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

Greer Gosnell and Daire McCoy†

May 15, 2020

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 2,400 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 inframarginal 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 one-off technology adoption behaviors in achieving energy system-level and environmental policy goals. Indeed, while some policies may target householders' recurring energy-wasting habits—leaving the lights on in unoccupied rooms, for example, or failing to turn the heat off when leaving the home—other perhaps more persistent energy conservation policies might target infrequent one-off behaviors or decisions.[1] For instance, economists have studied the impact of energy and fuel efficiency on consumers' purchasing decisions, finding mixed evidence: while some studies show that consumers are largely inattentive to future fuel costs (or savings) of the energy-consuming durables they adopt (Allcott and Taubinsky, 2015; Fowlie et al., 2015), others cannot reject the hypothesis of consumer attentiveness (Houde and Myers, 2019).

New technologies may particularly suffer from low take-up rates due to consumers' lack of experience and little understanding of the technology's benefits. 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 evidence to support these claims 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).

We contribute evidence regarding the import of the aforementioned 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: real-time information allows for efficient matching of energy supply with energy demand, improves predictions regarding requisite energy capacity at various times of the day and year, eliminates the need for manual meter readings, and provides the opportunity to incentivize shifts in demand to minimize system-level costs (Joskow, 2012).

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 energy usage, evidence is mixed regarding the propensity of households to engage with the meters' information to successfully reduce costs (Faruqui et al., 2010; National Audit Office, 2018). Second, while a smart meter allows for monthly bill payments commensurate with actual usage, consumers may still prefer to pay a fixed monthly fee for simplicity, budgeting, and consumption smoothing purposes.[2] Third, as historically passive users of energy often beholden to rigid daily routines, householders may struggle to shift demand considerably, rendering any increase in energy plan options welfare-neutral, at least in the short run (Burke and Abayasekara, 2018). Finally, system-level benefits could save householders money via supplier savings pass-through, though there is no guarantee that

[1]To illustrate the significance of such one-off decisions, in its 2014 assessment of proposed EU-wide performance standards, 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.

[2]It has been shown that consumers respond more to average rather than marginal pricing, as the cognitive effort required to understand more complex pricing can be substantial (Ito, 2014).

such savings will reach the consumer.

Yet, widespread smart meter adoption holds promise to considerably improve environmental outcomes through increased energy production efficiency—which reduces overall energy production and greenhouse gas emissions—and flexibility—which lowers the risk of blackouts and facilitates the integration of higher proportions of renewable energy into a given system's energy portfolio. For instance, in its extensive cost-benefit analysis most recently updated in 2019, the UK Government finds that the environmental and financial savings far outweigh the costs of rapid transition to a smart energy system.[3][4] In this case, how can a social planner understand and quantify the extent of resistance to the technology in question, and subsequently encourage adoption among reluctant or ambivalent consumers?

This research develops an incentive-compatible online experiment to elicit a representative panel of UK households' willingness-to-accept compensation (WTA) for smart meter installation following exposure to various treatments aimed at overcoming two relevant market failures: imperfect information and learning by using. We measure two main outcome variables, namely (i) whether the household adopts the smart meter without compensation, as well as (ii) the subsidy level necessary for non-adopting households to adopt (conditional on treatment received). From these responses, we reveal the significance of private and social information as well as learning-by-using externalities in the decision to adopt the technology, and infer adoption rates at various subsidy levels in this context.[5]

Our results suggest that offering subsidies of £10, £25, £50, and £100 would induce additional adoption of 4, 9, 24, and 53 percentage points from a baseline of 22% adoption. Pairing these subsidies with a social information campaign can boost these numbers by an additional 1-5 percentage points. Inframarginal costs dominate the cost of any subsidy programme, ranging from 53-83 percent of total costs. We present suggestive evidence that a £100 subsidy may be optimal from the perspective of minimizing the percentage of policy expenditures that are inframarginal, though of course the optimal subsidy will depend on the social welfare function being optimized.

Our research contributes to several relevant strands of literature, in particular those on non-market valuation, the energy efficiency gap, optimal subsidy design, and households' acceptance of publicly beneficial infrastructure upgrades. The combination of a randomized information treatment along with a Becker-DeGroot-Marshak valuation in eliciting

[3]https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/831716/smart-meter-roll-out-cost-benefit-analysis-2019.pdf

[4]It should be noted that past UK cost-benefit analyses of smart meter roll-out do not take into account a number of non-monetary costs, such as potential hassle costs from having to take time off work, or perceived privacy and health risks.

[5]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 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 level, 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 who could wait for a higher subsidy, and that this effect has a positive interaction with anticipated technical change.

WTA in a developed country context is novel. 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. A key difference between our work and the former is the valuation method we employ, and our elicitation of WTA rather than WTP. Our work differs from the latter in its application to an impure public good[6]—as opposed to a private good—in a developed world context.

In addition, we take steps to measure the non-monetary costs of existing barriers to smart meter adoption. This approach builds on work by Fowlie et al. (2015) who demonstrate evidence of non-monetary costs for energy-efficient home upgrades, though we go a step further to explicitly quantify the costs and provide evidence on the relative importance of various barriers. Our research shares similarities with List et al. (2018) who conduct a natural field experiment examining smart meter adoption and energy savings among British Gas customers.[7] Furthermore, we generalize the work of Boomhower and Davis (2014) by quantifying inframarginal costs across the entire potential subsidy distribution, providing a more thorough consideration of the optimal level of subsidy required. Finally, we add to a growing literature on the public acceptability of smart grid infrastructure,[8] widely accepted to be a necessary ingredient in enabling many countries' sustainable energy transitions.

The remainder of this paper is structured as follows. The next section provides brief contextual background regarding the technology in question and the UK's Smart Meter Implementation Programme. The third section provides details of the experimental and valuation methodologies deployed. The fourth section details the data collection process and provides summary statistics for the data collected. The fifth section outlines our empirical strategy and results. Our final section concludes with implications for policymakers and future research.

2 Background

A long-standing inefficiency in energy markets is the disconnect between retail prices paid by consumers and the marginal costs of supplying electricity. Smart meters allow real-time two-way communication, removing the technological barriers to setting prices that reflect costs of production (Joskow, 2012; Harding and Sexton, 2017). Smart metering may allow consumers to save energy and money (Faruqui et al., 2010), but of greater social benefit is their potential to pave a path toward a more flexible energy system, allowing optimization of generation and storage. Enhanced demand flexibility would enable more

[6] An impure public good is defined as a privately acquired good that generates both private and a public characteristic (Cornes and Sandler, 1994)

[7] The papers are complementary but have some key differences. While List et al. trialed incentives of £5 and £10, our use of a BDM mechanism allows us to estimate the impact of a wide range of potential incentives. Additionally, we combine our price elicitation with a randomized information treatment allowing us to determine the importance of oft-cited market failures in explaining adoption decisions. We conduct our analysis on customers of the largest 11 utilities in the UK, while List et al. work with one large utility. Finally, List et al. examined the impact of smart meters on subsequent energy consumption, which institutional barriers preclude us from doing in our study.

[8] See for example Fell et al. (2015); Spence et al. (2015); Bigerna et al. (2016); Sovacool et al. (2017).

efficient management of the energy system, allow for a greater proportion of intermittent renewables in the UK's energy mix, potentially reduce network operating costs, and enable consumers and suppliers to more efficiently engage with electric vehicle charging and other load shifting (Joskow, 2012). The potential for these private and social gains creates opportunities for technological innovation—such as the smart meter—to realize them.

Extensive cost-benefit analysis of smart metering led to the Smart Meter Implementation Programme (SMIP)—the single-most important domestic energy policy initiative ongoing in the UK—in 2013. The policy provides the legal framework to install about 48 million smart electricity and gas meters in UK households by 2020. It has been described as the most expensive and complex smart meter rollout in the world and the largest UK Government-run IT project in history (Lewis and Kerr, 2014). Successful implementation of the SMIP hinges on consumers' voluntary agreement to have the meters installed in their homes. However, a number of parties—including the UK's National Audit Office, the media, and interest groups—have expressed several concerns relating to the technical performance of the meters, data security and privacy, consumer vulnerability, and consumer resistance and ambivalence, among others (Sovacool et al., 2017). In addition, concerns over the SMIP's lack of clarity of purpose and minimal transparency in its communication of consumer benefits have overshadowed ambitious implementation efforts (House of Commons Science and Technology Committee, 2016).

Consumer resistance due to a range of factors has quite evidently inhibited rollout, as there were only 16.3 million meters installed and 13.4 million meters operating by the end of Q2 2019. The potential driving forces behind households' decisions to adopt remain unclear. In making this decision, a household must weigh up a range of costs and benefits, each with private, social, and intertemporal dimensions: costs are generally borne upfront (e.g., time off of work to accommodate installation, learning about the technology's functionality), while a greater proportion of the benefits will accrue in the future (e.g., in increasing one's own energy-saving awareness and altering habits, facilitating the emergence of alternative and potentially cheaper rate plan options or money-saving technological innovations, or reducing system costs that may pass through to consumers). In brief, the present value of the net benefits to a given household is idiosyncratic and may be positive or negative.

