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Abstract

In a global context of increasing water scarcity, reducing water use in the agricultural sector is one of the spearheads of sustainable agricultural and environmental policies. New technologies such as smart water meters are promising tools for addressing this issue, but their voluntary adoption by farmers has been limited. Conducting a discrete choice experiment with randomized treatments, we test two policy instruments designed to foster the voluntary adoption of smart water meters: a conditional subsidy and green nudges. The conditional subsidy is offered to farmers who adopt a smart meter only if the rate of adoption in their geographic area is sufficiently high (25%, 50% or 75%). In addition, we implement informational nudges by providing farmers specific messages regarding water scarcity and water management. With the responses of 1,272 French farmers, we show that both policy instruments are effective tools for fostering smart water meter adoption. Surprisingly, our results show that the willingness to pay for the conditional subsidy does not depend on the collective adoption threshold. We also demonstrate that farmers who receive an informational nudge are more likely to opt for a smart water meter. This result calls for a careful joint design of these two policy instruments.

Keywords : Behavioural economics, Choice experiment, Nudges, French farmers, Smart water meters, Social norms.

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Introduction

In August 2019, the World Resources Institute reported that water stress and water restrictions have globally increased in recent decades and have had a significant impact on all economic activities worldwide, and on agriculture more specifically[1]. Consuming 70% of the global water supply, the agricultural sector is indeed the greatest consumer of the world's water resources. This explains why optimizing its water consumption is often 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[2] 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-Ferret *et al.* (2019) conclude that using smart meters to induce changes in the irrigation decisions of farmers remains challenging[3].

A major issue with smart water meters in agriculture is the high level of reluctance of farmers to adopt them, in particular due to data privacy concerns. 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. We test three threshold levels: 25%, 50% and 75%. Second, since non-monetary interventions have a strong appeal for public authorities in charge of the agricultural sector (Wallander *et al.* , 2017), we study the impact of nudges on farmers' decision to adopt (or not) smart water meters. Based on the existing literature, which has investigated the behavioral factors that influence farmers' decisions to adopt new practices or technologies (Dessart *et al.* , 2019), we test two nudges. In the first nudge, farmers are reminded of the existence of water restrictions and of the importance of good management of water resources. The second nudge is a testimony by a farmer who has adopted a smart water meter with positive results. Our two nudges therefore rely on different psychological mechanisms including priming, commitment effects and social identity.

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 information on the water consumption of peer farmers (Chabé-Ferret *et al.* , 2019). Such information could be relevant 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 meter 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, we choose to implement this method in our study.

Our main contributions are as follows. First, we show that, on average, farmers have a preference for their current mechanical water 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, contrary to our expectations, the WTP for the conditional subsidy does not depend on the adoption threshold which conditions the payment of the subsidy. Third, despite our initial intuition that a high threshold of conditional subsidy may discourage smart meter adoption, we observe that our high threshold (75%) does not induce such an effect. 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 their beliefs except possibly through an anchoring bias. All these elements argue in favor of implementing a conditional subsidy with a high collective adoption threshold. Moreover, in the context of a high threshold, nudges increase voluntary adoption of smart meters.

The remainder of this article is organized as follows. In the first section, we present the literature related to the conditional subsidy and informational nudges. The second section details our experimental design, which combines a discrete choice experiment with different treatments and presents the data. We present the results in the third section and conclude with a discussion in the last section.

Inducing smart meter adoption by farmers

Subsidizing farmers

Smart water meters share similarities with public goods. 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 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 offer 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.

There are two main reasons 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 a large number of 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 efficient.

The second reason 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). Social norms appear to be rules that guide individual behaviors in a given situation, and these rules are influenced by one's perception of what other individuals do. 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[4].

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 can therefore ultimately change the social norm. Two parameters of a conditional subsidy may impact beliefs: the amount of the subsidy and the collective threshold to be reached 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 induce individual adoption of smart water meters.

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 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 or default options). Smart water metering is a new technology in agriculture and, therefore, less than 5% of French farmers have already adopted it: thus it 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.

First, we rely on agents' (i.e., farmers) personal engagement in sustainability to push them to adopt smart water meters. In this case, nudges may take the form of information provided before the decision is made with the use of *reminders* (Thaler & Sunstein, 2008), of the scarcity of water resources and the related consequences. In addition, a *priming* effect can be used, that is to say, a stimulus (Bargh & Gollwitzer, 1994; Bargh *et al.* , 2001) to raise awareness on the necessity to adopt smart water meters (through a question regarding the importance of water management, for instance). *Priming* has been shown to induce encouraging results in the literature (Bargh, 2006; Friis *et al.* , 2017; Bimonte *et al.* , 2020). A third approach is to involve agents through *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, especially, 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.

Second, we provide some farmers information regarding the behavior of their peers. This approach is based on *social identity*, which aims influence peer decisions in the direction of the majority of 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 the individual 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).

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 efficient in the absence of monetary incentives.

Material and methods

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 offered 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, 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 in the event abnormal water consumption 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

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, limited access to the farmer	No (ref.) Yes	Yes
Price	Purchase price of the smart meter	250 €, 500 €, 750 €, 1000 €, 1250 €, 1500 €	0 €
Conditional Subsidy	Subsidy conditional on i) smart meter adoption ii) a given percentage of farmers in the respondent's geaographic area adopt a smart meter	No subsidy (ref.) 300 € 600 €	No

SQ: Status Quo
ref.: Reference category

made available to the local water resource manager for the purpose of managing the water dams in the sector). 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) or mobile apps (Gu *et al.* , 2017) are examples in which 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 €, 1000 €, 1250 €, 1500 €. Note that, in some cases, the net amount of money finally paid by a farmer opting for a smart water meter could be negative if the threshold is reached. Indeed, the price can be lower than the conditional subsidy. These situations allow us to capture the potentially negative WTP of some farmers.

For each farmer, the status quo (SQ) is defined as opting to keep his/her current mechanical water meter. 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.

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, some follow-up questions, some questions on the respondent's current water meter and, finally, a section designed to elicit farmers' beliefs/predictions 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. The DCE-specific part is composed of six different choice cards which are successively proposed in random order to respondents who, therefore, make six choices between two different smart meters: "Meter 1" and "Meter 2", and a status quo option "I will keep my current meter". An example of a choice card is presented in Figure 1.

