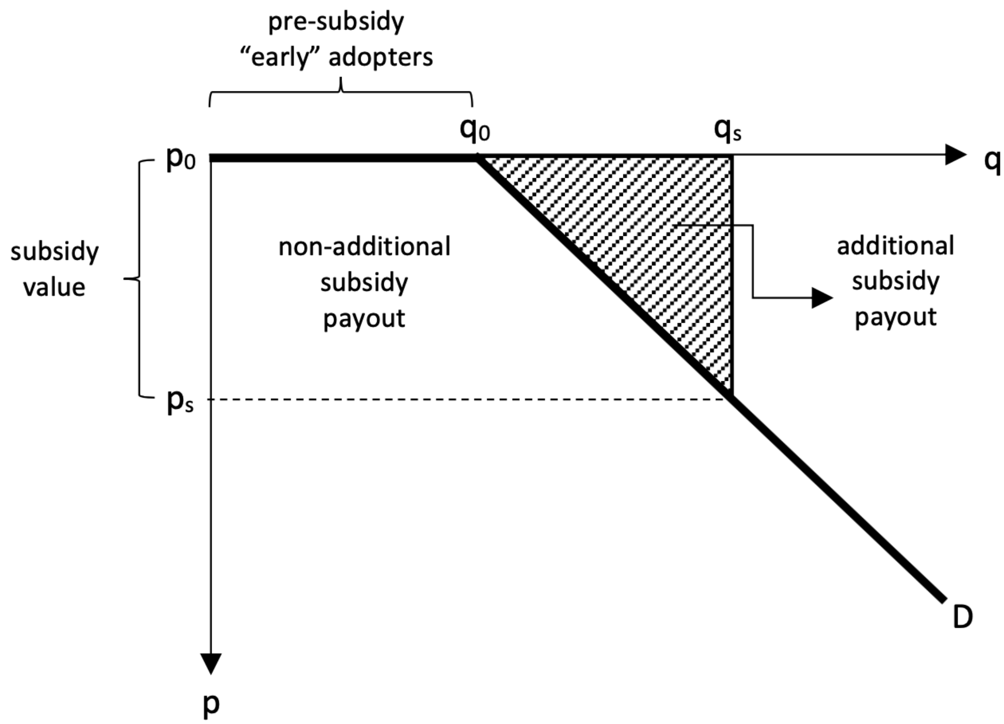


Figure 1: Non-Additional Subsidy Payout

Note: the price is negative as it based on the elicited WTA for those participants unwilling to adopt without compensation or who have a positive WTP. Non-additional subsidy payouts represent the amount of total subsidy payouts associated with non-additional participants.

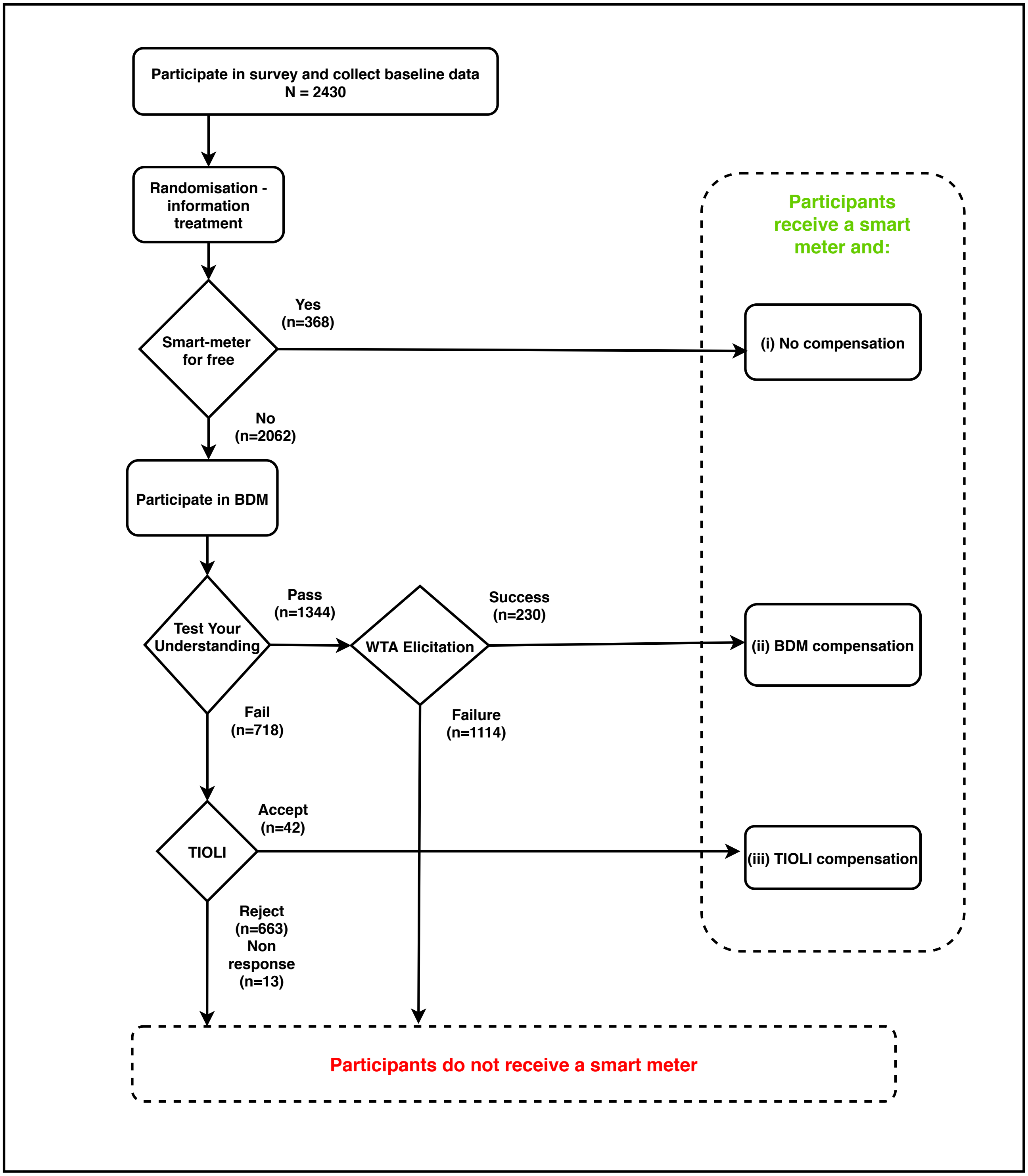


Figure 2: Survey Flow Chart for Eliciting Smart Meter Valuation

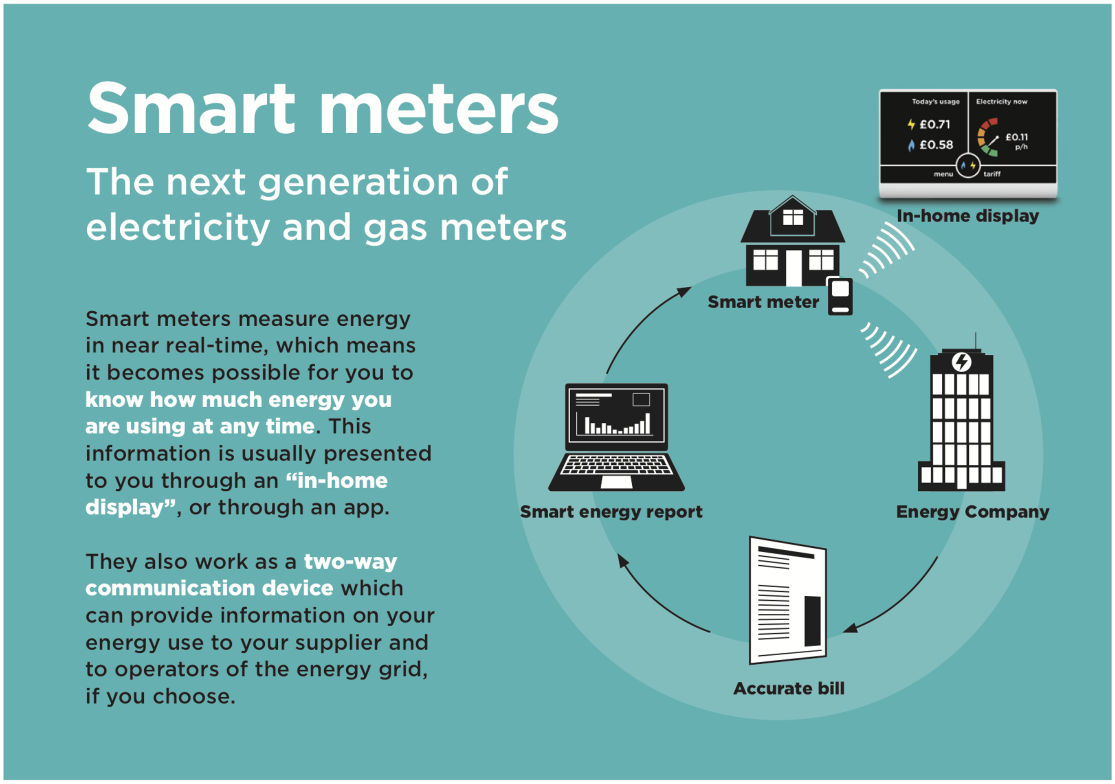
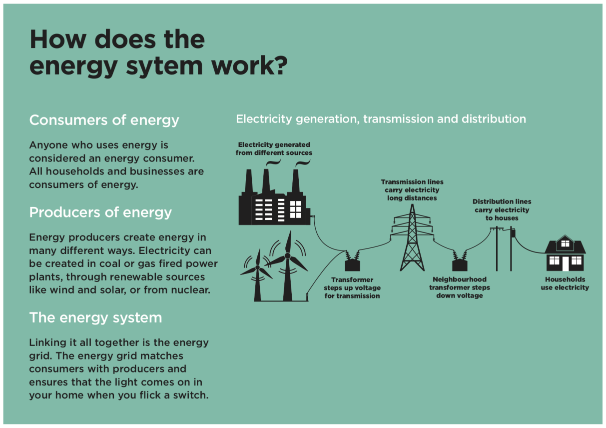
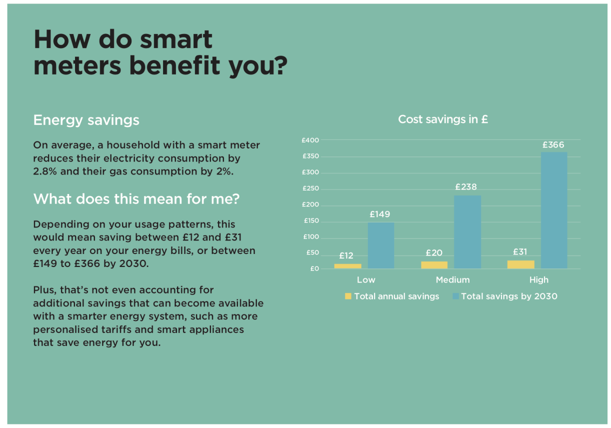