Not only may some households be unaware of the potential private and social benefits of smart meter installation, they may be reluctant to adopt for a number of reasons such as privacy (McKenna et al., 2012), financial costs (Balta-Ozkan et al., 2013), hidden costs (Gillingham and Palmer, 2014), or general disengagement with or distrust in their energy utility (Central Market Authority, 2016). In addition, energy utilities may have difficulty in accessing certain customers, or there may be physical and structural constraints associated with dwellings that make installation of smart meters impossible. In other cases, misaligned incentives and communication channels between landlords and tenants may constrain adoption in the private rented sector. Finally, the non-monetary costs of energy efficiency upgrades have been shown to deter households from installing free measures, even once households have become aware of the potential private benefits and made an application for a home upgrade (Fowlie et al., 2015).[9]

[9] More generally, a broad literature exists that examines the so-called "energy efficiency gap", a well-evidenced phenomenon suggesting that consumers do not invest in energy-saving technologies (such as insulation or replacement boilers) that may be privately beneficial. This gap is often attributed to imperfect information or inattention on the part of consumer (Allcott and Greenstone, 2012). Gillingham and Palmer (2014) provide

3 Methodology

We aim to quantify the importance of several identified market failures that serve as rational barriers to adoption of (potentially) 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.[10] 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. We do so using a survey experiment that captures adoption behavior and willingness-to-accept compensation for non-adopters, as described below.

3.1 Experimental Design

We designed a survey experiment using the Qualtrics survey software platform in which eligible household energy decision-makers may sign up to adopt a smart meter following treatment exposure. Those who decline to adopt the smart meter subsequently perform a willingness-to-accept compensation (WTA) elicitation exercise to determine the subsidy value at which they would adopt. The exercise is incentive-compatible in that respondents receive a payout equal to our randomly selected subsidy offer if our offer exceeds their stated WTA, though only once they supply the information required to sign them up for a smart meter; they may provide the latter in the survey itself or at any point in time over the following two weeks. Individuals who provide sufficient electricity account information are compensated with a versatile digital gift card for the offered subsidy amount; in exchange for the compensation provided, 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 smart meter installation. Figure 1 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.

an extensive overview of reasons why the gap may be smaller than perceived, and of both market failures and behavioral anomalies that may be contributing to the gap that exists.

[10]Note that a fourth market failure—(misconceived) 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. We do not think this issue is significant as only seven of the 791 respondents cited landlord/tenant issues when asked to provide information on factors influencing their choice of WTA. The fifth market failure—credit and liquidity constraints—does not apply in this context.

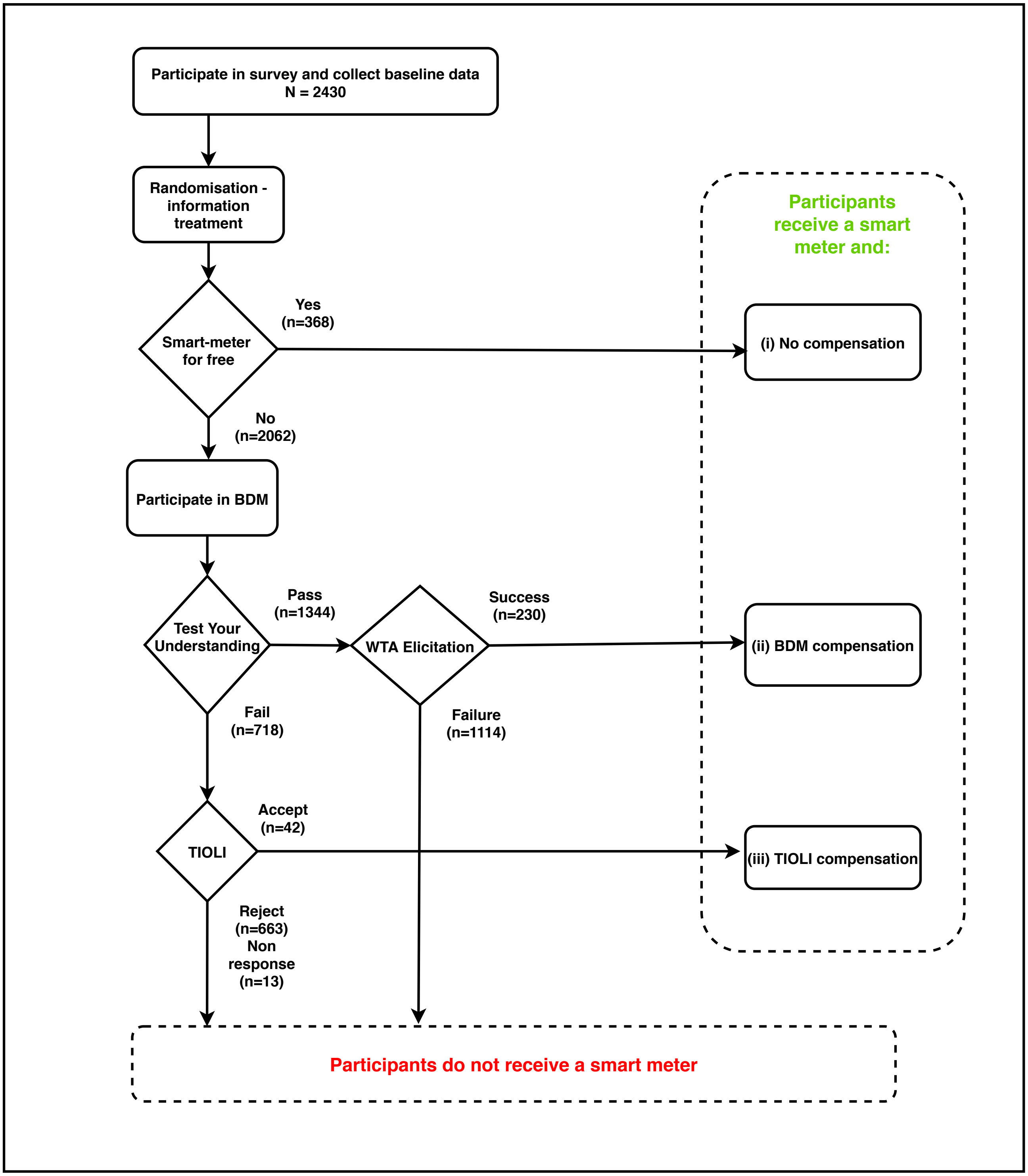


Figure 1: Survey Flow Chart for Eliciting Smart Meter Valuation

3.1.1 Treatments and Smart Meter Offer

Early in the survey, all eligible participants receive basic information regarding smart meters (see Figure 2) prior to treatment exposure for two reasons: (i) to verify that they do not already have and have not yet been offered a smart meter (as part of the eligibility criteria), and (ii) to ensure they share a base level of understanding regarding the good in question.

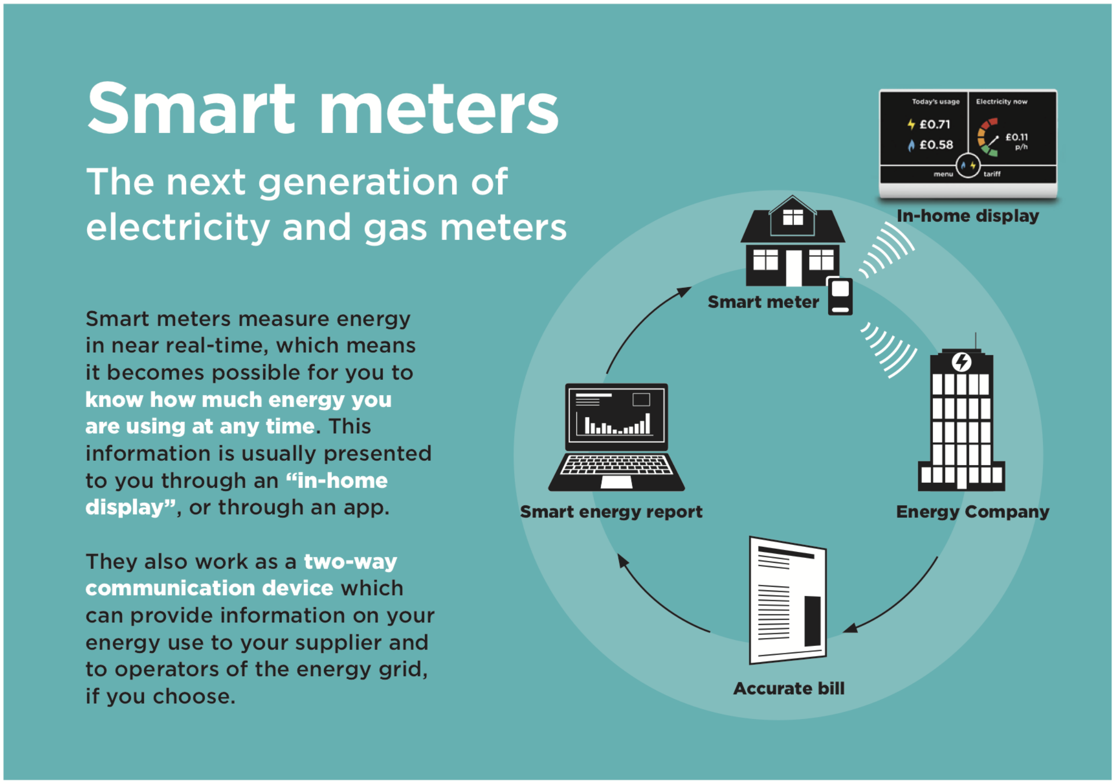
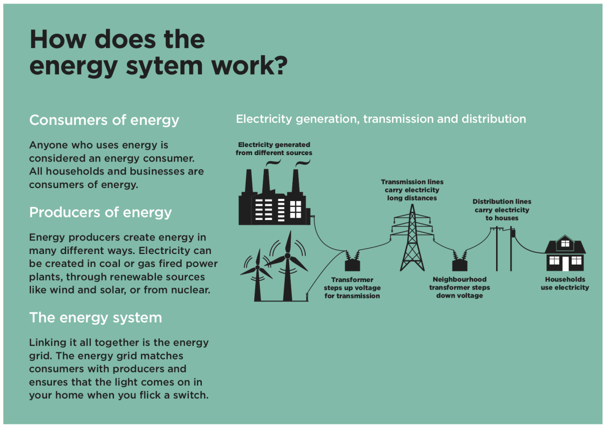


