Nudging and subsidising farmers to foster smart water meter adoption

Benjamin Ouvrard, Raphaële Préget, Arnaud Reynaud, Laetitia Tuffery

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Abstract

We use a discrete choice experiment with treatments to test if voluntary adoption of smart water meters by French farmers can be fostered by i) a collective conditional subsidy offered to farmers who adopt a smart meter only if the rate of adoption in their geographic area is sufficiently high, and ii) informational nudges. Using a sample of 1,272 farmers, we find contrasted results regarding our nudges, but we show that a conditional subsidy is an effective tool to foster adoption of smart meters. Interestingly, the willingness to pay for the conditional subsidy is equal to the subsidy amount and independent of the collective adoption threshold.

Keywords : Choice experiment, French farmers, Incentives, Nudges, Smart water meters.

Jel codes : *D70, Q18, Q25*

1 Introduction

Around 70 percent of freshwater worldwide is currently used for agriculture. By 2050, feeding a planet of 9 billion people will require an estimated 50 percent increase in agricultural production and a 15 percent increase in water withdrawals devoted to agriculture[1]. This explains why regulating agricultural water use in a context of water scarcity often has the highest priority for public authorities in charge of managing water resources.

There are various ways to deal with increasing water scarcity in the agricultural sector. Signaling water scarcity with high water prices has been widely promoted, but such a solution has often been politically difficult to implement (Davidson *et al.* , 2019). Increasing water supply is another option; however, the cost for developing new water resources is often prohibitive (Beh *et al.* , 2014). Water sharing agreements among farmers have also been proposed (Li *et al.* , 2018), but the robustness of such commitments to reduced water consumption remains challenging (Ambec *et al.* , 2013). A final alternative is the adoption by farmers of water-efficient agricultural practices (e.g., drought-tolerant crop varieties, deficit irrigation, etc.) and of new technologies (e.g., drip irrigation, smart water meters). While the former have been thoroughly studied (Alcon *et al.* , 2014; Skaggs, 2001;Saleth & Dinar, 2000; Yu & Babcock, 2010), evidence from the literature on the efficacy of smart water meters to improve water management remains limited. Some exceptions include Wang *et al.* (2017), who study smart water meters in China, Zekri *et al.* (2017),who look at smart meter use in Oman and Chabé-Ferret *et al.* (2019), who study the subject in France. Although Zekri *et al.* (2017) show that adopting smart water meters may result in significant gains in terms of groundwater management, Chabé-

[1]Conclusions of the expert forum "How to feed the world in 2050", published by the FAO in Oct. 2009. https://www.fao.org/news/story/fr/item/35656/icode/

Ferret *et al.* (2019) conclude that using smart meters to induce changes in farmers' irrigation decisions remains challenging[2].

A major issue with smart water meters in agriculture is the high level of reluctance on the part of farmers to adopt them, particularly due to data privacy concerns[3]. Indeed, smart meters imply a control and a remote monitoring. Thus, the consumption information is transmitted to the managers in quasi real-time, which allows to improve the management, to optimize the water releases and the restrictions in period of drought. The primary objective of our work is then, to test the efficacy of different policy instruments designed to foster the voluntary adoption of this technology by farmers. First, we offer a monetary incentive to farmers who are willing to adopt a smart water meter. We use a conditional subsidy similar to the collective bonus studied by Kuhfuss *et al.* (2016): a farmer who adopts a smart water meter gets a subsidy if the collective adoption rate in his/her geographical area reaches a given threshold. One of the desired objectives of this conditional subsidy is to reinforce a collective dynamic, mainly by influencing the collective perception of the social norm. We test three threshold levels: 25%, 50% and 75%. In addition, since non-monetary interventions have a strong appeal for public authorities in charge of the agricultural sector (Wallander *et al.* , 2017), and knowing that behavioral factors influence farmers' decisions to adopt new practices or technologies (Dessart *et al.*, 2019), we test two informational nudges to give them incentives to adopt smart water meters.

Another possible way to foster voluntary adoption of smart water meters by farmers is to introduce them to new services made possible by smart water meters. Farmers may, for instance, receive instant alerts in case of abnormal water consumption and access in-

[2] There is some empirical evidence of the positive impact of using smart meters for water management in the urban sector. Davies *et al.* (2014) report, for instance, that in Australia, households equipped with a smart water meter have reduced their water consumption by 6.8% compared to those who were not.

[3] Anecdotal evidence suggests that French farmers see smart water meters as new intrusive mechanisms to limit their access to water resources and irrigation (Montginoul et al. , 2019).

formation on the water consumption of peer farmers (Chabé-Ferret *et al.* , 2019). Such information could be beneficial for farmers if collective management of water resources needed to be implemented or simply because there is a natural tendency for individuals to look to others for standards on how to think, feel and behave (Baldwin & Mussweiler, 2018). Offering smart meters which provide services farmers value might be a way to induce adoption of this technology. Assessing how farmers value various services or characteristics of smart water meters remains challenging, due to our hypothetical experimental context. Since discrete choice experiments (DCE) are a well-established, state-of-the-art method to elicit preferences for hypothetical choice alternatives (Vossler et al., 2012), we implement this method here.

Our main results are as follows. First, we show that, on average, farmers prefer keeping their current situation (mechanical meter or no meter). However, if smart water meter adoption allows them to receive an alert in the event of abnormal water consumption and/or if data confidentiality is guaranteed, then most farmers have a positive willingness to pay (WTP) for these benefits. Second, we demonstrate that the two policy instruments (conditional subsidy and nudges) do induce farmers to adopt a smart water meter. However, conducting additional analyses on random answers to identify inattentive farmers, we no longer confirm our results for one of our two nudges. Third, contrary to our expectations, the WTP for the conditional subsidy does not depend much on the collective adoption threshold. Indeed, a high collective threshold (75%) does not discourage smart meter adoption. This is further confirmed by our study of farmers' beliefs (regarding the number of farmers in their area who would be willing to adopt a smart water meter): the threshold levels have no impact on these beliefs except possibly through an anchoring bias. These elements argue in favor of implementing a conditional subsidy with a high collective adoption threshold.

Our main contribution is to assess the joint effect of the conditional subsidy with the two nudges, therefore enriching the literature on the provision of incentives to foster the voluntary adoption of sustainable practices. Indeed, most studies generally focus on the effect of either monetary incentives or non-monetary ones, the studies by My & Ouvrard (2019) and Antinyan *et al.* (2020) being exceptions. Indeed, both studies compare, in a lab experiment, the effect of a tax with the effect of a nudge to increase the contributions to a public good (My & Ouvrard, 2019) or to curb the consumption of a good that determines subjects' social position (Antinyan *et al.* , 2020). We differ from these studies by considering the joint effect of these two types of incentives, instead of comparing them separately. Moreover, our respondents are farmers and not students, therefore enhancing the external validity of our study (Palm-Forster *et al.* , 2019).

The remainder of this article is organized as follows. In Section 2, we present the literature related to conditional subsidy and informational nudges. Section 3 details our experimental design, which combines a DCE with different treatments and presents the data. We provide the results in Section 4 and conclude in Section 5.

2 Monetary and non-monetary incentives to induce smart meter adoption by farmers

2.1 Smart water meters in agriculture

Smart water meters are connected devices that can store and transmit water consumption data at a high frequency. They are usually connected to an online platform allowing easy access to the collected data. The smart meters we consider here record information on water consumption, in quasi real time, and enable two-way communication between the meter and a central system (in our case the local water manager). An alternative more descriptive name than smart meters could be communicating meters to highlight their social function[4].

[4] We used "compteur communiquant" (communicating meters) in French in our survey, however the name "smart meters" seems more commonly used in English to designate this type of device. Moreover, the term "smart water meter" has already been used in the literature, see Chabé-Ferret et al. (2019) for example.

Smart meters can also serve to design new water policies (pricing strategies, water use reduction targets, etc.). For farmers, smart water meters may be associated with new services such as providing an early warning of unusual events (leakages, high water consumption, etc.) Use of smart water meters in agriculture, however, raises some privacy concerns since it is possible to identify certain actions of farmers while analyzing collected data. As a result, smart meter use as a water management tool still remains limited in the context of agriculture (Chabé-Ferret *et al.* , 2019). Less than 5% of French farmers currently have a smart meter[5].

2.2 Subsidizing farmers

Smart water meters share similarities with public goods as they allow precise and quasi real-time measurement of the individual water consumption of farmers. In areas where users are equipped with smart water meters, water resource managers can more easily forecast water resource needs (Monks *et al.* , 2019) and plan water releases. This provides public authorities some rationale to facilitate the utilization of smart meters by, for example, providing subsidies to farmers who adopt them.

Various subsidy schemes may be implemented to foster smart water meter adoption. The simplest is an equal lump-sum payment for any farmer who adopts smart water metering. In our study, we propose offering a *conditional collective subsidy* to each farmer who adopts smart water metering, on the condition that a sufficient proportion of farmers have opted for this type of device. In a different context, Kuhfuss *et al.* (2016) have shown that a conditional collective bonus can be a powerful incentive tool to induce farmer participation in agri-environmental schemes since a farmer's willingness to pay for the conditional collective bonus is much higher than the monetary value of the bonus. This

[5] This percentage is rather low, knowing that in France, 30% of the farmers irrigate, which corresponds to a total of 5% of the utilized agricultural area (CGDD & Parisse, 2018).

strong result is consistent with the hypothesis that farmers are more willing to provide environmental efforts when their neighbors also do so. We hypothesize that this social norm dimension may also be at play in a farmer's willingness to change their water meter.

There are two main factors that justify this conditional collective subsidy. The first is related to the gains to be expected from smart water meter adoption in terms of water management. To be effective for improving water management, smart water meters must be adopted by many farmers: the greater the number of smart meters on a watershed, the better the management of the resource and the lower the risk of water shortage This means that a certain adoption rate threshold in a geographic area needs to be reached in order to render this new technology effective. As such, the adoption of smart water meters shares some characteristics of a linear public good, but it remains difficult to know precisely how collective benefits would evolve according to the rate of smart water meters in a given geographic area. We, therefore, take advantage of this unknown to test the impact of several credible thresholds.

The second factor is related to the role played by social norms in the adoption of new technologies. Although social norms were first defined as expectations on behaviors that one should adopt in specific contexts (Schwartz, 1977), they now include one's expectations of what other individuals should do (Eymess & Florian, 2019). When individuals prefer to act like most others, beliefs can be self-sufficient, and altered expectations of what others might do can lead to rapid behavioral changes (Young, 2015). Thus, as claimed by Nyborg *et al.* (2016), a potentially powerful role of public policies is to provide good reasons for individuals to change their expectations of social norms. We argue that introducing a conditional collective subsidy is a way to modify farmers' expectations with respect to the importance of the adoption of smart water meters. Indeed, when agents have preferences for obtaining social approval, government subsidies can guide social norms for voluntary contributions to a public good[6].

Our conditional collective subsidy indicates to each farmer that the incentives to adopt smart meters have changed, not only for themselves but for others as well. This can directly impact their expectations on the rate of adoption by their peers and, thus, ultimately change the social norm. Two parameters of a conditional subsidy may impact farmers' beliefs: the amount of the subsidy and the collective threshold to be reached in order to get it. Usually, the standard threshold is 50% since social norms are considered to be driven by the majority. However, theoretical models of critical mass have shown how minority groups can initiate social change dynamics in the emergence of new social conventions, and the existence of tipping points has been empirically demonstrated (Centola *et al.* , 2018). Still, there is insufficient insight on the co-evolution of social norms and different policy instruments (Kinzig *et al.* , 2013). Here we attempt to understand how different thresholds (25%, 50% and 75%) related to the conditional subsidy influence individual adoption of smart water meters.

