Nudging and Subsidizing Farmers to Foster Smart Water Meter Adoption

Abstract

In a context of increasing scarcity, reducing water use in the agricultural sector is one of the spearheads of agricultural and environmental policies. New technologies such as smart water meters are promising tools to address this issue, but their voluntary adoption is often limited. Using a discrete choice experiment with randomized treatments on 1,272 French farmers, we test two policy instruments designed to foster the voluntary adoption of smart water meters by farmers: a conditional subsidy and nudges. The conditional subsidy is paid to farmers who adopt a smart meter only if the rate of adoption in their sector is sufficiently high (25%, 50% or 75%). In addition, we implement informational nudges by providing specific messages regarding water scarcity and water management to farmers. We show that both policy instruments are effective tools allowing to foster the 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 facing 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.

Introduction

In August 2019, the World Resources Institute reported that water stress and water restrictions have globally increased in the last decades, with a significant impact on all economic activities, and on agriculture more specifically[1]. With 70% of the water consumption at the world level, the agricultural sector is indeed the main consumer of water resources. This explains why optimizing water consumption by the agricultural sector has often the highest priority for public authorities in charge of managing water resources.

There are different ways to deal with increased water scarcity in the agricultural sector. Signaling water scarcity with high water prices has been widely promoted but such a solution has often happened to be politically difficult to implement (Davidson *et al.* , 2019). Increasing water supply is another option, however the cost for developing new water resources has often become 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 conditions remains challenging (Ambec *et al.* , 2013). A last alternative is the adoption by farmers of water-efficient agricultural practices (e.g. drought-tolerant crop variety, deficit irrigation, etc.) and of new technologies (e.g. drip irrigation, smart water meters). While the first have already been studied (Alcon *et al.* , 2014; Skaggs, 2001; Saleth & Dinar, 2000; Yu & Babcock, 2010), evidence from the literature on the use of smart water meters[2] to improve water management remains limited. Some exceptions include Wang *et al.* (2017) for China, Zekri *et al.* (2017) for Oman and Chabé-Ferret *et al.* (2019) for 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 for inducing changes in irrigation decision 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 different policy instruments designed to foster the voluntary adoption of smart water meters by farmers. First, we propose a monetary incentive offered to farmers adopting a smart water meter. We use a conditional subsidy similar to the collective bonus studied by Kuhfuss *et al.* (2016): a farmer having adopted a smart water meter gets a subsidy if the collective adoption rate reaches a given threshold in his/her geographical area. We propose to test three threshold levels: 25%, 50% or 75%. Second, since non-monetary interventions have a strong appeal for public authorities in charge of the agricultural sector (Wallander *et al.* , 2017), we propose to study the impact of nudges on farmer's decision to adopt 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 propose to test two nudges. In the first nudge, farmers are reminded the existence of water restrictions and the importance of a good management of water resources. The second nudge is a testimony made by a farmer who has already adopted a smart water meter. Our two nudges therefore rely on different psychological mechanisms including a priming, a commitment effects and social identity.

Another possible way to foster voluntary adoption of smart water meters by farmers is to offer new services to farmers made possible by smart water meters. Farmers may, for instance, receive instantaneous alert messages in case of abnormal water consumption. They may also obtain an information on water consumption of peer farmers (Chabé-Ferret *et al.* , 2019). Such information might be relevant for farmers if a collective management of water resources needs to be implemented or simply because there is a natural tendency for individuals to look to others as comparison standards for how to behave, think and feel (Baldwin & Mussweiler, 2018). Offering smart meters which include services valued by farmers might be a way to induce smart water meter adoption. Assessing how farmers value services or characteristics of smart water meters remains challenging due to their hypothetical nature. Since the discrete choice experiments (DCE) are a well-established state-of-the-art method to elicit preferences for hypothetical choice alternatives, we propose here to implement this method.