Two pilots were conducted in June and September 2019. Combining the data from the two pilots, we obtained 21 completed questionnaires corresponding to 126 choices. Our priors were estimated using this first pool of observations and the questionnaire was modified according to the feedback we received from respondents. Then, between November and December 2019, the questionnaire was emailed to 90,000 French farmers (20% of the total number of farmers in France) by a French pooling organization[5]. 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.

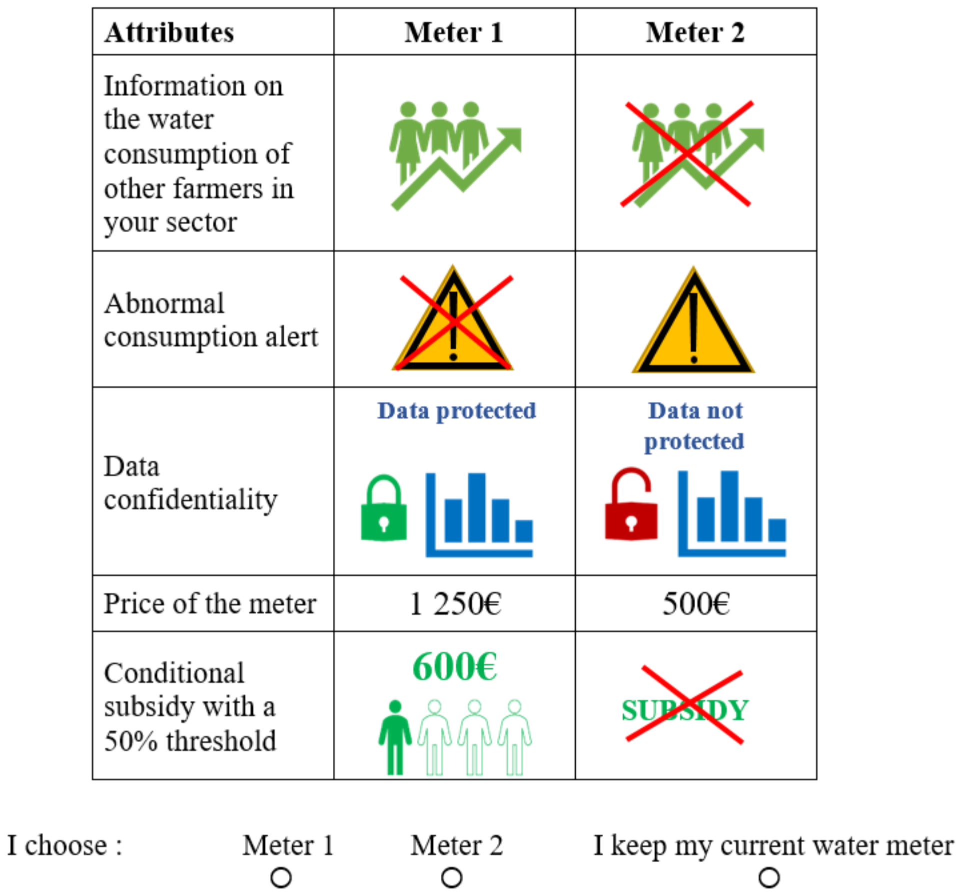

Figure 1: Example of a choice card

Econometric modeling

We rely on the Random Utility Model (RUM) in which a farmer's meter choice results from 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 $(i = 1, ..., I)$ chooses among j $(j = 1, ..., J)$ possible multi-attribute water meters, and that the associated utility U_{ijt} from alternative j in choice card t $(t = 1, ..., T)$ is:

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

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

We first use a conditional logit model (CL) to explain farmers' decisions in the DCE. In this approach, the utility is written as:

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

with X_{ijt} a vector which includes the attributes of the smart meter and an alternative specific constant related to the SQ (i.e., keeping the current mechanical water meter), β, a vector of parameters to be estimated, and ϵ the random unobserved utility component assumed to follow a type I extreme value distribution. This model assumes that the error term, ϵ, is independently and identically distributed (IID) across the population and irrelevant alternatives are independent (IIA). It is assumed that respondents are homogeneous in their taste parameter estimates. The IIA assumption can be tested using the Hausman test.

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

$$U_{ijt} = \beta_i X_{ijt} + \epsilon_{ijt} \tag{3}$$

where β_i terms are random parameters assumed to follow normal distributions, and ϵ is still considered IID.

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

$$WTP_x = \frac{-\beta_x}{\beta_{price}} \tag{4}$$

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. The calculation of such WTP becomes more complex with the ML model since it involves two random parameters, β_x and β_{price}. 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).

Treatments: *A "three by three" design*

Conditional subsidy with three thresholds

One attribute of the DCE 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: a reference group where the threshold 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 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 therefore 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.

Nudges

Farmers have been randomly assigned to two different nudges and to a reference "no nudge" group. Some farmers have been allocated to get a first nudge we call the "cocktail" nudge (see Appendix A.1). In the "cocktail" nudge: i) respondents are reminded of the existence of water restrictions, ii) respondents are asked to report to what extent they consider water management an important issue and, iii) respondents are asked to report to what extent they would be willing to commit to adopting better water management. The first question can be seen as a *priming* question, while the second is directly inspired from the theories of *commitment*. We follow the suggestion made by Dolan *et al.* (2012) and combine several types of nudges (*reminder*, *priming* and *commitment*) to increase their efficiency. The second nudge is 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 farmer's association of around 15,000 € annually). In order to give his testimony credibility, the name and the age of the farmer, as well as his photo[6] are included. This second nudge deals with farmers' *social identity*. We expect respondents to identify with this farmer's firsthand experience of adopting smart meter technology and consequently to more often choose a smart meter alternative themselves. Lastly, some farmers have been allocated to a reference ("no nudge") group where no particular information is provided.

Treatments

Combining the three conditional subsidy thresholds with the thee nudge groups, our experiment includes a total of nine different treatments. Each respondent was randomly assigned to a single treatment[7].

Empirical results

Sample and descriptive statistics

1,613 farmers completed the questionnaire, which corresponds to almost a 2% response rate. The "protest" and "incomprehension" responses, identified by the follow up questions, represent 242 respondents in total. They have been removed from our sample. Moreover, the 99 respondents who declared already having a smart meter are also removed since our work focuses on mechanisms and instruments to induce a voluntary switch from mechanical to smart water meters. Our final sample is, therefore, composed of 1,272 farmers across France.