2.3 Green nudges to foster smart meter adoption

In the past decade, there has been a growing literature regarding the potential of nudges to steer pro-environmental behaviors (Schubert, 2017). As a complement to the conditional collective subsidy incentive, we use nudges to induce farmers to adopt a smart water meter. Most studies using green nudges rely on social norms or default options. Studies that appeal to social norms to reduce water consumption have reported reductions of about 5% (Ferraro & Price, 2013; Brent *et al.* , 2016; Bhanot, 2017). Studies which have focused on the efficiency of default options to improve environmental quality have reported

[6] See also the literature that shows under which conditions government subsidies can increase private contributions to a public good (Andreoni & Bergstrom, 1996; Rege, 2004).

mixed results (Löfgren *et al.* , 2012; Egebark & Ekström, 2016; Ghesla *et al.* , 2019). In our case, we cannot consider these two types of nudges (i.e., social norms and default options) because smart water metering is a new technology in agriculture and cannot be viewed as the current norm among farmers. Moreover, the adoption of smart meters is not a default option that can be proposed to all farmers. Therefore, we use two other levers, in addition to a reference "No nudge" group.

First, some farmers have been allocated to get a first nudge we call "cocktail" nudge(see Appendix A.1). In the "cocktail" nudge, respondents are: i) reminded of the existence of water restrictions, ii) asked to report to what extent they consider water managementan important issue, iii) asked to report to what extent they would be willing to committo adopting better water management, and iv) provided a description of the meters as allowing for better water management and also for greater equity[7]. The first question can be seen as a *priming* question, while the second is directly inspired from the theories of *commitment*. *Priming* is the fact to implement a stimulus intended to raise respondents' awareness on a topic (the importance of water management in our case) or a behavior (Bargh & Gollwitzer, 1994; Bargh *et al.* , 2001). Encouraging results have been observed in the literature (Bargh, 2006; Friis *et al.* , 2017; Bimonte *et al.* , 2020). Regarding commitment, empirical evidence has shown that asking individuals to commit may be an effective way to change their behavior (Ariely & Wertenbroch, 2002; Baca-Motes *et al.*, 2012; Dolan *et al.* , 2012) and specially to foster pro-environmental behavior. For instance, Werner *et al.* (1995) showed that individuals who expressed environmental commitment were more likely to participate in a curbside recycling program. We follow the suggestion made by Dolan *et al.* (2012) and combine these three types of nudges

[7] Equity between farmers is improved as it becomes easier to precisely know the exact water consumption of each farmer. Then, it is possible, for instance, to make farmers pay in proportion of their consumption the costs related to the maintenance of water facilities. Moreover, smart meters avoid measurement errors in water consumption and limit the undetected risks of leakage. In this sense, farmers will pay what they really consume.

(*reminder*, *priming* and *commitment*) to increase their efficiency.

Second, we provide some farmers information regarding the behavior of their peers. This approach is based on *social identity*, which aims to influence peer decisions in the direction of most of the peer action. Indeed, empirical evidence in psychology (Goldstein & Cialdini, 2007; Swann Jr & Bosson, 2010; Rogers *et al.*, 2018) has emphasized that agents are more likely to follow a norm if they perceive themselves as similar to theindividual or group of reference. Evidence of the impact of the behavior of peer farmers on an individual farmer's behavior is mixed. In a context of agri-environmental schemes, Kuhfuss *et al.* (2016) report a positive impact. In Germany, Gillich *et al.* (2019) find that farmers are more likely to grow perennial crops for bioenergy purposes if their neighbors also grow them. On the contrary, Wallander *et al.* (2017) show that providing peer information has no effect on a farmer's own enrollment in the Conservation Reserve Program in the USA. Lastly, Villamayor-Tomas *et al.* (2019) show that the recommendation of conservation programs by farmers does not encourage other farmers to participate (Germany and Spain).

In our case, we provide a "testimony" by Yves, a 59-year-old farmer, who recounts his experience with smart water metering (see Appendix A.2). He indicates, among other information, that thanks to the adoption of smart water meters in his sector, it has been possible to reduce water losses by 15% to 20% annually (representing a financial gain for his local farmers' association of around 15,000€ annually). In order to give his testimony credibility, the name and age of the farmer, as well as his photo[8], are included. We expect respondents to identify with this farmer's first-hand experience of adopting smart meter technology and, consequently, to choose a smart meter alternative more often themselves. Finally, note that we provide nudges in addition to the conditional collective subsidy since recent evidence (Myers & Souza, 2020) highlights that nudges alone may not be

[8] In the Appendix, the farmer's face is hidden in the photo for the dissemination of the article, but it was visible in the questionnaire.

enough in the absence of monetary incentives.

3 Material and methods

3.1 Design of the Discrete Choice Experiment (DCE)

In order to elicit farmers' preferences regarding smart water meters, we conduct a DCE in which each farmer is presented a number of different water meters with various attributes and asked to select one. The choice of proposed attributes resulted from an interactive process involving discussions with a focus group of farmers and water resource managers about the water meter characteristics they considered most important. At the end of this process, and based on the feedback we received, we selected five attributes which are presented in Table 1.

The first attribute, *Information*, is access to the average water consumption of the other farmers in the respondent's geographic area. This allows farmers to compare their water consumption with that of their peers and to adjust their consumption accordingly if they wish. Such information has been used in studies to reduce electricity or water consumption (Schultz *et al.* , 2007; Allcott, 2011; Costa & Kahn, 2013; Ferraro & Price, 2013; Brent *et al.* , 2016; Chabé-Ferret *et al.* , 2019). The second attribute, *Alert*, is an instant message that informs farmers if abnormal water consumption is caused by a leak. Local stakeholders and farmers expressed particular interest in this attribute during our focus group meetings. The third attribute, *Confidentiality*, ensures full confidentiality of all individual data consumption registered by the smart meters (i.e., only made available to the local water resource manager for the purpose of managing the water dams in the sector). The confidentiality attribute should then be understood as the capacity to restrict access to water consumption records to the farmer. When confidentiality is not assured, the data may be made available to public water agencies or to the State. Several studies have emphasized that privacy concerns may decrease the likelihood of people adopting new technologies: instant messaging (Lowry *et al.* , 2011), biometrics (Miltgen *et al.* , 2013) and mobile apps (Gu *et al.* , 2017) are examples where privacy concerns constitute one of the main determinants of user adoption. The fourth attribute is the *conditional subsidy* associated with the purchase of a smart water meter.Three levels are possible: no subsidy, 300€ and 600€. The fifth attribute is the monetary attribute, the purchase price of the smart meter: 250€, 500€, 750€, 1,000€, 1,250€, 1,500€. In the survey, the status quo (SQ) is defined as opting to keep his/her current water meter, but since some farmers declare they do not have water meter, this alternative should be interpreted more generally as: "I keep my current situation"[9].

[9] 13% of farmers in our sample state they do not have water meter. We decided to keep them in our sample since we do not observe differences between farmers with a meter and farmers without. Results are qualitatively the same if we exclude the farmers who do not have water meter from our sample.

*Table 1: Description of meter attributes in the DCE

Attribute	Description	Levels	SQ
Information	Information on the average consumption of other farmers in the respondent's geographic area	No (ref.) Yes	No
Alert	Alert received on abnormal water consumption	No (ref.) Yes	No
Confidentiality	Water consumption data is confidential, access limited to the farmer	No (ref.) Yes	Yes
Price	Purchase price of the smart meter	250 €, 500 €, 750 €, 0 € 1000 €, 1250 €, 1500 €	
Conditional subsidy	Subsidy conditional on i) smart meter adoption ii) a given percentage of farmers in the respondent's geographic area adopt a smart meter	No subsidy (ref.) 300 € 600 €	No

SQ: Status quo
ref.: Reference category

The attribute levels for the SQ are: no information on the consumption of other farmers, no alert in the case of abnormal water consumption and maintained confidentiality of daily consumption information as none is tracked. Obviously, farmers do not receive a subsidy for the SQ, and there is no additional cost for them if they keep their current mechanical water meter or continue without water meter.

3.2 Implementation of the DCE

The online survey was implemented using the web-platform LimeSurvey (version 2.5). The survey includes five parts: an introduction and description of water meter attributes, the DCE, the follow-up questions, some questions on the respondent's current situation and, finally, a section designed to elicit farmers' beliefs about the number of their peers who would opt for a smart water meter. We have used the NGene software (Rose *et al.*, 2010) to generate an efficient design which minimizes the required sample size and number of choice cards. We have used priors obtained in two pilots, conducted in June and September 2019, to generate the final design and modify the questionnaire according to the feedback we received from respondents[10]. We do not use the data collected in the two pilots in our analyses.

The 18 different choice cards generated have been divided into three blocks. Each block is made up of six different choice cards. Respondents have been randomly assigned to a particular block. Within each block, the six choice cards are successively proposed in random order to respondents who make six choices between two different smart meters: "Meter 1" and "Meter 2", and a status quo option, "I keep my current meter". An example of a choice card is presented in Figure 1.

[10] Combining the data from the two pilots, we obtained 21 completed questionnaires corresponding to 126 choices, which we used to estimate the priors.

Between November and December 2019, the final questionnaire was emailed to 90,000 French farmers (20% of the total number of farmers in France) by a French polling organization[11]. The link to the questionnaire was sent through an introductory email informing recipients that the study was being conducted by the French Institute for Agricultural Research for a project on water management and new technologies.

To provide an incentive for farmers to participate in our study, we informed them that we would give 20€ to a charitable organization (Secours Populaire) for each set of one hundred questionnaires completed (Deutskens *et al.* , 2004). We chose the Secours Populaire since it is quite popular in France without being directly related to farmers.

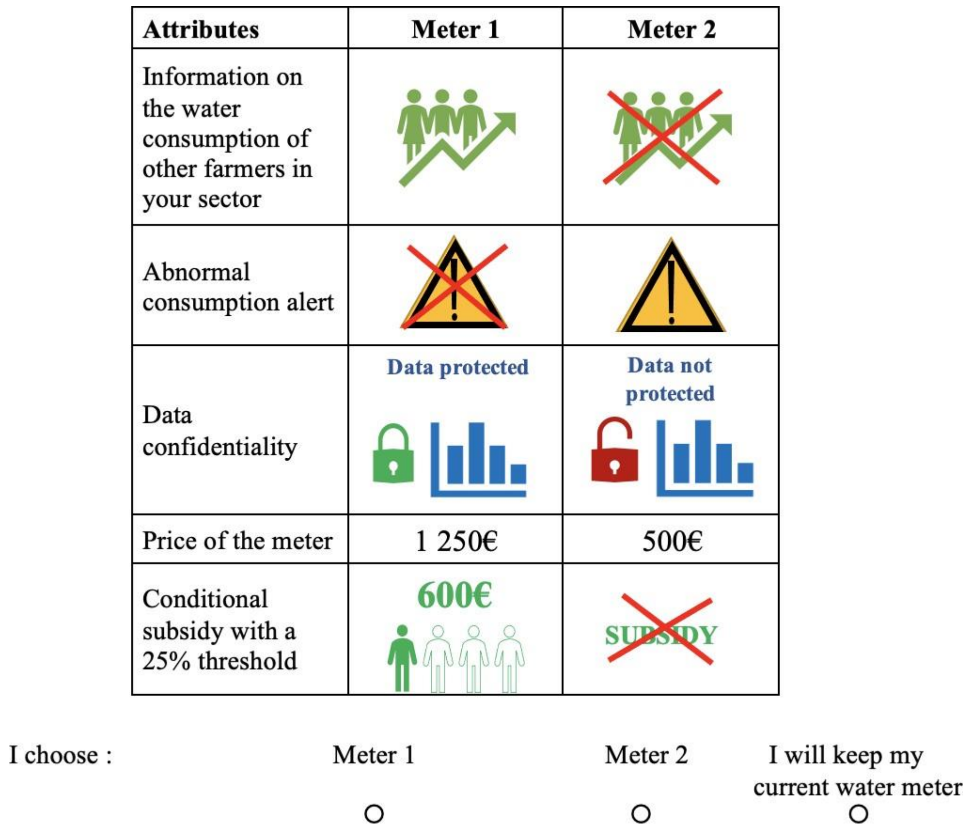

Figure 1: Example of a choice card

3.3 Choice modeling

We rely on the Random Utility Model (RUM) in which a farmer's meter choice results from

[11] The company BVA (https://www.bva-group.com/).

the maximization of the relative utility derived from the different alternatives (McFadden, 1974). Respondents choose the alternative providing the highest expected utility. The RUM model assumes that farmer i ($i = 1,\ldots,I$) chooses among j ($j = 1,\ldots,J$) possible multi-attribute water meters and that the associated utility U_{ijt} from alternative j in choice card t ($t = 1,\ldots,T$) is:

$$U_{ijt} = V_{ijt} + \epsilon_{ijt} \tag{1}$$

where V_{ijt} is the indirect utility from choosing water meter j, and ϵijt is the error term capturing the unobserved utility.