Our main contributions are the following. We first show that, on average, farmers have a preference for their current mechanical water meter. However, if the smart water meter adoption allows to receive an alert message in case of abnormal water consumption and/or if data confidentiality is guaranteed, then most farmers have a positive willingness to pay (WTP) for those smart water meters. Second, we demonstrate that the two policy instruments (conditional subsidy and nudges) induce farmers to adopt a smart water meter. However, and contrary to our expectations, the WTP for the conditional subsidy does not depend on the adoption threshold which condition the payment of the subsidy. Third, despite our first intuition that a high threshold of conditional subsidy may discourage the adoption of smart meters, we observe that our high threshold (75%)

does not induce such an effect, compared to lower ones (25% and 50%). This is, in addition, confirmed by our study of farmers' beliefs (regarding the adoption of smart water meters by other farmers in their sector): thresholds have no impact on their beliefs except through, possibly, an anchoring bias. All these elements argue in favor of implementing a conditional subsidy with a high collective adoption threshold. Moreover, in this context of a high threshold, nudges increase the voluntary adoption of smart meters.

The remaining of this article is organized as follow. We present in the first section the literature related to the conditional subsidy and green nudges. The second section details our experimental design which combines a discrete choice experiment with different treatments, and presents the data. We spell out the results in the third section, and a discussion concludes our paper in the last section.

Inducing smart meters' adoption by farmers

Subsidizing farmers to foster adoption

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

Various subsidy schemes may be implemented to foster their adoption. The most simple one is an equal lump-sum payment for all farmers adopting a smart water meter. Here, we consider a conditional collective subsidy that is a given amount of money which is offered to each farmer having adopted smart metering, conditional to the fact 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 farmers agri-environmental contracts' enrollment.

There are two main reasons justifying this conditional collective subsidy. The first one 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, 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 is the risk of water shortage. This means that a certain threshold of adoption rate in a sector needs to be reached to make this new technology socially efficient.

A second reason is related to the role played by social norms on 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 expectations about what other individuals should do (Eymess & Florian, 2019). Social norms appear to be rules that guide individual behaviors in given situation, and these rules are influenced by the perception about what other individuals do. When individuals prefer to act like most others, beliefs can be self-fulfilling, and altered expectations about what others will do can lead to rapid behavioral changes (Young, 2015). Thus, as claimed by Nyborg *et al.* (2016), a potentially powerful role of policies is to provide good reasons for individuals to change their expectations. We argue that introducing a conditional collective subsidy is a way to modify farmers' expectations with respect to the adoption of smart water meters. Indeed, when agents have preferences for social approval, government subsidies can crowd in 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 directly impacts their beliefs on the rate of adoption and therefore ultimately can change the social norm. Two parameters of this conditional subsidy may impact the beliefs: the level of subsidy and the collective threshold to be reached to get it. Usually, the announced threshold is 50% since it is considered that social norms are 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 adoption

In the last 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, we propose to use nudges to induce farmers to adopt a smart water meter. Most studies using green nudges rely on social norms or default options. Studies referring to social norms to reduce water consumption have reported reductions of water consumption by 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. Smart water metering is a new technology in agriculture and, therefore, less than 5% of French farmers have already adopted it: using a smart water meter cannot be viewed as the current norm among farmers. Moreover, the adoption of smart meters is not a default that can be proposed to all farmers. Therefore, we use two other levers.

First, we propose to rely on agents' involvement to push them to adopt smart water meters. In that case, nudges may take the form of information provision beforehand the decision-making using *reminders* (Thaler & Sunstein, 2008), regarding the scarcity of water resources and its 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 have 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 wrote environmental commitment are more likely to participate in a curbside recycling program.

Second, we propose to provide to some farmers some information regarding the behavior of others. This approach is based on *social identity*, which aims to make the behavior of one or several peers more salient in order to influence their decision in the direction of peer action. Indeed, empirical evidence in psychology (Goldstein & Cialdini, 2007; Swann Jr & Bosson, 2010; Rogers *et al.* , 2018) have emphasized that agents are more likely to follow a norm if they perceive themselves as being close to the individual or group of reference. Evidence of the impact on farmer's behavior of providing information regarding the behavior of other farmers are 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 grew them. On the contrary, Wallander *et al.* (2017) show that providing peer information has no effect on farmer's enrollment to the Conservation Reserve Program in the USA. Lastly, Villamayor-Tomas *et al.* (2019) show that having conservation programs recommended by farmers does not encourage other farmers to participate (Germany and Spain).