Descriptive statistics on our sample are presented in Table 2 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 degree 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 2.

Table 2: 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	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)

Table 3 summarizes the number of farmers randomly assigned in the nine treatments (subsidy thresholds × nudges). This design allows us to study the combined impact of the conditional subsidy and the nudges on smart meter adoption.

Table 3: Randomized allocation of farmers in the nine treatments

		Nudges			
		No nudge	Cocktail	Testimony	Total
Conditional subsidy	25% Threshold	125	168	109	402
	50% Threshold	141	181	115	437
	75% Threshold	155	167	110	433
	Total	421	516	335	1,272

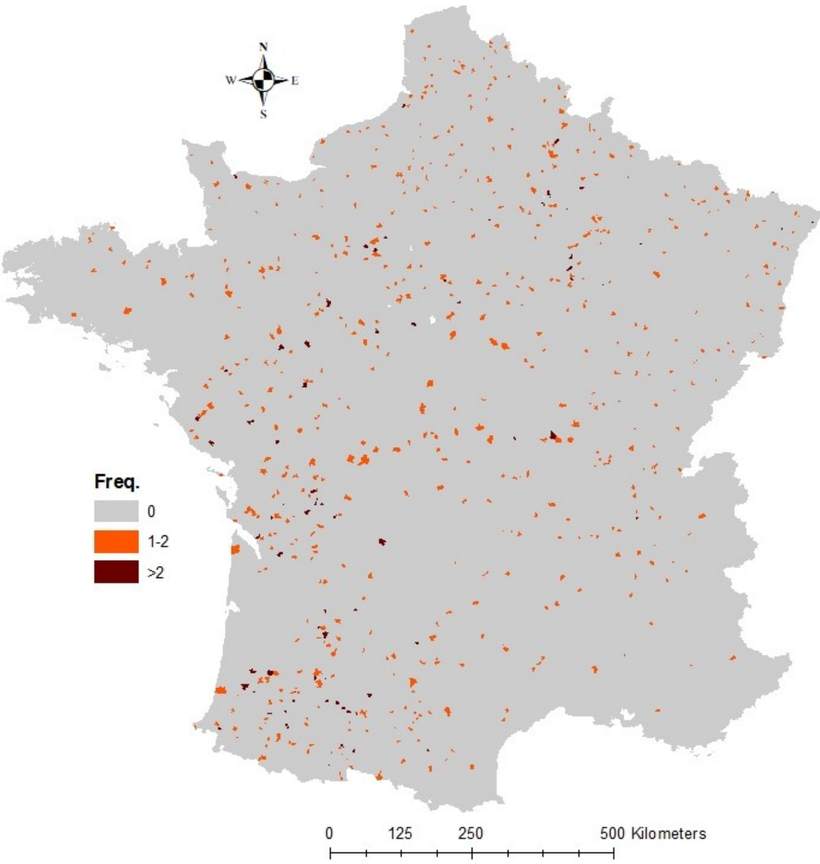

Figure 2: Spatial distribution of sampled farmers (France)

Individual choices and status quo responses in the DCE

On each choice card, a farmer selects his/her preferred option among three possible choices (SQ and two smart meter options). The SQ option was chosen, on average, on 49.5% of the choice cards (see table B.1 in the Appendix).

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 nudges is 54%, whereas it drops to 47.8% and 46.4% for farmers were assigned the cocktail and the testimony nudges, respectively. The direct effect of the conditional threshold on the proportion of SQ answers appears to be very limited.

Mixed logit estimation of the DCE

The results of the CL estimations are presented in Appendix C. We observe that 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. However, since the conclusion of

Table 4: Mixed logit estimations

	(1)	(2)	(3)	(4)	(5)
Mean					
Price (in k€)	-1.639***	-1.638***	-1.640***	-1.628***	-1.645***
	(0.073)	(0.072)	(0.073)	(0.072)	(0.073)
Information	-0.0518	-0.0551	-0.0540	-0.0348	-0.0449
	(0.078)	(0.078)	(0.078)	(0.077)	(0.078)
Alert	1.767***	1.775***	1.770***	1.753***	1.781***
	(0.082)	(0.082)	(0.082)	(0.081)	(0.083)
Confidentiality	1.304***	1.306***	1.302***	1.296***	1.309***
	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)
Subs.300	0.490***	0.440***	0.490***	0.491***	0.489***
	(0.085)	(0.133)	(0.085)	(0.085)	(0.137)
Subs.600	1.104***	1.108***	1.106***	1.111***	1.142***
	(0.072)	(0.108)	(0.072)	(0.072)	(0.115)
SQ	0.666***	0.676***	0.801***	0.982***	1.156***
	(0.116)	(0.116)	(0.169)	(0.167)	(0.216)
Subs.300xThresh.25%		-0.0108			-0.119
		(0.189)			(0.201)
Subs.300xThresh.75%		0.115			0.0756
		(0.184)			(0.195)
Subs.600xThresh.25%		-0.0779			-0.143
		(0.153)			(0.165)
Subs.600xThresh.75%		0.0988			0.0638
		(0.148)			(0.160)
SQxThresh.25%			-0.248		-0.295
			(0.216)		(0.241)
SQxThresh.75%			-0.170		-0.198
			(0.210)		(0.235)
SQxCocktail				-0.453**	-0.469**
				(0.198)	(0.202)
SQxTestimony				-0.526**	-0.523**
				(0.235)	(0.225)
N	22896	22896	22896	22896	22896
Log-likelihood	-5875.8	-5870.6	-5874.6	-5872.5	-5863.9

Standard errors in parentheses

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

the Hausman test is that the IIA assumption is not satisfied, we focus on the ML models.

In table 4, we report the results of the ML estimations, considering the full sample (standard deviation results are presented in Appendix D). In model (1), we estimate a simple model without considering the effects of the treatments (subsidy thresholds and nudges). In model (2) we interact the subsidy with the conditional thresholds, the 50% threshold being the reference, as it is the standard tipping point in the literature (Kuhfuss *et al.* , 2016). In model (3), we interact the alternative specific constant for the SQ with the thresholds, still considering 50% as the reference. The intuition is to capture whether or not a change in the conditional threshold can affect the choice of the SQ. In model (4) we assess the global effect of nudges on the SQ choice, whatever the threshold effect. Model (5) combines models (2), (3) and (4).