To account for the unobserved heterogeneity in tastes and preferences, we consider the mixed logit (ML) model (McFadden & Train, 2000). In the ML model, farmer i's utility ($i = 1,\ldots,I$) from choosing alternative j ($j = 1,\ldots,J$) in choice card t ($t = 1,\ldots,T$) is:

$$U_{ijt} = \beta_i X_{ijt} + \epsilon_{ijt} \tag{2}$$

Where X_{ijt} is a vector which includes the attributes of the smart meter, βi terms are the associated random parameters, and ϵ_{ijt} is an IID extreme value. To capture the specific nature of the status quo option in the DCE (i.e., keeping the current situation), X_{ijt} includes an alternative-specific constant related to the status quo: SQ is a dummy variable equal to one in the status quo alternative and to zero otherwise in all the choices.

By estimating the ML model represented by Equation (2), it is possible to compute the mean farmers' WTP for attribute x:

$$WTP_x = \frac{-\beta_x}{\beta_{price}} \tag{3}$$

where β_x and β_{price} are the parameters associated with attribute x and the monetary attribute (i.e., the price of the water meter) respectively. To facilitate the calculation of the WTP, we estimate a ML model where the monetary attribute is fixed whereas all other parameters are specified as random parameters. This approach is a standard practice in the literature when conducting a DCE (Gillich *et al.* , 2019).

From the estimation results of the ML model, we can also simulate the adoption rate of a specific smart meter (Train, 2009). The average probability $Prob_j$ of a farmer choosing a specific smart meter j with attributes X_j over keeping his/her current situation SQ defined by X_{SQ} can be simulated as follows:

$$Prob_j = \frac{e^{\beta X_j}}{e^{\beta X_j} + e^{\beta X_{SQ}}} \tag{4}$$

3.4 Treatments: A "three by three" design

We test two different instruments to foster the adoption of smart water meters by farmers: a conditional subsidy and a nudge.

Our monetary instrument is included in the DCE. Indeed, one attribute is the possibility to receive a conditional subsidy. This subsidy, obtained by a farmer who adopts a smart meter, is conditional to the proportion of farmers in the same geographic area who also adopt a smart meter. Previous studies have designated a 50% threshold (Kuhfuss*et al.* , 2016). Here, farmers have been randomly assigned to three groups (i.e., three different versions of the DCE): a reference group, where the threshold of the conditional subsidy attribute is set to 50% and two other groups: one with a low threshold set at 25% and one with a high threshold set at 75%. To farmers in the low threshold group, a 25% threshold may appear more realistic to reach than a 50% threshold as this new smart meter technology is not yet widespread. This low threshold can also imply that the development of smart meters may take time before becoming widely adopted. Conversely, the designation of the higher threshold may lead some farmers to believe that the 75% target desired by the public authorities is rapidly achievable and that there may be real enthusiasm for smart meters. Of course, in a probabilistic approach, a low threshold seems easier to reach, whereas a high threshold may appear unattainable and could become a disincentive. Consequently, the different thresholds can have at least two opposite impacts on a farmer's WTP for the subsidy. Either way, the different thresholds may impact farmers' beliefs about the potential adoption rate and, thus, the decision of whether or not to adopt smart water meter technology.

In addition, farmers have been randomly assigned to two different nudges or to a reference "No nudge" group, where no information is communicated (see Section 2.3).

Combining the three conditional subsidy thresholds with the three nudge groups, our experiment therefore includes a total of nine different treatments (subsidy thresholds × nudges). Each respondent was randomly assigned to a single treatment to run a between-subjects design experiment.

4 Empirical results

4.1 Sample and descriptive statistics

About 90,000 farmers were contacted to take our survey, but we do not know exactly how many farmers received and read our invitation email. A total of 10,344 followed the link provided in the invitation email (about 12%). Among the 10,344 farmers who connected to our survey, 3,499 (34%) started to respond to the DCE, and 1,613 completed it (16%). This dropout of respondents is not surprising given that the DCE was quite demanding from a cognitive point of view. Using some follow-up questions, we removed 98 respondents (i.e., 6% of those who completed the DCE) reporting that they already had a smart meter installed and for whom the issue of switching from no meter or mechanical meter to smart water meters was not relevant. To those who have always chosen the SQ we asked them why. Then, we excluded 175 protest respondents (11%), which correspond to those who answered, “It is not for the farmers to make the effort” or “I am against smart meters, whatever their price or subsidy”. In addition, we excluded 64 respondents who declared that they did not understand the DCE. Finally, our final sample is composed of 1,272 farmers across France, which corresponds to 12% of farmers who followed the link provided in the invitation email.

Regarding irrigation, our sample comprises 81% of farmers equipped with a mechanical water meter, 6% who don’t know and 13% who do not have any meter. Going into the details, among the 47% of irrigating farmers, 94% of them are equipped with a mechanical meter, 3% do not know and 3% do not have any water meter. On the 53% of farmers who are not irrigating farmers, 70% of them are equipped with a mechanical meter, 8% do not know and 22% do not have any water meter. In France, 80% of water consumed by the agricultural sector is used for irrigating crops (mainly maize), the remaining 20% being used for watering livestock, building maintenance, etc.[12] All irrigating farmers are equipped with water meters (either mechanical meters or smart meters) allowing them to report their water consumption to French public authorities (Water Agencies). For non-irrigating farmers (in particular those using water for livestock watering), it is not mandatory to have a specific water meter allowing to make the distinction between in-house water consumption (drinking, cooking, washing, etc.) and the water consumption corresponding to their professional activity. But in practice, almost all non-irrigating farmers have a specific water meter for their professional activity or at least a sub-metering system (“compteur divisionnaire” in French) allowing to measure water consumption for their professional activity. The reason is that according to the French legislation[13], farmers using water for livestock watering don’t have to pay for any pollution fee to the Water Agency, whereas all other users (including households) have to. To benefit from this water pollution

[12] See: http://www.donnees.statistiques.developpement-durable.gouv.fr/lesessentiels/essentiels/eau-prelevements.htm

[13] See: https://www.bulletin-officiel.developpement-durable.gouv.fr/documents/Bulletinofficiel-0005908/eat_20080005_0100_0005.pdf;jsessionid=141CEC1F72C7322A389BED147F394D23

fee exemption for their professional activity, most of non-irrigating farmers are equipped with specific meters or sub-metering systems for their professional water consumption. Following this information, the question of the voluntary adoption of communicating meters seems relevant for all farmers, whether they are irrigating farmers or not. We therefore keep the whole sample for the econometric analysis.

Socio-economic descriptive statistics on our sample are presented in Table B.1 and are compared with data from the 2010 French agricultural census. In our sample, we observe an over-representation of young men (< 40 years old) with a high level of education (i.e., a master's degree) in field crops and polyculture. However, we have an acceptable spatial distribution representativeness of our sample at the French scale, as shown by Figure C.1.

4.2 Treatment randomization

Each respondent who begins the survey is randomly assigned to a particular treatment. Figure D.1 in Appendix D provides a description of the process used to conduct the randomized assignment of respondents, and Table 2 summarizes the number of farmers randomly allocated to the nine treatments.

Table 2: Randomized allocation of farmers in the nine treatments

		Nudges			
		No nudge	Cocktail	Testimony	Total
Conditional subsidy	25% Threshold	125 (9.8%)	168 (13.2%)	109 (8.6%)	402 (31.6%)
	50% Threshold	141 (11.1%)	181 (14.2%)	115 (9.0%)	437 (34.4%)
	75% Threshold	155 (10.5%)	167 (13.1%)	111 (8.7%)	433 (34.0%)
	Total	421 (33.1%)	516 (40.6%)	335 (26.3%)	1,272 (100.0%)

Our final sample is equally split into the three conditional subsidy thresholds. Concerning the nudges, we observe an over-representation of respondents who received the *Cocktail* and an under-representation of those who saw the *Testimony*. As shown inTable 2, sample sizes differ across treatments from 109 respondents in the *Testimony*× 25% Threshold treatment to 181 respondents in the *Cocktail*× 50% Threshold treatment. Whatever the conditional subsidy threshold, respondents in the *Cocktail* nudge are over-represented, whereas those in the *Testimony* are under-represented. Treatment imbalance could be a concern if respondent drop-out is systematic and not random. To check this issue, we investigate the presence of selective respondent dropouts using a series of tests. In Figure D.1 in Appendix D, we first explore how attrition dropout varies across treatments at different steps of the survey. As can be seen, it is not possible to detect any particular step in our survey which may explain differentiated dropouts among treatments. Figure D.1 reveals that the ratio between the final sample size and the number of respondents who have begun the DCE is similar in all treatments (between 30% and 40%). However, focusing on the share of respondents who complete the DCE compared to those who start it per nudge treatment group (No nudge, Cocktail or Testimony), we observe lower completion rates in the Testimony (40.55%) compared to the two othergroups (48.06% in the Cocktail and 48.83% in the No nudge). Still, as we next show, we do not think this is an issue as we do not observe significant differences in farmers' characteristics between treatments.

Second, in Table D.1 in Appendix D, we investigate whether respondents differ between treatments. The Kruskal-Wallis tests show that there is no statistically significant difference for the distributions of our observable variables (gender, age, education, activity) across the nine treatments. Third, we check whether sample size difference across treatments can be related to the design of the DCE. Hence, respondents have been randomly assigned to a particular block made up of six choice cards, and three different blocks have been used in total. In Table D.2 in Appendix D, we show that the allocation of respondents to DCE blocks is similar across blocks and that allocation to blocks and treatments is orthogonal as expected.

We conclude that the imbalance of sample sizes across treatments does not result from a sample selection problem (on observables or treatments), nor is it the result of using three different blocks of choice cards in the DCE.

4.3 Individual choices and status quo responses in the DCE

On each choice card, a farmer selects his/her preferred option among three possible choices: two smart meter options and the SQ option (his/her current situation). Statistics on SQ choices, by treatment, are presented in Table 3. Note that this percentage of SQ choices does not allow us to infer any average potential rate of adoption of smart water meters in our sample. On the other hand, since we have a "three by three"experimental design that is well balanced across blocks, we can compare this percentage among the different treatments.

Table 3: Percentage of farmers choosing the SQ option in the DCE (by treatment)

		Nudges			
		No nudge	Cocktail	Testimony	Total
	25% Threshold	50.5%	47.6%	45.1%	47.8%
Conditional subsidy	50% Threshold	55.1%	48.1%	49.7%	50.8%
	75% Threshold	55.9%	47.8%	44.3%	49.8%
	Total	54.0%	47.8%	46.4%	49.5%

An effect of our nudges can be noted in this percentage. The proportion of SQ answers in the sample by farmers who did not receive any nudges is 54%, whereas it drops to 47.8% and 46.4% for farmers assigned to the cocktail and testimony nudges, respectively. The direct effect of the conditional threshold on the proportion of SQ answers appears to be very limited. These first raw results suggest that the level of the threshold seems to have little impact on the overall probability of a farmer choosing a smart meter but that our two nudges could make a significant difference compared to our control group (i.e., "No nudge").

4.4 Mixed logit estimation of the DCE

In Table 4, we report the results of the ML estimations[14] considering the full sample[15]. In the four model specifications presented in Table 4, the price attribute has been considered as a non-random parameter, whereas all other parameters are specified as random parameters following normal distribution. All our empirical specifications include an alternative-specific constant (ASC) *SQ* to take into account the specific nature of the status quo alternative that corresponds to the respondent's current situation. This ASC includes indistinct smart meter characteristics not included in our attributes as well as the transaction cost of smart meter adoption.

In model (1), we estimate a simple model where the utility is specified following Equation (2) without considering the effects of the treatments (subsidy thresholds and nudges). In model (2), we interact the ASC for the SQ with the conditional thresholds, the 50% threshold being the reference, as it is the standard tipping point in the literature (Kuhfuss *et al.* , 2016). We wish to test whether or not a change in the conditional threshold can affect the choice of the SQ. In model (3), we interact the ASC for the SQ with nudges, the "No nudge" being the reference category in this case. In model (4) we assess the combined effect of nudges and subsidy thresholds on the SQ choice, the reference

[14] We have also estimated the choice model using a simple conditional logit model. All the coefficients of the smart meter attributes, as well as those for the subsidy and the two instruments, are significant and with the expected signs. Since the conclusion of the Hausman test is that the assumption of independence of irrelevant alternatives is not satisfied, we focus here only on the ML models.

