Valuation of Drivers and Barriers to Smart Meter Adoption in the UK: A Survey Experiment*

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Abstract

To facilitate a sustainable energy transition, governments and innovators have encouraged the adoption of smart technologies in the home that allow for increased flexibility in centralized energy grids. The ambitious Smart Meter Implementation Programme in the United Kingdom has indisputably failed to achieve its objective of equipping all UK dwellings with smart meters by 2020, perhaps due to some or all of several identified barriers to adoption of allegedly welfare-enhancing energy technology in the home. By partnering with the UK's energy regulator, this research uses an incentive-compatible online experiment to elicit the willingness-to-accept of a representative panel of over 2,400 UK households for smart meter installation. Randomized information treatments allow for assessment of the impact on adoption and willingness-to-accept of several purported market failures in relation to smart meter adoption, namely information asymmetries regarding the personal and social benefits of smart meter adoption as well as information regarding accumulated positive 'learning-by-using' externalities. We explore treatment effects for a range of potential subsidy values, and discuss implications for policymakers in encouraging residential smart meter adoption.

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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. 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 importance of energy and fuel efficiency on consumers' purchasing decisions and have found mixed evidence: while some studies find 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). Newer technologies may suffer from low take-up rates due to lack of experience and little understanding of the technology's benefits, highlighting disincentives for early adoption and costs of asymmetric information (Jaffe and Stavins, 1994a; Gillingham and Palmer, 2014). Whether and how a government should intervene depends on the drivers of (perhaps inefficiently) low adoption (Jaffe and Stavins, 1994b).

We study the case of such a 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 of the technology 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-cut. 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 budgeting and consumption smoothing purposes. 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. Finally, system-level benefits could save householders money via supplier savings pass-through, though there is no guarantee that such savings will reach the consumer.

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

[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.

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).[2]

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] In this case, how can a social planner understand and quantify the extent of resistance to the technology in question, and subsequently encourage adoption amongst 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 of five relevant market failures (as outlined in Gillingham and Palmer, 2014). We measure two main outcome variables, namely whether the consumer adopts the smart meter for free as well as the subsidy level necessary for varying proportions of the population to adopt (conditional on treatment received). From these responses, we quantify the significance of private and social information as well as learning-by-using in the decision to adopt the technology, and infer adoption rates at various subsidy levels in this context.[4]

The paper is structured as follows. The next section provides contextual background regarding the UK's Smart Meter Implementation Programme. The third section provides details of the experimental and valuation methodologies deployed. The fourth section

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

[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]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.

details the data collection process and provides summary statistics for the data collected. The fifth section outlines our empirical strategy and results. We conclude the paper with a final section providing implications for policymakers and future research.

2 Policy Context

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 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 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 smart electricity and gas meters in about 50 million UK household 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 install meters 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, amongst others (Sovacool et al., 2017). In addition, concerns have been raised over the SMIP's lack of clarity of purpose and transparent communication of benefits to consumers (House of Commons Science and Technology Committee, 2016).

Consumer resistance due to a range of factors has clearly inhibited rollout, as there were only 16.3 million meters installed and 13.4 million meters operating by the end of Q2 2019. The driving forces behind households' decisions to adopt remain unclear. In making this decision, a household must weigh up a range of costs and benefits. Both costs and benefits have private, social, and intertemporal dimensions; costs are generally borne upfront (e.g., time off 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.

3 Methodology

We aim to quantify the importance of several identified market failures that serve as rational barriers to adoption of purportedly 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 failures that fail to match energy prices to their true marginal (social) cost.[5] 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 design a survey experiment using the Qualtrics survey software platform in which 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 elicitation exercise (see section 3.2). All eligible participants receive basic information regarding smart meters 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 have some level of understanding regarding the good in question. Once we confirm eligibility, the participant views one of four randomly selected 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. 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 1.

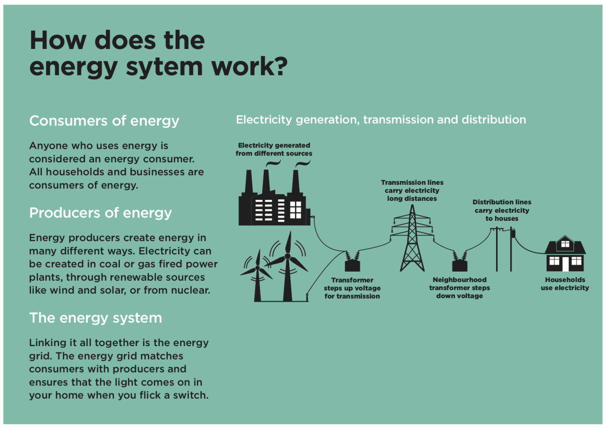
Due to lack of pre-experimental data on participants, we do not stratify the randomization but instead use the Qualtrics *Randomizer* tool to randomly assign individuals who take the survey to receive one of the above four conditions. When we reached 2000 responses we then adjusted the (treatment) quotas 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 9).

3.2 WTA Elicitation

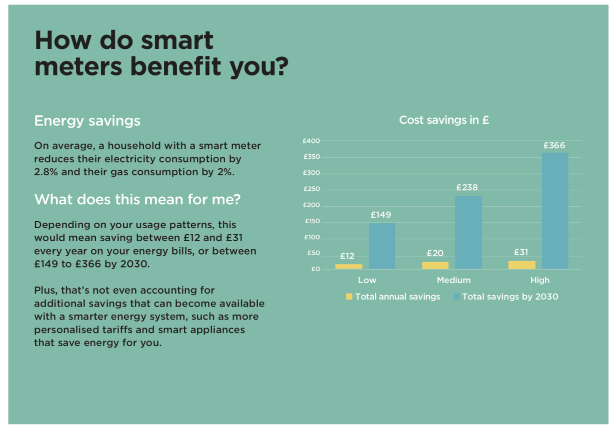
3.2.1 Valuation methods

Environmental economics aims to incorporate the social costs of any project or policy into the decision making of social planners using cost-benefit analysis. If one aggregates the costs and benefits of a given project or policy and the outcome suggests a positive net

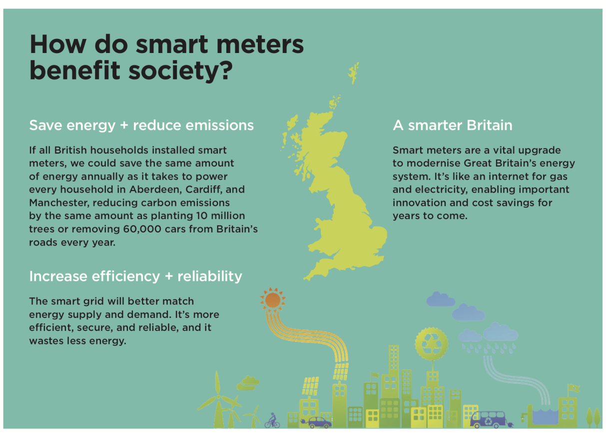
[5] Note that a fourth market failure—(misconceived) principal-agent issues—may also play a role here if tenants do not realize that they do not need their landlords' permission to adopt a smart meter in their rental property.