The positive and significant sign of the coefficient associated to the *SQ* (alternative specific constant for the status quo) indicates that farmers have a preference for keeping their mechanical water meter rather than adopting a smart meter. Adopting a smart meter therefore appears to be a constraint for them for reasons not taken into account by the DCE attributes.

We now look at the effect of attributes and instruments on farmers' choices. We note that all the coefficients associated to the attributes are significant at 1% 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. This coefficient is not significant, a result that is in line with Chabé-Ferret *et al.* (2019), who have found that providing farmers information on water use by peers does not induce any significant change in water use behavior. This result could also be explained by a strong response heterogeneity, as we can see on the standard deviation (SD) part of table D.1 in the Appendix. Respondents have 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). Moreover, the two levels for the subsidy have positive and significant coefficients, which means that, independent of the level of the threshold, the subsidy has, on average, a significant impact on farmers' choices, although the payment of the subsidy is conditional.

Thresholds for the conditional subsidy do not appear to play any role in farmers' decisions 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 €). Model (3) also indicates that the thresholds for the conditional subsidy do not significantly impact the choice of the SQ.

From model (4), it can be noted that the two nudges significantly induce farmers to choose the SQ less often, indicating that nudges may be useful communication tools for influencing farmers to adopt new technologies.

Lastly, all results discussed above appear robust when they are simultaneously taken into account in model (5).

In table 5, we report the results of the ML estimations by nudge and by conditional subsidy threshold (i.e., for all nine treatments) to assess whether the smart meter attributes have the same effect across the different treatments.

Similarly to the results presented in table 4, we find that the coefficients of the *Alert*, *Confidentiality* and *Price* attributes are significant, with the expected signs. Results regarding the attribute of receiving information on other farmers' water consumption are less intuitive and in general not significant. The coefficient of this attribute is, however, negative and significant (at the 1% level) in the "No nudge" group and positive and significant (at the 5% level) in the "Testimony" group and in both cases for the 50% reference threshold group.

The "Testimony" nudge seems to modify farmers' perception regarding the *Information* attribute. This may be explained by the content of our nudge: in the testimony, the farmer emphasizes the collective benefits that were realized thanks to the smart water meters (reduction of financial losses for the local farmers' association, detection of leakages, etc.). Farmers who are assigned the testimony may perceive access to other farmers' information as necessary to benefit from such advantages.

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 €). However, the effect of a 300 € subsidy is significant (at a 5% confidence level) in only three treatments out of nine. In addition, these results appear to be independent of the subsidy threshold, which does not seem to influence a farmer's choice of whether or not to adopt a smart meter.

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€)	-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***	-0.000296	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)
N	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

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

Analysis of willingness to pay (WTP)

The interpretation of coefficient estimates in the indirect utility functions is not straightforward except in terms of the 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. WTP estimates presented in table 6 are computed using results of the ML model estimated by thresholds and by nudge groups (table 5). The first column is based on model (1) of table 4.

Considering the full sample, respondents have, on average, a WTP of 406 € to stay with the SQ and keep their mechanical water meter (see table 6, column "Full sample", SQ variable). To induce adoption of a smart water meter (without any additional attributes), a farmer should thus be paid at least 406 €.

However, when we introduce different smart meter attributes, the WTP becomes positive : 670 € (1078 - 406) on average if the smart meter includes the *Alert* attribute, 390 € (796 - 406) if *Confidentiality* is guaranteed on individual data and water consumption, and 1468 € (1078 + 796 - 406) if the smart meter includes both attributes (*Information* is globally non-significant). For the treatment sub-samples, when all attributes are considered, the total WTP varies from 911 € with no nudge and no subsidy, to 3103 € with a 600 € subsidy and a 75% conditional threshold combined with the "Cocktail" nudge. These results highlight the value of these monetary and non-monetary incentives estimated from farmers' choices.

From the results between groups, we observe increasing trends for the WTP estimates for the 75% threshold groups ("No nudge" and "Cocktail") and for the "nudged" groups, compared to the "No nudge" groups (whatever the threshold). This confirms that nudges can be used as a communication tool to emphasize certain attributes. Similar results were found in Ouvrard *et al.* (2020).

However, these trends are not significantly different from each other with regard to standard errors. Only two specific estimates are significantly different from the others. First, the *Confidentiality* attribute for the 75% threshold group, combined with the "No nudge" group corresponds to a WTP that is 250% higher than the 25% threshold group, with confidence intervals that do not overlap. For the *Alert* attribute, we observe the same WTP for the 75% threshold combined with the "No nudge" group.

Table 6: WTP for all group estimations

		No nudge			Cocktail			Testimony		
	Full sample	25% Thres.	50% Thres.	75% Thres.	25% Thres.	50% Thres.	75%Thres.	25% Thres.	50% Thres.	75% Thres.
SQ	406*	307	178	707*	167	267	471*	535	862*	288
	[254;558]	*[-89;703]*	[-89; 703]	*[203; 1211]*	[-224;558]	[-79;613]	*[47;895]*	[-67;1137]	*[284;1441]*	[-281;814]
Information	-32	-167	-320*	-236	40	-144	115	218	323*	186
	[-125;64]	*[-457;123]*	[-552; -89]	*[-549;78]*	[-193;272]	[-402;113]	[-134;364]	[-112;548]	*[30;615]*	[-108;480]
Alert	1078*	955*	704*	1212*	*841**	981*	1269*	*1436**	1354*	1073*
	[968;1189]	*[654;1256]*	*[457;951]*	*[829;1595]*	*[571;1111)*	*[716;1246]*	*[920;1618]*	*[974;1899]*	*[96;1745]*	*[698;1449]*
Confidentiality	796*	430*	671*	1105*	798*	569*	1353*	843*	771*	762*
	[689;902]	*[164;695]*	*[427;915]*	*[729;1485]*	*[530;1067]*	*[316;821]*	*[963;1743]*	*[426;1260]*	*[442;1099]*	*[369;1156]*
Subs 300	299*	190	263	306	336*	118	527*	0	632*	263
	[200;398]	*[-76;456]*	*[-1;527]*	[-60;672]	*[72;601]*	[-119;356]	*[256;797]*	[-411;411]	*[300;963]*	[-134;660]
Subs 600	674*	501*	570*	899*	641*	586*	837*	597*	815*	659*
	[580;768]	*[255;748]*	*[342;799]*	*[564;1234]*	*[397;886]*	*[357;815]*	*[553;1121]*	*[242;952]*	*[491;1139]*	*[306;1011]*

Note: The WTP, the mean, and the confidence interval at 95% are computed from table 4, column (1) for the "Full sample" column, and from table 5 for all other columns. * if the WTP is significant.