Finally, note that we consider nudges in addition to the conditional collective subsidy since recent evidence (Myers & Souza, 2020) highlights that nudges alone may not be efficient when monetary incentives are not at stake.

Material and methods

Design of the Discrete Choice Experiment (DCE)

In order to elicit farmers' preferences regarding smart water meters, we use a DCE where each farmer is asked to select his preferred meter among a set of possible ones, each meter being characterized by some specific attributes. The choice of attributes has resulted from an interactive process involving farmers and water managers. Attributes have been discussed in a focus group to understand the most important characteristics of water meters for farmers and for water managers. At the end of this process we selected five attributes which are presented in Table 1.

The first attribute, *information*, is the access to the average water consumption of the other farmers in the respondent geographic sector. This allows farmers to compare themselves and, therefore, to adapt, or not, their consumption. Such piece of information was 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 a message received in the case of abnormal water consumption. This alert allows farmers to be informed in the event of a leak or a fraudulent tie-up. Local stakeholders and farmers were particularly in favor of this attribute during our focus group meetings. The third attribute, *confidentiality*, is related to the confidentiality of individual data and historic consumption. This attribute proposes a full confidentiality of the daily consumption registered by the smart meters (*i.e.*, only made available to the local manager in order to manage the water dams in the sector). When confidentiality is not assured, the data may be made available to water public agencies or to the state. Several studies have emphasized that privacy concerns may decrease the likelihood to adopt 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 users 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 €. Since the price and the conditional subsidy have been defined separately, the net amount of money finally paid by a farmer opting for a smart water meter could be negative, in some cases so as to capture potentially negative WTP of some farmers.

For each farmer, the status quo (SQ) is defined as keeping his/her current mechanical water meter. The attribute levels for the SQ are: no information on the others' consumption, no alert in the case of abnormal water consumption and no daily consumption information, so the confidentiality is respected. Obviously, farmers do not receive subsidy and there is no additional cost for them if they keep their current mechanical water meter.

Table 1: Description of meter attributes in the DCE

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

SQ: Status Quo.
ref.: Reference category.

Implementation of the DCE

The online survey has been implemented using the web-platform LimeSurvey (version 2.5). The survey includes five parts: an introduction and description of attributes, the DCE, some follow-up questions, some questions on the current respondent water meter and, finally, a part dedicated to farmer beliefs elicitation.

We have used the NGene software (Rose *et al.* , 2010) to generate an efficient design which minimizes the required sample size and choice cards number. The DCE specific part is composed by six different choice cards successively proposed in a randomized order to respondents who, therefore, have six choices to make between two different smart meters, "Meter 1" and "Meter 2", and a status quo option "I keep my current meter". An example of choice card is presented in Figure 1.