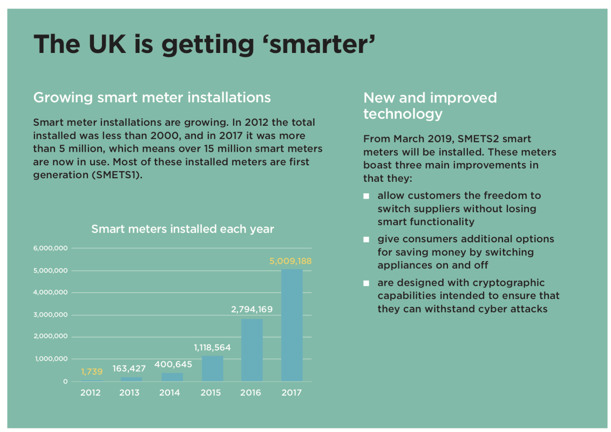
Control



Treatment 1: Private Benefits



Treatment 2: Social Benefits



Treatment 3: Learning-by-Using

Figure 1: Experimental Treatments

present value (NPV) that outweighs the NPVs of all other alternatives, then economists would recommend implementation on the grounds of maximizing social efficiency. However, valuing environmental goods and bads is not straightforward given the lack of markets governing their exchange.

Environmental economists have therefore designed a range of tools to recover the non-market values of these goods. Due to issues surrounding hypothetical bias and consequentiality, we direct our focus toward two incentive-compatible value elicitation methods. One simple method—'take-it-or-leave-it' (TIOLI)—simply 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 flesh out a demand curve), the Becker-DeGroot-Marschak (BDM) method circumvents the requisite iterative process of the TIOLI method by directly eliciting an exact WTA—i.e. a single selling price—using a second-price auction against an unknown bidder. 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.

In addition to the precision of the method—and the resulting implications for requisite sample size and budget to infer a demand curve—Berry et al. (2015) point out that the BDM mechanism offers additional practical advantages over TIOLI. If there is a wide range of prices over which the researcher is eager to understand WTA, then TIOLI can be quite impractical. 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.

The contextual features of the service we aim to value more closely reflect those that favor BDM rather than TIOLI. As mentioned, 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.

3.2.2 Design considerations

Aside from its lower comprehensibility relative to TIOLI, some methodological difficulties are worth mentioning. 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 price, the surveyor risks extracting valuations that are perhaps unreasonable or, at the very least, infeasible to pay out.[6]

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 ran a pilot to determine whether an anchoring effect exists in our BDM context.[7] Specifically, in delimiting the potential buying price, we test 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.

We therefore decided 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].[8] With regard to the former, we explained in our instructions that energy companies have provided incentives of £5, £10, and £50 as an example.[9] To anchor, we ensured that all examples in the 'test of understanding' for both bids and offers fell in the range of (£0, £100].

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

[6] 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.

[7] 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 £30 incentives.

[8] Note that due to budget constraints we had to lower the offer range to £0-£50.

[9] 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. Were interested in learning what that 'right incentive' might be for you, if any.

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. 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 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. 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 duplicates by name, IP address, and email address—of which there were 109 survey responses—and have removed these responses from the data.

We aim to attenuate these 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 7.1.1)—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 7.1.2), and if they missed one or more they could make a second and a third attempt. If there were any errors on the third attempt, they were provided a TIOLI offer and did not participate in the BDM exercise (see Figure 2). We also 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 7.1.3). The first question is a multiple-response multiple choice question in which respondents check any box that applies as to 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 (iv) '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 akin to the above from which we can glean further information.

3.3 Incentive compatibility

To avoid hypothetical bias and maximize the likelihood that elicited WTA values are incentive-compatible, we partnered with the UK electricity and natural gas regulator, Ofgem, so that we could actually sign respondents up to get 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. 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.[10] For those who agree to get the smart meter via the BDM or TIOLI mechanism 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 retailers, restaurants, 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. 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.

[10] 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.