Moreover, the estimated WTP related to the subsidy attribute is, on average, and in most cases, greater than the level of the proposed conditional subsidy (600 €). These figures show that farmers value the subsidy more highly than its expected value. While the conditional subsidy is doubled, from 300 € to 600 €, on average the WTP estimated is more than twice as high between the two amounts of this attribute (see "All sample", the total WTP of 299 € and 674 €, respectively, for a subsidy of 300 € and 600 €). Secondly, what is surprising is that the WTP for the subsidy in the three threshold groups is not significantly different. Even though the 75% threshold is far from the rate of adoption expected by most farmers, the results show that nevertheless farmers place a high value on the subsidy. Yet, farmers should anticipate that the subsidy will most likely not be paid. This should theoretically reduce their WTP for this subsidy, but this is not the case.

To summarize, besides demonstrating that farmers do have, on average, a WTP for smart water meters provided that the smart meters include certain characteristics or services, these results show the interest for policymakers to consider utilizing incentive instruments such as nudges and high conditional subsidies with a high threshold to encourage farmers to adopt such new technologies.

Do beliefs about smart meter adoption by other farmers play a role?

Our subsidy being conditional on 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. Those who believe that many of their peers will adopt this new technology may be influenced by the expected behavior of their peers and thus more likely to choose a smart water meter option instead of the SQ.

To assess this point, we measure farmers' predictions regarding the likely number of smart meter adoption by other farmers in their geographic area through three questions in which we vary the conditional threshold. We propose a hypothetical situation similar to those proposed in the DCE, where each farmer is asked to provide his beliefs about the number of farmers who might adopt a smart water meter. We first consider the conditional subsidy threshold used in the DCE (i.e., related to each treatment group: 25%, 50% or 75%). Then, we repeat the question for the two other thresholds. Figure 3 presents the script of the question used.

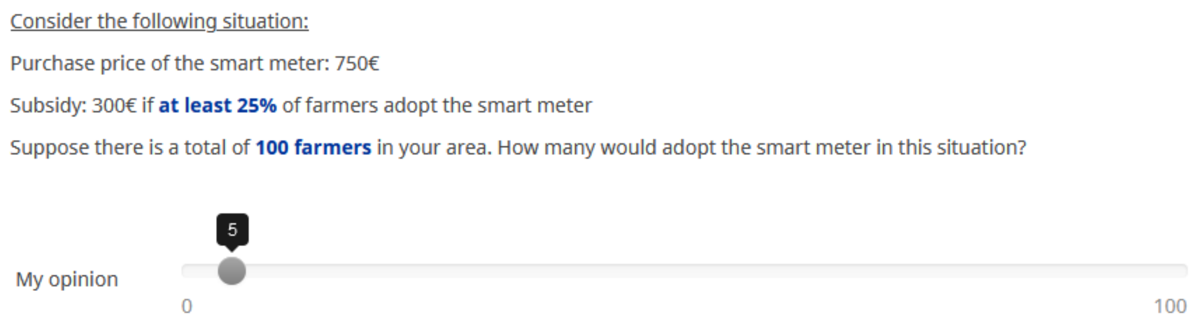

Figure 3: Script used to elicit farmers' beliefs on smart meter adoption by peer farmers

We present the results in table 7. If we first consider the mean row in table 7, the farmers predict on average over the three treatments that 27.7 (of 100) farmers will adopt a smart water meter when a 50% threshold is set. This number is quite stable whatever the conditional subsidy threshold in the question. It slightly decreases from 28.6 with a 25% threshold to 26.9 with a 75% threshold: the higher the conditional subsidy threshold, the lower the number of peer farmers predicted to adopt the smart water meter. However, this difference is not significant. Going further into the analysis, it also appears that, for a given treatment, there are few variations in farmers' beliefs when the threshold changes in the different questions. This is observed in every threshold group and particularly in the 25% treatment, where there is no difference between the answers.

Second, holding constant the threshold set in the question related to belief, the higher the threshold in the treatment, the higher the estimate of smart meter adoption by other farmers: from 26.1 for a 25% threshold group to 32.9 for a 75% threshold group. These results are significantly different from one another. One possible interpretation is that farmers were affected by the anchoring bias, i.e., they were influenced by the threshold they saw in the choice cards. Overall, these observations tend to confirm our past results obtained in 4, namely that threshold groups do not seem to matter.

From a public policy point of view, this additional result confirms that governments may have an interest in implementing conditional collective subsidies with high thresholds to influence farmers' perception of the norm and, therefore, foster the adoption of smart water meters.

Table 7: Beliefs on how many farmers will adopt smart water meters

Thresholds of the treatments	Thresholds set in the questions 25%	50%	75%	Mean	SD
25%	26.0	26.2	26.1	26.1	*20.6*
50%	30.5	29.1	27.8	29.2	*20.6*
75%	34.6	32.7	31.5	32.9	*22.3*
Mean	28.6	27.7	26.9		
SD	*23.3*	*22.6*	*24.7*		

Note: This table presents the average of the respondents' beliefs for each of the three questions (columns), studied by subsidy threshold groups (rows) i.e., 25%; 50% and 75% in both cases

Discussion and 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.

Therefore, our study aims at : i) assessing French farmers' WTP for specific characteristics of smart water meters and, ii) testing different monetary and non-monetary instruments to encourage voluntary adoption of smart meters by farmers.

We propose an original approach combining a DCE with 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 they have a preference for their current mechanical water meter. Both the Alert and Confidentiality attributes matter, but the former accounts the most in the total WTP. 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 push farmers to more often choose a smart water meter option. In particular, the effect of the conditional subsidy does not rely on the threshold to reach. Third, 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 they believed 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 encourage massive adoption of new technologies. Such a conditional subsidy could be completed with a nudge, similar to the two we added to the subsidy incentive.

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 discrete choice experiment 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.