[15] We carried out estimates by separating irrigating farmers and non-irrigating farmers, the results not being significantly different, we keep the estimates on the full sample.

category being the treatment with 50% threshold and “No nudge”.

The positive and significant sign of the mean coefficient associated to the random parameter *SQ* indicates that farmers have, on average, a preference for keeping their current situation (mechanical meter or no meter) rather than adopting a smart meter. A very large heterogeneity among farmers is, however, documented with the estimate for the standard deviation (SD) of the random parameter SQ being significant as well, and about 2-4 times larger than the estimated mean. The SD represents the heterogeneity and variation in the preferences of the respondents. The larger the SD of the random parameter, the greater the variation in respondents’ preferences. This result confirms the assumption of a non-constant status quo effect across respondents and that there is a large mass of the farmer population that prefers moving away from the status quo.

We now look at the effect of attributes on farmers’ choices. We note that all the coefficients associated to the attributes are significant at the 1% level with the expected sign in all models, except for the attribute related to the ability to receive information on the water consumption of other farmers. Although the mean coefficient for the random parameter *Information* is never significant, the very high and significant SD reveals a strong response heterogeneity among farmers. This result could be related to the work of Chabé-Ferret *et al.* (2019), who have found that providing farmers information on water use by peers does not induce any significant change in their average water use behavior. Respondents have, on average, a preference for receiving an alert in case of abnormal water consumption and for retaining the confidentiality of their data (positive and significant coefficient for these two attributes), but a significant heterogeneity is also documented in all estimated models. Lastly, the two levels for the subsidy have positive and significant coefficients, which means that, on average, independent of the level of the threshold, the subsidy significantly increases the probability of a farmer choosing a smart meter, although the payment of the subsidy is conditional.

We now investigate the effects of the thresholds of the conditional subsidy and the effects of our two nudges on farmers' preferences for the status quo. Model (2) reveals that varying the threshold for the conditional subsidy does not have any significant impact on the choice of the SQ: farmer's preferences for keeping their current situation rather than adopting a smart meter appear to be unaffected by the threshold for the conditional subsidy.

In contrast, from model (3), it can be noted that the two nudges significantly induce farmers to choose the SQ less often compared to farmers in the "No nudge" treatment, indicating that nudges may be useful communication tools for influencing farmers to adopt new technologies. Similar results on the potential of nudges to better communicate on policies have been documented in Ouvrard et al. (2020)'s DCE. In model (4), we finally interact the thresholds for the conditional subsidy with nudges in order to assess their combined impact on farmers' preferences for the SQ. The two nudges induce farmers to choose the SQ less often compared to farmers in the "No nudge" treatment, but only when they are combined with a 75% threshold for the conditional subsidy. A possible interpretation of this result could be that being conditional cooperators, French farmers react to nudges by moving away from the status quo only if this decision is also encouraged by a strong social norm.

Table 4: Mixed logit estimations with SQ Interactions.

	(1)		(2)		(3)		(4)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Price (in k€)	-1.639***		-1.640***		-1.628***		-1.647***	
	(0.073)		(0.073)		(0.072)		(0.075)	
Information	-0.0518	1.363***	-0.0540	1.365***	-0.0348	1.348***	-0.0529	1.369***
	(0.078)	(0.115)	(0.078)	(0.116)	(0.077)	(0.113)	(0.078)	(0.119)
Alert	1.767***	1.216***	1.770***	1.217***	1.753***	1.195***	1.777***	1.241***
	(0.082)	(0.098)	(0.082)	(0.098)	(0.081)	(0.098)	(0.084)	(0.102)
Confidentiality	1.304***	1.623***	1.302***	1.630***	1.296***	1.617***	1.304***	1.644***
	(0.091)	(0.116)	(0.091)	(0.117)	(0.091)	(0.113)	(0.091)	(0.117)
Subs.300	0.490***	0.468**	0.490***	0.474**	0.491***	0.379	0.487***	0.520**
	(0.085)	(0.228)	(0.085)	(0.226)	(0.085)	(0.302)	(0.086)	(0.228)
Subs.600	1.104***	0.660***	1.106***	0.660***	1.111***	0.666***	1.114***	0.683***
	(0.072)	(0.139)	(0.072)	(0.137)	(0.072)	(0.131)	(0.073)	(0.136)
SQ	0.666***	2.519***	0.801***	2.508***	0.982***	2.426***	1.052***	2.325***
	(0.116)	(0.117)	(0.169)	(0.119)	(0.167)	(0.126)	(0.258)	(0.133)
SQ×Thresh.25%			-0.248	0.445				
			(0.216)	(0.419)				
SQ×Thresh.75%			-0.170	0.102				
			(0.210)	(0.350)				
SQ×Cocktail					-0.453**	0.271		
					(0.198)	(0.428)		
SQ×Testimony					-0.526**	1.039*		
					(0.235)	(0.562)		
SQ×No Nudge 25%							-0.171	1.117*
							(0.380)	(0.627)
SQ×No Nudge 75%							0.0460	1.183**
							(0.355)	(0.576)
SQ×Cocktail 25%							-0.580	1.606***
							(0.353)	(0.620)
SQ×Cocktail 50%							-0.449	0.075
							(0.328)	(0.522)
SQ×Cocktail 75%							-0.580*	0.213
							(0.331)	(0.581)
SQ×Testimony 25%							-0.629	1.054*
							(0.394)	(0.633)
SQ×Testimony 50%							-0.284	1.736***
							(0.404)	(0.551)
SQ×Testimony 75%							-0.809**	0.058
							(0.392)	(1.879)
Observations	22896		22896		22896		22896	
Log-likelihood	-5875.8		-5874.6		-5872.5		-5868.5	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.1 in Appendix E replicates ML estimations of Table 4 but thresholds and nudges are now intersected with the conditional subsidy attribute. The reference level for this attribute is "No subsidy" and two subsidy amounts are proposed in the choice cards (300€ and 600€). Whether the two levels of subsidy are crossed with the thresholds or nudges, independently (model 2 and 3) or jointly (model 4 and 5, and E.2 which gives the results of a multinomial logit model with random parameters), none of the coefficients of these interaction variables is significant. In other words, no treatment group significantly impacts the conditional subsidy attribute whether it is at 300€ or 600€. It is interesting to highlight that the threshold that must be collectively met to receive the subsidy does not impact farmers' choices in the DCE. In model (2), relative to a 50% threshold, the two other thresholds (25% and 75%) do not have a significant effect on farmers' perceptions of the conditional subsidy regardless of its amount (300€ or 600€).

A first concern with the results presented in Table 4 could be that the estimates may suffer from a respondent inattention bias due to hypothetical nature of the discrete choice experiment. To investigate this issue, we have followed Malone and Lusk (2018)'s approach by identifying the fraction of inattentive respondents, i.e., the fraction of respondents whose choice behavior is statistically indistinguishable from random answers. It appears that 37.1% of our respondents are classified as random respondents (33.5% in Malone and Lusk, 2018). In Table F.1 in Appendix F, we have then replicated Table 4 by excluding all respondents predicted to belong to the share of respondents having answered randomly in the discrete choice experiment. Although the results are qualitatively the same than those reported in Table 4, two significant changes should be noticed. First, the coefficient associated to the *Information* attribute, that is negative, is now significant in all estimations (but with high heterogeneity as the coefficient of the S.D. is always significant at the 1% level). Second, coefficients associated to the Testimony nudge in Table F.1 in Appendix F are not anymore significant. This indicates that the significant effect of the Testimony nudge (based on social norms) reported in Table 4 is partly driven by the sample of random respondents. Thus, the evidence is inconclusive regarding this nudge.

A second concern regularly raised in the context of DCE is related to the hypothetical bias (Murphy et al., 2005), that is, in our case, the fact that farmers may not report their true preferences for smart water meters because of the hypothetical context. This bias may occur for several reasons such as a lack of political consequentiality (i.e., respondents do not believe that their answers can inform policymakers), strategic behaviors or social desirability motives (Colombo et al., 2022). Different techniques, summarized by Colombo et al. (2022), can be implemented either before the choice experiment takes place, or after, to reduce it. One of the most common techniques relies on use of cheap talk before the start of the DCE (e.g., Carlsson et al., 2005; Wuepper et al., 2012), but the results are rather inconclusive (see Chowdhrury et al., 2011, and Moser et al., 2014, for opposite results). Another solution is to use reminders to enhance, for instance, political consequentiality (Vossler et al., 2012). Ex-post methods range from certainty follow-up questions (e.g., Blomquist et al., 2009) to methods that combine, in addition to the obtained data from the DCE, data from revealed preferences studies (e.g., Brooks and Lusk, 2010). In our case, we acknowledge that we have not formally addressed the potential hypothetical bias because we have neither implemented cheap talk nor certainty follow-up questions. Regarding cheap talk, we feared that its effect could have interfered with our nudges. We have however started our survey by emphasizing the name of our research institute (for political consequentiality), and we have proposed to farmers a topic they are very familiar with (water conservation). We have devoted a lot of efforts to ensure a high level of credibility of the survey (that was tested with the two pilots). We expect the impact of the hypothetical bias to be limited in our case. However, to check whether our results are driven by hypothetical bias, we have look at sub-samples in our data, distinguishing between farmers who are more and less likely to exhibit hypothetical bias. We found that the potential hypothetical bias does not significantly interact with the results of our instruments.[16] So we feel relatively confident that our results are generally correct. Nevertheless, we acknowledge that we could have some degree of hypothetical bias in our study.

4.5 Mixed logit estimations by treatment

We now investigate how farmers' decisions in the DCE are impacted in each treatment when both the conditional subsidy thresholds and nudges are taken into account simultaneously. In Table 5, we report the results of the ML estimations for all nine treatments. The results presented independently for the nine treatments are however quite noisy.

One could argue that this is explained by a lack of power due to the low number of respondents per treatment that is automatically much lower (141 farmers per treatment on average). Still, conducting power analyses, we do find that our sample size per treatment is enough, except for the analyses of the coefficients associated to the *Information* and *Subs.300* attributes, as well as for the *SQ* coefficient[17].We must therefore remain cautious in interpreting these coefficients.

Overall, we observe robust results regarding most of our attributes across the treatments. Similarly, to results presented in Table 4, we find that the mean coefficients of the *Alert* and *Confidentiality* attributes are always significant, with the expected signs. A large heterogeneity of responses among farmers is documented for both attributes whatever the treatment considered. Results regarding *Information* are less intuitive and in general not significant, but significant heterogeneity (at the 1% level for seven out of the nine treatments) is documented. We will further investigate in the next section the source of this high level of heterogeneity, but it appears to be somehow related to our

[16] Details and results are available in an online supplementary material.

[17] To compute the minimum required sample size for the estimated coefficients in our DCE, we follow de Bekker-Grob et al. (2015)'s approach. The results are available upon request.

treatments. Indeed, *Information* appears to be rejected by most farmers at the exception of those in the Testimony treatment (with the conditional subsidy at a 50% level) who seem to positively value it. Regarding the effect of the conditional subsidy, we find that the coefficients of this attribute are always positive and significant (at the 1% level) for a large subsidy (i.e., 600€), with significant heterogeneity as documented with the SD part for six out of the nine estimations. However, the effect of a 300€ subsidy is significant (at a 5% confidence level) in only three treatments out of nine, with very few heterogeneity. Results are in line with our past observations: the threshold that must be collectively met to receive the subsidy has no effect on farmers' perception of the subsidy. Finally, the ASC for the SQ is significant in only three of the nine treatments.

It is difficult to draw conclusions from Table 5, by treatment, and to clearly show possible cross effects of our two instruments. An alternative way to analyze the impact of our instruments is to consider our three-by-three design independently and to estimate different MLs per threshold on the one hand, and by nudge on the other hand. This allows us to divide our sample into only 3 sub-samples by threshold and by nudge, and thus, to greatly increase the reliability of our results. The analysis by threshold and by nudge is done in Table G.1 in Appendix G. From these results, we confirm all our basic results obtained with model (1) in Table 4 for each of the six MLs, despite strong individual heterogeneity. These results per threshold and per nudge are further analyzed in the following section.