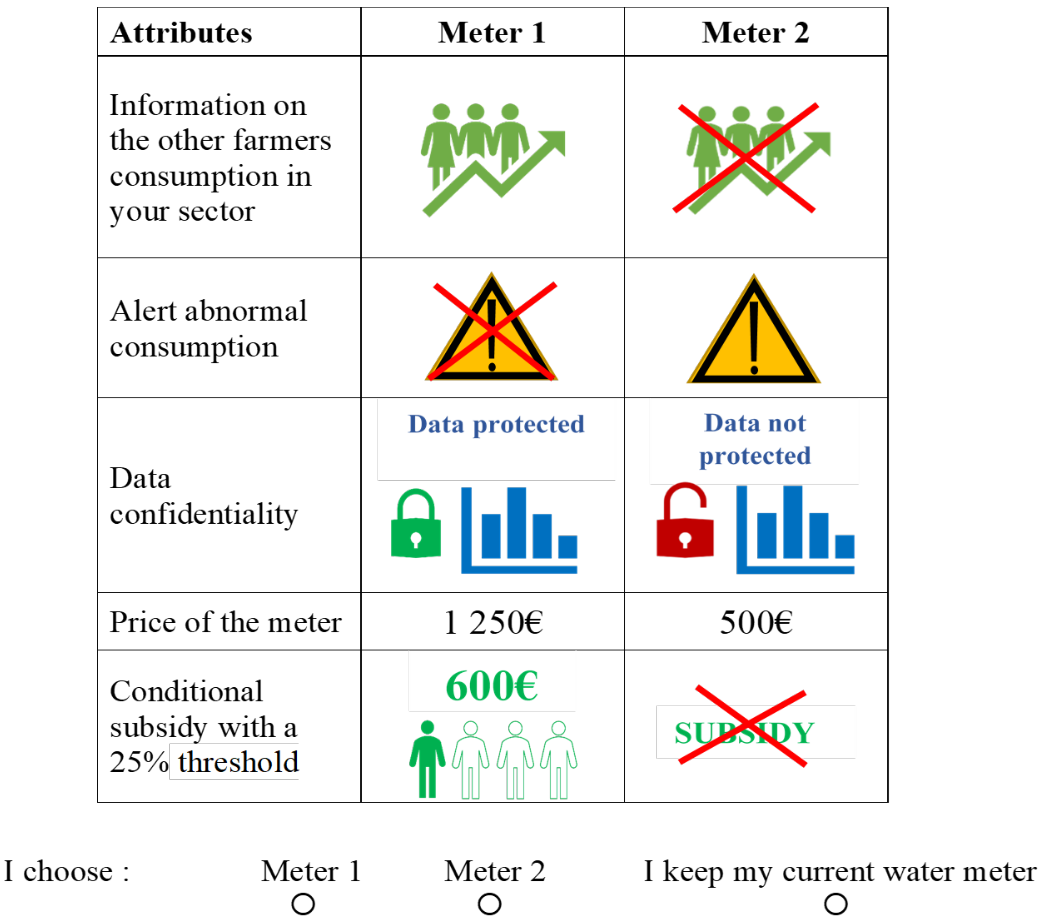


Figure 1: Example of a choice card.

Two pilots have been conducted in June and September 2019. Combining the two pilots' data, we have obtained 21 completed questionnaires corresponding to 126 choices. Our priors have been estimated using this first pool of observations and the questionnaire was modified according to the feedback we received from respondents. Then, the questionnaire has been sent by email, from November to December 2019, by a French pooling organization[5] to 90,000 French farmers. This mailing list represents almost 20% of the total number of farmers in France. The link of the questionnaire was sent through an introductory email informing that the study was conducted by the French Institute for Agricultural Research (INRAE), for a project on water management and new technologies. To provide incentives to farmers to participate to our study, we informed them that we would give 20€ to a charitable organization (Secours Populaire) for each set of hundred questionnaires completed (Deutskens *et al.* , 2004). We have chosen this charitable organization since it is popular enough in France without being directly related to farmers.

Econometric modelling

We rely on the Random Utility Model (RUM) in which a farmer 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 unobserved utility.

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

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

with X_{ijt} a vector which includes the attributes of the water smart meter and α an alternative specific constant related to the SQ (keep the current mechanical water meter), β 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 error terms, ϵ, are 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:

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

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 decided to 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 using 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 are who also adopt the smart meter. Previous studies have considered a 50% threshold (Kuhfuss *et al.* , 2016). Here, farmers will be randomly assigned to three groups: a reference group where the threshold is set to 50% and two other groups with a low threshold set at 25% and a high threshold set at 75%. In the low threshold group, 25% may appear more realistic to reach than a 50% threshold, as this new technology is not yet widespread. This low threshold can also suggest that the development of smart meters may take time before to become the majority. Conversely, the announcement of the high 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 a 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 can lead to discouragement. Consequently, the different thresholds can have at least two opposite impacts on farmers' WTP for the subsidy. Either way, the different thresholds may change farmers' beliefs about the adoption rate and thus farmers' decision about smart meters.