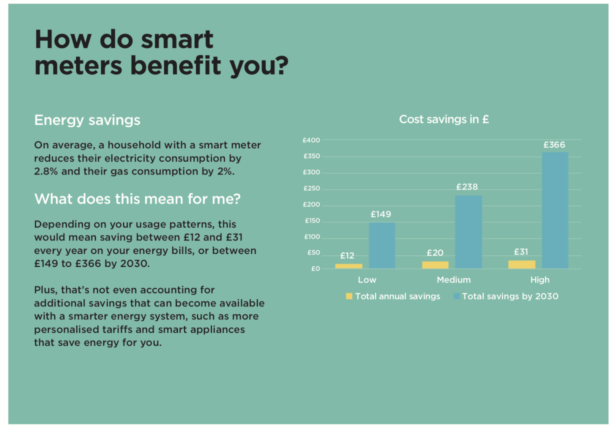
Figure 2: Smart meter description

Once we confirm eligibility, the participant views 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); (iii) information on the social benefits of smart meter adoption (Treatment 2); and (iv) information on bygone 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 complement 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 3.

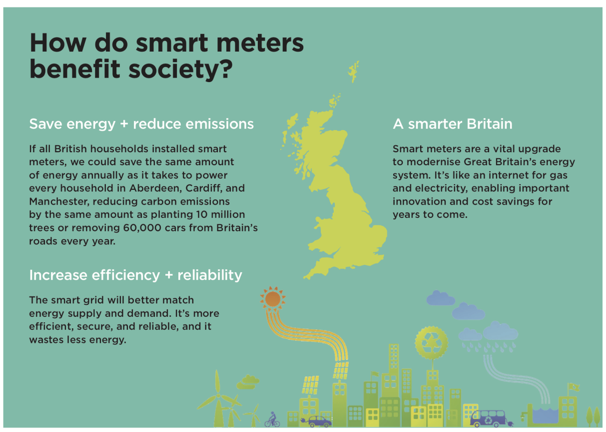
[11]Due to lack of pre-experimental data on participants, we do not stratify the randomization but instead use the Qualtrics *Randomizer* tool to randomly assign individuals who take the survey to receive one of the above four conditions. When we reached 2000 responses we then adjusted the (treatment) 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).



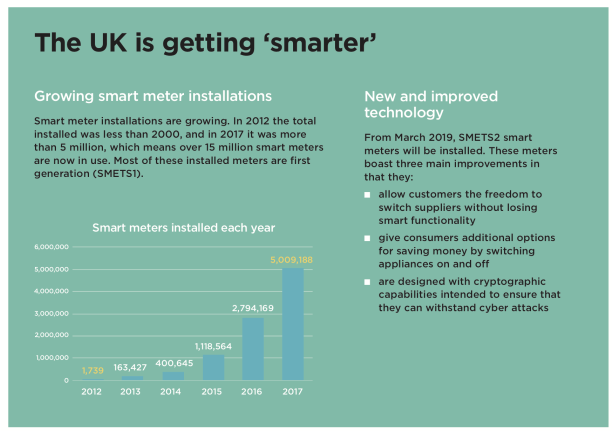
Control



Treatment 1: Private Benefits



Treatment 2: Social Benefits



Treatment 3: Learning-by-Using

Figure 3: Experimental Treatments

Immediately following treatment exposure, we ask participants whether they would like to adopt a smart meter.[12] Those who say yes subsequently provide us with sociodemographic and attitudinal information, and may then supply the account information necessary for us to sign them up to receive a smart meter through Ofgem. Those who decline 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.

3.1.2 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,

[12]Unlike Allcott and Taubinsky (2015), we do 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 free of charge 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.

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 (or selling price) from respondents by offering to pay them an unknown (and, in our case, double blind) amount b—the researcher's buying price—in the event that the latter exceeds the former. Since sellers (i.e. survey respondents) do not know the value of b in advance, they essentially cognitively engage in an iterative TIOLI process, asking themselves whether they would be willing to accept b in exchange for the service for every possible value that b could take, thereby ultimately identifying and stating their true selling prices.

As highlighted in Berry et al. (2020), TIOLI can be quite impractical if there is a wide range of prices over which the researcher is eager to understand WTA. In our case, consumers' WTA 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 one's true WTA and potential treatment effects. In other words, if a researcher is interested in the impact of various treatments on one's WTA and only one or two prices are offered as part of a TIOLI survey, then the researcher can only identify the treatment effect at that/those price level(s). Therefore, without the assumption of a constant treatment effect, TIOLI could preclude identification of a treatment effect when one indeed exists for some individuals or at some price points for which insufficient data were collected. Finally, if compensation received could be a predictor of subsequent behaviors—e.g., in our case, actual smart meter installation—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 fairly limited sample size. We therefore perform a BDM exercise to elicit WTA for individuals who demonstrate comprehension via a 'test of understanding', and present a TIOLI offer of £10 to those who do not pass this test (see Appendix A.1.2 for screenshots of the comprehension test).[13]

[13]We selected the TIOLI offer of £10 to replicate the findings of the only field experiment to our knowledge to incentivize adoption of smart meters in the UK (List et al., 2018). The authors find that, among British Gas

Design considerations. Apart from BDM's lower comprehensibility relative to TIOLI, some methodological difficulties are worth noting. Foremost, and particularly when the market for such a service is missing or unfamiliar, 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, at the very least, infeasible to pay out.[14]

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 exists in our BDM context.[15] Specifically, in delimiting the potential buying price, we tested three designs—a £50 maximum, a £100 maximum, and an unstated maximum—while restricting the treatment randomization to only display the control condition. We found that making the range explicit significantly suppresses valuations and concentrates them near the maximum of the range.[16]

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 offer range of (£0, £100].[17] 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.[18] To anchor, we ensured that all examples in the 'test of understanding' for both

customers, a £5 or £10 incentive increased take-up by 6.1% from a baseline adoption rate of 18.1%. Of those in our sample who rejected a free meter (and failed the test of understanding), we find that 6.0% of individuals agree to adopt the smart meter when presented with the TIOLI offer of £10, which is highly consistent with the findings of List et al. (2018).

[14]To understand the implications of various solutions to this issue for the valuation of a familiar commodity—here, subjects are endowed with a voucher for gasoline—Bohm et al. (1997) conduct an experiment in which they compare 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 find 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. Similarly, Vassilopoulos et al. (2018) find an anchoring effect of the buying price range when selling mugs, and Sugden et al. (2013) find an anchoring effect of both the buying and selling price range for several goods whose market value is £5.

[15]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.

[16]This question was experimentally tested during the pilot phase. Results are available on request and will form the basis of an additional research paper.

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

[18]Survey text: "Given your answer to the [free meter] 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

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.

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' by taking the survey multiple times and trying to guess at a value that would give them money in return for installing a smart meter. We identified all survey response duplicates by name, IP address, and the email address they provided (of which there were 109) and have removed these responses from the data.

We aim 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 follows extensive BDM instructions (see Appendix A.1.1)—involves 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 1). We also capture a weak measure of comprehensibility directly following the instructions in which we ask the respondent to indicate whether they felt they understood the instructions.

Second, we ask two specific questions regarding individuals' rationale for having denied a free meter and selected a particular WTA value (see Appendix A.4 and A.6). The first question is a multiple-response multiple choice question in which respondents check any box that aligns with their reasoning for denying the free smart meter. Responses include (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 asks 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

interested in learning what that 'right incentive' might be for you, if any."

provided information related to their choice of WTA.

3.1.3 Incentive compatibility

To avoid hypothetical bias and maximize the likelihood that elicited WTA values are incentive compatible, 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 in the survey that all decisions were incentive compatible in this way.[19] Individuals who express that they would like a smart meter (with or without compensation from the BDM or TIOLI exercises) are subsequently asked to provide their electricity account details so that we may pass them along to their respective suppliers.[20] Those who agree to get the smart meter via the BDM or TIOLI mechanism and who go on to provide complete account information receive Tango Gift Card e-vouchers that may be used at a large number of global and UK-specific (online) retailers, restaurants, ride-share services, and the like.

Of those who signed up to receive a smart meter, 62/397 (15.6%) of affirmative free meter respondents, 29/246 (11.8%) of BDM 'winners', and 2/46 (4.3%) of affirmative TIOLI respondents provided sufficiently complete information for us to sign them up.[21,22] All had the opportunity to provide their complete account details within the main survey. Otherwise, they could indicate that they did not have their details to hand, in which case they were sent a follow-up survey link to provide their information.