Table 5: Mixed logit estimations by treatment

	No nudge			Cocktail			Testimony		
	25% Thres.	50% Thres.	75% Thres.	25% Thres.	50% Thres.	75% Thres.	25% Thres.	50% Thres.	75% Thres.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean									
Price (in k e)	-2.244***	-1.817***	-1.629***	-1.669***	-1.734***	-1.597***	-1.511***	-1.830***	-1.303***
	(0.304)	(0.222)	(0.225)	(0.204)	(0.197)	(0.200)	(0.238)	(0.286)	(0.196)
Information	-0.374	-0.582***	-0.384	0.0663	-0.250	0.184	0.329	0.590**	0.242
	(0.331)	(0.219)	(0.261)	(0.198)	(0.228)	(0.202)	(0.251)	(0.272)	(0.195)
Alert	2.142***	1.279***	1.974***	1.403***	1.701***	2.027***	2.170***	2.477***	1.399***
	(0.338)	(0.208)	(0.272)	(0.208)	(0.203)	(0.243)	(0.309)	(0.359)	(0.209)
Confidentiality	0.964***	1.218***	1.801***	1.332***	0.986***	2.161***	1.274***	1.411***	0.993***
	(0.314)	(0.240)	(0.302)	(0.238)	(0.238)	(0.305)	(0.315)	(0.332)	(0.251)
Subs.300	0.426	0.477*	0.498	0.561**	0.205	0.841***	-0.0003	1.156***	0.343
	(0.312)	(0.253)	(0.310)	(0.232)	(0.214)	(0.227)	(0.317)	(0.338)	(0.270)
Subs.600	1.125***	1.036***	1.465***	1.070***	1.017***	1.337***	0.902***	1.492***	0.858***
	(0.281)	(0.205)	(0.235)	(0.193)	(0.188)	(0.202)	(0.249)	(0.283)	(0.208)
SQ	0.689	0.323	1.152***	0.279	0.463	0.753**	0.808*	1.578***	0.375
	(0.420)	(0.385)	(0.354)	(0.320)	(0.287)	(0.307)	(0.430)	(0.477)	(0.333)
SD									
Information	2.182***	1.157***	1.257***	1.331***	1.747***	1.173***	0.834*	1.344***	0.661*
	(0.417)	(0.324)	(0.389)	(0.273)	(0.294)	(0.293)	(0.451)	(0.388)	(0.394)
Alert	1.553***	0.704**	1.489***	1.154***	1.141***	1.513***	1.284***	1.465***	0.727**
	(0.406)	(0.349)	(0.307)	(0.285)	(0.258)	(0.313)	(0.324)	(0.360)	(0.321)
Confidentiality	1.951***	1.124***	1.548***	1.502***	1.525***	1.964***	1.989***	1.657***	1.394***
	(0.375)	(0.321)	(0.393)	(0.293)	(0.322)	(0.328)	(0.381)	(0.455)	(0.294)
Subs.300	0.965*	0.0349	1.554***	0.559	0.248	0.104	0.777	0.0972	0.794
	(0.522)	(0.515)	(0.459)	(0.574)	(0.624)	(0.621)	(0.491)	(0.679)	(0.557)
Subs.600	0.984**	0.347	0.883**	0.504	0.720**	0.419	1.071***	0.783**	0.758**
	(0.393)	(0.528)	(0.377)	(0.381)	(0.331)	(0.421)	(0.355)	(0.390)	(0.361)
SQ	2.831***	3.156***	2.606***	2.575***	2.090***	2.166***	2.772***	3.390***	2.186***
	(0.438)	(0.399)	(0.372)	(0.309)	(0.275)	(0.278)	(0.408)	(0.497)	(0.322)
Observations	2250	2538	2790	3024	3258	3006	1962	2070	1998
Log-likelihood	-550.1	-595.3	-678.1	-793.5	-857.4	-775.5	-510.6	-483.4	-562.5

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.6 WTP and simulated adoption rates

The interpretation of the coefficient estimates in the indirect utility functions is not straightforward except in terms of significance. Another convenient way to present the results is in terms of marginal WTP, defined as the marginal rate of substitution between a given attribute and the monetary attribute of the DCE. The first column of Table 6 is based on model (1) of Table 4. The last six columns are computed from the Table G.1.

Considering the full sample, respondents have, on average, a WTP of 406€ to stay with the SQ and, thus, to keep their current situation (see Table 6, column "Full sample", SQ variable). Excluding the impact of the attributes considered in this survey, this amount of 406€ corresponds to the implicit cost of changing to a smart meter.

We also observe that respondents have significant positive WTP for most smart meter attributes. Except for the fact that the result is globally non-significant for *Information*, the average WTP for the *Alert* attribute is 1,078€, and respondents are willing to pay on average 796€ to ensure the *Confidentiality* of their individual data on water consumption.

Table 6: WTP

WTP from ML	Full sample	25%	50%	75%	No nudge	Cocktail	Testimony
SQ	406	316	411	517	410	325	498
	[254; 558]	[60; 572]	[153; 669]	[242; 791]	[154; 665]	[100; 550]	[162; 834]
Information	-32	-13	-90	23	-234	-9	234
	[-125; 61]	[-177; 151]	[-245; 66]	[-139; 186]	[-396; -71]	[-156;139]	[52; 416]
Alert	1 078	1 043	994	1 211	933	1 026	1 295
	[968; 1189]	[849; 1237]	[819; 1169]	[998; 1424]	[757; 1110]	[856; 1196]	[1049; 1542]
Confidentiality	796	672	644	1 093	735	887	774
	[689; 902]	[491; 852]	[483; 805]	[874; 1311]	[566; 904]	[716; 1057]	[548; 1000]
Subs. 300	299	210	274	411	256	322	303
	[200; 398]	[36; 385]	[114; 435]	[226; 597]	[89; 423]	[175; 469]	[81; 525]
Subs. 600	674	602	645	810	645	679	715
	[580; 768]	[443; 762]	[495; 796]	[626; 993]	[493; 797]	[533; 824]	[510; 919]
Nb farmers	1272	402	437	433	421	516	335

Note : WTP in €, and confidence intervals, between brackets, at 95%.

The estimated WTP related to the two levels of the subsidy attribute are worth discussing. Indeed, one would expect the WTP for a conditional subsidy to be lower than the amount of the subsidy, since farmers who have adopted the smart meter face a risk of not getting this subsidy if the collective adoption rate is too low. It turns out that the WTP for the conditional subsidy of 300€ and of 600€ are similar to the monetary value of the subsidy (respectively 299€ and 674€ on average). Our WTP amounts for the conditional subsidy are not as high as those obtained in Kuhfuss *et al.* (2016) for their conditional collective bonus, but they show that respondents value the use of a conditional subsidy as a tool to encourage more farmers to opt for a smart meter.

The next three columns in Table 6 detail the WTP for each attribute according to the threshold's level of the conditional subsidy (25%, 50% and 75%) and the last three columns show the WTP for each attribute of the *No nudge*, *Cocktail* and *Testimony* groups. Considering the threshold treatments, the WTP for the subsidy is significantly higher than the monetary value of the subsidy only when both the amount of the subsidy and the threshold level are high (600€ and 75% respectively), the 95% confidence interval being [626; 993]. This result suggests that there may be some kind of complementarity between the amount of the subsidy and the level of the threshold with a super additive effect The high subsidy amount would more than counterbalance the discouragement of not reaching a threshold as high as 75%. Regarding the nudge treatments, while in the *Testimony* group farmers are willing to pay for the *Information* attribute, we observe the opposite in the *No nudge* group. This may be explained by the content of our nudge: in the testimony, the farmer emphasizes the collective benefits that have been realized thanks to smart water meters (reduction of financial losses for the local farmers' association, detection of water leakages, etc.). Farmers who are assigned to the testimony may, therefore, believe access to other farmers' information necessary in order to benefit from such advantages.

Figure 2 illustrates the global impact of the attributes (including the conditional subsidy), the threshold of the subsidy and the nudges on the average probability of adoption, calculated from the equation 4, which we assimilate here to an adoption rate (Train, 2009). In each graph, the reference smart meter we consider includes the *Alert* and

Confidentiality attributes and a *Conditional subsidy* of 300€ unless otherwise specified. The adoption rates are computed using estimation results from model (1) of Table 4 for graphs (a) and (b), from Table G.1 for graphs (c) and (d) and from Table 5 for graphs (e), (f) and (g) according to the price of the smart meter (from 250€ to 1500€ as proposed in the DCE). Of course, all adoption rates decrease as the price of the smart meter increases.

From graph (a) of Figure 2 we clearly observe that the adoption rate of a smart meter that includes the *Alert* and *Confidentiality* attributes is much higher than the adoption rate of a smart meter that does not include these two attributes. For example, for a smart meter at a price of 1,000€ with a conditional subsidy of 300€, removing *Alert* and *Confidentiality* would decrease the adoption rate from 49% down to only 4%. Graph (b) of Figure 2 illustrates the impact of the amount of the conditional subsidy for our reference smart meter with *Alert* and *Confidentiality* attributes. As mentioned previously, including a conditional subsidy has about the same impact on WTP as reducing the price of the smart meter by the same amount. For a smart meter at 1,000€ with a conditional subsidy of 300€, the adoption rate is 49%, which is about the same for a smart meter at 700€ with no conditional subsidy, or for a smart meter at 1300€ with a 600€ conditional subsidy. The difference is that the conditional subsidy is public money paid only if the threshold is reached. From graph (c) we can also see the global impact of our two nudges. Compared to the *No nudge* situation, the adoption rate increases by 11% in the case of the *Cocktail* nudge (from 40% to 51%) and even by 14% if the *Testimony* is presented to farmers (from 40% to 54%). However, we showed previously that the results regarding this second nudge are not robust. In graph (d) we observe a limited impact of the thresholds. Nevertheless, compared to a standard 50% threshold, announcing a 25% threshold does not increase the adoption rate much, although this low threshold is much easier to reach and, thus, makes the payment of the conditional subsidy more likely. The fact that the highest curve corresponds to a 75% threshold indicates that this high threshold does not discourage farmers. For a smart meter at 1.000€, the adoption rate is 44% for a collective threshold set at 50% and increases to 47% for a 25% threshold and to 54% for a 75% threshold.