Nudges

Farmers have been randomly assigned to two different nudges, and to a reference group, the "no nudge" group. Some farmers have been allocated to a first nudge we call "cocktail" (see Appendix A.1). In the "cocktail" nudge: i) respondents have been reminded the existence of water restrictions, ii) respondents have been asked to report to which extent they consider water management as an important issue and, iii) respondents have been asked to report to which extent they would be willing to commit to adopt a better water management. The first question can be seen as a *priming* question, while the second one is directly inspired from the theories of *commitment*. We follow the suggestion made by Dolan *et al.* (2012) in combining different types of nudges (*reminder*, *priming* and *commitment*) to increase their efficiency. The second nudge is a "testimony" made by Yves, a 59 years old farmer, who feeds back his real experience with smart water metering (see Appendix A.2). The farmer 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 around 15,000 € annually). In order to give credibility and realism, this testimony goes with the name and the age of the farmer as well as his photo[6]. This second nudge deals with farmers' *social identity*. Showing an example of farmer having already adopted such a smart meter, we expect respondents to identify to this farmer and to choose more often alternatives with the smart meter. Lastly, some farmers have been allocated to a reference group ("no nudge") where no particular information has been 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 have completed the questionnaire which corresponds to almost a 2% response rate. The "protest" and "incomprehension" answers, identified by the follow up questions, represent 242 respondents in total. They have been removed from our sample. Moreover, the 99 respondents who declared having already a smart meter are also removed since our work focuses on mechanisms and instruments to induce voluntary adoption of smart water meters. Our final sample is therefore composed by 1,272 farmers across France.

Table 2: Statistics on final sample and on 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)

Descriptive statistics on our farmer sample are presented in Table 2 and are compared with data from the 2010 French agricultural census. We observe an over-representation of young men (< 40 years old) with high degree of education (*i.e.*, masters degree) in field crop and polyculture activities in our sample. However, we have an acceptable spatial distribution representativeness of our sample at the French scale, as shown by Figure 2.

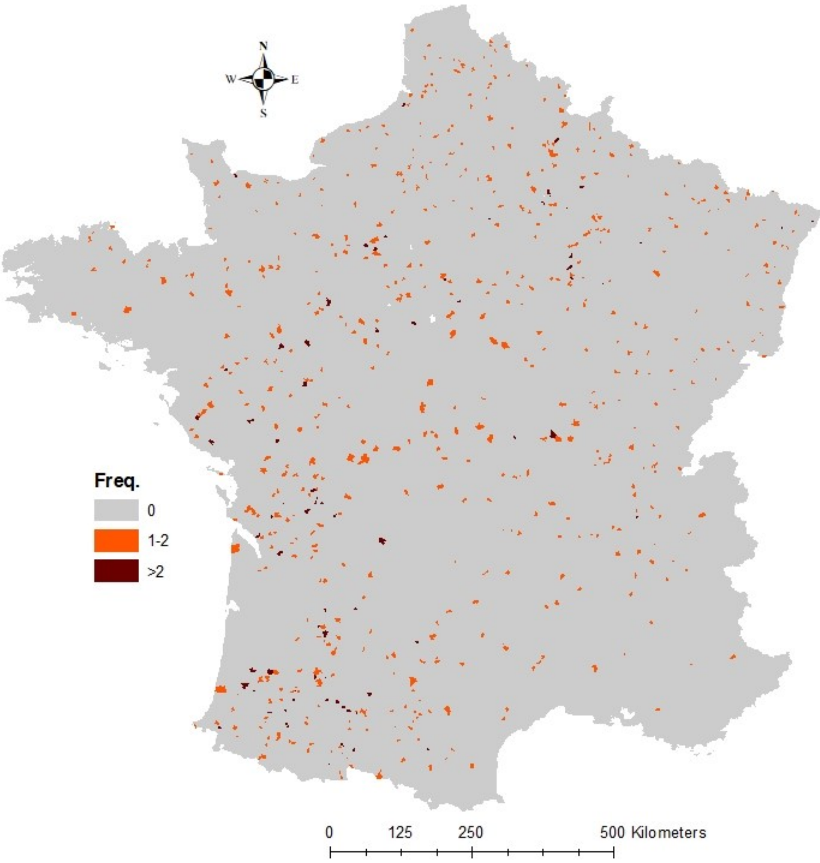


Figure 2: Spatial distribution of sampled Farmers (France)