This work has some limitations. One of the limitations, often associated with revealed preference methods, is that the declaration of intent is not the behavior observed. Potential strategic bias is standard in this type of study. However, concerning the incentives studied and effects related to the conditional thresholds and to the nudges: as we randomly defined the treatment groups, the relative response difference between the "No nudge" group and the other two treatment groups are therefore clearly linked to the instruments. Another limitation deals with the subsidy cost. Due to the smart meter's contribution to the public good, the subsidy we proposed is financed by the regulator. However, with a subsidy of 600 € per farmer, the total amount to pay could be quite high in the sectors where the threshold is indeed reached, which is more likely to be the case if the threshold is low. Thus the amount and the threshold of the conditional subsidy must be clearly defined.

We conclude with directions that can be taken in future research. Further research is needed to explore other incentive instruments on smart water meter adoption. Indeed, in a free riding context, two monetary incentive tools can be used: a subsidy to reward the voluntary adoption of smart meter technology and a tax to punish free riding behavior. In this work we choose to test the subsidy in the case of the adoption of the smart meter. A possible development would be to study the effect of a tax on mechanical meter holders. 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.

References

Alcon, Francisco, Tapsuwan, Sorada, Brouwer, Roy, & de Migue, María D. 2014. Adoption of irrigation water policies to guarantee water supply: A choice experiment,Environmental Science Policy. *Environmental Science Policy*, **44**, 226–236.

Allcott, Hunt. 2011. Social norms and energy conservation. *Journal of Public Economics*, **95**(9-10), 1082–1095.

Allcott, Hunt, & Kessler, Judd B. 2019. The welfare effects of nudges: A case study of energy use social comparisons. *American Economic Journal: Applied Economics*, **11**(1), 236–76.

Ambec, Stefan, Dinar, Ariel, & McKinney, Daene. 2013. Water sharing agreements sustainable to reduced flows. *Journal of Environmental Economics and Management*, **66**(3), 639 – 655.

Andreoni, James, & Bergstrom, Ted. 1996. Do Government Subsidies Increase the Private Supply of Public Goods? *Public Choice*, **88**(09), 295–308.

Ariely, Dan, & Wertenbroch, Klaus. 2002. Procrastination, deadlines, and performance: Self-control by precommitment. *Psychological science*, **13**(3), 219–224.

Baca-Motes, Katie, Brown, Amber, Gneezy, Ayelet, Keenan, Elizabeth A, & Nelson, Leif D. 2012. Commitment and behavior change: Evidence from the field. *Journal of Consumer Research*, **39**(5), 1070–1084.

Baldwin, Matthew, & Mussweiler, Thomas. 2018. The culture of social comparison. *Proceedings of the National Academy of Sciences*, **115**(39), E9067–E9074.

Bargh, John A. 2006. What have we been priming all these years? On the development, mechanisms, and ecology of nonconscious social behavior. *European journal of social psychology*, **36**(2), 147–168.

Bargh, John A, & Gollwitzer, Peter M. 1994. Environmental control of goal-directed action: automatic and strategic contingencies between situations and behavior.

Bargh, John A, Gollwitzer, Peter M, Lee-Chai, Annette, Barndollar, Kimberly, & Trötschel, Roman. 2001. The automated will: nonconscious activation and pursuit of behavioral goals. *Journal of personality and social psychology*, **81**(6), 1014.

Beh, Eva H.Y., Dandy, Graeme C., Maier, Holger R., & Paton, Fiona L. 2014. Optimal sequencing of water supply options at the regional scale incorporating alternative water supply sources and multiple objectives. *Environmental Modelling Software*, **53**, 137 – 153.

Bhanot, Syon P. 2017. Rank and response: A field experiment on peer information and water use behavior. *Journal of Economic Psychology*, **62**, 155–172.

Bimonte, Salvatore, Bosco, Luigi, & Stabile, Arsenio. 2020. Nudging pro-environmental behavior: evidence from a web experiment on priming and WTP. *Journal of Environmental Planning and Management*, **63**(4), 651–668.

Brent, Daniel A, Cook, Joseph H, & Olsen, Skylar. 2016. Social Comparisons, Household Water Use, and Participation in Utility Conservation Programs: Evidence from Three Randomized Trials (vol 2, pg 597, 2015). *Journal of the Association of Environmental and Resource Economists*, **3**(2), 523–+.

Centola, Damon, Becker, Joshua, Brackbill, Devon, & Baronchelli, Andrea. 2018. Experimental evidence for tipping points in social convention. *Science*, **360**(06), 1116–1119.

Chabé-Ferret, Sylvain, Le Coent, Philippe, Reynaud, Arnaud, Subervie, Julie, & Lepercq, Daniel. 2019. Can we nudge farmers into saving water? Evidence from a randomised experiment. *European Review of Agricultural Economics*, **46**(3), 393–416.

Costa, Dora L, & Kahn, Matthew E. 2013. Energy conservation "nudges" and environmentalist ideology: Evidence from a randomized residential electricity field experiment. *Journal of the European Economic Association*, **11**(3), 680–702.

Davidson, Brian, Hellegers, Petra, & Namara, Regassa Ensermu. 2019. Why irrigation water pricing is not widely used. *Current Opinion in Environmental Sustainability*, **40**, 1 – 6. System dynamics and sustainability.

Davies, Kirsten, Doolan, Corinna, van den Honert, Robin, & Shi, Rose. 2014. Water-saving impacts of Smart Meter technology: An empirical 5 years, whole-of-community study in Sydney, Australia. *Water Resources Research*, **50**(9), 7348–7358.

Dessart, François J, Barreiro-Hurlé, Jesús, & van Bavel, René. 2019. Behavioural factors affecting the adoption of sustainable farming practices: A policy-oriented review. *European Review of Agricultural Economics*, **46**(3), 417–471.

Deutskens, Elisabeth, De Ruyter, Ko, Wetzels, Martin, & Oosterveld, Paul. 2004. Response rate and response quality of internet-based surveys: An experimental study. *Marketing letters*, **15**(1), 21–36.

Dolan, Paul, Hallsworth, Michael, Halpern, David, King, Dominic, Metcalfe, Robert, & Vlaev, Ivo. 2012. Influencing behaviour: The mindspace way. *Journal of Economic Psychology*, **33**(1), 264–277.

Egebark, Johan, & Ekström, Mathias. 2016. Can indifference make the world greener? *Journal of Environmental Economics and Management*, **76**, 1–13.

Eymess, Tillmann, & Florian, Diekert. 2019. Dissecting Social Norms of Cooperation: A Conditional Process Analysis.

Ferraro, Paul J, & Price, Michael K. 2013. Using nonpecuniary strategies to influence behavior: evidence from a large-scale field experiment. *Review of Economics and Statistics*, **95**(1), 64–73.