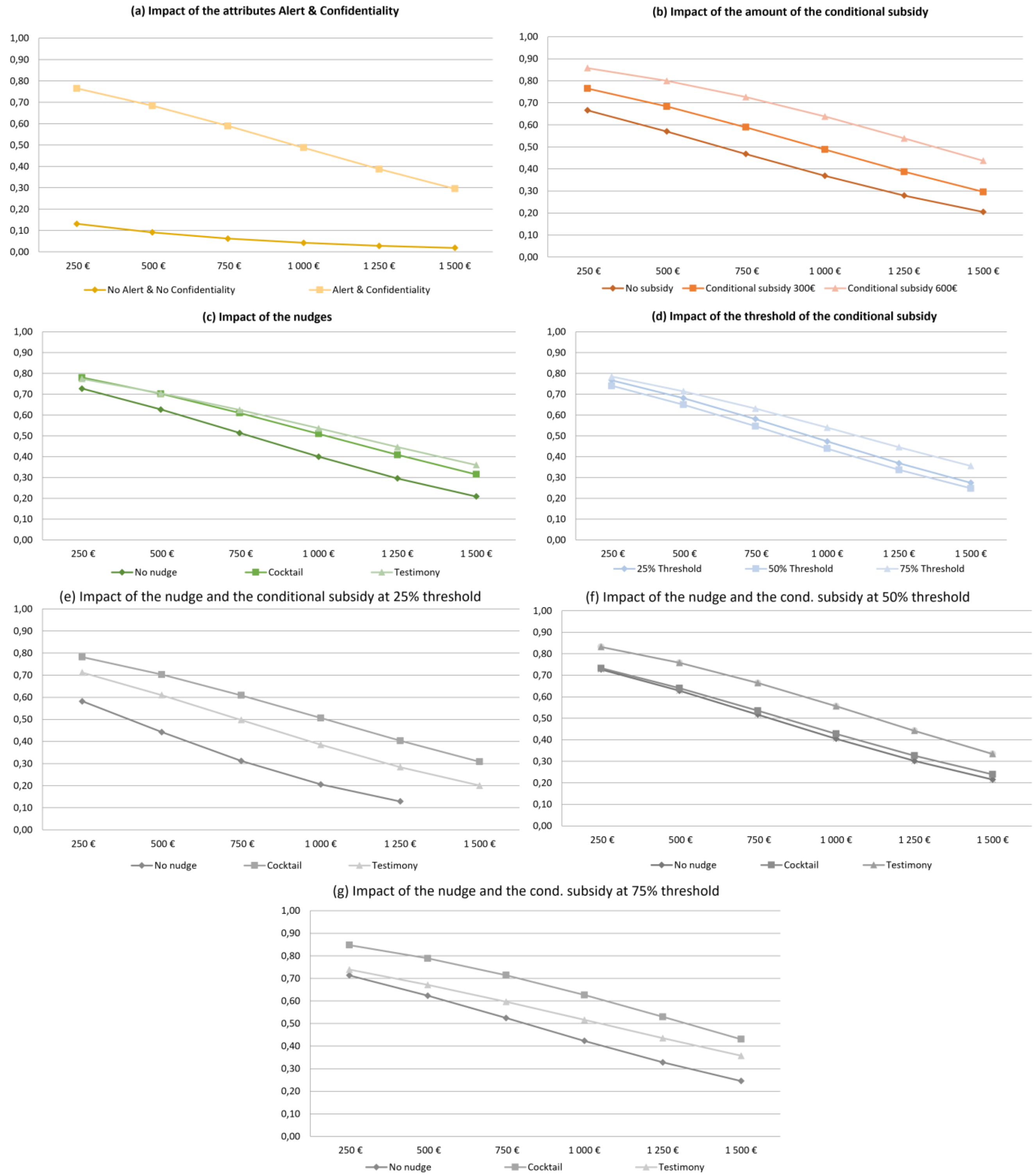

Figure 2: Probability of choosing a smart water meter

Notes: The x-axis is the price in € of the smart meters and the y-axis is the probability of choosing a smart meter. Simulations (a) and (b) are based on Table 4, (c) and (d) are based on Table G.1 and (e),(f), and (g) are based on Table 5.

Figures (e), (f), (g) represent the combination of the threshold and the nudges. We observe that whatever the threshold, both nudges (i.e., *Cocktail* and *Testimony*) increase the probability to choose a smart meter. For a meter of 1.000€ and a threshold of 25% the probability is 20% without any nudge, 40% with the *Testimony* and 50% with the *Cocktail* (Figure e). The result is similar, but with smaller differences, for the 75% threshold (Figure f). Finally, the gap disappears between *No nudge* and *Cocktail* for the 50% threshold (Figure g).

4.7 Beliefs about smart meter adoption by other farmers

The subsidy being conditional on achieving a given threshold of farmer participation, the willingness to adopt a smart water meter may depend on whether or not farmers believe this threshold will be reached. Farmers who expect that a high share of their peers will adopt this new technology are more likely to choose a smart water meter option instead of remaining with the SQ.

To assess the role played by farmer's beliefs, we have proposed after the DCE-part of the survey a hypothetical situation, similar to those presented in the DCE. In that specific situation, the price of the smart water meter was fixed at 750€ and the amount of the conditional subsidy at 300€. In a kind of within-subject comparison, each farmer has been asked to provide his belief about the share of peers who might adopt a smartwater meter (see Figure 3) successively for the three conditional subsidy thresholds used in the DCE (i.e., 25%, 50% and 75%)[18].

[18] Note that for simplicity, we have not specified anything about non-monetary attributes (Information, Alert and Confidentiality). This is not really an issue since we compare responses within respondents.

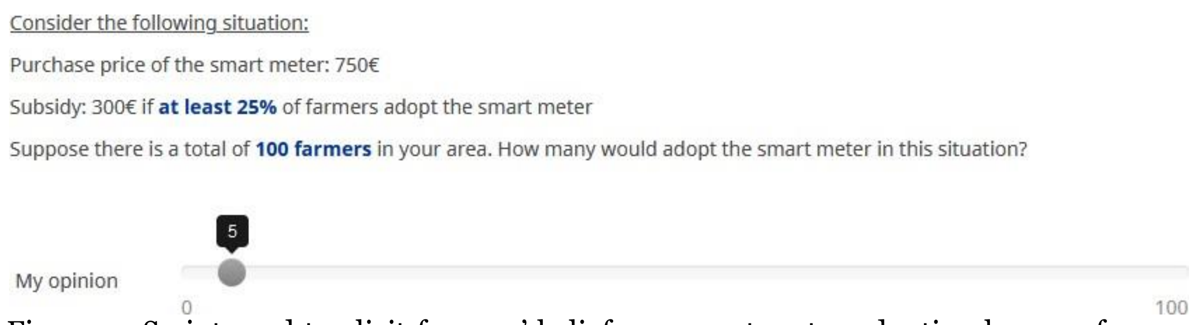

Figure 3: Script used to elicit farmers' beliefs on smart meter adoption by peer farmers

We first analyze in Table 7 how beliefs vary depending upon the conditional subsidy thresholds used in the belief elicitation questions (column 2 "Full sample"). With a 50% conditional subsidy threshold, farmers believe that on average 29.4% of their peers will adopt a smart meter. This average percentage remains quite stable whatever the conditional subsidy thresholds used in the question (30.5% and 28.5% for a threshold at 25% and 75%, respectively). Although, we find that the percentage of peer farmers predicted to adopt the smart water meter tends to decrease with the conditional subsidy threshold, this relationship is not statistically significant. The main result is that the threshold does not have any significant impact on farmer's beliefs regarding peer's adoption rate. This result holds when the sample is split according to threshold treatment groups used in the DCE (columns 3-5), and in particular for farmers who have faced a threshold at 25%in the DCE (average farmer's beliefs vary only from 26.0% to 26.2% in that case, see column 3).

Table 7: Beliefs on the percentage of farmers adopting smart meters according to conditional subsidy thresholds (price = 750€ and conditional subsidy = 300€)

Threshold used in the belief elicitation question	Full sample	Threshold in the DCE		
		25%	50%	75%
25%	30.5	26.0	30.5	34.6
	(22.9)	(20.5)	(22.4)	(24.7)
50%	29.4	26.2	29.1	32.7
	(22.2)	(21.6)	(20.7)	(23.7)
75%	28.5	26.1	27.8	31.5

	(24.6)	(25.2)	(25.2)	(23.2)
Global average beliefs over the 3 questions		26.1 (20.6)	29.2 (20.6)	32.9 (22.3)

Note: This table presents the average of the respondents' beliefs for each of the three conditional subsidy thresholds (25%; 50% and 75%). Column 2 provides the results for the full sample. In columns 3-5, results are disaggregated according to the conditional subsidy thresholds farmers have faced in the DCE. Standard deviation into parentheses.

Second, we assess if farmer's beliefs are affected by the threshold, they have faced in the DCE (between-subject treatment comparison)[19]. The higher the threshold in the DCE, the higher the belief regarding smart meter adoption by their peers. Table 7 shows that the global average beliefs over the three questions vary from 26.1% with a 25% threshold in the DCE to 32.9% with a 75% threshold in the DCE. One possible interpretation for this result could be an anchoring bias: when answering to the belief elicitation questions, farmers may be influenced by the threshold they have been previously confronted in the DCE. The public announcement of a specific target through the conditional threshold may lead farmers to unconsciously internalize this target as a social norm, which significantly impacts their beliefs. If the threshold is low (25%), farmers may perceive this target as relatively low and therefore anticipate a low take-up. On the contrary, if public authorities announce a high threshold (75%), farmers may perceive this high target as a strong injunctive norm. Farmers may think that a 75% threshold corresponds to a large majority likely to rapidly shift the social norm towards the adoption of smart meters. Thus, a high threshold may act as a nudge.

Overall, these observations of the two contradictory effects of the conditional subsidy threshold tend to confirm our past results, namely that threshold level has a limited impact on farmers' choices. From a public policy point of view, these additional results provide a motivation for public authorities to implement conditional subsidies with high

[19] With our 3×3 treatment design, farmers have been allocated in the DCE to one of the three threshold treatment groups (25%, 50%, 75%).

thresholds to influence farmers' perceptions of the norm and, therefore, foster the adoption of smart water meters.

5 Conclusion

Although improving efficiency of water use in agriculture is a clear objective of the European Common Agricultural Policy (CAP), water scarcity remains a critical issue in Europe. Agriculture must therefore both contribute to the mitigation of this problem and adapt to the expected increase in droughts. In this context, new water use technologies, such as smart water meters, allow for significant improvement of irrigation and water use for local water resource managers.

The main objectives of our study were i) to assess French farmers' WTP for specific characteristics of smart water meters and, ii) to test different monetary and non-monetary instruments to encourage voluntary adoption of smart water meters by farmers. We have proposed an original approach combining a DCE with randomized treatments to test the impact of different thresholds of a conditional subsidy and two types of nudges (a "cocktail" of nudges and a testimony).

We obtain three main takeaways. First, farmers do express, on average, a WTP for smart water meters that provide an alert service and data confidentiality, although there is a cost for respondents for moving away from their current situation. However, the results on the *Information* attribute are strongly heterogeneous and mostly non-significant. In a sense, this is in line with the results obtained by Allcott &Kessler (2019), who show that, when offered the possibility of receiving Home Energy Reports with information on the energy consumption of other households, 34% of the respondents stated negative WTP: they did not want to receive information on others' consumption. Second, from a global point of view, the combination of both the nudges and the conditional subsidy pushes farmers to choose a smart water meter option more often. However, having in mind our additional analysis on random answers, while we confirm the effect of the Cocktail nudge, we no longer detect any significant effect of the Testimony nudge. We must therefore interpret the results on the nudges with caution. Moreover, this suggests that, to be effective, nudges need to be tested and they need a careful design of the DCE. Third, the effect of the conditional subsidy does not rely much on the required participation threshold. Going deeper in our analysis, we show that farmers are not discouraged by a high conditional threshold of 75%. This is confirmed with our study of farmers' predictions of the number of farmers in their geographic area who would adopt a smart water meter. In terms of a public policy perspective, this indicates that regulators have an interest in proposing conditional subsidies with a high threshold to influence farmers' prediction toward a higher rate of adoption without discouraging smart water adoption. In addition, a high threshold may reduce the potential costs of the policy since the threshold has a lower probability of being reached.

This paper contributes to the literature which shows that individuals have a preference for the adoption of behavior which is in line with social norms. From a public policy point of view, our contribution is twofold. First, to our knowledge this is the first DCE conducted at the national scale with more than a thousand farmers' responses, allowing us to conclude more generally on the effects of incentive policies and their application to other case studies. Second, we provide guidelines for policies related to water management in agriculture. Our result indicates that the government should disseminate information on the benefits and development of smart water meters (in a specialized journal or information bulletin, for example), in order to convince other farmers to adopt this technology.

Nevertheless, this work has some limitations. One, often associated with stated preference methods, is that the declaration of intent may not match observed behavior. A potential strategic bias may be feared in stated preference surveys, but this bias is likely to be limited in a DCE. Concerning the effects related to conditional thresholds and nudges, since treatment groups have been randomly defined, they should be affected in the same way by a strategic bias. In addition, we cannot exclude a potential hypothetical bias that may lead to an overestimation of farmers' WTP for smart meters. Another limitation deals with the subsidy cost. Due to the smart meter's contribution to the public good, the subsidy we proposed is funded by the regulator. However, with a subsidy of 600€ per farmer, the total amount to be paid could be substantial if the threshold is reached, which is more likely to occur for low thresholds. Thus, the level of the subsidy and the conditional threshold must be carefully defined. Finally, an additional study testing smart meter demand according to different cost scenarios (varying price and conditional subsidy) should be conducted to determine the most effective targeted incentive instrument.

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A Presentation of nudges

A.1 Cocktail

As an actor in your territory, you are undoubtedly aware of the fact that periods of water restriction during the summer pose an environmental challenge and create a shortfall for agriculture.