Table 3 summarizes the number of farmers randomly assigned in the nine treatments (subsidy thresholds × nudges). This design allows 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	Threshold 25%	125	168	109	402
	Threshold 50%	141	181	115	437
	Threshold 75%	155	167	110	433
	Total	421	516	335	1,272

Individual choices and status quo responses in the DCE

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

An effect of our nudges can be noticed on this percentage. The proportion of SQ answers without nudge is 54%, whereas it drops to 47.8% and 46.4% for farmers facing the Cocktail and the Testimony nudges, respectively. The direct effect of the conditional subsidy on the proportion of SQ answers appears much 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 attributes, as well as those for the subsidy and the two instruments, are significant and with the expected signs. However, since the conclusion of the Hausman test is that the IIA assumption is not satisfied, we focus on ML models.

In table 4, we report the results of 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 a change in the conditional threshold can affect, or not, the choice of the SQ. In model (4) we assess the global effect of nudges on the choice of the SQ, abstracting from the effects of the threshold of the conditional subsidy. Model (5) combines model (2), (3) and (4).

The positive and significant sign of the *SQ* (alternative specific constant for the status quo) indicates that farmers have a preference for the SQ, *i.e.*, 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 farmer's choices. We obtain that all the coefficients associated to the attributes are significant at 1% and with the expected sign in all models, except for the attribute related to the possibility to receive

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
ll	-5875.8	-5870.6	-5874.6	-5872.5	-5863.9

Standard errors in parentheses

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

information on the other farmers' water consumption. This coefficient is not significant. This result is in line with Chabé-Ferret *et al.* (2019) who have found that providing to farmers an information on water use by peers does not induce any significant change in water use behavior. The absence of significance for the attribute related to the possibility to receive information on the other farmers' water consumption could also be explained by a strong response heterogeneity, as we can see on the standard deviation (SD) part of the table D.1 in Appendix. Respondents have a preference for receiving an alert in case of abnormal water consumption and for the confidentiality of their data (positive and significant coefficient for these two attributes). Moreover, the two levels for the subsidy have positive and significant coefficient, which means that, independently from 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 on farmer's decisions in the DCE. In model (2), relatively to a 50% threshold, the two other thresholds (25% and 75%) do not have a significant effect on the perception of the conditional subsidy regardless of its level (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 noticed that the two nudges induce farmers to significantly choose less often the SQ. This indicates that nudges may be useful as communication tools to give incentive farmers to adopt smart meters.

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 ML estimations per nudge and per conditional subsidy threshold (*i.e.*, for the nine treatments) to assess whether the smart meters attributes have the same effect across the different treatments.

Similarly to the results presented in table 4, we find that the coefficients of the attributes *Alert*, *Confidentiality* and *Price* are significant with the expected signs. Results regarding the possibility to receive information on the other farmers' water consumption are less intuitive. The possibility to receive information on the other farmers' water consumption is 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, in both cases for the 50% reference threshold. The testimony nudge seems to modify farmers' perception regarding this attribute. This may be explained by the content of our nudge: in the testimony, the farmer emphasizes the collective benefits that were made possible thanks to the smart water meters (reduction of counting losses for the local farmers' association, detection of leakages, etc.). Farmers who receive the testimony may perceive the information attribute as necessary to benefit from these advantages.

Table 5: Mixed logit estimations by treatment

	No nudge			Cocktail			Testimony		
	Thresh.25%	Thresh.50%	Thresh.75%	Thresh.25%	Thresh.50%	Thresh.75%	Thresh.25%	Thresh.50%	Thresh.75%
	(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
ll	-550.1	-595.3	-678.1	-793.5	-857.4	-775.5	-510.6	-483.4	-562.5

Standard errors in parentheses

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

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 amount of subsidy (*i.e.*, 600 €). However, the effect of a subsidy of 300 € is significant at a 5% confidence level) only in three treatments out of nine. In addition, these results appear to be independent of the subsidy threshold, which does not seem to influence or discourage the farmers' choice for a smart meter.