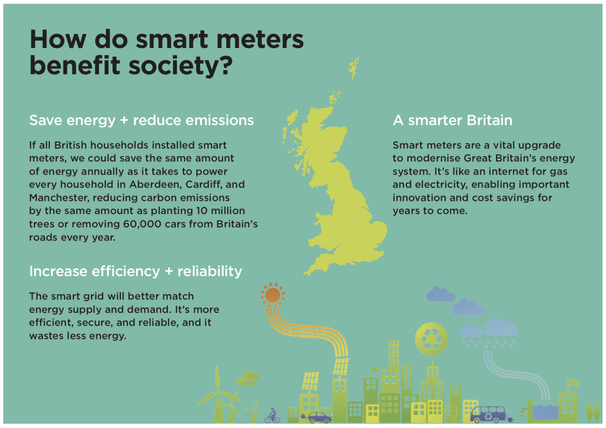
Figure 3: Smart Meter Description



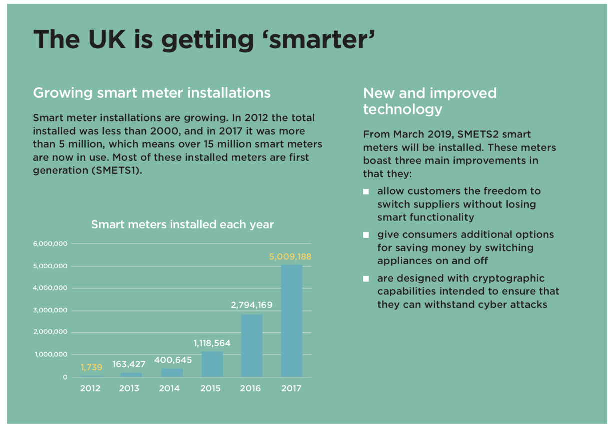
Control



Treatment 1: Private Benefits



Treatment 2: Social Benefits



Treatment 3: Learning-by-Using

Figure 4: Experimental Treatments

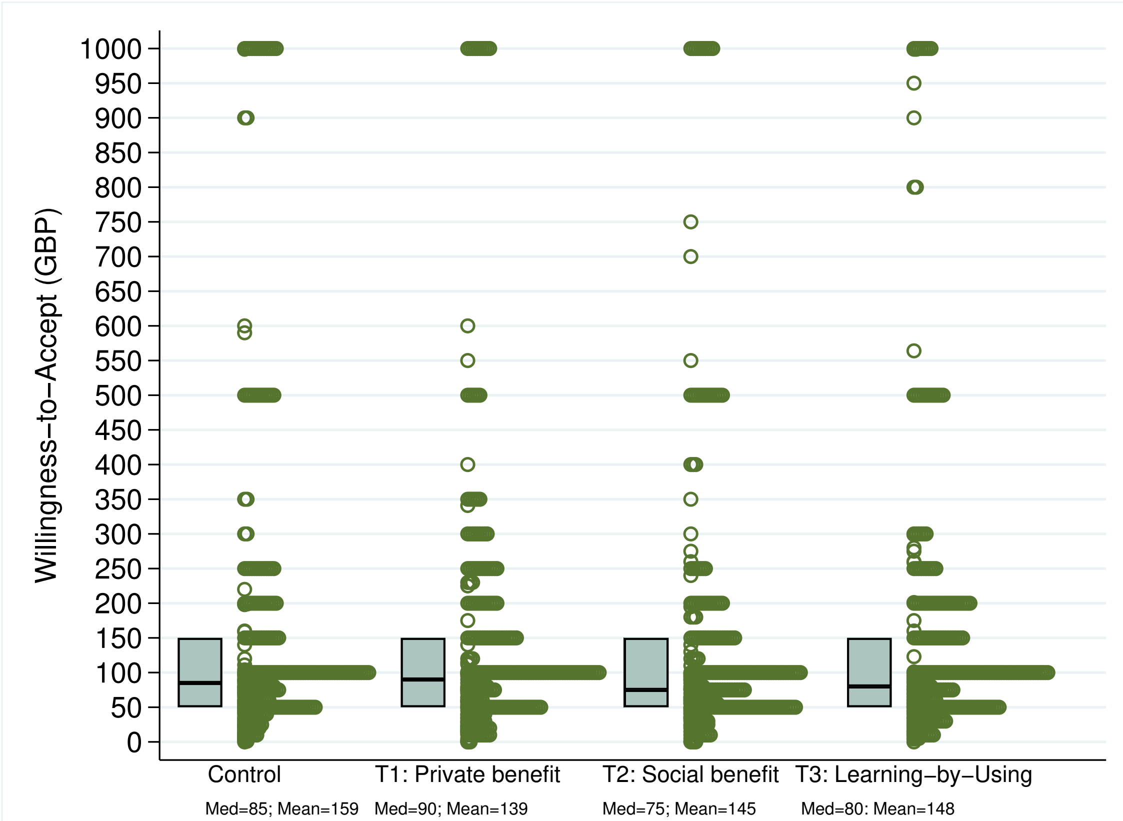


Figure 5: Distribution of WTA Values by Treatment

Note: The boxes on the left present the median and interquartile range (IQR) of WTA for the study group specified on the horizontal axis, with the full distribution of the data presented on the right; the length of the bars is in proportion to the number of observations at each WTA value on the vertical axis. WTA is constrained to be less than or equal to £1000, containing over 98% of the sample

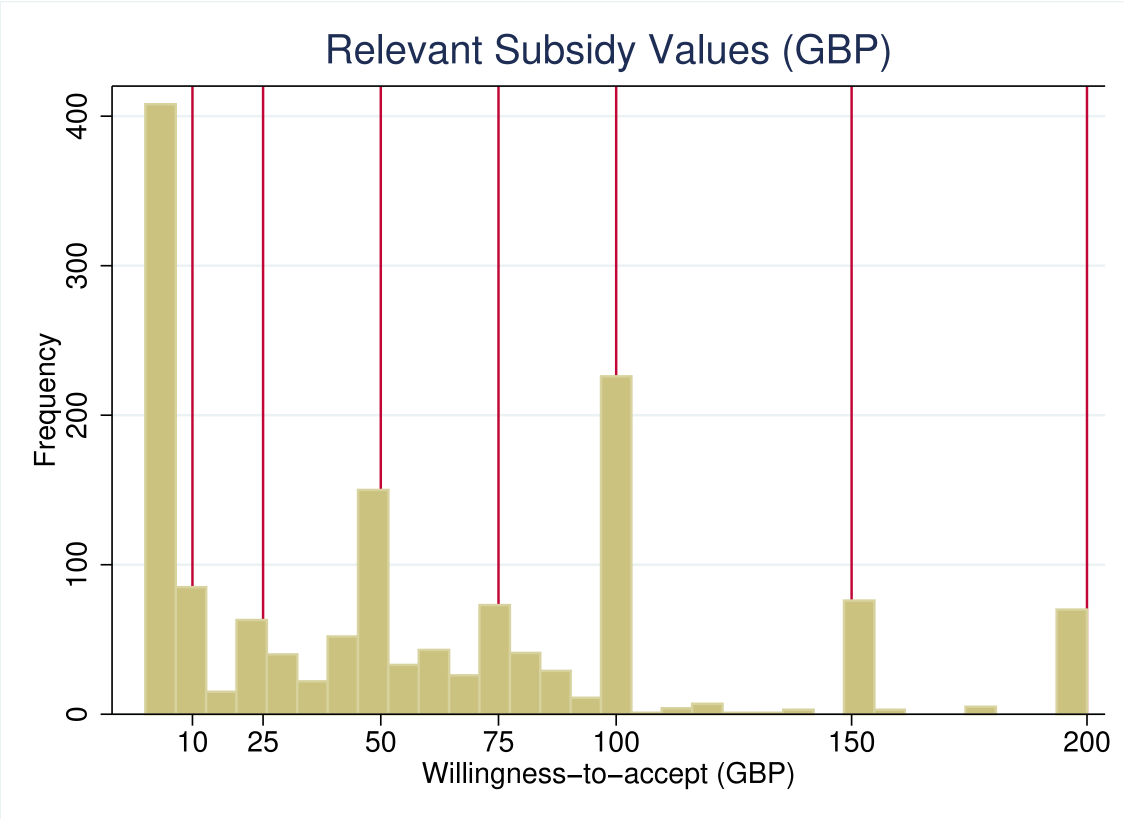


Figure 6: Subsidy Values Used in the Analysis

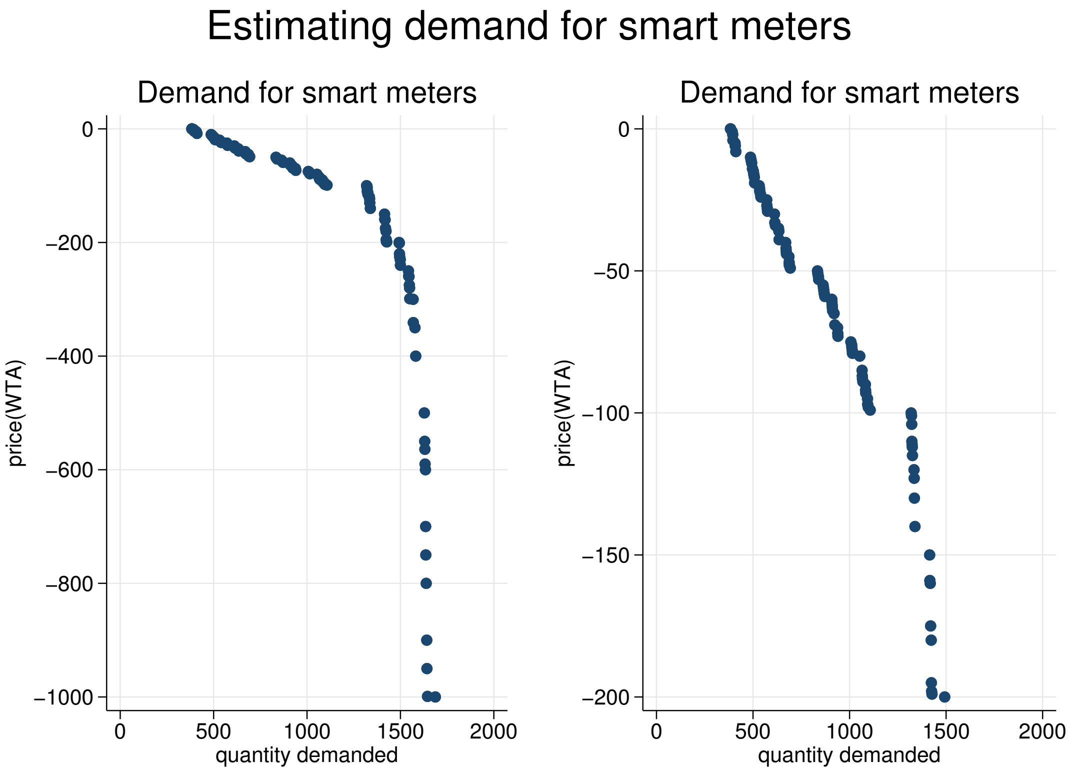


Figure 7: Estimated Demand Curve for Smart Meters

Note: The left panel presents a demand curve restricted at £1000 or less, the right is restricted at £200 or less.