Friis, Rasmus, Skov, Laurits, Olsen, Annemarie, Appleton, Katherine, Saulais, Laure, Dinnella, Caterina, Hartwell, Heather, Depezay, Laurence, Monteleone, Erminio, Giboreau, Agnes, & Perez-Cueto, Federico. 2017. Comparison of three nudge interventions (priming, default option, and perceived variety) to promote vegetable consumption in a self-service buffet setting. *PLoS ONE*, **12**(05).

Ghesla, Claus, Grieder, Manuel, & Schubert, Renate. 2019. Nudging the Poor and the Rich–A Field Study on the Distributional Effects of Green Electricity Defaults. *Energy Economics*, 104616.

Gillich, Caroline, Narjes, Manuel, Krimly, Tatjana, & Lippert, Christian. 2019. Combining choice modeling estimates and stochastic simulations to assess the potential of new crops – The case of lignocellulosic perennials in Southwestern Germany . *GCB Bioenergy*, **11**(1), 289–303.

Goldstein, Noah J, & Cialdini, Robert B. 2007. The spyglass self: a model of vicarious self-perception. *Journal of personality and social psychology*, **92**(3), 402.

Gu, Jie, Xu, Yunjie Calvin, Xu, Heng, Zhang, Cheng, & Ling, Hong. 2017. Privacy concerns for mobile app download: An elaboration likelihood model perspective. *Decision Support Systems*, **94**, 19–28.

Kinzig, Ann P., Ehrlich, Paul R., Alston, Lee J., Arrow, Kenneth, Barrett, Scott, Buchman, Timothy G., Daily, Gretchen C., Levin, Bruce, Levin, Simon, Oppenheimer, Michael, Ostrom, Elinor, & Saari, Donald. 2013. Social Norms and Global Environmental Challenges: The Complex Interaction of Behaviors, Values, and Policy. *BioScience*, **63**(3), 164–175.

Kuhfuss, Laure, Préget, Raphaële, Thoyer, Sophie, & Hanley, Nick. 2016. Nudging farmers to enrol land into agri-environmental schemes: the role of a collective bonus. *European Review of Agricultural Economics*, **43**(4), 609–636.

Li, Man, Xu, Wenchao, & Zhu, Tingju. 2018. Agricultural Water Allocation under Uncertainty: Redistribution of Water Shortage Risk. *American Journal of Agricultural Economics*, **101**(1), 134–153.

Löfgren, Åsa, Martinsson, Peter, Hennlock, Magnus, & Sterner, Thomas. 2012. Are experienced people affected by a pre-set default option—Results from a field experiment. *Journal of Environmental Economics and management*, **63**(1), 66–72.

Lowry, Paul Benjamin, Cao, Jinwei, & Everard, Andrea. 2011. Privacy concerns versus desire for interpersonal awareness in driving the use of self-disclosure technologies: The case of instant messaging in two cultures. *Journal of Management Information Systems*, **27**(4), 163–200.

McFadden, Daniel. 1974. *Conditional Logit Analysis of Qualitative Choice Behavior*. Chap. 4, pages 105–142.

McFadden, Daniel, & Train, Kenneth. 2000. Mixed MNL models for discrete response. *Journal of applied Econometrics*, **15**(5), 447–470.

Miltgen, Caroline Lancelot, Popovič, Aleš, & Oliveira, Tiago. 2013. Determinants of end-user acceptance of biometrics: Integrating the “Big 3” of technology acceptance with privacy context. *Decision Support Systems*, **56**, 103–114.

Monks, Ian, Stewart, Rodney A., Sahin, Oz, & Keller, Robert. 2019. Revealing Unreported Benefits of Digital Water Metering: Literature Review and Expert Opinions. *Water*, **11**(4).

Myers, Erica, & Souza, Mateus. 2020. Social comparison nudges without monetary incentives: Evidence from home energy reports. *Journal of Environmental Economics and Management*, 102315.

Ouvrard, Benjamin, Abildtrup, Jens, & Stenger, Anne. 2020. Nudging Acceptability for Wood Ash Recycling in Forests: A Choice Experiment. *Ecological Economics*, **177**, 106748.

Rege, Mari. 2004. Social Norms and Private Provision of Public Goods. *Journal of Public Economic Theory*, **6**(1), 65–77.

Rogers, Todd, Goldstein, Noah J, & Fox, Craig R. 2018. Social mobilization. *Annual review of psychology*, **69**, 357–381.

Rose, J.M., Collins, A.T., Bliemer, M.C.J., & Hensher, D.A. 2010. *Ngene, 1.0.2.* ed. Statistical Software, ChoiceMetrics Pty Ltd.

Saleth, R.Maria, & Dinar, Ariel. 2000. Institutional changes in global water sector: trends, patterns, and implications. *Water Policy*, **2**(3), 175 – 199.

Schubert, Christian. 2017. Green nudges: Do they work? Are they ethical? *Ecological Economics*, **132**, 329 – 342.

Schultz, P Wesley, Nolan, Jessica M, Cialdini, Robert B, Goldstein, Noah J, & Griskevicius, Vladas. 2007. The constructive, destructive, and reconstructive power of social norms. *Psychological science*, **18**(5), 429–434.

Schwartz, Shalom H. 1977. Normative influences on altruism. *Pages 221–279 of: Advances in experimental social psychology*, vol. 10. Elsevier.

Skaggs, R.K. 2001. Predicting drip irrigation use and adoption in a desert region. *Agricultural Water Management*, **51**(2), 125 – 142.

Swann Jr, William B, & Bosson, Jennifer K. 2010. Self and identity.

Thaler, Richard, & Sunstein, Cass. 2008. Nudge: The gentle power of choice architecture. *New Haven, Conn.: Yale.*

Villamayor-Tomas, Sergio, Sagebiel, Julian, & Olschewski, Roland. 2019. Bringing the neighbors in: A choice experiment on the influence of coordination and social norms on farmers' willingness to accept agro-environmental schemes across Europe. *Land Use Policy*, **84**, 200 – 215.

Wallander, Steven, Ferraro, Paul, & Higgins, Nathaniel. 2017. Addressing Participant Inattention in Federal Programs: A Field Experiment with The Conservation Reserve Program. *American Journal of Agricultural Economics*, **99**(4), 914–931.