Analysis of willingness to pay (WTP)

The interpretation of coefficient estimates in the indirect utility functions is not straightforward except for the significance. One more convenient way is to present the results 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 so to keep their mechanical water meter (see table 6, column "Full sample", SQ variable). To induce adoption of a smart water meter (without any additional service), a farmer should then be paid at least 406 €.

However, when we introduce different smart meters attributes, the WTP becomes positive : 670 € on average if the smart meter includes the *Alert* attribute, 390 € if *Confidentiality* is guarantee on individual data and historic consumption, and 1480 € 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 a nudge "Cocktail". This highlights the importance of these monetary and non-monetary incentives for farmers.

Table 6: WTP for all group estimations

		No nudge			Cocktail			Testimony		
	Full sample	Thres. 25%	Thres. 50%	Thres. 75%	Thres. 25%	Thres. 50%	Thres. 75%	Thres. 25%	Thres. 50%	Thres. 75%
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 a 95%, are computed from table 4, column (1) for the "Full sample" column, and all table 5 for other columns. * if the WTP is significant.

From the results between groups, we observe increasing trends for the WTP estimates for the 75% threshold groups (for the "No nudge" and "Cocktail") and for the nudged groups, compared to the "No nudge" (whatever the threshold). This confirms that nudging can be used as a communication tool to emphasize some 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* for the 75% threshold, combined with the "No nudge", corresponds to a WTP 250% higher than the 25% thresholds group, with confidence intervals that do not overlap. For the *Alert*, we observe the same for the 75% threshold combined with "No nudge".

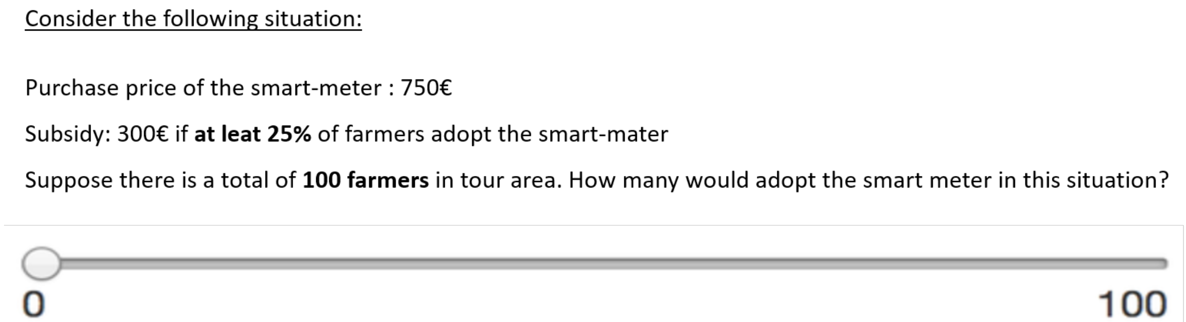
Moreover, the estimated WTP related to the subsidy attribute are, on average, and in most cases, greater than the level of the proposed conditional subsidy (600 €). These figures show that farmers value the subsidy more than its expected value. While the conditional subsidy is doubled, from 300 € to 600 €, on average the WTP estimated are 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 are not significantly different. Even if the 75% threshold is far from most farmers' expected rate of adoption, they value the subsidy quite high.

To summarize, besides demonstrating that farmers do have, on average, a WTP for smart water meters provided that smart meters include some characteristics or services, these results show the interest for policymakers to consider incentive instruments such as nudge and a high conditional subsidy with a high threshold to foster farmers to adopt such a new technology.

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

Our subsidy being conditional on a given threshold, the choice to adopt a smart water meter may depend on farmers' perception that this threshold will be reached. Ultimately, this depends on individual beliefs regarding the number of farmers in their geographical area who will adopt the smart meter: those who believe that many peers will adopt this new technology may be influenced the expected behavior of their peers and thus may choose more often an option with a smart water meter instead of the SQ.

To assess this point, we have measured farmers' beliefs regarding the adoption of smart water meters by other farmers in their sector through three questions in which we vary the threshold. We have proposed a hypothetical situation similar to the ones faced in the DCE where each farmer is asked to provide his beliefs about the proportion of farmers who may 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.