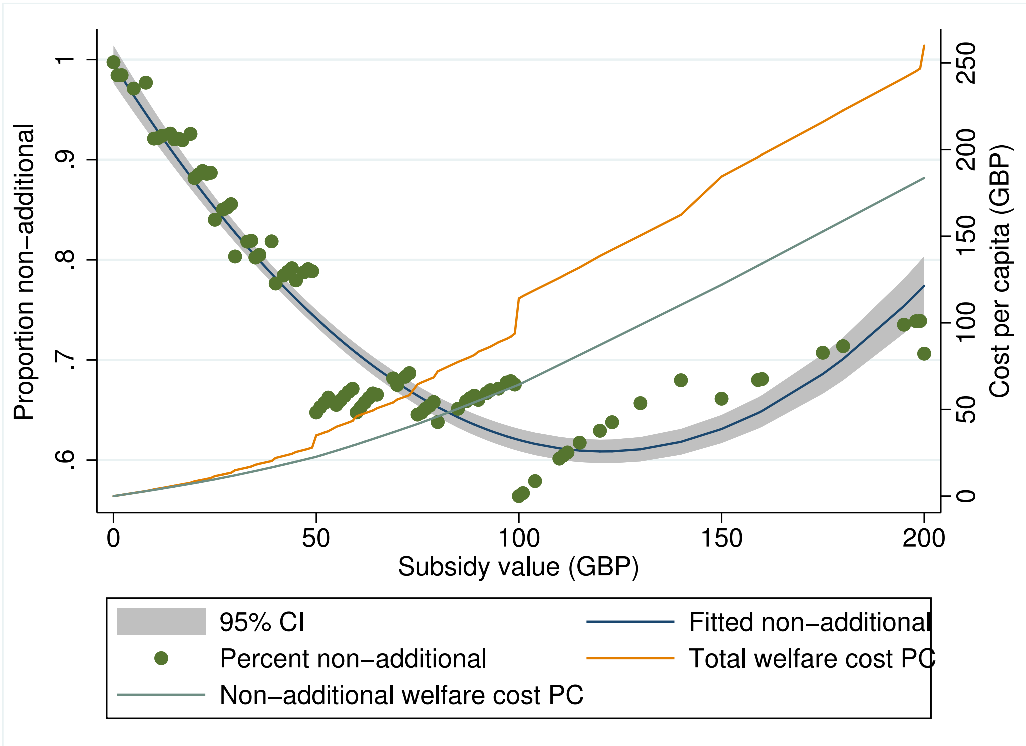


Figure 8: Non-Additional (Inframarginal) and Total Costs as a Function of Subsidy Value

Note: The green dots and fitted line denote the proportion of total costs that are non-additional (left axis) as a function of subsidy value. The orange and blue lines denote the per capita level of total and non-additional costs (right axis) as a function of subsidy value.

9 Tables

Table 1: Summary of uncompensated adoption

Treatment	N	Mean
Control	608	0.150
Treatment 1	608	0.147
Treatment 2	609	0.160
Treatment 3	605	0.152

Note: Of the 2430 respondents, 15.1% (n=368) indicated that they wanted to adopt a smart meter without need for compensation.

Table 2: Self-reported and Revealed Comprehension of BDM Exercise

	Self Reported		
Failed Rounds	No	Yes	Total
0	18	822	840
1	16	406	422
2	6	70	76
3	101	612	713
Total	144	1,962	2,106

Table 3: Regression of Comprehension Outcomes on Observable Characteristics

	Understand	Failed Test
Treatment 2: Private	0.004	-0.001
	(0.020)	(0.033)
Treatment 3: Social	0.009	0.007
	(0.020)	(0.032)
Treatment 4: Learning	0.013	-0.032
	(0.020)	(0.032)
Receiving Welfare Benefits	0.004	-0.103***
	(0.020)	(0.032)
Income: £10K-£16K	0.018	-0.062
	(0.028)	(0.045)
Income: £16K-£20K	0.050	-0.079
	(0.033)	(0.054)
Income: £20-£25K	0.015	-0.092*
	(0.031)	(0.050)
Income: £25K-£35K	0.011	-0.106**
	(0.030)	(0.048)
Income: £35K-£45K	0.006	-0.179***
	(0.034)	(0.055)
Income: £45K-£60K	0.042	-0.199***
	(0.033)	(0.053)
Income: £60K-£80K	0.064	-0.200***
	(0.039)	(0.064)
Income: Over £80K	0.001	-0.172**
	(0.043)	(0.070)
Education: Exams (Age 16)	0.098***	-0.152***
	(0.031)	(0.051)
Education: Exams (Age 16-19)	0.107***	-0.255***
	(0.034)	(0.056)
Education: Vocational Qualification	0.079**	-0.168***
	(0.037)	(0.060)
Education: Degree Equivalent	0.095***	-0.263***
	(0.033)	(0.053)
Constant	0.810***	0.629***
	(0.050)	(0.081)

Note: The dependent variables in the linear probability model are two binary variables capturing whether the respondent self-reported understanding of the exercise prior to taking the comprehension test ("Understand") and failed the comprehension test in the first round ("Failed Test"). We include all observable covariates and report only Treatment and covariates that significantly predict at least one of the two outcomes. All included covariates include treatment, gender, welfare, renting status, region, supplier, income, and education. Reference categories for income and education are "Below £10,000" and "No formal education", respectively. Standard errors are included in parentheses below the estimates. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table 4: Treatment Effects on Adoption of Smart Meters Without Compensation

	(1)	(2)
Treatment 1: Private	-0.003	-0.002
	(0.019)	(0.020)
Treatment 2: Social	0.010	0.008
	(0.014)	(0.014)
Treatment 3: Learning	0.002	0.001
	(0.018)	(0.016)
Constant	0.150***	0.110***
	(0.008)	(0.028)
Observations	2,430	2,430
R-squared	0.000	0.019
Controls	NO	YES

Note: The dependent variable in the regression is a binary variable capturing whether the respondent agreed to adopt a smart meter without compensation. Controls include gender, age, income, and region. Standard errors are included in parentheses below the estimates and are clustered at the supplier level. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table 5: Treatment Effects on Adoption of Smart Meters for Relevant Subsidy Values: TIOLI Included

	(1) $c = 10$	(2) $c = 25$	(3) $c = 50$	(4) $c = 75$	(5) $c = 100$	(6) $c = 150$	(7) $c = 200$
Treatment 1: Private	0.006	0.018	0.018	-0.005	-0.019	0.003	-0.008
Standard error	(0.031)	(0.023)	(0.026)	(0.023)	(0.024)	(0.024)	(0.021)
Wild bootstrap p-value	0.872	0.460	0.527	0.859	0.431	0.960	0.689
Treatment 2: Social	0.042**	0.021	0.049**	0.066**	0.011	0.025	0.026
Standard error	(0.017)	(0.021)	(0.018)	(0.019)	(0.025)	(0.018)	(0.014)
Wild bootstrap p-value	0.013	0.340	0.015	0.026	0.658	0.337	0.163
Treatment 3: Learning	-0.001	-0.011	0.033	0.027	-0.014	-0.007	0.008
Standard error	(0.020)	(0.024)	(0.025)	(0.023)	(0.024)	(0.020)	(0.020)
Wild bootstrap p-value	0.952	0.686	0.288	0.302	0.597	0.753	0.709
Constant	0.302***	0.445***	0.588***	0.686***	0.881***	0.852***	0.908***
	(0.059)	(0.067)	(0.068)	(0.049)	(0.038)	(0.036)	(0.022)
Observations	1,751	1,751	1,751	1,751	1,751	1,751	1,751
R-squared	0.031	0.038	0.042	0.041	0.044	0.042	0.047
Controls	YES	YES	YES	YES	YES	YES	YES

Note: The dependent variable in the regression is a binary variable capturing whether the respondent agreed to adopt a smart meter for a price in the range of [0, c]. Controls include gender, age, income, and region. Standard errors are included in parentheses below the estimates and are clustered at the supplier level. Wild cluster bootstrap p-values are reported underneath to address concerns relating to the small number of clusters. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table 6: Inframarginal Participation and Welfare Costs

	A: Adoption			**B: Subsidy payouts**			**C: Total program costs**			
Subsidy (1)	Total (%) (2)	Total (n) (3)	NA (%) (4)	NA (5)	Total (6)	NA p.c. (7)	NA (8)	Total (9)	Total p.c. (10)	NA/Total (11)
£0	22%	369	-	-	-	-	-	-	-	-
£10	26%	445	83%	£3,690	£4,450	£2	£4,797	£5,785	£3	83%
£25	31%	529	70%	£10,365	£13,225	£6	£13,475	£17,193	£8	78%
£50	46%	792	47%	£23,590	£39,600	£14	£30,667	£51,480	£18	60%
£75	56%	965	38%	£43,390	£72,375	£25	£56,407	£94,088	£33	60%
£100	75%	1277	29%	£67,515	£127,700	£39	£87,770	£166,010	£51	53%
£150	80%	1373	27%	£131,365	£205,950	£77	£170,775	£267,735	£100	64%
£200	85%	1451	25%	£200,015	£290,200	£117	£260,020	£377,260	£152	69%

Note: In the table, "NA" is short for "non-additional" and "p.c." is short for "per capita". Panel A provides information on sample smart meter adoption at various subsidy levels, excluding TIOLI takers (n=1711). In line with BD, non-additional adoption refers to the percentage of adopters receiving a given subsidy who would have adopted the smart meter without a subsidy. The costs in panel B refer to subsidy payouts from the government to individuals if a given subsidy were to be implemented in our sample, with normalization provided in the "per capita" columns. Panel C replicates panel B but incorporates efficiency costs of $\eta = 1.3$ to provide a more realistic welfare assessment.

A Appendices

A.1 Survey Materials

A.1.1 Becker-DeGroot-Marschak Exercise Instructions

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Given your answer to the previous question, we'd like to see what it might take to change your mind about getting a smart meter. Think of it this way – if someone said they would pay you to have a smart meter installed in your home, how much money would you ask for?