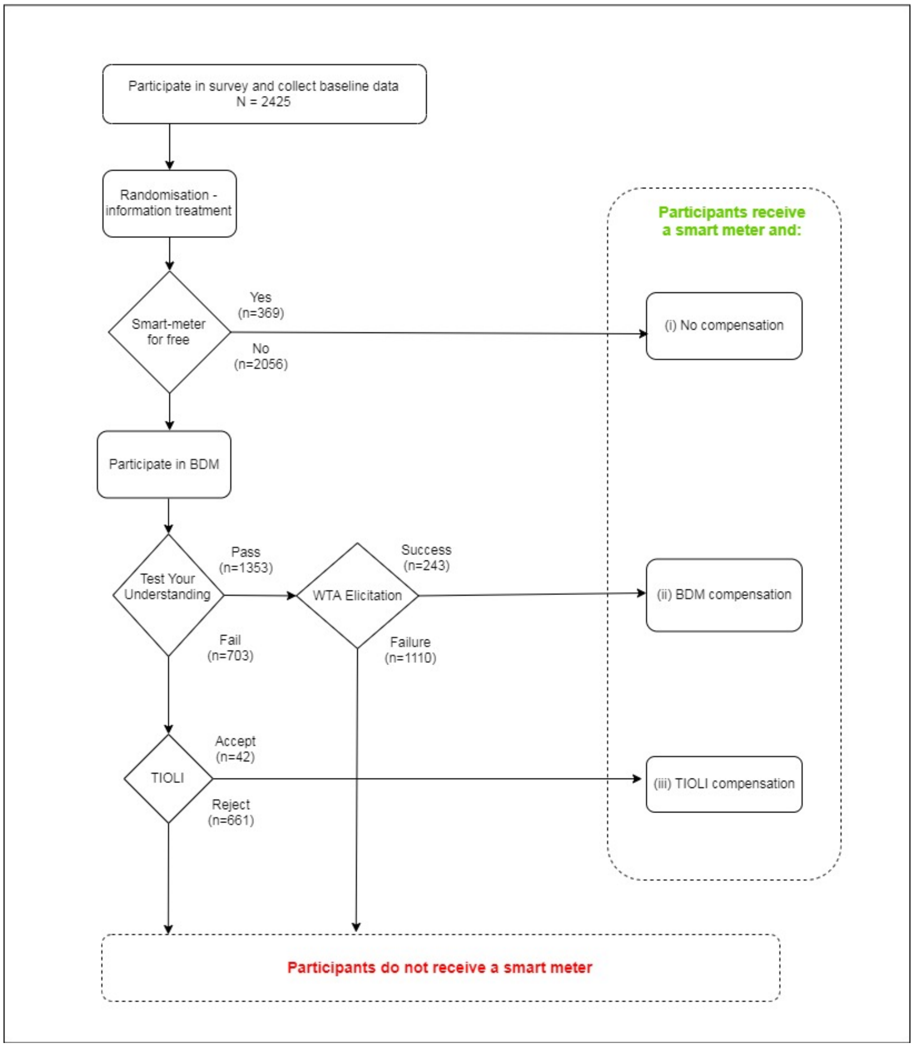


Figure 2: Survey Flow Chart for Eliciting Smart Meter Valuation

3.4 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:

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

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 3). This analysis considers both the WTA of respondents who decline the free meter and provide a WTA valuation in the BDM exercise (i.e. the 'conditional-on-positive' sub-sample), as well as a composite measure that additionally includes those who accepted a free meter or the TIOLI offer. Thus, in light of the selection bias that arises in the COP 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.

3.5 Sample size calculations

Given the original plan to perform a Tobit regression analysis[11], 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[12] 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.

[11]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.

[12]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, leaving 2,432 valid responses in total.

4 Data

4.1 Composition of sample

The study is based on a sample of adult (18+) UK residents whose characteristics reflect those of the national population and who neither have smart meters installed in their homes nor have been offered smart meters by their energy provider. The panel was recruited via Qualtrics. Sample quotas for gender, age, education, and region are set to match those of the UK population at large.

The sample size consists of 2,432 household decision-makers. 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 at large is necessary in order to glean insights into the motivations of the sub-population relevant to the research question.

Columns 1-5 of Table 9 provide a comparison of our sample to the national population. The sample is broadly representative along most dimensions including gender, age, 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 amongst 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 9 reports p-values for tests of the difference in the mean of each variable between control and each treatment group. 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. An F-test for joint orthogonality of all variables, also reported in Table 9, 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. This variable represents the proportion of participants who agree 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	SD	Min	Max
Control	607	0.150	0.357	0	1
Treatment 1	607	0.147	0.354	0	1
Treatment 2	606	0.160	0.367	0	1
Treatment 3	605	0.152	0.359	0	1

Note: Of the 2431 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

The range of WTA values elicited is highly skewed. Within certain ranges it approximates a normal distribution (see the Appendix) however applying a conditional mean estimation framework is problematic. To further illustrate this point Table 2 displays summary statistics for each treatment group for values of WTA less than or equal to £1000 (95th percentile) and £200 (80th percentile). In Panel A the mean WTA for the control group is greater than for all treatment groups. However, in Panel B this difference is no longer present. This feature of the WTA distribution underlines the importance of correctly specifying the range of the dependent variable in any analysis.

Table 2: Summary of subsidized adoption for selected values of WTA

Treatment	Min	Max	Mean	Median	N
Panel A: WTA ≤ £1000					
Control	0	1000	159	85	315
Treatment 1	0	1000	138	90	317
Treatment 2	0	1000	143	75	309
Treatment 3	0	1000	148	80	330
Panel B: WTA ≤ £200					
Control	0	200	78	75	265
Treatment 1	0	200	75	75	265
Treatment 2	0	200	78	75	267
Treatment 3	0	200	80	73	280

In order to overcome this issue, we focus on specific subsidy values, or mass-points of the WTA distribution. The subsidy values examined here (i.e. the selected c values) have been selected 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 28%, 33%, 48%, 75%, 85%, and 93% for c=10, 25, 50, 100, 200, and 500, 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. Figure 3 presents the chosen values graphically.

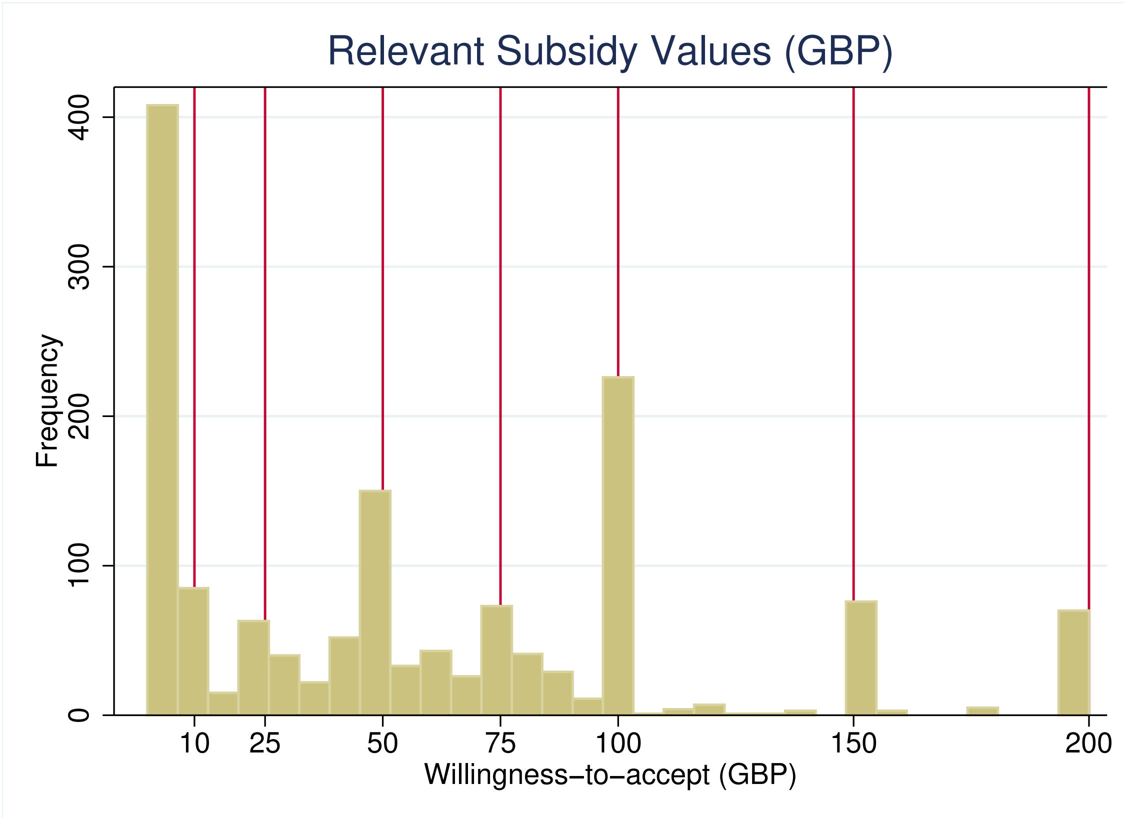


Figure 3: Subsidy values chosen for analysis

4.3 BDM Comprehension and WTA Data Quality

Of the 2,432 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.[13] 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,

[13]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 3: 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.