1. In that context, is water management important to you?
(*"Yes, very", "Quite important, yes", "Not particularly", "Not at all"*)

2. Would you be willing to commit to better management of the water resource?
(*"Yes, absolutely", "I believe so, yes", "Not particularly", "Not at all"*)

In territories that are already equipped, smart meters allow for better management of water resources thanks to the precision and frequency of the data they provide. Better counting also allows for greater equity among farmers.

A.2 Testimony

Testimony of Yves D., 59 years old, farmer in the Tarn-et-Garonne region

Yves has been involved for more than 3 years in improving water management in his geographic area.

"Since we installed smart meters in our sector, we have been able to significantly reduce counting losses for our local farmers' association. We have gone from 15%-20% of annual losses to 3% today, which amounts to about 15,000 euros of revenue for the association. Indeed, not only are the smart meters more accurate than the mechanical ones, but in addition they allow us to quickly see if there is a leak. We can more easily track our water consumption and better manageit. Water management has become more equitable between the different farmers of our local farmers' association."

B Descriptive Statistics

Table B.1: Statistics on final sample and 2010 agricultural census

	Our sample %	Agriculture census %
Gender		
Male	89.5	77.3
Age		
< 40	21.9	5.0
[40;60]	63.8	44.5
> 60	14.2	50.5
Education		
No degree	0.9	19.4
FCGE	0.4	26.9
CAP or BEP	9.4	28.9
GCE "A-level"	27.0	14.9
BAC+2	47.8	5.1
BAC+5	14.5	4.8
Activity		
Field crop	38.0	27.2
Polyculture	29.1	13.2
Viticulture	6.2	14.5
Market gardening	2.9	3.4
Fruit production	3.6	4.5
Cattle breeding	13.9	25.4
Sheep sector / Pig farming	6.4	11.7

Note: French Certificate of General Education (FCGE), General Certificate of Education Advanced Level (GCE “A-Level”), Youth Training or BTEC First Diploma (CAP or BEP), Diploma of Higher Education (BAC+2) and Master’s Degree (BAC+5)

C Location of sampled farmers in France

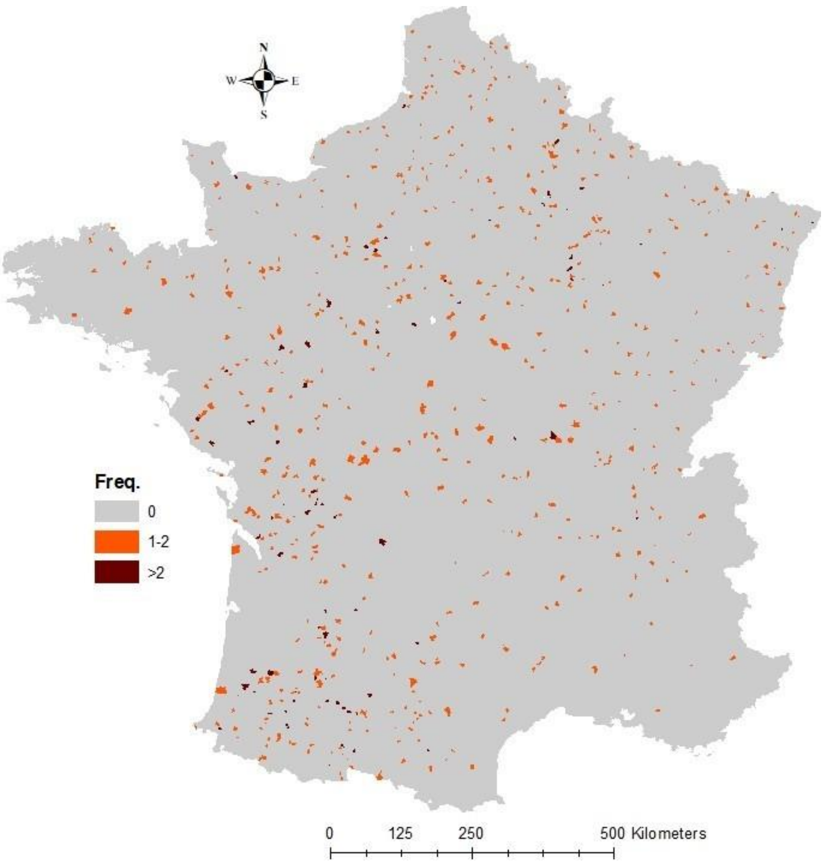

Figure C.1: Spatial distribution of sampled farmers (France).

Note: Each spatial unit corresponds to a postal code. Our observations are spread across the twelve French regions and over a total of 200 communes, with 116 communes registering at least two respondents. The maximum number of respondents in one spatial unit is six.

D Treatment balancing tests

Figure D.1: Sample attrition by treatments

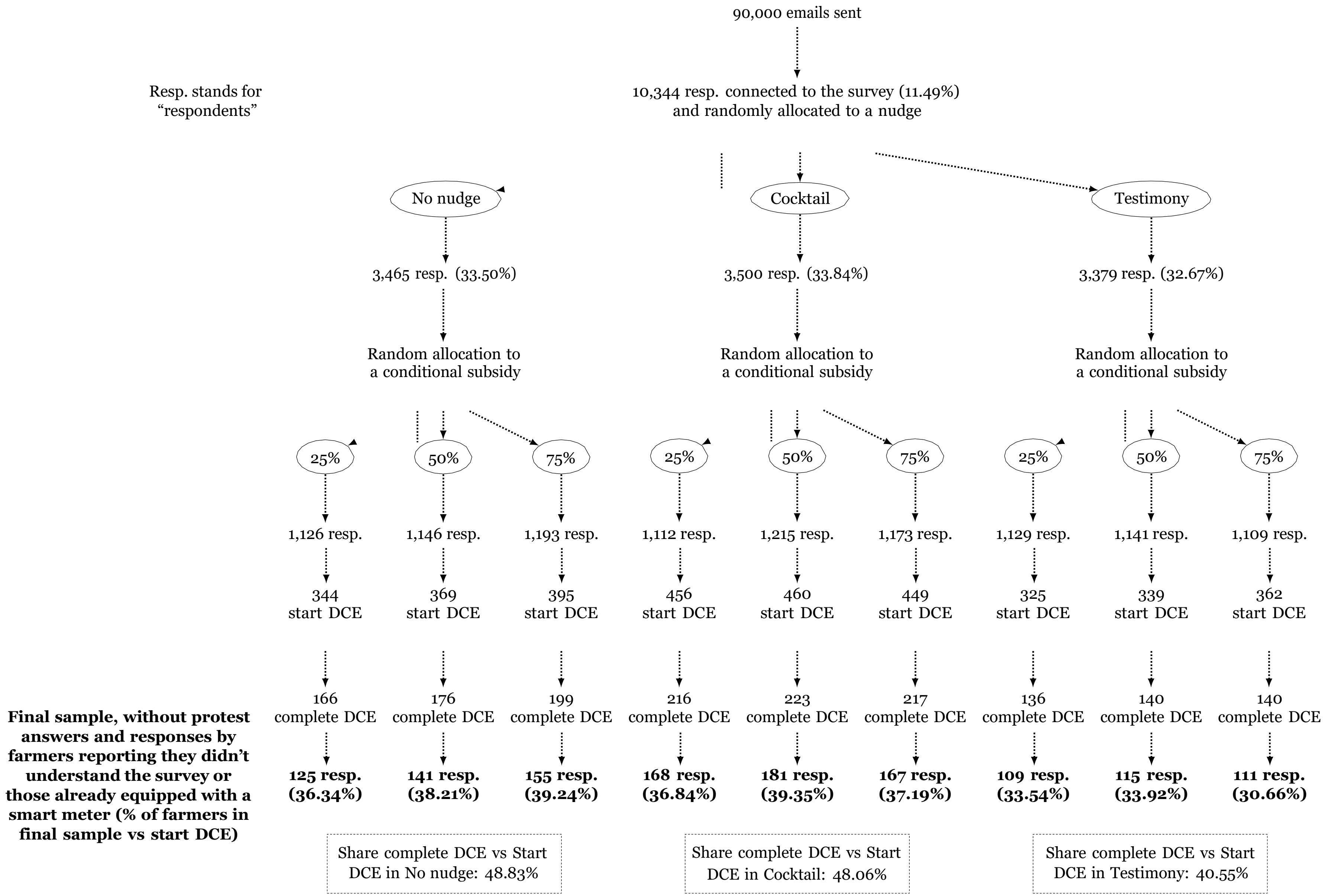

Table D.1: Characteristics of Respondents by Treatment and KW H test

%	All sample	Control 25% Thres	Control 50% Thres	Control 75% Thres	Cocktail 25% Thres	Cocktail 50% Thres	Cocktail 75% Thres	Testimony 25% Thres	Testimony 50% Thres	Testimony 75% Thres	KW test *p-value*	Detectable variation in S.D.*
Gender												
Male	0.89	0.87	0.89	0.85	0.92	0.91	0.91	0.93	0.86	0.90	0.416	0.07
Age												
< 40	0.22	0.25	0.18	0.20	0.21	0.21	0.22	0.26	0.19	0.28	0.667	0.10
[40;60]	0.64	0.62	0.70	0.66	0.66	0.64	0.63	0.60	0.65	0.55	0.491	0.12
> 60	0.14	0.13	0.12	0.14	0.13	0.15	0.15	0.15	0.16	0.17	0.971	0.08
Education												
No degree	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.00	0.01	0.02	0.658	0.02
FCGE	0.00	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.906	0.02
CAP or BEP	0.09	0.09	0.12	0.08	0.07	0.14	0.08	0.12	0.10	0.06	0.265	0.07
GCE "A-level"	0.27	0.31	0.21	0.26	0.36	0.27	0.24	0.23	0.24	0.30	0.126	0.11
BAC+2	0.48	0.44	0.48	0.50	0.46	0.44	0.52	0.47	0.49	0.50	0.888	0.12
BAC+5	0.14	0.14	0.16	0.16	0.10	0.14	0.14	0.18	0.17	0.12	0.708	0.08
Activity												
Field crop	0.47	0.47	0.347	0.55	0.49	0.44	0.50	0.43	0.42	0.47	0.535	0.12
Polyculture	0.37	0.40	0.35	0.30	0.36	0.38	0.38	0.46	0.36	0.40	0.391	0.12
Viticulture	0.07	0.09	0.05	0.07	0.04	0.10	0.06	0.05	0.08	0.07	0.475	0.06
Market gardening	0.04	0.02	0.03	0.03	0.03	0.06	0.02	0.03	0.07	0.05	0.377	0.05
Fruit production	0.04	0.02	0.02	0.03	0.05	0.04	0.02	0.06	0.09	0.03	0.133	0.05
Cattle breeding	0.15	0.18	0.17	0.12	0.21	0.17	0.11	0.13	0.11	0.12	0.196	0.09
Sheep sector / Pig farming	0.06	0.10	0.08	0.11	0.03	0.04	0.06	0.06	0.04	0.06	0.061	0.06

Note: French Certificate of General Education (FCGE), General Certificate of Education Advanced Level (GCE "A-Level"), Youth Training or BTEC First Diploma (CAP or BEP), Diploma of Higher Education (BAC+2) and Master's Degree (BAC+5).

*: We provide the variation of the considered variable that the Kruskal-Wallis test can identify with a 80% power level.

Table D.2: Allocation of Respondents to blocks in the DCE by treatment

	No nudge			Cocktail			Testimony		
	25% Thres.	50% Thres.	75% Thres.	25% Thres.	50% Thres.	75% Thres.	25% Thres.	50% Thres.	75% Thres.
Block 1	35 (28%)	48 (34%)	54 (35%)	46 (27%)	59 (33%)	49 (29%)	38 (35%)	42 (37%)	34 (31%)
Block 2	39 (31%)	35 (25%)	59 (38%)	56 (33%)	55 (30%)	57 (34%)	45 (41%)	40 (35%)	47 (42%)
Block 3	51 (41%)	58 (41%)	42 (27%)	66 (39%)	67 (37%)	61 (37%)	26 (24%)	33 (29%)	30 (27%)

E Estimations with Subsidy Interactions

Table E.1: Mixed logit estimations with Subsidy Interactions.