This research project is about answering this question. In the past, various energy companies in the UK have offered a range of incentives for customers to adopt smart meters (for example, £5 or £10 in club card points, or £50 off your next bill, and so on). It appears that some customers will sign up to get a smart meter only if given the right incentive. We're interested in learning what that 'right incentive' might be for you, if any.

Link: Why might you be paid to install a smart meter?

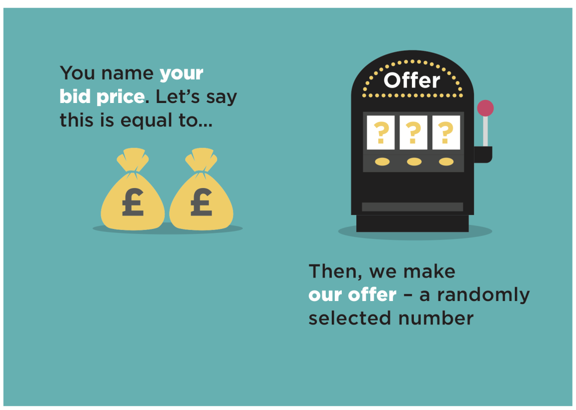
THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

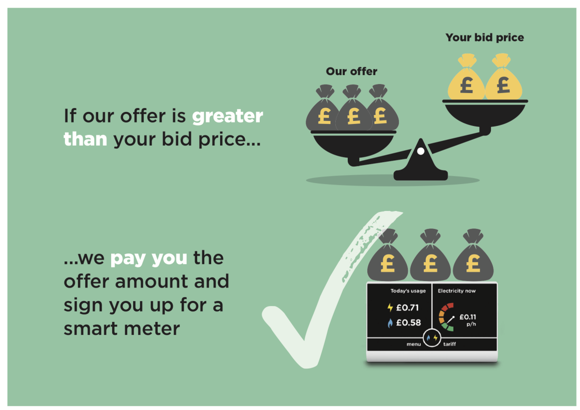
To make things realistic, we'll use our research funding to give you a chance to state your price and *actually* be paid in exchange for signing up to get a smart meter installed. **It works like this:**

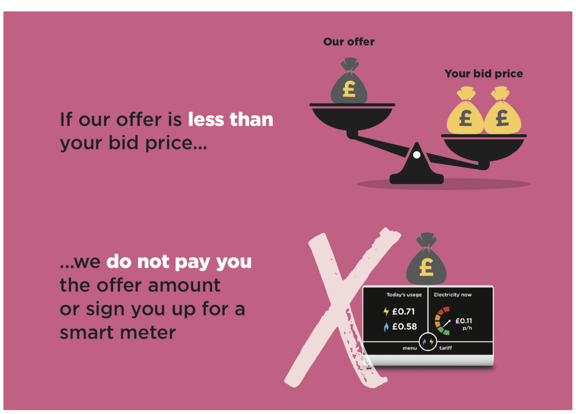
1. First, we will ask you to tell us your **bid price** – the minimum amount of money you would need to be paid before you would agree to have a smart meter installed by your energy supplier.

2. Second, we will make **our offer** – this will be a randomly drawn number greater than 0. That is, a new offer is drawn for every survey taker.

3. Our offer may be greater or less than your bid price. If our offer is greater, we will pay you our offer and sign you up to get a smart meter installed. Otherwise, no exchange occurs. The following stylized graphics explain further.







A.1.2 BDM Comprehension

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

We will now test your understanding. You must correctly answer the three test questions below before you can proceed to the exercise. If one of the three is incorrect, you will be asked to correctly answer a new set of three questions to try again.

Say your **bid price** is £14 and **our offer** is £70.

What happens next?

- ○ I will receive £14 in exchange for sharing my details with my electricity supplier via this survey to begin the smart meter installation journey.
- ○ I will receive £70 in exchange for sharing my details with my electricity supplier via this survey to begin the smart meter installation journey.
- ○ I will receive nothing and will not share my details with my supplier to install a smart meter.

Say your **bid price** is £85 and **our offer** is £26.

What happens next?

- ○ I will receive £85 in exchange for sharing my details with my electricity supplier via this survey to begin the smart meter installation journey.
- ○ I will receive £26 in exchange for sharing my details with my electricity supplier via this survey to begin the smart meter installation journey.
- ○ I will receive nothing and will not share my details with my supplier to install a smart meter.

Say your **bid price** is £5 and **our offer** is £93.

What happens next?

- ○ I will receive £5 in exchange for sharing my details with my electricity supplier via this survey to begin the smart meter installation journey.
- ○ I will receive £93 in exchange for sharing my details with my electricity supplier via this survey to begin the smart meter installation journey.
- ○ I will receive nothing and will not share my details with my supplier to install a smart meter.

A.1.3 BDM Response

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Now please enter your bid price in the box below. Please round to the nearest whole number (i.e no decimals)

Remember: if the random offer drawn is below your bid price, nothing happens. If the offer exceeds your bid price, you will have a chance of winning the amount of the offer in exchange for signing up to get a smart meter installed in your home.

Please let us know why you've chosen this amount. (optional)

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

When asked whether you wanted a smart meter for free, you indicated that you did not. What is your primary reason (or reasons) for not wanting a smart meter installed in your home?

Please check all that apply.

☐ Privacy/security concerns	☐ I do not think I will save energy/money
☐ Too much hassle	☐ I do not trust my energy supplier
☐ Health concerns	☐ Other (please specify below):

A.2 Sample size calculations

Given the original plan to perform a Tobit regression analysis[36], we ran sample size calculations for the binary outcome variable of whether individuals adopt a meter without compensation as well as the continuous outcome of WTA. With regard to the former, the 15% baseline (control group) adoption assumption was derived from our pilot experiment, where just under 300 individuals took the first part of the 'control' version of the survey as it exists in the study. Expected payout is based on what would have been paid out (i.e. the payout for individuals whose bid price was less than our offer) to individuals had we paid 100% of individuals in the pilot (in which we paid a randomly determined 10% of participants). Additionally, the expected percentage of individuals to undertake the BDM and TIOLI exercises was also taken directly from the pilot study.

With an anticipated 2500 individuals taking the survey[37] and four groups (one control, three treatment) in total, we were powered to detect around a 6 percentage point difference in smart meter uptake from a baseline of 15% uptake without compensation. For the continuous outcome, we were powered to detect a 4.8-6.7% change in willingness to accept. This calculation is based on a constrained maximum WTA of £100. More detail is available in the project pre-registry on the Open Science Framework.

[36]In our pre-registry we anticipated using a Tobit regression analysis to provide insight into the continuous WTA variable. We instead perform the analysis as outlined here due to the intuitive interpretation of the results, the lack of clarity surrounding the appropriate upper limit upon which to censor the data (if at all), and the objections raised in Angrist and Pischke (2008) and Boyle (2017) against using Tobit in this circumstance (i.e. the need to make distributional assumptions on the latent WTA variable, and the potential 'missing information' for individuals at the tails of the distribution who may be the most vulnerable to ensuing policy prescriptions). Using a binary dependent variable additionally reduces noise from any given participant, particularly those who may have misunderstood the exercise or submitted protest responses.

[37]Though we terminated the survey upon receipt of 2500 seemingly valid responses, we identified a number of repeat survey takers who have since been removed from the data. Of the 109 suspected duplicates, 70 were not initially identified by our survey providers. We removed these participants leaving 2,430 valid responses in total.

A.3 Descriptive statistics

Table A1: Descriptive statistics and balance table

Demographic variables	Proportion					Test of Equality (P-value)		
	Population	C: Control	T1: Private benefit	T2: Social benefit	T3: Learning-by-using	C = T1	C = T2	C = T3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender								
Female	0.51	0.51	0.51	0.52	0.52	0.909	0.795	0.817
Age								
18-24	0.12	0.14	0.16	0.15	0.14	0.173	0.613	0.982
25-34	0.19	0.24	0.21	0.22	0.23	0.244	0.423	0.760
35-44	0.18	0.23	0.23	0.22	0.20	0.891	0.742	0.169
45-54	0.20	0.18	0.16	0.20	0.20	0.320	0.454	0.294
55-64	0.17	0.11	0.13	0.11	0.12	0.293	0.791	0.840
65 or older	0.14	0.10	0.10	0.11	0.12	0.925	0.772	0.507
Education								
No formal qualifications	0.06	0.06	0.05	0.05	0.06	0.518	0.527	0.795
GCSE, O Level, CSE	0.28	0.34	0.36	0.37	0.35	0.433	0.261	0.518
A and AS Level or equiv.	0.12	0.17	0.16	0.16	0.17	0.643	0.551	0.838
Other Voc. Qual/Foreign qual.	0.27	0.09	0.11	0.08	0.09	0.253	0.359	0.854
Degree or higher	0.27	0.35	0.33	0.35	0.34	0.395	0.871	0.614
Income								
Below £10,000 per year	0.15	0.15	0.13	0.13	0.14	0.506	0.410	0.760
£10,000 - £16,000 per year	0.19	0.17	0.18	0.17	0.17	0.764	0.950	0.781
£16,000 - £19,999 per year	0.14	0.08	0.08	0.10	0.10	0.674	0.186	0.154
£20,000 - £24,999 per year	0.14	0.13	0.13	0.12	0.13	0.866	0.740	0.882
£25,000 - £34,999 per year	0.16	0.16	0.16	0.16	0.16	0.937	0.947	0.957
£35,000 - £44,999 per year	0.10	0.10	0.11	0.10	0.09	0.570	0.767	0.708
£45,000 - £59,999 per year	0.06	0.12	0.12	0.12	0.12	0.930	0.938	0.844
£60,000 - £79,999 per year	0.03	0.05	0.05	0.06	0.05	0.794	0.701	0.908
Over £80,000 per year	0.03	0.04	0.03	0.04	0.04	0.358	0.660	0.777
Region								
East Midlands	0.07	0.08	0.08	0.08	0.07	0.751	0.757	0.395
East of England	0.10	0.08	0.08	0.06	0.08	0.674	0.215	0.588
London	0.14	0.11	0.11	0.14	0.13	0.783	0.046	0.153
North East	0.05	0.05	0.05	0.04	0.03	0.894	0.684	0.196
North West	0.11	0.13	0.10	0.10	0.11	0.105	0.107	0.390
South East	0.14	0.14	0.17	0.16	0.15	0.150	0.325	0.402
South West	0.09	0.10	0.08	0.09	0.11	0.367	0.701	0.340
West Midlands	0.09	0.09	0.11	0.10	0.08	0.503	0.915	0.427
Yorkshire and the Humber	0.08	0.09	0.09	0.08	0.08	0.761	0.762	0.850
Scotland	0.08	0.10	0.08	0.11	0.09	0.424	0.503	0.498
Wales	0.05	0.05	0.05	0.04	0.05	0.788	0.786	0.882
F test for joint orthogonality								
Number of obs	2,429							
F(31, 2397)	0.6							
Prob $\geq$ F	0.9595							