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

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 here.

Table 5 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 levels. However,

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

	(1)	(2)
Treatment 1: Private	-0.003	-0.002
	(0.019)	(0.020)
Treatment 2: Social	0.009	0.008
	(0.014)	(0.014)
Treatment 3: Learning	0.002	0.001
	(0.018)	(0.016)
Constant	0.150***	0.109***
	(0.008)	(0.028)
Observations	2,432	2,432
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. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

information on the social benefits of smart grid infrastructure appear to influence decisions in a positive direction for various subsidy levels.[14] While failure to comprehend the BDM mechanism dramatically reduced our sample size for this exercise by about a third, it appears that the social benefits intervention played a role in boosting adoption rates, and with (marginal) 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. The coefficients remain positive (though not significant) for the other subsidy values considered. Though we are under-powered to reject the null hypothesis of equal adoption across Control and Treatment 1, there is some indication that private benefits also may sway some (just under 2 percentage points) of individuals who would be persuaded under a £25 or £50 subsidy.

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

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

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

Given that those participants who undertook the TIOLI exercise failed the BDM comprehension test and are observably different across certain characteristics, we also include

[14] We caution the reader to bear in mind that these results will undergo a number of quality checks in the coming weeks; we are currently taking a much closer look at the motivations for respondents' valuations—10-20 cases of which we can already identify as the result of miscomprehension—and we will continue undertaking this exercise to report more robust results.

two additional sets of analysis for completeness. Table 6 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 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 are reduced suggesting that inclusion of the TIOLI strengthens the results from Table 5.

Table 6: 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 **??** 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 4.0 percentage point increase in uptake. Taken altogether, the social benefit intervention has an impact at multiple subsidy values and, at the £10 subsidy value in particular, our results would appear to be partially driven by the inclusion of those who accepted the TIOLI offer in our analysis.

Table 7: 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 $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

5.3 Robustness tests

When selecting our sample we chose to select only customers of the 11 largest UK suppliers.[15] This group was chosen as they represent 88% of total market share, and the retail electricity market in the UK has over 50 suppliers in total making it practically impossible to co-ordinate an offer of a smart meter installation for all companies.

As we then select our sample from a subset of the population, our standard errors must be clustered to reflect this sampling design issue and we cluster at the level of the supplier (Abadie et al., 2017). Given we have only 11 suppliers we chose a method of

[15] 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

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.

The three figures in Appendix 7.4 present confidence intervals and p-values following a wild bootstrap estimation with 2000 replications for the results presented in Table 5. The results provide further evidence that information on the social benefits of smart grid infrastructure (Treatment 2) appear to influence decisions in a positive direction for various subsidy levels. 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.

5.4 Estimating demand for smart meters

Figure 4 presents cumulative demand curves for smart meters based on the elicited WTA (or 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 both an unrestricted demand curve and a demand curve for those participants whose WTA was £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.

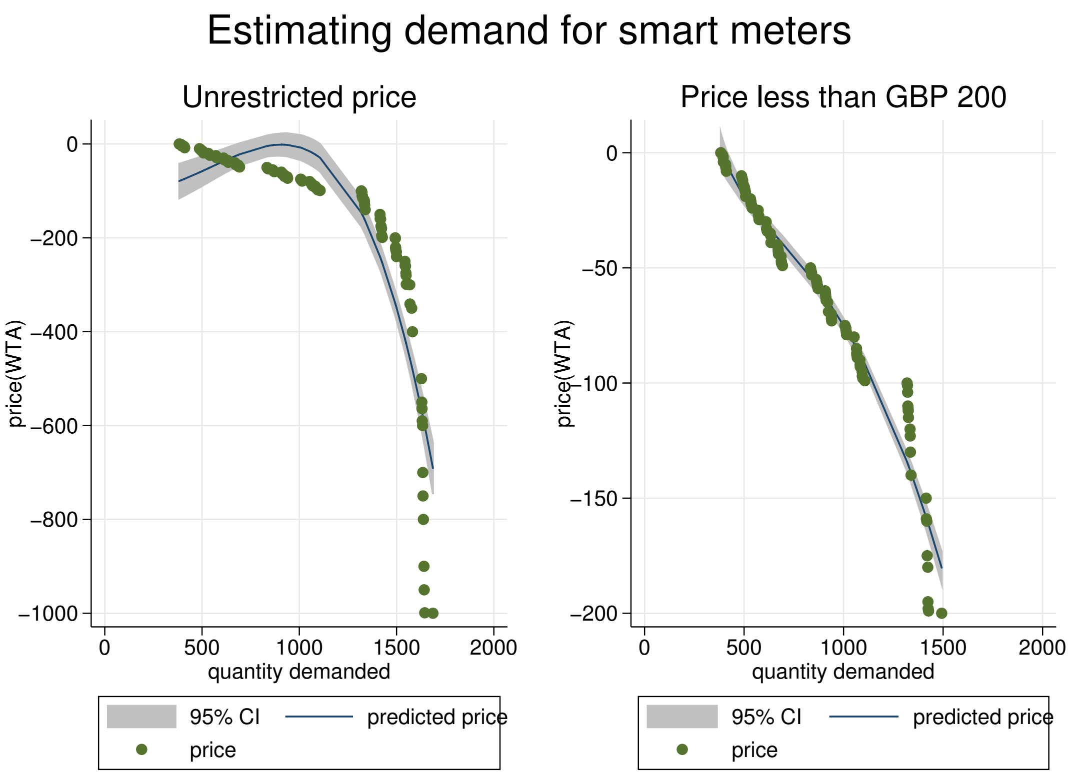


Figure 4: Estimated demand curve for smart meters

5.5 Cost-effectiveness and welfare implications

In line with Boomhower and Davis (2014), we conduct a cost efficiency and welfare analysis for the subsidy values under consideration. Whereas the aforementioned observe marginal adoption behavior at two discontinuities, we observe this behavior at every point along the demand curve.[16] To provide comparable analysis, however, we focus on the selected mass points within the plausible subsidy range of (0, 200], as considered in our regression analysis.