3.2 Empirical Strategy

We consider two primary outcome variables of interest. The first is a binary measure that captures whether the participant adopts a smart meter for free after having viewed the randomized information provided. We estimate a linear probability model using OLS regression, which we specify as follows:

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

[19] Prior to explaining the BDM exercise, we state, "To make things realistic, well 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."

[20] In order to receive the meter, individuals must supply their first and last names, postcode, email address, electricity account number, and the Meter Point Administration Number (or MPAN), which features on most electricity bills and can be found on one's meter. 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.

[21] The gap between our offer and the respondents' WTA is no different across those who accepted and those who did not (£26.64 vs. £25.89, t-test, p=0.86), nor is there a difference in acceptance based on the offer itself (£57.5 vs £59.3, t-test, p=0.73). Treatment received and survey duration also do not have a statistically significant impact on account information provision.

[22] While the sign-up rate is admittedly low, low-uptake in energy efficiency schemes is not uncommon. Fowlie et al. (2015) find in their study on the non-monetary costs of the Weatherization Assistance Programme that even after extensive efforts to encourage uptake, only 15% of treated households submitted an application, and less than 6% received an upgrade. In their case the upgrade was worth on average $5000.

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 accept a free meter 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 5). That is, in light of the selection bias that arises in the 'conditional-on-positive' effect of a two-part model (as noted in Angrist and Pischke, 2008), 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 again T_i is the treatment group assignment of individual i, X_i is a vector of observable covariates, and ϵ is a random error term. Supplementary to the above analysis, we discuss the demand curve for smart meters and consider the welfare implications in terms of inframarginal participation and excess government spending for each of the subsidy values considered.

4 Data

4.1 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.[23] Sample quotas for gender, age, education, and region were set to match those of the UK population at large.

The sample consists of 2,430 household decision-makers[24]. The sample differs from the population only to the extent that they have agreed to take part in survey research as part of a panel. They do not have smart meters installed in their homes, though this deviation from the UK population is necessary in order to glean insights into the motivations of the sub-population relevant to the research question.

Columns 1-5 of Table A1 provide a comparison of our sample to the national population. The sample is broadly representative along most dimensions including gender, age,

[23] 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.

[24] We provide additional information on sample size calculations in Appendix A.2

education, income, and region, with some 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 (although balanced across treatments). 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.

Region 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, as a robustness check we will also include baseline control variables in our main specifications.

4.2 Dependent variables

4.2.1 Adoption without compensation

Table 1 presents the descriptive statistics for our first outcome variable, which is the proportion of participants who agreed to adopt a smart meter for no payment following exposure to either the control or treatment information. The mean level of adoption is broadly similar across all groups with participants in Treatment 2 having the highest adoption rate of 16%.

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 to the free meter question, 15.2% (n=369) indicated that they wanted to adopt a smart meter for free.

4.2.2 Subsidized adoption

Among those who did not wish to adopt a meter without compensation and passed our BDM test of understanding, the range of WTA values elicited is highly skewed, as demonstrated by Figure 4, which here is constrained at a maximum WTA of£1000. The boxes on the left present the median and inter-quartile 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. The IQR is between £50-150 for all groups, though Treatment 2 has a marginally lower median than Treatment 3 and both are lower than Treatment 1 and the Control group. The mean WTA is lowest for Treatment 1. 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.[25]

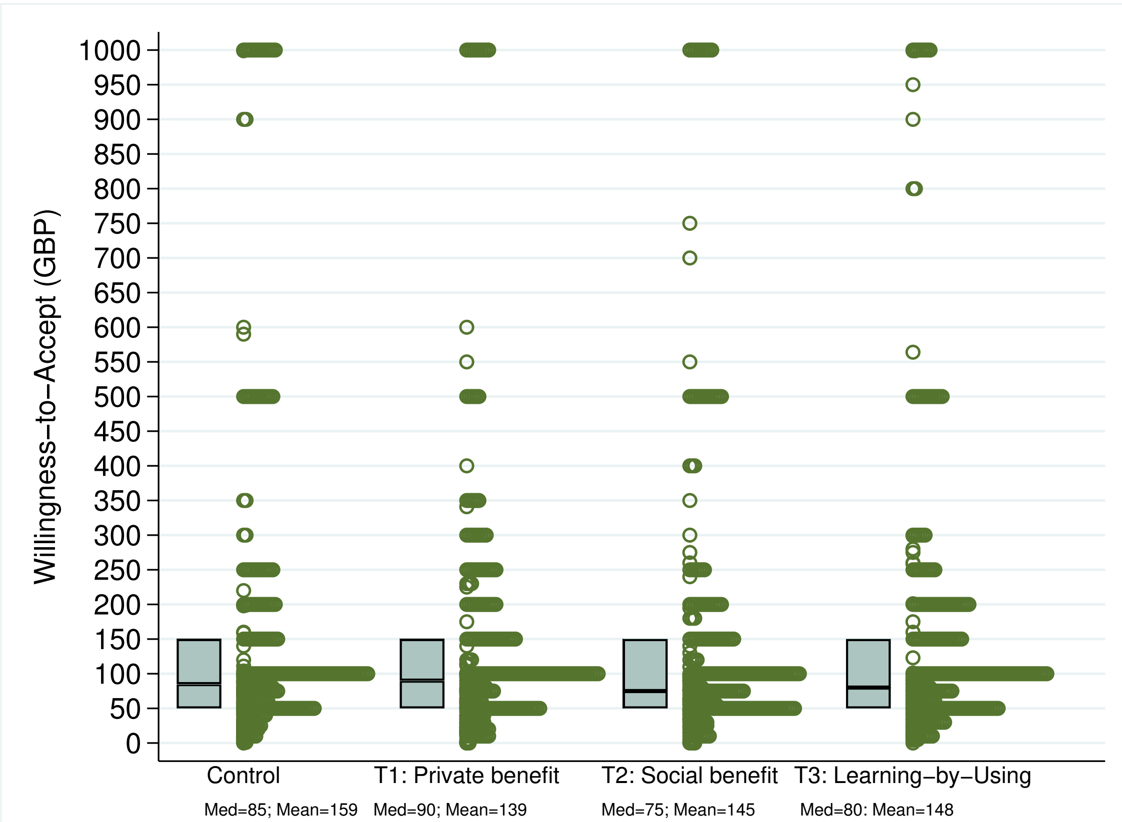


Figure 4: Distribution of WTA values by treatment

The approach we take is to focus on specific subsidy values that represent mass points of the WTA distribution. The subsidy values examined here (i.e. the c values) have been chosen based on the high frequency of their selection by respondents of the WTA exercise and the seemingly 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 adopt a smart meter under the provision of a £50 subsidy (a quarter for a £10 subsidy, a third for a £25 subsidy, etc.). Figure 5 presents the selected mass points graphically.

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

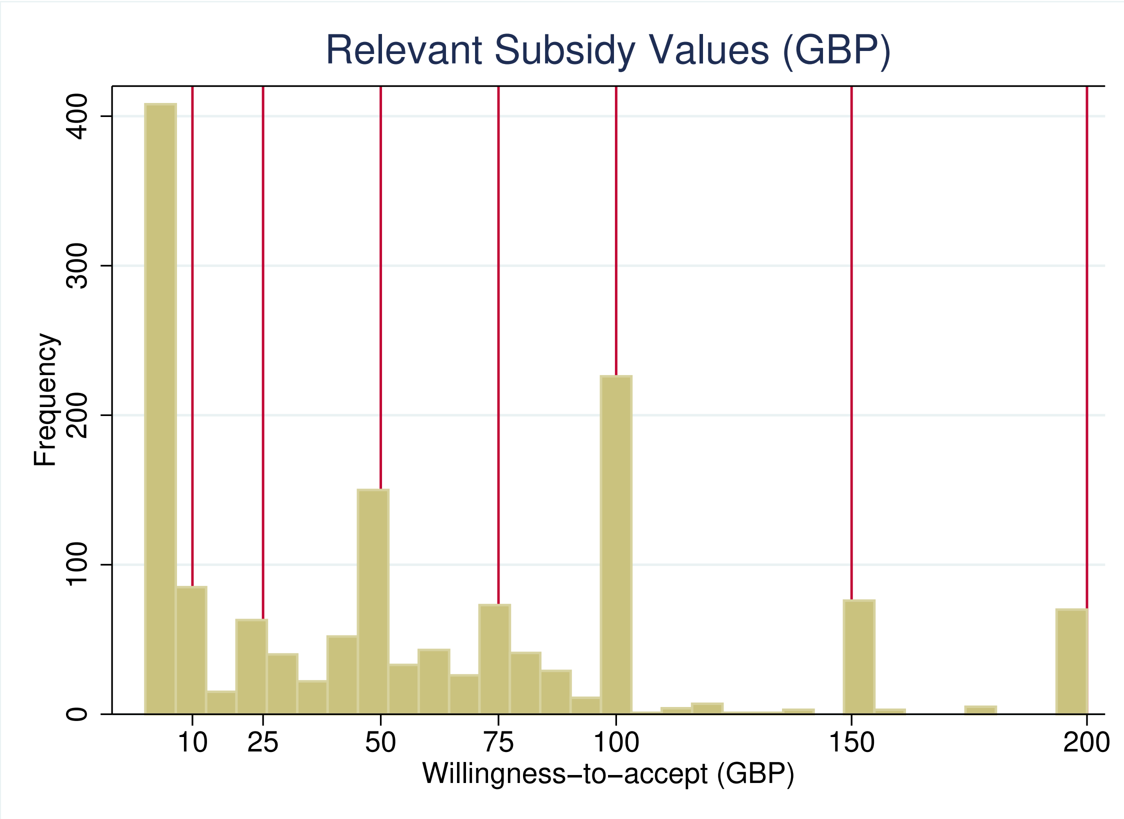


Figure 5: Subsidy values chosen for analysis

4.3 BDM Comprehension and WTA Data Quality

Of the 2,430 respondents, 2,063 indicated that they did not want a free smart meter when asked. After providing extensive instructions, we asked whether respondents felt confident they understood the BDM valuation exercise, and 93.15% of the 2,058 responses answered in the affirmative (five individuals did not respond). Even so, 41.0% (n=846) of the 2,063 respondents who did not want a free smart meter 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. 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.[26] Finally, three individuals who passed the BDM comprehension test neglected to provide a WTA.