	(1)		(2)		(3)		(4)		(5)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Price (in k€)	-1.639***		-1.638***		-1.638***		-1.641***		-1.651***	
	(0.073)		(0.072)		(0.073)		(0.073)		(0.074)	
Information	-0.0518	1.363***	-0.0551	1.391***	-0.0629	1.385***	-0.0487	1.353***	-0.0746	1.424***
	(0.078)	(0.115)	(0.078)	(0.113)	(0.078)	(0.114)	(0.078)	(0.116)	(0.079)	(0.117)
Alert	1.767***	1.216***	1.775***	1.213***	1.764***	1.206***	1.783***	1.218***	1.770***	1.222***
	(0.082)	(0.098)	(0.082)	(0.099)	(0.082)	(0.099)	(0.082)	(0.099)	(0.082)	(0.100)
Confidentiality	1.304***	1.623***	1.306***	1.616***	1.301***	1.618***	1.307***	1.622***	1.320***	1.629***
	(0.091)	(0.116)	(0.091)	(0.114)	(0.091)	(0.117)	(0.091)	(0.118)	(0.092)	(0.116)
Subs.300	0.490***	0.468**	0.440***	0.287	0.393***	0.363	0.384*	0.128	0.485***	0.523**
	(0.085)	(0.228)	(0.133)	(0.315)	(0.136)	(0.275)	(0.218)	(0.259)	(0.086)	(0.211)
Subs.600	1.104***	0.660***	1.108***	0.433*	1.097***	0.456*	1.111***	0.643***	1.138***	0.242
	(0.072)	(0.139)	(0.108)	(0.224)	(0.113)	(0.272)	(0.071)	(0.141)	(0.175)	(0.287)
SQ	0.666***	2.519***	0.676***	2.511***	0.660***	2.492***	0.674***	2.551***	0.660***	2.499***
	(0.116)	(0.117)	(0.116)	(0.114)	(0.116)	(0.115)	(0.117)	(0.119)	(0.116)	(0.114)
Subs. 300×Thresh 25%			-0.0108	0.547						
			(0.189)	(0.443)						
Subs. 300×Thresh 75%			0.115	0.765***						
			(0.184)	(0.297)						
Subs. 600×Thresh 25%			-0.0779	0.674***						
			(0.153)	(0.241)						
Subs. 600×Thresh 75%			0.0988	0.588**						
			(0.148)	(0.294)						
Subs. 300×Cocktail					0.147	0.060				
					(0.172)	(0.425)				
Subs. 300×Testimony					0.107	0.746**				
					(0.204)	(0.358)				
Subs. 600×Cocktail					0.0413	0.491*				
					(0.143)	(0.293)				
Subs. 600×Testimony					-0.0373	0.602*				
					(0.161)	(0.330)				
Subs. 300×No Nudge 25%							0.0472	0.727		
							(0.322)	(0.538)		
Subs. 300×No Nudge 75%							-0.130	1.201***		
							(0.334)	(0.422)		
Subs. 300×Cocktail 25%							0.233	0.621		
							(0.291)	(0.383)		
Subs. 300×Cocktail 50%							-0.0866	0.546		
							(0.286)	(0.546)		
Subs. 300×Cocktail 75%							0.303	0.058		
							(0.282)	(0.495)		
Subs. 300×Testimony 25%							-0.161	0.705		
							(0.349)	(0.653)		
Subs. 300×Testimony 50%							0.435	0.016		
							(0.322)	(0.650)		
Subs. 300×Testimony 75%							0.139	0.1.266***		
							(0.346)	(0.465)		
Subs. 600×No Nudge 25%									-0.157	0.576
									(0.257)	(0.499)
Subs. 600×No Nudge 75%									0.105	0.750*
									(0.246)	(0.440)
Subs. 600×Cocktail 25%									-0.00360	0.619
									(0.236)	(0.398)
Subs. 600×Cocktail 50%									-0.0144	0.647*
									(0.230)	(0.349)
Subs. 600×Cocktail 75%									0.0323	0.551
									(0.233)	(0.342)
Subs. 600×Testimony 25%									-0.149	0.957***
									(0.272)	(0.316)
Subs. 600×Testimony 50%									-0.0274	0.438
									(0.254)	(0.423)
Subs. 600×Testimony 75%									-0.0695	1.047***
									(0.272)	(0.327)
Observations	22896		22896		22896		22896		22896	
Log-likelihood	-5875.8		-5870.6		-5874.0		-5868.6		-5871.1	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.2: GMNL with interactions

	Mean	SD
Price (in k€)	-1.646***	
	(0.073)	
Information	-0.040	1.361***
	(0.078)	(0.112)
Alert	1.777***	1.201***
	(0.081)	(0.102)
Confidentiality	1.307***	1.623***
	(0.091)	(0.112)
Subs. 300	0.391*	0.058
	(0.229)	(0.270)
Subs. 600	1.111***	0.165
	(0.181)	(0.276)
SQ	0.648***	2.555***
	(0.116)	(0.115)
Subs. 300×No Nudge 25%	-0.007	0.729
	(0.334)	(0.627)
Subs. 300×No Nudge 75%	-0.138	1.350***
	(0.352)	(0.392)
Subs. 300×Cocktail 25%	0.265	0.410
	(0.230)	(0.505)
Subs. 300×Cocktail 50%	-0.090	0.193
	(0.294)	(0.727)
Subs. 300×Cocktail 75%	0.310	0.0258
	(0.297)	(0.584)
Subs. 300×Testimony 25%	-0.339	0.998**
	(0.368)	(0.449)
Subs. 300×Testimony 50%	0.515	0.056
	(0.340)	(0.638)
Subs. 300×Testimony 75%	0.197	1.362***
	(0.364)	(0.485)
Subs. 600×No Nudge 25%	-0.140	0.544
	(0.268)	(0.42)
Subs. 600×No Nudge 75%	0.136	0.705
	(0.255)	(0.502)
Subs. 600×Cocktail 25%	0.030	0.769***
	(0.250)	(0.298)
Subs. 600×Cocktail 50%	-0.061	0.679*
	(0.243)	(0.367)
Subs. 600×Cocktail 75%	0.0670	0.567*
	(0,243)	(0,320)
Subs. 600x×Testimony 25%	-0.187	0.756
	(0.277)	(0.500)
Subs. 600×Testimony 50%	0.099	0.348
	(0.265)	(0.714)
Subs. 600×Testimony 75%	0.003	0.984***
	(0.280)	(0.332)
Observations	22896	
Wald $\chi^2(23)$	866.0	
Log likelihood	-5868.4	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

F Mixed logit estimations with SQ interactions (non-random sample only)

Table F.1: Mixed logit estimations with SQ Interactions (non-random answers only)

	(1)		(2)		(3)		(4)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Price (in k e)	-3.368***		-3.379***		-3.357***		-3.374***	
	(0.155)		(0.157)		(0.155)		(0.156)	
Information	-0.451***	1.590***	-0.427***	1.558***	-0.454***	1.573***	-0.446***	1.556***
	(0.134)	(0.178)	(0.132)	(0.182)	(0.134)	(0.178)	(0.133)	(0.180)
Alert	3.159***	1.798***	3.180***	1.769***	3.149***	1.787***	3.169***	1.783***
	(0.170)	(0.150)	(0.170)	(0.146)	(0.169)	(0.151)	(0.169)	(0.154)
Confidentiality	2.500***	1.785***	2.516***	1.801***	2.496***	1.788***	2.504***	1.812***
	(0.170)	(0.200)	(0.174)	(0.208)	(0.171)	(0.201)	(0.171)	(0.199)
Subs.300	1.120***	0.0276	1.125***	-0.0958	1.112***	-0.0171	1.116***	-0.0205
	(0.133)	(0.305)	(0.134)	(0.322)	(0.133)	(0.328)	(0.133)	(0.316)
Subs.600	1.894***	1.332***	1.896***	1.364***	1.896***	1.302***	1.898***	1.344***
	(0.143)	(0.181)	(0.144)	(0.181)	(0.143)	(0.181)	(0.144)	(0.179)
SQ	1.841***	0.974***	1.948***	-1.021***	2.022***	0.937***	2.127***	0.831***
	(0.161)	(0.153)	(0.198)	(0.142)	(0.199)	(0.189)	(0.275)	(0.203)
SQ×Thresh.25%			-0.0652	-0.108				
			(0.193)	(0.674)				
SQ×Thresh.75%			-0.150	0.0595				
			(0.183)	(0.370)				
SQ×Cocktail					-0.341*	0.375		
					(0.186)	(0.543)		
SQ×Testimony					-0.178	-0.330		
					(0.205)	(0.545)		
SQ×No Nudge 25%							-0.379	0.0723
							(0.330)	(0.970)
SQ×No Nudge 75%							0.0248	0.530
							(0.313)	(0.400)
SQ×Cocktail 25%							-0.215	0.592
							(0.325)	(0.561)
SQ×Cocktail 50%							-0.471	0.711*
							(0.311)	(0.414)
SQ×Cocktail 75%							-0.670**	0.0862
							(0.300)	(0.778)
SQ×Testimony 25%							-0.266	0.643
							(0.363)	(1.099)
SQ×Testimony 50%							-0.0673	-1.212**
							(0.376)	(0.526)
SQ×Testimony 75%							-0.414	-0.360
							(0.369)	(1.326)
Observations	15210		15210		15210		15210	
Log-likelihood	-2891.3		-2890.0		-2888.8		-2885.0	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

G Mixed logit estimations by threshold and nudge group

Table G.1: Mixed logit estimations by threshold and nudge group

	25% Thres.	50% Thres.	75% Thres.	No nudge	Cocktail	Testimony
	(1)	(2)	(3)	(4)	(5)	(6)
Mean						
Price (in k€)	-1.732***	-1.727***	-1.510***	-1.848***	-1.634***	-1.445***
	(0.135)	(0.129)	(0.120)	(0.142)	(0.112)	(0.132)
Information	-0.0231	-0.155	0.0352	-0.432***	-0.0142	0.338**
	(0.145)	(0.137)	(0.125)	(0.154)	(0.123)	(0.133)
Alert	1.807***	1.717***	1.829***	1.725***	1.677***	1.872***
	(0.156)	(0.136)	(0.140)	(0.149)	(0.123)	(0.160)
Confidentiality	1.163***	1.112***	1.651***	1.359***	1.449***	1.118***
	(0.164)	(0.150)	(0.160)	(0.168)	(0.146)	(0.163)
Subs.300	0.365**	0.474***	0.621***	0.473***	0.526***	0.438***
	(0.158)	(0.146)	(0.146)	(0.162)	(0.127)	(0.169)
Subs.600	1.043***	1.115***	1.223***	1.193***	1.109***	1.033***
	(0.133)	(0.123)	(0.123)	(0.133)	(0.111)	(0.133)
SQ	0.547***	0.710***	0.780***	0.757***	0.531***	0.719***
	(0.212)	(0.209)	(0.187)	(0.220)	(0.174)	(0.226)
SD						
Information	1.539***	1.504***	1.066***	1.502***	1.427***	0.933***
	(0.192)	(0.191)	(0.211)	(0.223)	(0.169)	(0.242)
Alert	1.422***	1.114***	1.245***	1.271***	1.195***	1.133***
	(0.183)	(0.189)	(0.176)	(0.189)	(0.155)	(0.191)
Confidentiality	1.796***	1.453***	1.650***	1.624***	1.652***	1.546***
	(0.213)	(0.210)	(0.194)	(0.216)	(0.176)	(0.206)
Subs.300	0.651*	0.246	0.668**	0.760**	0.202	0.601
	(0.339)	(0.361)	(0.323)	(0.301)	(0.482)	(0.490)
Subs.600	0.736***	0.617***	0.721***	0.674**	0.594***	0.711***
	(0.220)	(0.219)	(0.205)	(0.275)	(0.220)	(0.247)
SQ	2.608***	2.703***	2.312***	2.769***	2.241***	2.626***
	(0.216)	(0.206)	(0.185)	(0.226)	(0.161)	(0.230)
Observations	7236	7866	7794	7578	9288	6030
Log-likelihood	-1867.3	-1958.2	-2032.5	-1842.1	-2442.7	-1572.2

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$