Using similar back-of-the-envelope calculations to those undertaken in Boomhower and Davis (2014), we demonstrate that inframarginal participation costs dominate the total costs of any subsidy program, ranging from 53-83% of total costs. Of course, the larger is the subsidy value, the higher the government transfer, so the inframarginal participation cost increases 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 any of the lower subsidy values considered.[17] Normalizing these costs indicates that these subsidy offers

[16]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 part of our analysis on the sample for whom we have elicited WTA valuation, including those who accepted a free meter (i.e. WTA=£0). This sample includes 1711 participants).

[17]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 higher subsidy

Table 8: Inframarginal Participation and Welfare Costs

Subsidy Value	Total Adoption	Total Adoption	Incremental Adoption	Total Inframarginal Adoption	Total Subsidy Transfer	Inframarginal Subsidy Transfer	Total Cost	Inframarginal Cost	Inframarginal / Total Cost	Total Cost Per Capita	Inframarginal Cost Per Capita
£0	22%	369	369	0	-	-	-	-	0%	£0	£0
£10	26%	445	76	369	£4,450	£3,690	£5,785	£4,797	83%	£3.38	£2.80
£25	31%	529	84	445	£13,225	£10,365	£17,193	£13,475	78%	£10.05	£7.88
£50	46%	792	263	529	£39,600	£23,590	£51,480	£30,667	60%	£30.09	£17.92
£75	56%	965	173	792	£72,375	£43,390	£94,088	£56,407	60%	£54.99	£32.97
£100	75%	1277	312	965	£127,700	£67,515	£166,010	£87,770	53%	£97.03	£51.30
£150	80%	1373	96	1277	£205,950	£131,365	£267,735	£170,775	64%	£156.48	£99.81
£200	85%	1451	78	1373	£290,200	£200,015	£377,260	£260,020	69%	£220.49	£151.97
Total		1711									

would lead to 'excess spending' of approximately £2, £14, and £39 per capita. When we consider the efficiency costs of making these transfers, and using the presumed efficiency cost in Goulder and Williams III (1997), the costs increase further. Finally, considering additionality for these three subsidy levels over a baseline of £0, the percentage of non-additional adopters (which declines with subsidy value by design if we assume elasticity of demand$\geq$1) is 83%, 47%, and 29%.

6 Discussion and Next Steps

To explore the implications of our results for policy, we must carefully consider the net benefits of adopting smart meters to both households and society at large. Based on the UK Government's Department of Business Energy and Industrial Strategy's (BEIS) own cost-benefit analysis (BEIS, 2019) the net benefit to society is about £5.7 billion in total, or about £212 per household. This estimation is based on a total benefit calculation of £16.7 billion to the UK economy or about £615 per person.[18] BEIS estimate the total costs to be around £10.7 billion or £404 per person. This estimate includes the costs of the meters, installation, and the communication hub system.

In addition to BEIS' estimated costs, and in line with conjectures and evidence from the literature (Jaffe and Stavins, 1994a; Gillingham and Palmer, 2014; Fowlie et al., 2015), our survey feedback suggests that householders have a range of concerns—for instance, regarding data security, the potential health impacts from smart meter radiation, the hassle costs of having to take time off work during installation, and the expectation that smart meters will not actually save them money. Whether real or perceived, each of these factors constitute an additional cost from the perspective of the householder, and they should not be neglected when considering the causes of low take-up rates.

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) and that suppliers—themselves facing decisions regarding when it is worthwhile to provide more advanced energy plan options that require a smart meter—will be offering plans that increase the attractiveness of adoption. The social planner may therefore have duelling incentives: (i) to provide subsidies

under consideration.

[18]Of this total, 32% comes from energy cost savings that households will accrue directly, 49% from supplier cost savings (which may or may not be passed on to households), and the remainder comprises carbon savings from increased renewable generation and system-level operational efficiency gains.

for adoption early on to both capture low-WTA users at no or low cost (i.e. price discriminate) and address learning-by-using and network externalities, and (ii) to delay subsidy provision or increases to avoid subsidizing inframarginal consumers, where the very possibility of the latter in itself may induce households to postpone adoption even further (Langer and Lemoine, 2018).[19]

From a static perspective, and taking BEIS's calculations at face value, it would be cost-effective for the UK government to subsidize each smart meter installation up to £212.[20] However, it is extremely unlikely that such high subsidy levels would be considered given that current subsidies offered by energy suppliers are in the £5-£50 range. Our data suggest that a subsidy of £10 would increase demand for a smart meter about 5 percentage points from a baseline of 15%.[21] 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, and 25 percentage points from a baseline of 21% adoption, and that pairing these subsidies with a social information campaign can boost these numbers by an additional 2-5 percentage points.

In addition to financial incentives, policy makers will need to engage more with households in order to encourage adoption. Our results suggest that a broader information campaign, not solely focused on private benefits, could encourage increased uptake of smart meters.

We must stress that the results we present in this draft are preliminary. In addition to a range of robustness tests related to comprehension and protest responses, further analysis will explore heterogeneity in results across a range of dimensions including income, education, environmental interest (as proxied by attitude toward renewable energy), engagement in energy-saving behaviors, trust in institutions (as proxied by trust in government and energy suppliers), risk preferences and interest in technology (as proxied by ownership and optimism toward technology).

[19] 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.

[20] This assertion assumes not only that the Government's CBA is optimal but also that there are no distortions induced by subsidization; a back-of-the-envelope calculation using

[21] 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), though it increases adoption by 6 percentage points in the sample of respondents who answered the TIOLI question.

7 Appendices

7.1 Survey Materials

7.1.1 Becker-DeGroot-Marschak Exercise Instructions

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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?