Given that 35% of individuals who declined a free smart meter failed the comprehension test, it is important to understand for whom we are measuring WTA. Using χ^2-tests to determine the impacts of several socio-demographic characteristics—namely gender,

[26] 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.

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

welfare status, region, supplier, employment status, tenure, income, and education—as well as treatment on self-reported BDM understanding and comprehension test failure, we find that employment (p=0.052), income (p=0.010), and education (p=0.001) all predict the former while welfare (p=0.056), employment (p=0.059), income (p=0.000), and education (p=0.000) predict the latter. We therefore likely over-represent more educated and higher-income 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.

5 Results

5.1 Adoption without compensation

We first investigate the likelihood that an individual adopts a smart meter without compensation following exposure to the information treatment. The output of the linear probability model following equation (1) (see Table 3, 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.

5.2 Subsidized adoption

We now turn to the impacts of the treatments on smart meter adoption rates under a number of possible subsidy schemes. 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 3: 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 4 exhibits the results from the linear probability model following equation (2). The results indicate that neither information on private benefits nor on 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. Though we cannot reject the null hypothesis of equal adoption across Control and Treatment 1, there is some indication that interacting private benefits with a £25 or £50 subsidy may also sway some individuals (just under 2 percentage points).

Table 4: 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. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

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. In addition, we report wild bootstrap p-values in our primary estimation results, presented in Table 4. These robustness checks support the findings presented above.

We also elicit information on subjective barriers to adoption, which we use to provide evidence on the society-wide barriers inhibiting participants from adopting smart meters. Participants cited a range of barriers, The most frequently cited 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.

5.3 Estimating demand for smart meters

Eliciting precise willingness-to-accept using the BDM method permits construction of a demand curve for the good in question; in our case, given we are estimating willingness-to-accept rather than willingness-to-pay, the prices in our demand curve are negative.[27] Figure 6 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 for free 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 restricted 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. The curve is reasonably linear up to a price of approximately £200. At this point an inflection point in the demand curve suggests that subsidies of larger amounts may not result in substantially more demand. Appendix A.7 presents demand curves by treatment group. For WTA values greater than £200 the demand curve for Treatment 3 appears to the right of the others. The shift to the right of the demand curve for Treatment 2 becomes visible at lower WTA values, in line with our econometric results.

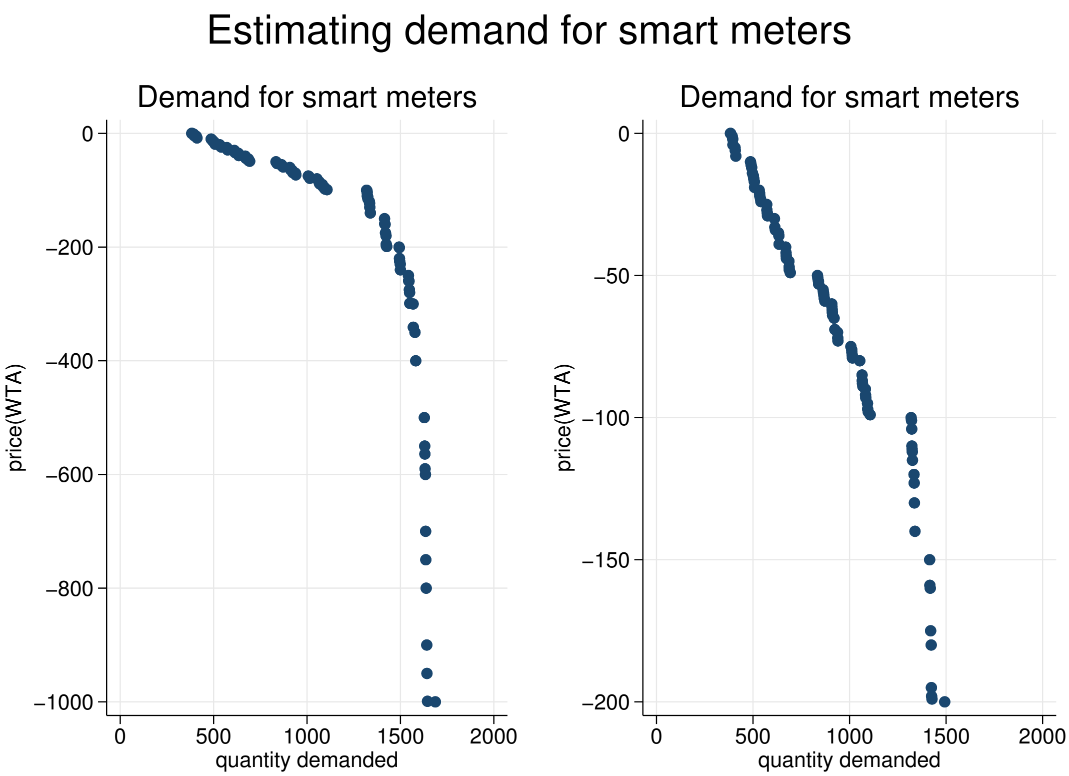


Figure 6: Estimated demand curve for smart meters. The left panel presents a demand curve restricted at £1000 or less, the right is restricted at £200 or less.

[27]The present value of the net benefits derived from smart meter adoption to a given household is idiosyncratic and maybe positive or negative. We provide a discussion of the relevant costs and benefits in Section 2. As outlined in Section 4.1 we focus our analysis on those households who do not have, nor have been offered a smart meter. People 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. We do not explicitly attempt to measure their willingness-to-pay.

5.4 Cost effectiveness and welfare implications

In line with Boomhower and Davis (2014; 'BD' hereafter), we conduct a cost efficiency and welfare analysis for the subsidy values under consideration. We consider inframarginal costs to be the additional amount the government would have to pay relative to the next lowest subsidy value considered. For example, under a £25 subsidy in our discrete analysis, individuals who accept a free meter cost an additional £25 to the government, and individuals who do not accept a free meter but do accept for a £10 subsidy cost an additional £15.

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—we observe willingness-to-accept for smart meters at each point along the demand curve.[28] To first provide comparable analysis to that of BD, we focus on the selected mass points within the plausible subsidy range of (£0, £200], as considered in our main regression analyses.

Using similar back-of-the-envelope calculations to those undertaken in BD, we demonstrate in Table 5 (column 11) that inframarginal participation costs dominate the total costs of any subsidy program, ranging from 53-83% of total costs for the subsidy values considered.[29] Of course, the larger is the subsidy value, the higher the government transfer to any participating household, so the absolute inframarginal participation cost increases substantially as the subsidy value increases. For instance in the case of £10, £50, and £100 subsidy offers, the inframarginal costs 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).[30]

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 and Williams III (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>1—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) inframarginal costs, costs per capita, and additionality—to optimize her social welfare function.

[28] 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 free meter (i.e. WTA=£0) in the 'discrete' analysis (i.e. Table 5); this subsample includes 1711 participants. Given there are no inframarginal costs of adoption at a subsidy level of £0, free meter adopters are naturally excluded from the 'continuous analysis' below (i.e. Figure 7).

[29] Boomhower and Davis (2014) find that 69-84% percent of total costs are inframarginal in their context.

[30] Note that the subsidy values selected for this analysis will affect these numbers, since the 'inframarginal cost' is only considered to be the difference between the subsidy offer at which one adopts and the subsidy offered.

Table 5: Inframarginal Participation and Welfare Costs

A: Adoption				B: Subsidy transfers			C: Total costs			D: Percent inframarginal
Subsidy value (1)	Total adoption (%) (2)	Total adoption (n) (3)	Non-additional (%) (4)	IM subsidy transfer (5)	Total subsidy transfer (6)	IM transfer per capita (7)	IM cost (8)	Total cost (9)	Total cost per capita (10)	IM as percent of total cost (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, "IM" is short for "inframarginal". 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 the inframarginal and total transfers from the government to individuals if a given subsidy were to be implemented in our sample, with normalization provided with per capita transfers. Panel C replicates panel B but incorporates efficiency costs of $\eta = 1.3$. Panel D shows inframarginal spending as a percentage of total spending.