Wang, Xiaowei, Shao, Jingli, Van Steenbergen, Frank, & Zhang, Qiulan. 2017. Implementing the Prepaid Smart Meter System for Irrigated Groundwater Production in Northern China: Status and Problems. *Water*, **9**(6).

Werner, Carol M., Turner, Jane, Shipman, Kristen, Twitchell, F. Shawn, Dickson, Becky R., Bruschke, Gary V., & von Bismarck, Wolfgang B. 1995. Commitment, behavior, and attitude change: An analysis of voluntary recycling. *Journal of Environmental Psychology*, **15**(3), 197 – 208. Green Psychology.

Young, H. Peyton. 2015. The Evolution of Social Norms. *Annual Review of Economics*, **7**(1), 359–387.

Yu, Tian, & Babcock, Bruce A. 2010. Are US corn and soybeans becoming more drought tolerant? *American Journal of Agricultural Economics*, **92**(5), 1310–1323.

Zekri, Slim, Madani, Kaveh, Bazargan-Lari, Mohammad Reza, Kotagama, Hemesiri, & Kalbus, Edda. 2017. Feasibility of adopting smart water meters in aquifer management: An integrated hydro-economic analysis. *Agricultural Water Management*, **181**, 85 – 93.

Notes

[1]See https://www.wri.org/applications/aqueduct/country-rankings/.

[2]A smart water meter is a connected device that can store and transmit water consumption data at a high frequency. Smart water meters are usually combined with an advanced metering infrastructure and an internet platform, allowing easy access to the collected data. Smart meters usually work through two-way communication via a wireless network connection. Data regarding real-time water consumption is transmitted to each farmer through the internet platform, and this information is usually also available to the local water resource manager allowing them to more efficiently manage water resources, for instance, though better planning of water releases.

[3]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.

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

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

[6]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.

[7]Randomization tests on the nine treatments were done and are available on request.

A *Presentation of nudges*

A.1 *Cocktail*

As an actor in your territory, you are 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, very", "Quite important, 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 have 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% to 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 manage it. Water management has become more equitable between the different farmers of our local farmers' association."

B *Statistics on SQ choice*

Table B.1: Percentage of farmers choosing the SQ in the DCE (by treatment)

		Nudges			
		No nudge	Cocktail	Testimony	Total
Conditional subsidy	25% Threshold	50.5%	47.6%	45.1%	47.8%
	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%

C *Estimation of the DCE with a conditional logit*

Table C.1: Conditional logit estimations

	(1)	(2)	(3)	(4)	(5)
Price (in k€)	-1.241***	-1.016***	-1.016***	-1.017***	-1.016***
	(0.046)	(0.043)	(0.043)	(0.043)	(0.043)
Information	0.181***	0.136***	0.137***	0.138***	0.137***
	(0.040)	(0.036)	(0.036)	(0.036)	(0.036)
Alert	1.326***	1.142***	1.142***	1.145***	1.144***
	(0.045)	(0.041)	(0.041)	(0.041)	(0.041)
Confidentiality	0.791***	0.690***	0.690***	0.692***	0.692***
	(0.042)	(0.040)	(0.040)	(0.040)	(0.040)
Subs.300	0.523***	0.353***	0.407***	0.408***	0.406***
	(0.054)	(0.082)	(0.058)	(0.058)	(0.094)
Subs.600	0.767***	0.671***	0.696***	0.695***	0.712***
	(0.049)	(0.065)	(0.046)	(0.046)	(0.076)
SQ	0.899***	0.661***	0.709***	0.849***	0.905***
	(0.065)	(0.059)	(0.067)	(0.068)	(0.084)
Subs.300x25%Thres.		0.128			-0.0102
		(0.101)			(0.131)
Subs.300x75%Thres.		0.0382			0.0137
		(0.100)			(0.130)
Subs.600x25%Thres.		0.0295			-0.0869
		(0.081)			(0.107)
Subs.600x75%Thres.		0.0456			0.0319
		(0.079)			(0.105)
SQx25%Thres.			-0.112*		-0.144
			(0.057)		(0.087)
SQx75%Thres.			-0.0388		-0.0316
			(0.056)		(0.087)
SQxCocktail				-0.249***	-0.248***
				(0.055)	(0.055)
SQxTestimony				-0.325***	-0.325***
				(0.061)	(0.061)
N	22896	22896	22896	22896	22896
Log-likelihood	-10926.4	-7145.9	-7144.9	-7130.1	-7127.5

Standard errors in parentheses

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

D *Estimation of the DCE with a mixed logit*

Table D.1: Mixed logit estimations - Results of the SD

	(1)	(2)	(3)	(4)	(5)
SD					
Information	1.363***	1.391***	1.365***	1.348***	1.374***
	(0.115)	(0.113)	(0.116)	(0.113)	(0.113)
Alert	1.216***	1.213***	1.217***	1.195***	1.226***
	(0.098)	(0.099)	(0.098)	(0.098)	(0.101)
Confidentiality	1.623***	1.616***	1.630***	1.617***	1.623***
	(0.116)	(0.114)	(0.117)	(0.113)	(0.115)
Subs.300	-0.468**	-0.287	-0.474**	-0.379	-0.130
	(0.228)	(0.315)	(0.226)	(0.302)	(0.282)
Subs.600	0.660***	-0.433*	0.660***	-0.666***	-0.539***
	(0.139)	(0.224)	(0.137)	(0.131)	(0.201)
SQ	2.519***	2.511***	2.508***	2.426***	2.440***
	(0.117)	(0.114)	(0.119)	(0.126)	(0.119)
Subs.300x25%Thres.		-0.547			-0.779***
		(0.443)			(0.274)
Subs.300x75%Thres.		0.765***			0.787***
		(0.297)			(0.283)
Subs.600x25%Thres.		0.674***			0.547*
		(0.241)			(0.305)
Subs.600x75%Thres.		-0.588**			-0.510
		(0.294)			(0.337)
SQx25%Thres.			-0.445		1.106***
			(0.419)		(0.356)
SQx75%Thres.			0.102		0.303
			(0.350)		(0.369)
SQxCocktail				0.271	0.0528
				(0.428)	(0.428)
SQxTestimony				1.039*	-0.143
				(0.562)	(0.574)
N	22896	22896	22896	22896	22896
Log-likelihood	-5875.8	-5870.6	-5874.6	-5872.5	-5863.9

Standard errors in parentheses

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

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