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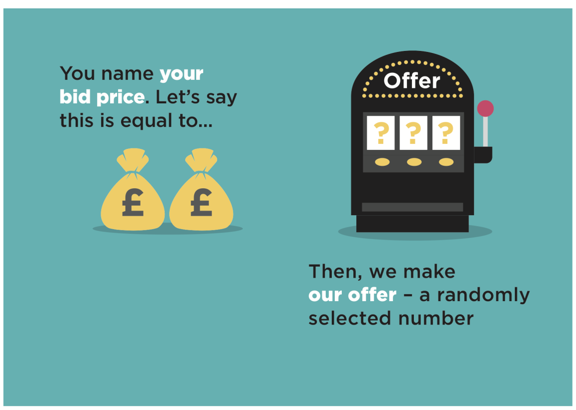
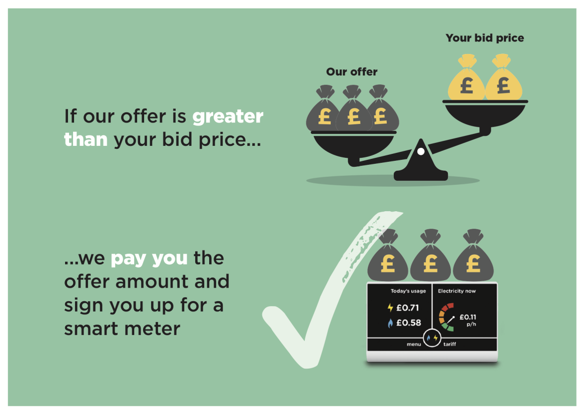
To make things realistic, we'll use our research funding to give you a chance to state your price and *actually* be paid in exchange for signing up to get a smart meter installed. **It works like this:**

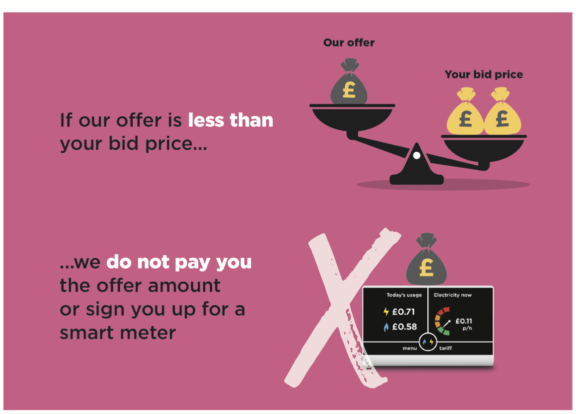
1. First, we will ask you to tell us your **bid price** – the minimum amount of money you would need to be paid before you would agree to have a smart meter installed by your energy supplier.

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.







7.1.2 BDM Comprehension

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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.

7.1.3 BDM Response

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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)

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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):

7.2 Descriptive statistics

Table 9: Descriptive statistics and balance table

Demographic variables	Population	C: Control	Proportion T1: Private benefit	T2: Social benefit	T3: Learning-by-using	Test of Equality (P-value) C = T1	C = T2	C = T3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender								
Female	0.51	0.51	0.52	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	0.32	0.35	0.33	0.395	0.871	0.614
Income								
Below £10,000 per year	0.15	0.14	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	0.14	0.13	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	0.09	0.674	0.215	0.588
London	0.14	0.11	0.11	0.15	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	2,424							
F(30, 2393)	0.61							
Prob > F	0.9525							

7.3 Kernal density plots of WTA

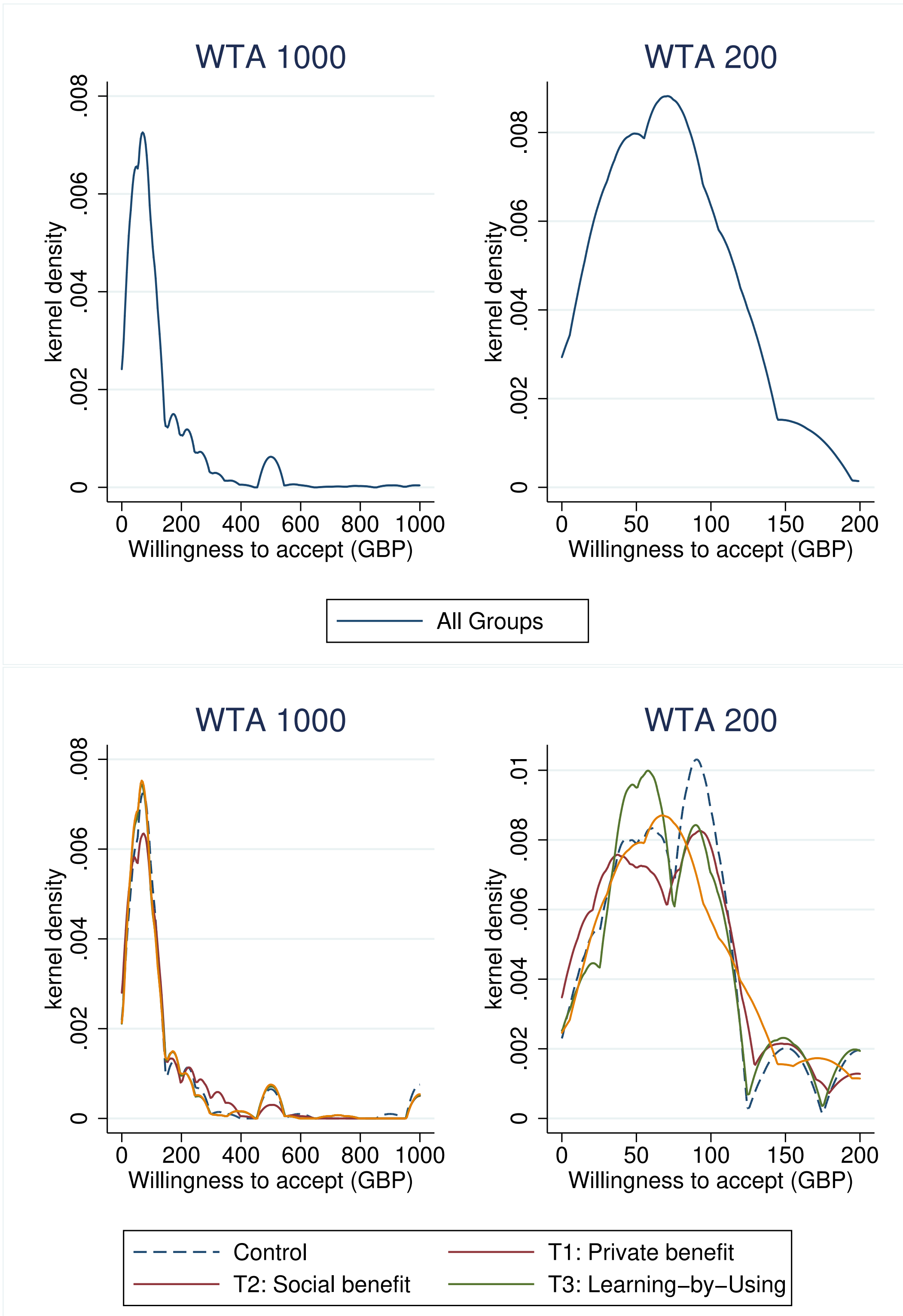

Figure 5: Kernel density plots of willingness-to-accept at mass-points of WTA distribution