To improve upon the above insights into optimal subsidy provision—where the subsidy values considered affect the outputs in the table—Figure 7 utilizes the continuous nature of our WTA elicitation to present the results from Table 5 for a continuous range of potential subsidies. For our sample, a local minimum in the proportion of total costs that are inframarginal is observed at a subsidy value of £100. This feature of the data suggests that while inframarginal costs dominate any potential subsidy scheme, should a social planner decide to subsidize smart meter adoption, the optimal level is £100 from the perspective of minimizing the percentage of spending that is inframarginal. However, given the jump in the proportion of adopters at a subsidy value of £100, we also see an increase in the total welfare cost per capita—calculated as the inframarginal welfare cost multiplied by the number of adopters at each subsidy increment, normalized by the total number of adopters—at £100. This increase in the total welfare cost coincides with a higher adoption rate, which also enters into the policymakers' social welfare function.

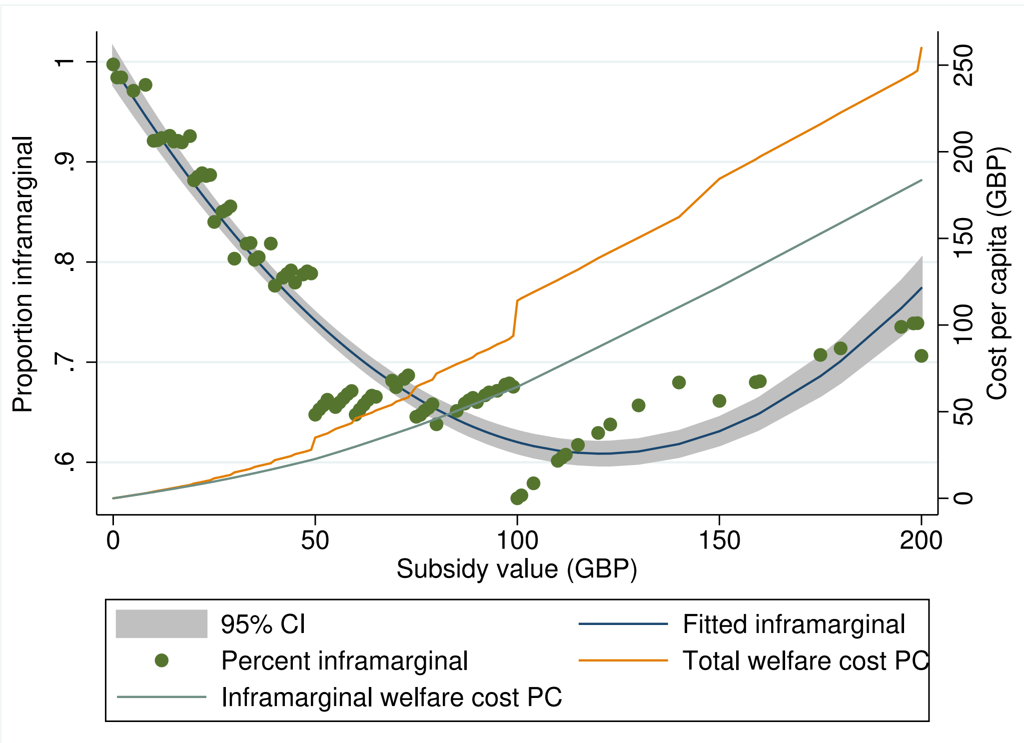


Figure 7: Inframarginal and total costs as a function of subsidy value (y-axis). The green dots and fitted line denote the proportion of total costs that are inframarginal (left axis) as a function of subsidy value. The orange and blue lines denote the per capita level of total and inframarginal costs (right axis) as a function of subsidy value.

Hence, conditional on choosing a positive subsidy value, if maximizing adoption rates and minimizing the percentage of spending that is inframarginal are sufficiently prioritized over total spending, the policymaker should offer a £100 subsidy for smart meter adoption. Of course, the optimal subsidy will depend on 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 Conclusion

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. Our research demonstrates a method to identify and measure barriers to adoption and devise an appropriate policy response. In doing so, we build on past research by Jaffe and Stavins (1994a); Gillingham and Palmer (2014); Fowlie et al. (2015) among others in identifying non-monetary costs and other barriers to adoption. We then generalize important work by Boomhower and Davis (2014) to estimate the inframarginal costs of any potential subsidy scheme.

Based on the UK Government's own cost-benefit analysis, society could benefit from subsidizing each smart meter installation up to £212.[31] Our results suggest that a subsidy of £10 would increase demand for a smart meter about 5 percentage points from a baseline of 15%.[32] Excluding the sample of respondents who did not pass the test of understanding for the BDM exercise (since we do not have WTA information for those who rejected the TIOLI offer), we infer that offering £10, £25, and £50 would induce additional adoption of 4, 9, 24 percentage points from an updated baseline of 22% adoption, and that pairing these subsidies with a social information campaign can boost these numbers by an additional 2-5 percentage points. Inframarginal costs dominate the cost of any subsidy programme, ranging from 53-83 percent of total costs. From the perspective of minimizing the percentage of policy expenditures that are inframarginal, our data suggest a £100 subsidy could be optimal, though the information campaigns tested here do not positively interact with this subsidy level with statistical significance.

We recommend that policymakers identify the appropriate evidence-based policy measure by carefully considering objectives relating to dynamic and inframarginal policy costs and incentives, as well as ideal thresholds of system-wide adoption. With respect to increasing energy technology uptake, we recommend that policy makers rigorously engage 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 ad campaigns touting their benefits (see A.6).

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, supplier inter-operability). The social planner may therefore have duelling 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

[31] 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 and Williams III (1997)'s efficiency loss parameter, the government would be willing to subsidize up to £163.

[32] 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.

households to postpone adoption even further (Langer and Lemoine, 2018).[33]

In the case of the UK's Smart Meter Implementation Programme, a broader 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.

[33] Our qualitative survey feedback provides evidence of the latter phenomenon in that a significant number of individuals alluded to future technological progress to justify current non-adoption, even despite not having been offered this multiple-choice option explicitly.

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A Appendices

A.1 Survey Materials

A.1.1 Becker-DeGroot-Marschak Exercise Instructions

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.

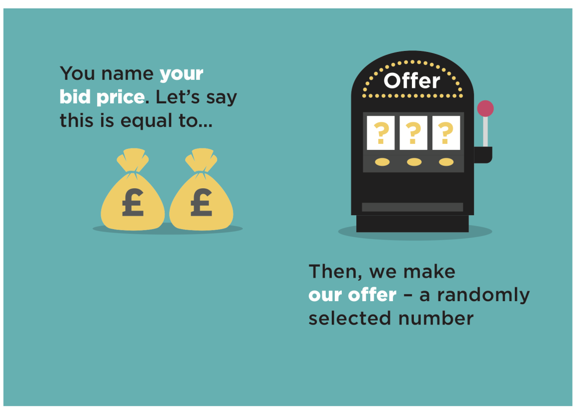
Link: Why might you be paid to install a smart meter?

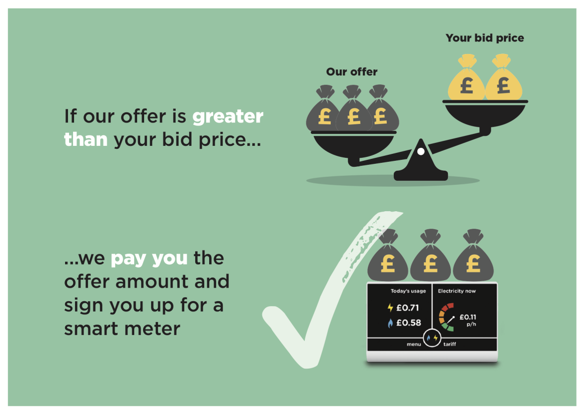
To make things realistic, we'll use our research funding to give you a chance to state your price and *actually* be paid in exchange for signing up to get a smart meter installed. **It works like this:**

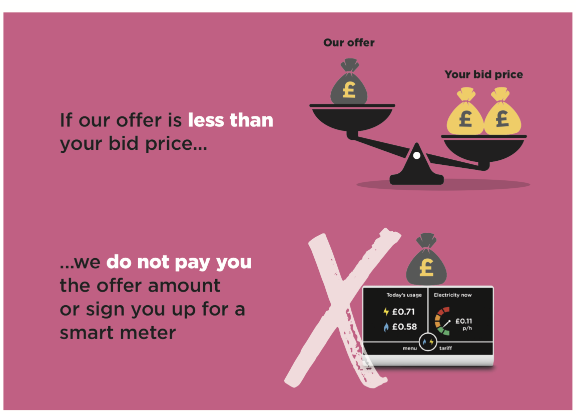
1. First, we will ask you to tell us your **bid price** – the minimum amount of money you would need to be paid before you would agree to have a smart meter installed by your energy supplier.

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

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

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)

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[34], we ran sample size calculations for the binary outcome variable of whether individuals adopt a meter for free 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 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[35] and four groups (one control, three treatment) in total, we were powered to detect around a 6 percentage point difference in (free) smart meter uptake from a baseline of 15% uptake. 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.

[34]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.