Note: Columns 1-5 present information on the breakdown of key sociodemographic variables within the general population (column 1) and each treatment group (columns 2-5). Columns 6-8 presents p-values for a test of equality between the control and each treatment group. The number of observations in the above F test is 2429 as education information was not provided by one participant

Table A2: Summary statistics at Willingness to Accept cut-off points

WTA Range	**Statistic**	**Control**	**Treatment 1**	**Treatment 2**	**Treatment 3**
WTA $\leq$ 10000	Mean (GBP)	294	390	334	338
	Median (GBP)	90	99	80	94
WTA $\leq$ 1000	Mean (GBP)	159	139	145	148
	Median (GBP)	85	90	75	80
WTA $\leq$ 500	Mean (GBP)	108	108	110	111
	Median (GBP)	80	83	75	76
WTA $\leq$ 200	Mean (GBP)	78	76	78	80
	Median (GBP)	75	75	75	75
WTA $\leq$ 150	Mean (GBP)	69	69	70	68
	Median (GBP)	71	65	60	60
WTA $\leq$ 100	Mean (GBP)	63	60	61	60
	Median (GBP)	60	55	55	55
WTA $\leq$ 75	Mean (GBP)	43	39	46	43
	Median (GBP)	50	40	50	50
WTA $\leq$ 50	Mean (GBP)	32	31	35	34
	Median (GBP)	35	30	40	40
WTA $\leq$ 25	Mean (GBP)	15	14	13	15
	Median (GBP)	17	15	10	12
WTA $\leq$ 10	Mean (GBP)	6	6	6	8
	Median (GBP)	7	10	8	10

A.4 Robustness

A.4.1 Comparison of BDM and TIOLI survey participants

Given that those participants who undertook the TIOLI exercise failed the BDM comprehension test and are observably different across certain characteristics, we also include two additional sets of analysis for completeness.

Table A3 presents the results of our analysis of treatment effects following removal of the TIOLI participants and participants who are willing to adopt without any compensation. This group consists only of those who undertook the BDM valuation exercise. The social benefits intervention has a statistically significant effect only for a subsidy value of £75 (β=6.6 percentage points, p=0.084), though the effect size is almost identical for the £50 subsidy value in a regression in which we exclude TIOLI but include those who accepted a meter without compensation, suggesting that we may simply be underpowered once we remove significant portions of our sample from the analysis. Table A4 presents the results from analysis of just the TIOLI participants with all others removed. Again the social benefit treatment has an impact resulting in a 4 percentage point increase in uptake.

Taken altogether, the social benefit intervention has an impact at multiple subsidy values and, at the £10 subsidy value in particular, our results would appear to be partially driven by the inclusion of those who accepted the TIOLI offer in our analysis.

Table A3: Treatment Effects on Adoption of Smart Meters for Relevant Subsidy Values: BDM group only

	(1) $c = 10$	(2) $c = 25$	(3) $c = 50$	(4) $c = 75$	(5) $c = 100$	(6) $c = 150$	(7) $c = 200$
Treatment 1: Private	0.022	0.036	0.037	0.006	-0.015	0.011	-0.004
Standard error	(0.017)	(0.017)	(0.034)	(0.026)	(0.033)	(0.036)	(0.029)
Wild bootstrap p-value	0.2025	0.1465	0.3955	0.807	0.623	0.771	0.894
Treatment 2: Social	0.014	-0.011	0.035	0.066**	0.005	0.027	0.027
Standard error	(0.015)	(0.017)	(0.025)	(0.029)	(0.040)	(0.029)	(0.023)
Wild bootstrap p-value	0.3965	0.5555	0.1705	0.0835	0.9095	0.458	0.395
Treatment 3: Learning	0.014	0.002	0.052	0.041	-0.012	-0.004	0.014
Standard error	(0.010)	(0.016)	(0.037)	(0.029)	(0.027)	(0.024)	(0.025)
Wild bootstrap p-value	0.2395	0.923	0.256	0.1665	0.674	0.87	0.577
Constant	0.100***	0.286***	0.473***	0.603***	0.845***	0.806***	0.880***
	(0.028)	(0.044)	(0.048)	(0.038)	(0.037)	(0.043)	(0.033)
Observations	1,304	1,304	1,304	1,304	1,304	1,304	1,304
R-squared	0.033	0.058	0.049	0.048	0.053	0.050	0.057
Controls	YES	YES	YES	YES	YES	YES	YES

Note: The dependent variable in the regression is a binary variable capturing whether the respondent agreed to adopt a smart meter for a price in the range of [0, c]. The sample is restricted to the BDM group only. Controls include gender, age, income, and region. Standard errors are included in parentheses below the estimates and are clustered at the supplier level. Wild cluster bootstrap p-values are reported underneath to address concerns relating to the small number of clusters $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table A4: Treatment Effects on Adoption of Smart Meters for Relevant Subsidy Values: TIOLI only

	(1) TIOLI
Treatment 1: Private	-0.011
Standard error	(0.009)
Wild bootstrap p-value	0.2545
Treatment 2: Social	0.040**
Standard error	(0.016)
Wild bootstrap p-value	0.0435
Treatment 3: Learning	0.021
Standard error	(0.021)
Wild bootstrap p-value	0.377
Constant	1.068***
	(0.062)
Observations	705
R-squared	0.038
Controls	YES

Note: The dependent variable in the regression is a binary variable capturing whether the respondent agreed to adopt a smart meter for a price in the range of £10. The sample is restricted to the TIOLI group only. Controls include gender, age, income, and region. Standard errors are included in parentheses below the estimates and are clustered at the supplier level. Wild cluster bootstrap p-values are reported underneath to address concerns relating to the small number of clusters $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

A.4.2 WTA data quality

Section 2.2.2 describe a range of potential concerns one might have with valuations elicited through a BDM experiment. We undertake a number of steps to ensure good data quality. Firstly, we collected detailed self-reported reasons from each participant for their choice of WTA value. We categorized open-ended responses from 793 participants[38] into 53 detailed reasons. Each reason was then further categorized into 14 composite reasons. Table A5 provides further information. A key concern for our analysis is the existence of participants who may engage in strategic behavior, appear to not fully understand the exercise, and who may have been anchored by our instructions in their WTA valuation[39]. Table A6 provides results from our primary estimations with any suspected anchoring, strategic behavior, or miscomprehension removed. The results are qualitatively similar to those of our main estimations.

Table A5: Reason given for WTA value

Reason Category	Count	Percentage
Suspected anchoring	7	1%
Concerns about smart meters	58	7%
Constrained by external factors	24	3%
To cover costs	81	10%
Do not want a smart meter	130	16%
Fair price	187	24%
Inconvenience/hassle costs	103	13%
Suspected miscomprehension	31	4%
No reason given/arbitrary	107	13%
Unknown reason	6	1%
Strategic	33	4%
Concerns about suppliers/energy costs	13	2%
Want a smart meter	13	2%
	793	100%

[38] As we did not force a response on this question due to survey length, we collected information from 793 respondents out of a total of 1304 who undertook the BDM exercise

[39] As described in Section 2.2.2 we also conducted a pilot experiment to mitigate anchoring in the design of the exercise.

Table A6: Treatment Effects on Adoption of Smart Meters for Relevant Subsidy Values: Suspected miscomprehension, strategic behavior and anchoring removed

	(1) $c = 10$	(2) $c = 25$	(3) $c = 50$	(4) $c = 75$	(5) $c = 100$	(6) $c = 150$	(7) $c = 200$
Treatment 1: Private	0.007	0.019	0.024	-0.002	-0.018	0.003	-0.008
	(0.029)	(0.018)	(0.027)	(0.021)	(0.024)	(0.026)	(0.023)
Treatment 2: Social	0.038**	0.020	0.054***	0.071***	0.015	0.029	0.028*
	(0.014)	(0.019)	(0.017)	(0.019)	(0.027)	(0.020)	(0.015)
Treatment 3: Learning	0.001	-0.005	0.038	0.031	-0.009	-0.003	0.012
	(0.020)	(0.022)	(0.028)	(0.023)	(0.021)	(0.019)	(0.019)
Constant	0.301***	0.434***	0.582***	0.686***	0.877***	0.848***	0.903***
	(0.064)	(0.060)	(0.061)	(0.045)	(0.038)	(0.035)	(0.023)
Observations	1,707	1,707	1,707	1,707	1,707	1,707	1,707
R-squared	0.029	0.036	0.040	0.040	0.045	0.043	0.049
Controls	YES	YES	YES	YES	YES	YES	YES

Note: The dependent variable in the regression is a binary variable capturing whether the respondent agreed to adopt a smart meter for a price in the range of [0, c]. Any participants suspected of strategic behavior, miscomprehension or anchoring in their WTA valuation are removed. Controls include gender, age, income, and region. Standard errors are included in parentheses below the estimates and are clustered at the supplier level. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Additionally, the 14% adoption follow-through discussed in section 2.2.3 begs the question of whether our elicited WTA valuations represent a lower bound of WTA in the economy, and whether the treatments impacted follow-through. We therefore explore whether there are differences across those who "adopt" via the survey—i.e. through answering in the affirmative when asked if they want a smart meter without compensation or in the TIOLI exercise, or by stating a WTA below our offer in the BDM exercise—and those who follow through on providing complete information to enable our facilitation of the sign-up process. We therefore investigate whether relevant factors, including treatment received, length of time the participant had already spent taking the survey, and the difference between our offer and stated WTA, predict participants' effort to supply us with complete information. Table A7 presents the results for the former two factors, and the following subsection discusses the latter. We find no evidence to suggest a difference between "stated" and "actual" adopters.

Table A7: The Effect of Treatment and Survey Duration on Stated vs. Actual Adoption

	(1)	(2)
VARIABLES	Treatment	Duration
Treatment 1: Private	0.011	
	(0.061)	
Treatment 2: Social	0.068	
	(0.054)	
Treatment 3: Learning	0.076	
	(0.075)	
Survey Duration		-0.000
		(0.000)
Constant	0.078	0.116***
	(0.043)	(0.036)
Observations	233	233
R-squared	0.011	0.000

Note: The dependent variable in the regression is a binary variable capturing whether the respondent provided sufficient deatils to sign-up to receive a smart meter (n=29). The sample is restricted to those who were allocated a reward. Standard errors are included in parentheses below the estimates and are clustered at the supplier level. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

A.4.3 Comparison of offer and elicited WTA

This section provides further information on the distribution of offers and WTAs, the difference between them, and a comparison of this difference between stated and actual adopters. In response to a reviewer question, we first present the distribution of offers graphically in Figure A1. As described in the paper, the randomization procedure generated a uniform distribution between (£0, £100].