7.4 Additional results

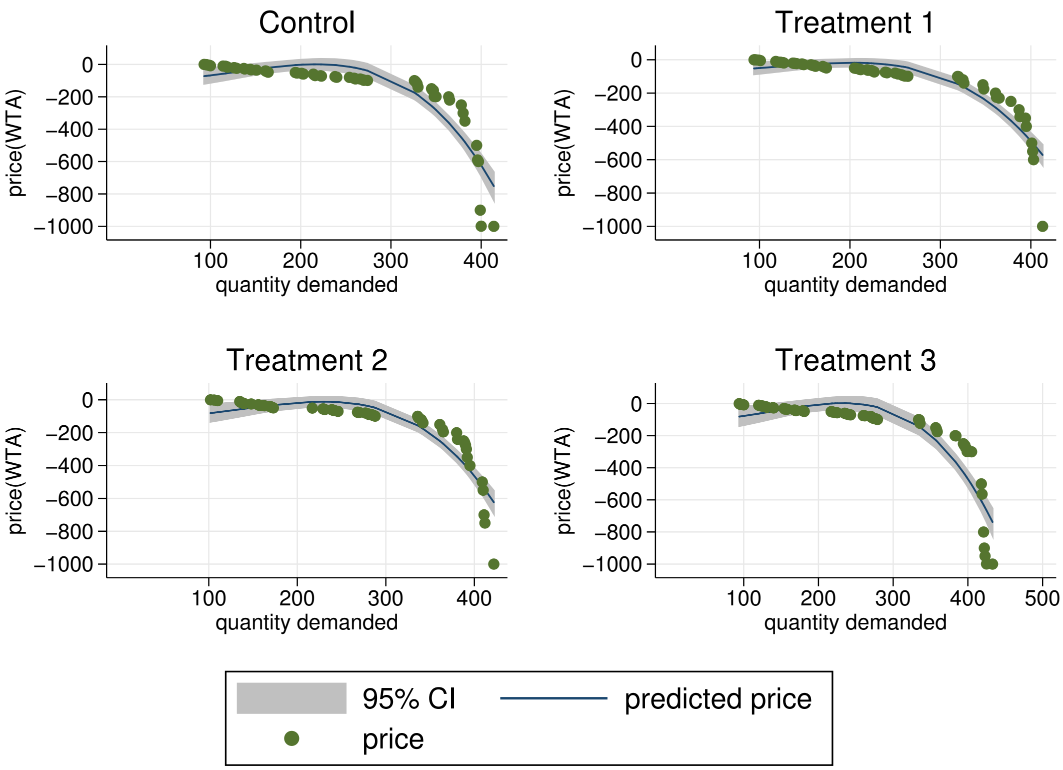

Figure 6: Estimated demand curve for smart meters by Treatment

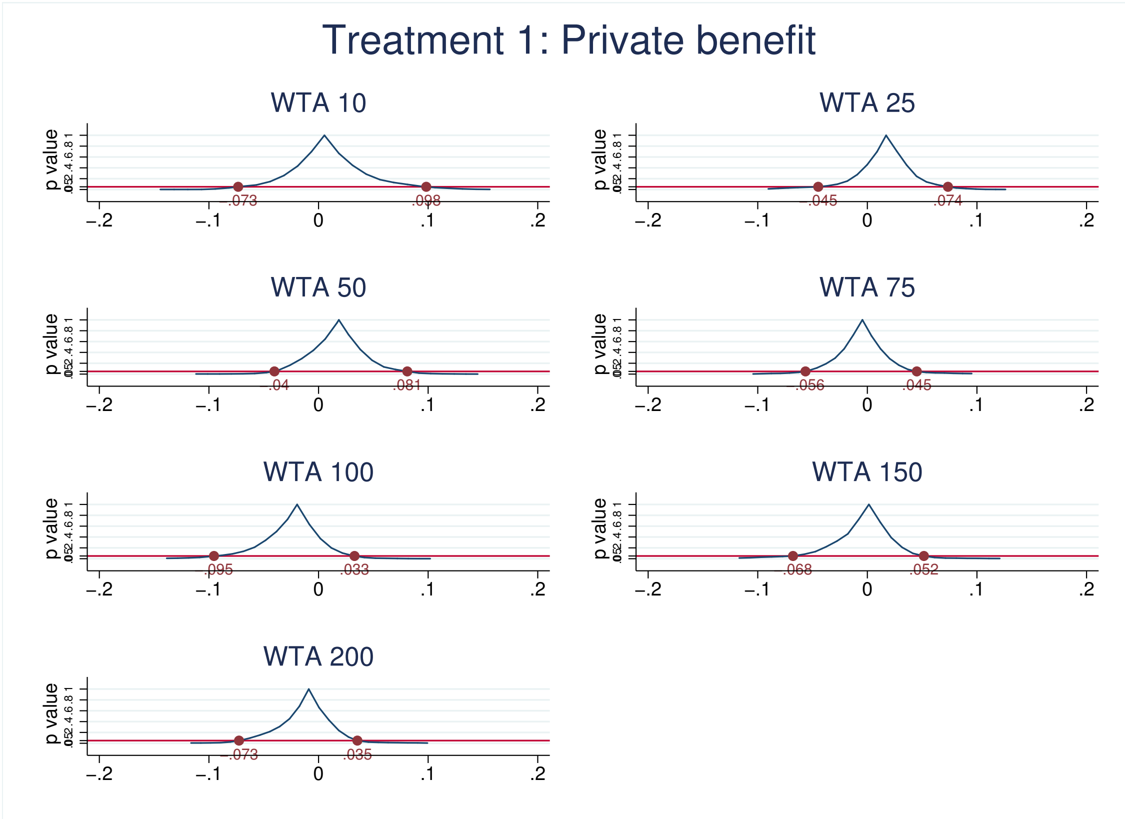

Figure 7: Treatment 1: 95% Confidence Interval of treatment effect following Wild Bootstrap estimation of standard errors with 2000 replications