[35]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 three additional sets of analysis for completeness. Table A3 presents results of the main estimation following removal of those participants who accepted the TIOLI offer of £10. The social benefits intervention still has an effect with marginal statistical significance for subsidy values of £50 (β=3.6 percentage points, p=0.068) and £75 (β=5.4 percentage points, p=0.072). However, both the magnitude and significance of the coefficients attenuate, suggesting that inclusion of the TIOLI participants strengthens the results from Table 4, particularly when considering the £10 subsidy.

Table A4 presents the results from an analysis 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 the regression in which we exclude TIOLI but include those who accepted a free meter, suggesting that we may simply be underpowered to detect some effects once we remove significant portions of our sample from the analysis. Table A5 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.

A.4.2 WTA data quality

Section 3.1.2 describe a range of potential concerns one might have with valuations elicited through a BDM experiment. We undertake a number of steps to ensure 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[36] into 53 detailed reasons. Each reason was then further categorized into 14 composite reasons. Table A6 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[37]. Table A7 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.

[36] Unfortunately we did not force a response on this question and as a result collected information from 793 respondents out of a total of 1304 who undertook the BDM exercise

[37] As described in Section 3.1.2 we also conducted a pilot experiment to mitigate anchoring in the design of the exercise.

A.4.3 Sensitivity analysis

When selecting our sample we chose to include only customers of the 11 largest UK suppliers.[38] This group represents 88% of total market share, and 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 chose 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 A1, A2 and A3 present confidence intervals and p-values following a wild bootstrap estimation with 2000 replications for the results presented in Table 4. 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. Again, some evidence exists that communication of private benefits (Treatment 1) may also influence individuals who would be persuaded under a £25 or £50 subsidy.

Finally, Table A8 presents results from a logistic regression model which are substantively similar to our primary OLS specification.

[38] 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.

Table A3: Treatment Effects on Adoption of Smart Meters for Relevant Subsidy Values: TIOLI Excluded

	(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	0.017	-0.008	-0.024	-0.003	-0.014
Standard error	(0.031)	(0.022)	(0.025)	(0.022)	(0.024)	(0.024)	(0.023)
Wild bootstrap p-value	0.857	0.439	0.500	0.751	0.335	0.919	0.543
Treatment 2: Social	0.026	0.005	0.036*	0.054*	0.000	0.014	0.015
Standard error	(0.020)	(0.023)	(0.019)	(0.019)	(0.027)	(0.021)	(0.018)
Wild bootstrap p-value	0.206	0.835	0.068	0.072	0.996	0.553	0.462
Treatment 3: Learning	-0.007	-0.017	0.028	0.022	-0.019	-0.012	0.003
Standard error	(0.019)	(0.023)	(0.024)	(0.023)	(0.025)	(0.021)	(0.021)
Wild bootstrap p-value	0.724	0.483	0.306	0.378	0.493	0.583	0.896
Constant	0.269***	0.421***	0.573***	0.677***	0.887***	0.858***	0.918***
	(0.047)	(0.059)	(0.065)	(0.048)	(0.039)	(0.040)	(0.028)
Observations	1,726	1,726	1,726	1,726	1,726	1,726	1,726
R-squared	0.032	0.038	0.042	0.040	0.044	0.042	0.046
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 A4: 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]. 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 A5: Treatment Effects on Adoption of Smart Meters for Relevant Subsidy Values: TIOLI

	(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. 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 A6: 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%

Table A7: 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. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table A8: Treatment Effects on Adoption of Smart Meters for Relevant Subsidy Values: Logistic Regression Results

VARIABLES	(1) WTA 10	(2) WTA 25	(3) WTA 50	(4) WTA 75	(5) WTA 100	(6) WTA 150	(7) WTA 200
Treatment 1: Private	0.047	0.085	0.084	-0.013	-0.102	0.017	-0.069
	(0.155)	(0.092)	(0.107)	(0.088)	(0.135)	(0.167)	(0.175)
Treatment 2: Social	0.208***	0.097	0.215***	0.298***	0.075	0.186	0.221*
	(0.069)	(0.088)	(0.067)	(0.080)	(0.152)	(0.130)	(0.125)
Treatment 3: Learning	0.012	-0.027	0.141	0.115	-0.059	-0.026	0.079
	(0.106)	(0.107)	(0.114)	(0.095)	(0.120)	(0.121)	(0.150)
Constant	-0.843***	-0.207	0.367	0.800***	1.945***	1.813***	2.431***
	(0.307)	(0.291)	(0.264)	(0.198)	(0.241)	(0.248)	(0.229)
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. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

A.4.4 Sensitivity: Wild bootstrap confidence intervals

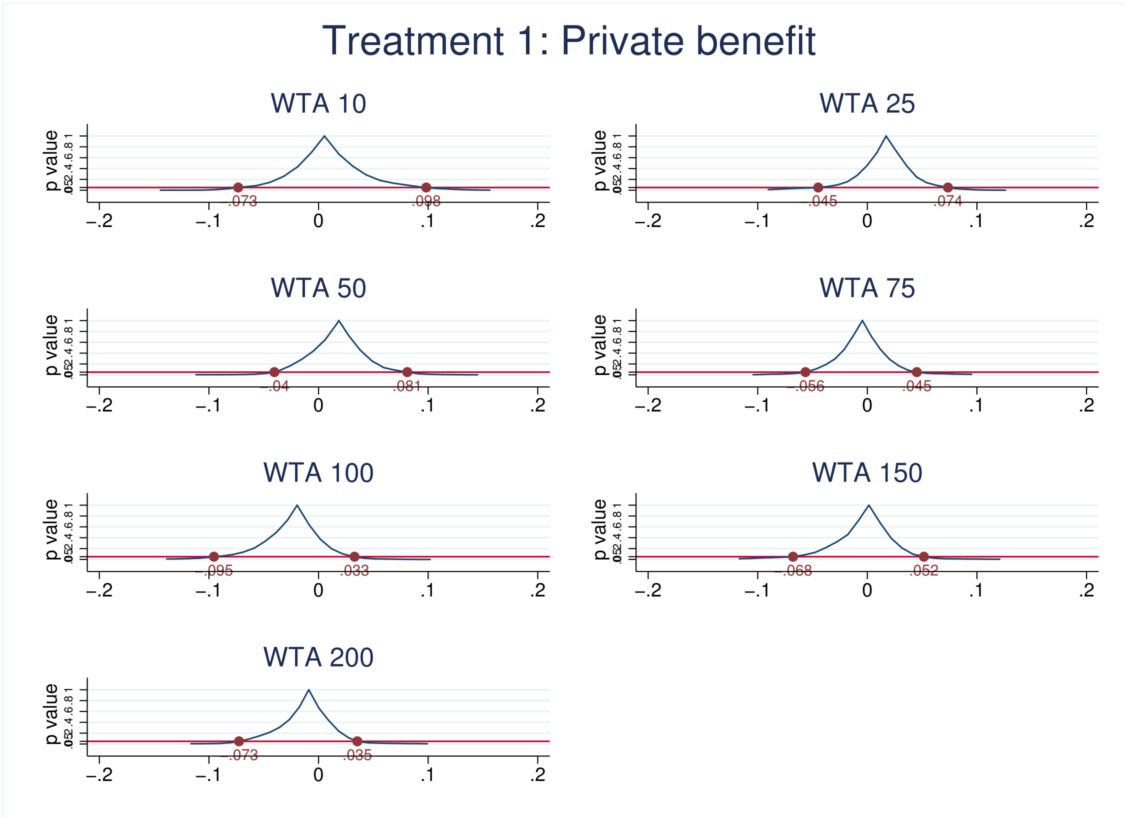


Figure A1: Treatment 1: 95% Confidence Interval of treatment effect following Wild Bootstrap estimation of standard errors with 2000 replications