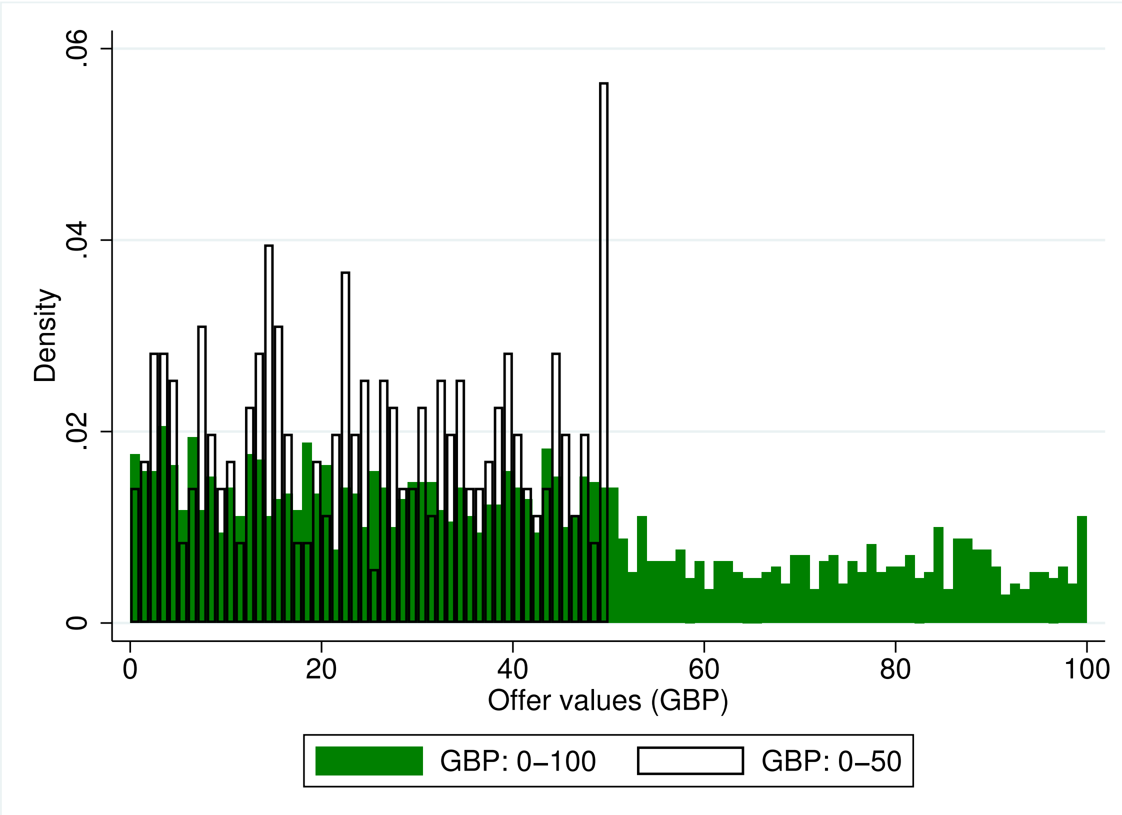


Figure A1: Distribution of offer values. Note that during the trial we lowered the maximum offer from £100 (n=1701) to £50 (n=354) due to budget constraints.

We next compare each offer with the elicited WTAs. This comparison is to assess whether there is a difference between those participants who collect their reward and sign-up for a smart-meter and those who do not. It may be the case that some participants may understate their true WTA and as a result, the offer is not sufficient to encourage adoption. If this is the case, it might be that the difference between offer and WTA is greater for those who enroll than those who do not.

Figure A2 presents a comparison of the distribution of the difference between offer and WTA (Offer-WTA). Based on a graphical inspection we do not observe any difference, which is confirmed by the results of a two-sample Kolmogorov-Smirnov test for equality of the distribution functions displayed in Table A8. Given a lack of pre-registered priors, we test three possible hypotheses: (i) that the 'reward not collected' distribution is lower than that for 'reward collected'; (ii) that the 'reward collected' distribution is lower than 'reward not collected'; (iii) that the distributions are different. Based on the results we fail to reject the null hypothesis in each case that the distributions are the same.

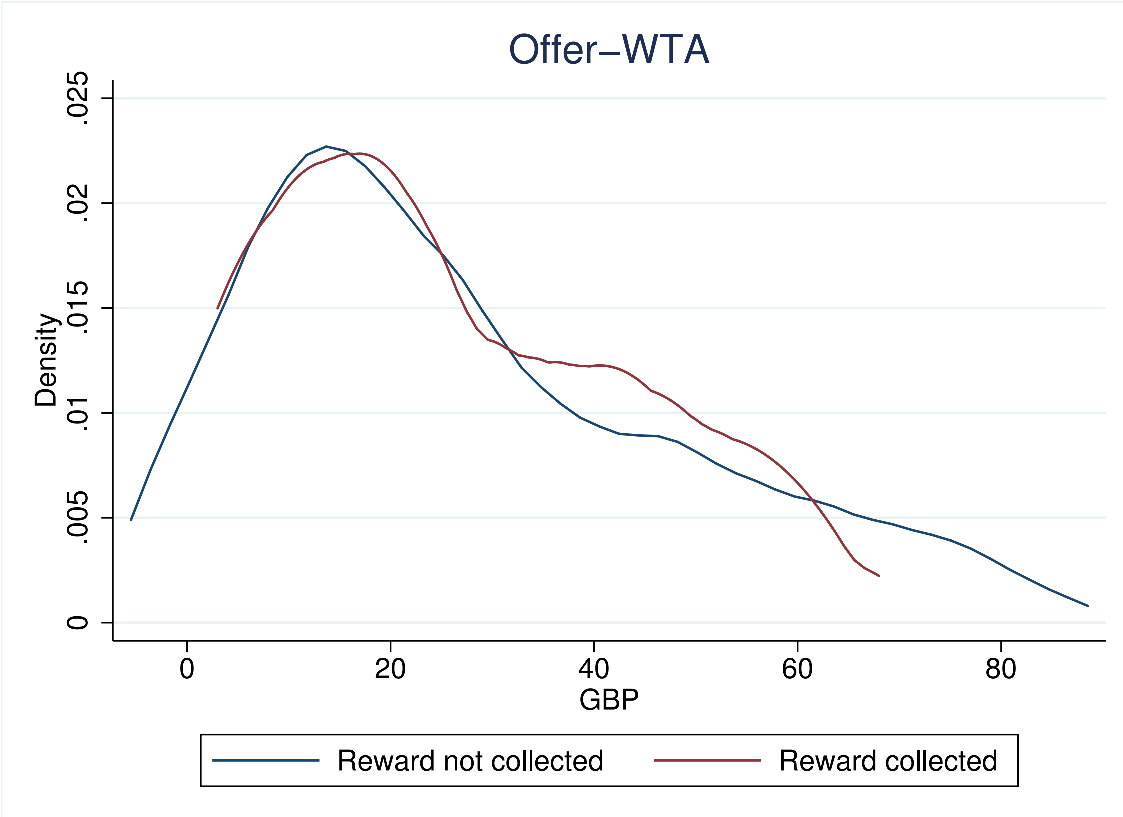


Figure A2: Kernel density estimate of distribution of difference between offer and WTA, comparing participants who did not claim their reward with those who did. The sample is restricted to n=233 participants with a WTA of £100 or less and who are eligible to receive a reward. We obtained information from n=29 participants who collected their reward.

Table A8: Two-sample Kolmogorov-Smirnov test for equality of distribution functions

	Offer - WTA	
Smaller group	Difference	P-value
Reward not collected	0.1007	0.616
Reward collected	-0.1037	0.598
Combined K-S:	0.1037	0.959

Note: The sample is restricted to n=233 participants with a WTA of £100 or less and eligible for a reward. We obtained information from n=29 participants who collected their reward.

Overall we find no evidence that the difference between offer and WTA influences the decision to collect the reward, and that those who do not collect their reward may be under-reporting their true WTA. However, we can only test this for those participants who were eligible and those who followed-through and collected their reward.

A.4.4 Additional analysis

When selecting our sample we chose to include customers of the 11 largest UK suppliers, representing 88% of total market share.[40] The retail electricity market in the UK has over 50 suppliers in total, making it practically impossible to coordinate smart meter installation offers for customers of all suppliers.

Our standard errors must be clustered to reflect this sampling design and we cluster at the level of the supplier (Abadie et al., 2017). Given that we have only 11 suppliers, we perform a method of clustering robust to this feature of our data. Canay et al. (2018) provide evidence that the wild bootstrap method developed by Cameron et al. (2008) is robust in settings with as few as five clusters. Roodman et al. (2019) provide an implementable routine to perform this analysis in Stata and suggest the use of "Webb" weights when the number of clusters approximates 10.

Figures A3, A4 and A5 present confidence intervals and p-values following a wild bootstrap estimation with 2000 replications for the results presented in Table 5. The results provide further evidence that information on the social benefits of smart grid infrastructure (Treatment 2) appear to influence decisions in a positive direction for various subsidy levels.

Finally, Table A9 presents results from a logistic regression model, which are substantively similar to our primary OLS specification.

Table A9: Treatment Effects on Adoption of Smart Meters for Relevant Subsidy Values: Logistic Regression Results

	(1) WTA 10	(2) WTA 25	(3) WTA 50	(4) WTA 75	(5) WTA 100	(6) WTA 150	(7) WTA 200
Treatment 1: Private	1.048	1.089	1.088	0.987	0.903	1.017	0.933
	(0.163)	(0.100)	(0.116)	(0.087)	(0.122)	(0.170)	(0.164)
Treatment 2: Social	1.231***	1.102	1.240***	1.348***	1.078	1.205	1.247*
	(0.085)	(0.097)	(0.084)	(0.107)	(0.163)	(0.157)	(0.157)
Treatment 3: Learning	1.012	0.973	1.151	1.122	0.943	0.974	1.082
	(0.107)	(0.104)	(0.131)	(0.106)	(0.113)	(0.118)	(0.162)
Constant	0.431***	0.813	1.444	2.225***	6.995***	6.131***	11.372***
	(0.132)	(0.237)	(0.381)	(0.440)	(1.688)	(1.519)	(2.601)
Observations	1,708	1,708	1,708	1,712	1,712	1,708	1,708
Controls	YES	YES	YES	YES	YES	YES	YES

Note: The dependent variable in the regression is a binary variable capturing whether the respondent agreed to adopt a smart meter for a price in the range of [0, *c*]. . Controls include gender, age, income, and region. Standard errors are included in parentheses below the estimates and are clustered at the supplier level. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

[40] At the time of sampling these were British Gas, EDF, EON, npower, Scottish Power, SSE, Co-op, Shell Energy (formerly First Utility), Ovo, Utilita and Utility Warehouse.