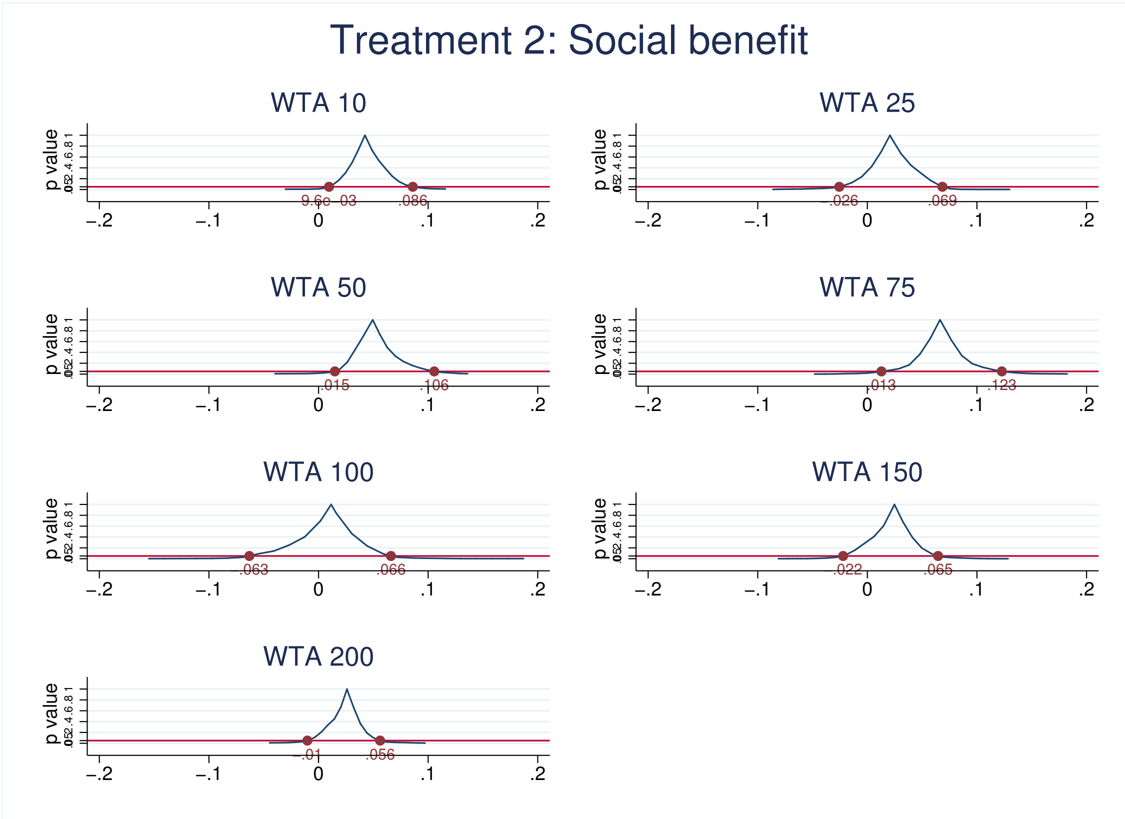

Figure 8: Treatment 2: 95% Confidence Interval of treatment effect following Wild Bootstrap estimation of standard errors with 2000 replications

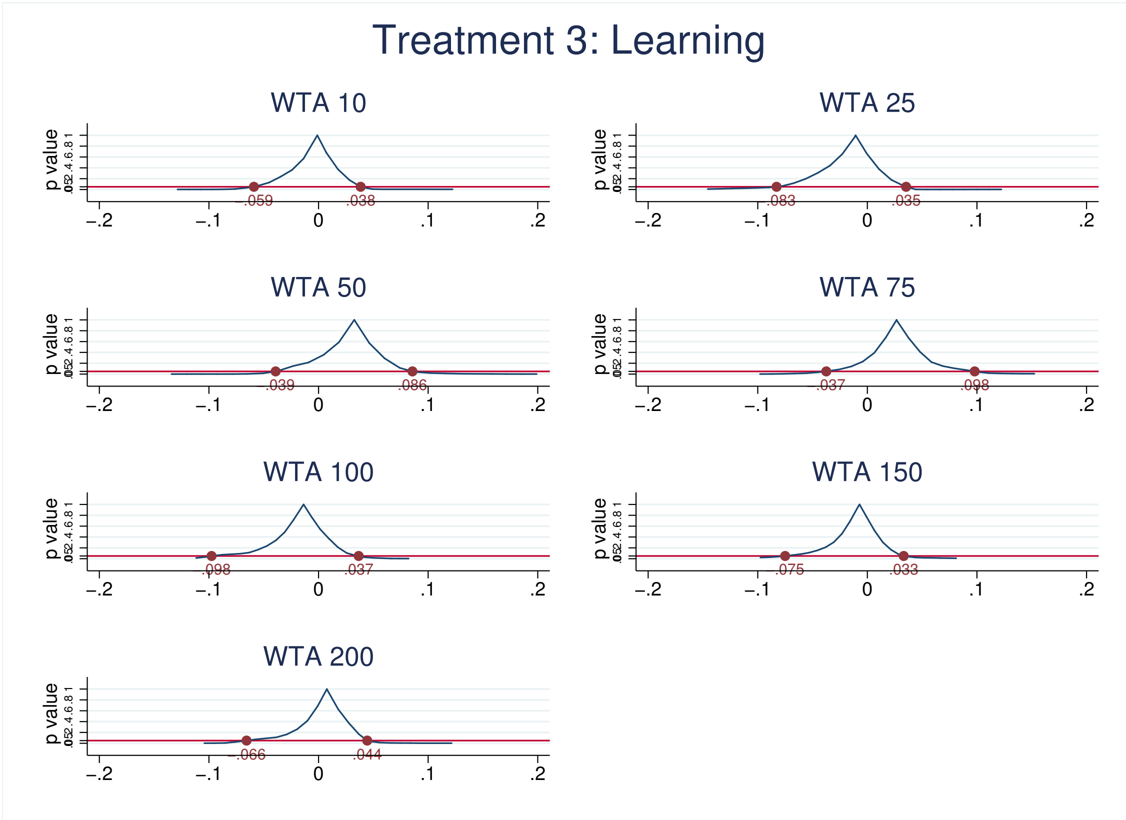

Figure 9: Treatment 3: 95% Confidence Interval of treatment effect following Wild Bootstrap estimation of standard errors with 2000 replications

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