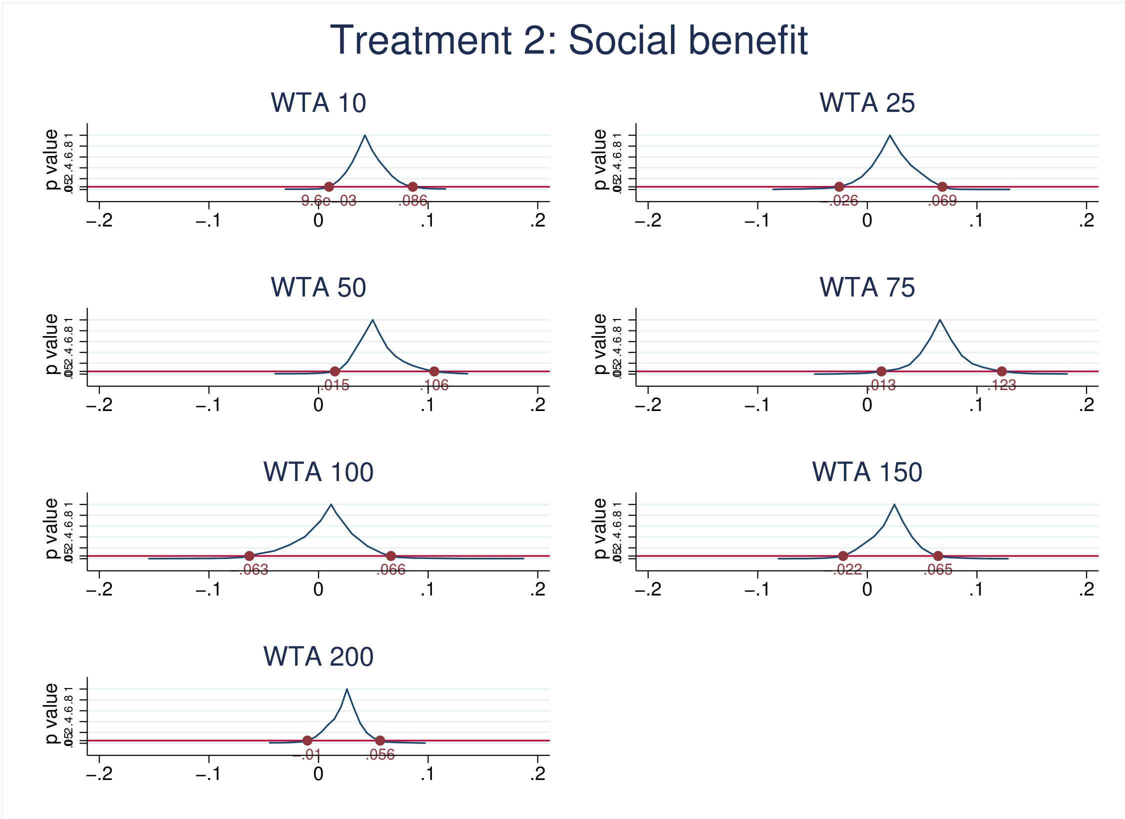


Figure A2: Treatment 2: 95% Confidence Interval of treatment effect following Wild Bootstrap estimation of standard errors with 2000 replications

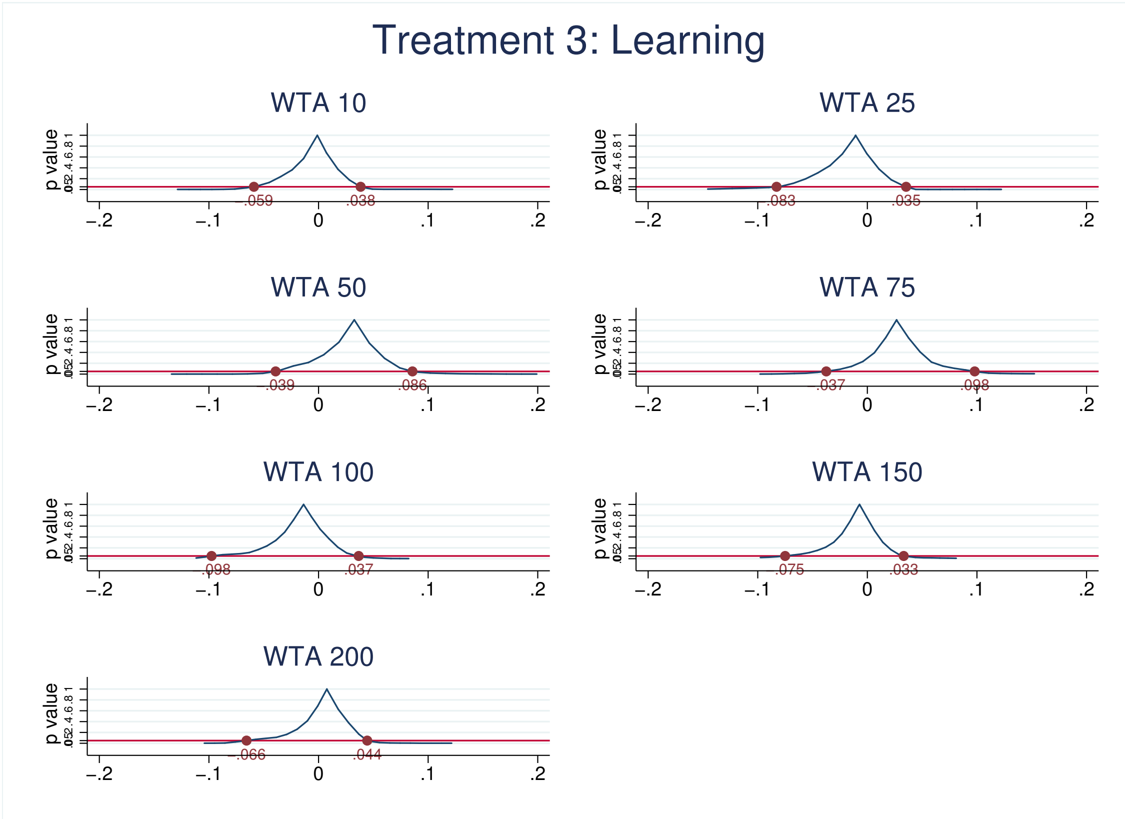


Figure A3: Treatment 3: 95% Confidence Interval of treatment effect following Wild Bootstrap estimation of standard errors with 2000 replications

A.5 Heterogeneity results

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.[39]

Our first hypothesis (H1) conjectured that low-income households will be more likely to (a) adopt a free meter 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 free meter, 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.

[39] Table A9 provides supporting results for the estimations regarding risk preferences. All other results are available on request.

Table A9: 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 A10 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 A11). 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 a tenth hold concerns about the health impacts of smart meter adoption.

Table A10: Self-reported reasons for not wanting a smart meter

Reason Category	Count	Percentage	Mean WTA
Hassle	809	25%	£136
Privacy/security	659	21%	£192
Wont 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 A11: Detailed categorisation 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.[40] We estimate the model for a range of maximum WTA values. Figure A4

[40] 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 A4: 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

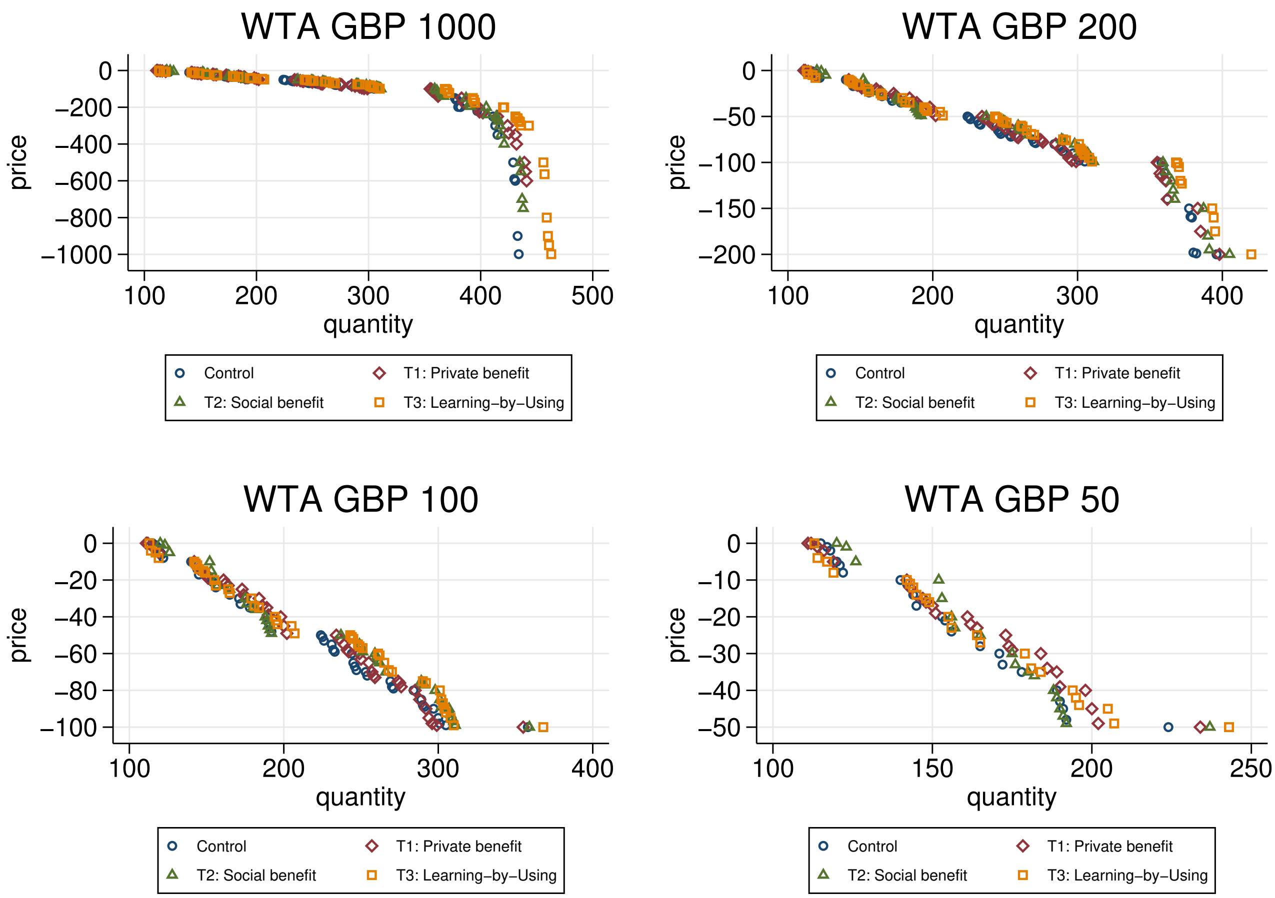


Figure A5: Estimated demand curves for smart meters by treatment

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