A.4.5 Sensitivity: Wild bootstrap confidence intervals

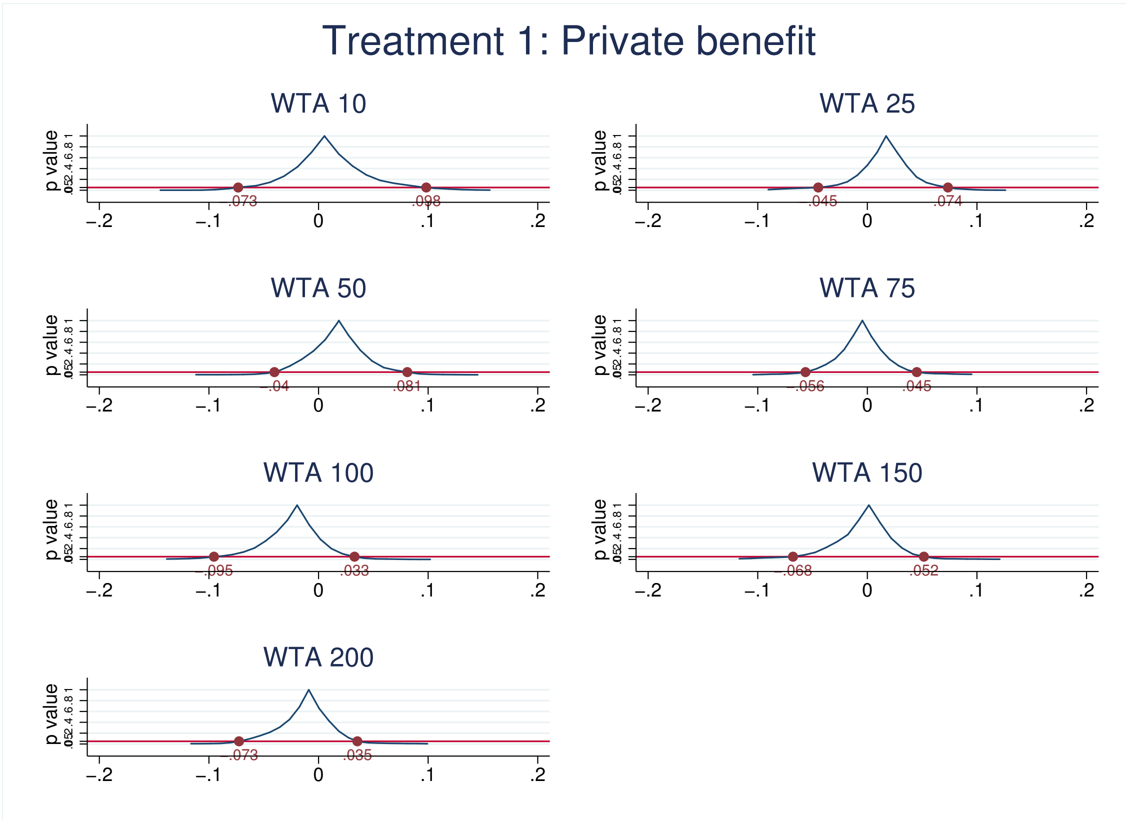


Figure A3: Treatment 1: 95% Confidence Interval of treatment effect following Wild Bootstrap estimation of standard errors with 2000 replications

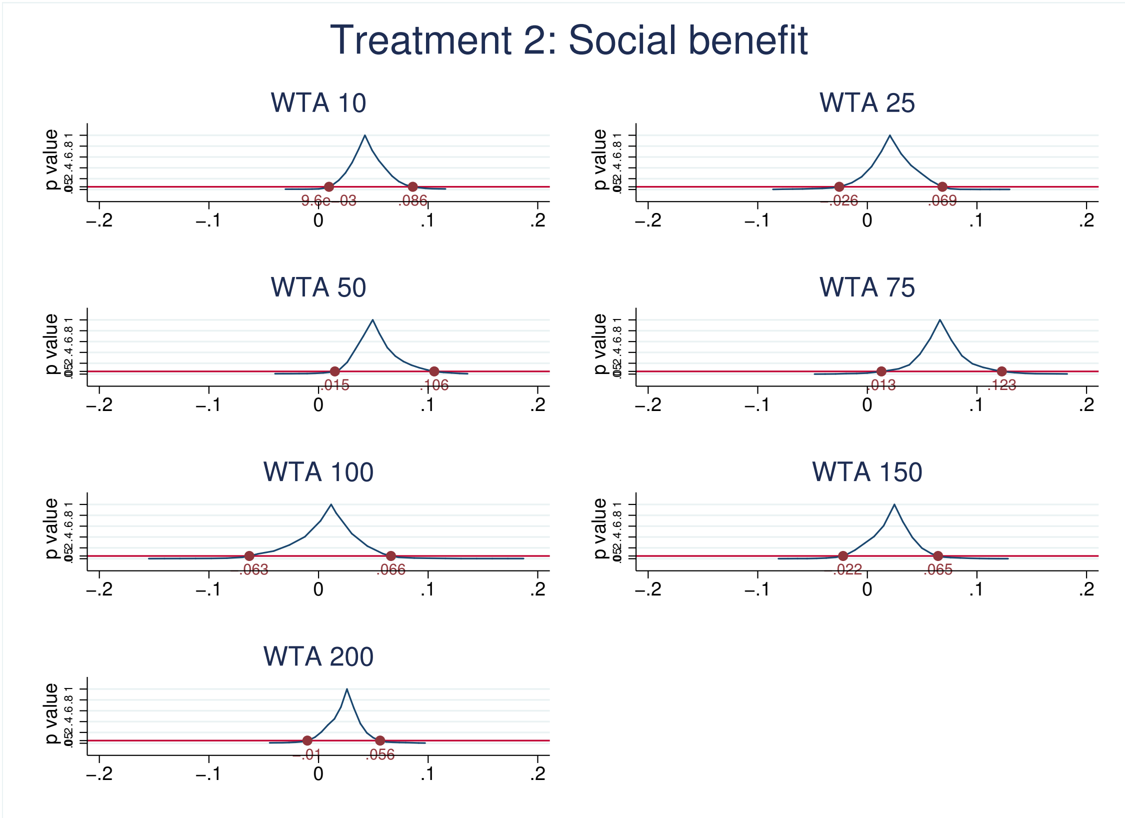


Figure A4: Treatment 2: 95% Confidence Interval of treatment effect following Wild Bootstrap estimation of standard errors with 2000 replications

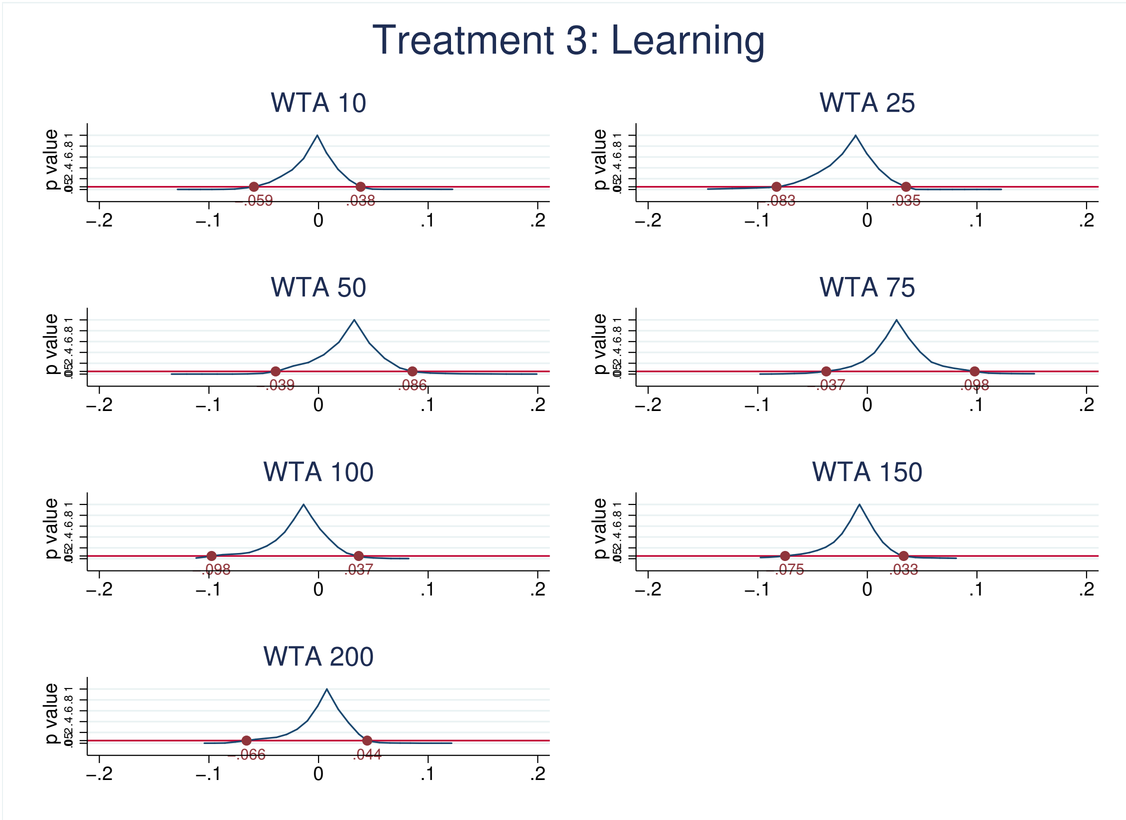


Figure A5: Treatment 3: 95% Confidence Interval of treatment effect following Wild Bootstrap estimation of standard errors with 2000 replications

A.5 Heterogeneity

We base our heterogeneity analysis on the exploratory hypotheses proposed in our project pre-registration. Below we outline each of our hypotheses and state whether they are supported by our results.[41]

Our first hypothesis (H1) conjectured that low-income households will be more likely to (a) adopt a meter without compensation or (b) state a lower WTA than higher-income households due to higher marginal utility of income in Treatment 1 (Private Benefit). We find that this hypothesis is unsupported by our results along both dimensions.

Our second hypothesis (H2) was that individuals with more interest in and knowledge of environmental issues and undertakings will respond more favorably to Treatment 2 (Social Benefit). That is, we posited that higher rankings on any of the following scales would positively interact with social information: (a) education; (b) environmental interest (as proxied by attitude toward renewable energy); (c) engagement in energy-saving behaviors, and/or; (d) trust in institutions (as proxied by trust in government and energy suppliers). We find that H2a is unsupported: degree holders are no more likely to respond to Treatment 2 than those without a degree. Our analysis of H2b is inconclusive, though the sign of the coefficient is generally going in the direction of support and is significant for a subsidy of £50. H2c is unsupported, and if anything we find that people who undertake more energy-saving behaviors are less likely to respond to Treatment 2 at higher subsidy levels. H2d is also largely unsupported, in that more trust in suppliers or government does not lead to a higher response to Treatment 2. The exception to this result is a statistically significant and positive impact of higher trust in government interacted with a subsidy value of £200.

Our third and final hypothesis (H3) anticipated that individuals who are (a) more risk averse or (b) have higher revealed interest in technology (as proxied by ownership and optimism toward technology) would be more affected by Treatment 3 (Learning), since this treatment aims to alleviate concerns about privacy and security while touting a new and upgraded technology. We find that H3a is supported by our results: Treatment 3 increases the likelihood that risk-averse individuals adopt smart meters for all subsidy levels from £10 upwards. We do not observe a statistically significant effect for risk-seeking participants. Treatment 2 also increases the likelihood that risk-averse individuals adopt a meter without compensation, and the effect is also present for all subsidy levels from £10 upwards. On the other hand, H3b is unsupported; while the sign of the coefficient is generally consistent with the hypothesis, the effect is neither consistent nor significant across models.

[41] Table A10 provides supporting results for the estimations regarding risk preferences. All other results are available on request.

Table A10: Heterogeneity Analysis of Treatment Effects on Adoption of Smart Meters for Relevant Subsidy Values

	(1) Participation effect	(2) WTA 10	(3) WTA 25	(4) WTA 50	(5) WTA 75	(6) WTA 100	(7) WTA 150	(8) WTA 200
Treatment 1: Private	-0.017	-0.030	-0.028	-0.047	-0.085***	-0.056**	-0.031	-0.040
	(0.023)	(0.037)	(0.025)	(0.029)	(0.025)	(0.024)	(0.023)	(0.022)
Risk Averse	-0.099***	-0.166***	-0.178***	-0.209***	-0.241***	-0.147***	-0.153**	-0.155***
	(0.027)	(0.037)	(0.030)	(0.042)	(0.037)	(0.044)	(0.063)	(0.047)
T1*Risk Averse	0.044	0.134**	0.159***	0.234***	0.285***	0.124	0.108	0.102**
	(0.050)	(0.050)	(0.050)	(0.068)	(0.068)	(0.071)	(0.062)	(0.039)
Treatment 2: Social	-0.020	-0.009	-0.023	0.008	0.015	-0.016	-0.008	-0.023
	(0.024)	(0.029)	(0.030)	(0.013)	(0.014)	(0.035)	(0.021)	(0.014)
T2*Risk Averse	0.093*	0.169**	0.150**	0.151***	0.191***	0.104**	0.123***	0.173***
	(0.047)	(0.073)	(0.065)	(0.035)	(0.054)	(0.036)	(0.037)	(0.032)
Treatment 3: Learning	-0.026	-0.037	-0.044	-0.003	-0.033	-0.052*	-0.036	-0.035
	(0.020)	(0.031)	(0.031)	(0.036)	(0.029)	(0.026)	(0.021)	(0.022)
T3*Risk Averse	0.082	0.136**	0.133**	0.124*	0.206***	0.142***	0.108*	0.155***
	(0.048)	(0.059)	(0.058)	(0.063)	(0.049)	(0.036)	(0.052)	(0.048)
Constant	0.145***	0.355***	0.500***	0.659***	0.768***	0.925***	0.900***	0.954***
	(0.024)	(0.052)	(0.057)	(0.056)	(0.038)	(0.041)	(0.044)	(0.031)
Observations	2,430	1,714	1,714	1,714	1,714	1,714	1,714	1,714
R-squared	0.024	0.036	0.044	0.051	0.053	0.052	0.052	0.059
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Note: The dependent variable in columns (1-8) is a binary variable capturing whether the respondent agreed to adopt a smart meter for a price in the range of $[0, c]$. Controls include gender, age, income, and region. Standard errors are included in parentheses below the estimates and are clustered at the supplier level. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

A.6 Analysis of Barriers

Our survey elicits information on subjective barriers to adoption, which we use to provide evidence on the society-wide barriers inhibiting participants from adopting smart meters. Table A11 presents information on the count and percentage of participants who selected each of the five primary reasons cited for non-adoption: hassle costs, privacy or security concerns, belief that the device will not lead to savings, lack of trust in energy suppliers and health. Respondents were not limited to citing a single concern, and they could additionally input unlisted reasons by selecting 'other' and providing a text response (Table A12). From this table, we glean that about three-quarters of non-adopters do not believe in the purported savings the meters could facilitate, about two-thirds cite hassle costs as important to their decision not to adopt, a slim majority worry that the meters may threaten their privacy or security, and one in ten hold concerns about the health impacts of smart meter adoption.

Table A11: Self-reported reasons for not wanting a smart meter

Reason Category	Count	Percentage	Mean WTA
Hassle	809	25%	£136
Privacy/security	659	21%	£192
Won't save money/energy	861	27%	£163
Don't trust supplier	319	10%	£194
Health	115	4%	£267
Other	424	13%	£145

Note: Total percentage is greater than 100 as participants were able to select more than one reason. WTA distribution is winsorised at £1000.

Table A12: Detailed categorization of 'Other' reason for refusing a smart meter

Reason Category	Count	Percentage
Concerns about smart meters	122	29%
Constrained by external factors	151	36%
Do not want a smart meter	46	11%
Inconvenience/hassle costs	15	4%
No reason given/arbitrary	14	3%
Concerns about suppliers/energy costs	3	1%
Want a smart meter in the future	43	10%
Want to wait	25	6%
	419	100%

In order to more explicitly assess the impact of self-reported barriers on WTA we next estimate a series of linear probability models with continuous WTA as the dependent variable and each barrier included as independent variables, along with a set of control variables.[42] We estimate the model for a range of maximum WTA values. Figure A6

[42]We do not observe any substantive difference in results when we control for treatment indicator.

presents the results graphically. Interpreting the top-left quadrant, for those participants whose WTA is £1000 or less, those who cite health concerns report a WTA of approximately £100 greater than those who do not. This estimate is considerably higher than the approximately £50 increase in WTA associated with the next highest barriers, which are privacy concerns and lack of trust in suppliers. The observed ranking of barriers is similar when we consider individuals stating a WTA of £500 or less, but this pattern does not hold for lower ranges. We are cautious about over-interpreting these results due to the imprecision of the estimates. Our reading would indicate that a small number of participants citing health concerns (and to a lesser degree, privacy and lack of trust in suppliers) have very high WTA values. For participants with a lower WTA no clear ordering emerges.

Figure A6: Relationship between WTA and self-reported barriers. Note: Results presented are from a linear probability estimation with continuous WTA as the dependent variable. The regressions include control variables and clustered standard errors at the supplier level. Bars around the point estimates indicate the 95 percent confidence interval.

A.7 Demand curves by treatment

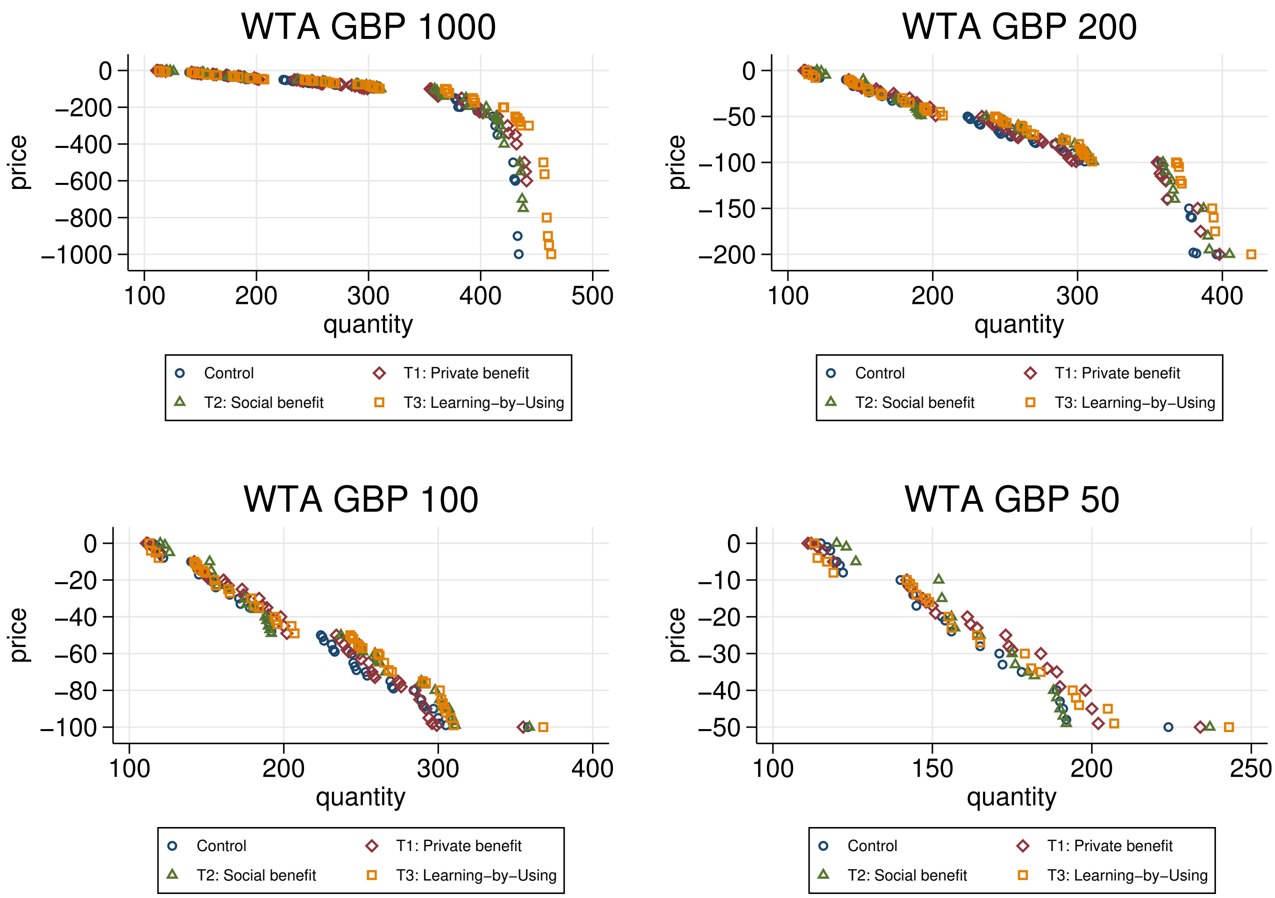


Figure A7: Estimated demand curves for smart meters by treatment

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