Consider the following situation:

Purchase price of the smart-meter : 750€

Subsidy: 300€ if **at leat 25%** of farmers adopt the smart-mater

Suppose there is a total of **100 farmers** in tour area. How many would adopt the smart meter in this situation?

Figure 3: Script used to elicit beliefs on adoption by other farmers

We present the results in table 7. If we fist consider the mean row in table 7, the farmers belief on average over the three treatments that 27.7 farmers (among 100) will adopt a smart water meter when a 50% threshold is set in the question. This number is quite stable whatever the question (*i.e.*, when we vary the conditional subsidy threshold in the question). It slightly decreases from 28.6 with a 25% threshold to 26.9 for a 75% threshold: the higher is the conditional subsidy threshold, the lower are the beliefs about adoption of the smart water meter by other farmers. However, this difference is no significant. Going further into the analysis, it also appears that, for a given treatment, there is few variations in farmers' beliefs when the threshold changes in the different questions. This is observed in every threshold groups and particularly in the 25% treatment where there is no difference between the answers.

Second, holding constant the threshold set in the belief question (in column), the higher is the threshold in the treatment (in line), the higher are the beliefs about adoption of the smart water meter by other farmers: from 26.1 with a 25% threshold group to 32.9

for a 75% threshold group. This result is 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 table 4, namely that thresholds groups do not seem to matter.

Table 7: Beliefs on adoption of smart water meters by other farmers

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

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' beliefs regarding the norm and, therefore, foster the adoption of smart water meters.

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 technologies on water use, such as smart water meters, allow for a significant improvement of the irrigation and the water use for local water managers.

Therefore, our study aims at : i) assessing the 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 different thresholds of a conditional subsidy and two types of nudges (a cocktail of nudges and a testimony) on French farmers.

We obtain three main takeaways. First, farmers do express, on average, a WTP for smart water meters which include an alert service and data confidentiality, although they have a preference for their 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, regarding the possibility to receive Home Energy Reports with information on the other households' energy consumption, 34% of the respondents stated negative WTP: they dislike receiving information on the others. Second, from a global point of view, both the nudges and the conditional subsidy allow to push farmers to choose more often options with a smart water meter. In particular, the effect of the conditional subsidy does not rely on the conditional threshold. Third, going deeper in our analysis, we show that farmers are not discouraged by a high conditional threshold of 75% compared to lower ones. Besides, this is confirmed with our study of farmers' beliefs regarding their perception of the number of farmers in their sector who would adopt a smart water meter. In terms of public policies perspective, this indicates that regulators have an interest in proposing conditional subsidies with high threshold to encourage a massive adoption of new technologies. Such a conditional subsidy could be completed with a nudge, as we emphasize that the two effects are additive.

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, in our knowledge this is the first discrete choice experiment conducted at the national scale with more than a thousand farmers' responses. This allows 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 has to disseminate information on the benefit and the development of smart water meters (in a specialized journal or information bulletin for example), in order to convince other farmers to do the same.

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 effects related to the conditional thresholds and to the nudges, as we randomly defined treatment groups, the relative response difference between "No nudge" group and the treatments are therefore clearly linked to the instruments. Another limitation deals with the subsidy cost. Given the public good dimension of the smart meter, the subsidy we proposed is financed by the regulator. However, with a subsidy of 600 € per farmers and an adoption threshold of 75%, the total amount to pay could be quite high in the sectors where that threshold is indeed reached. Thus the amount and the threshold of the conditional subsidy must be defined.

We conclude with directions that can be taken in future research. Further research is needed to explore other incentive instruments on smart water meters' adoption. Indeed, in a free riding context, two monetary incentives tools can be used, a subsidy to reward the voluntary adoption of smart meter and a tax to punish free riding behavior. In this work we choose to test the subsidy in the case of the adoption of 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 costs scenarios (varying price and conditional subsidy) has to be conducted to conclude on targeted incentive instrument.

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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 the water consumption 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 work usually through two-way communication via a wireless communications network. Data regarding real-time water consumption are transmitted to each farmer through the internet platform, and this information is usually also available to the water manager allowing to manage more efficiently water resources for instance though a better planning of water releases.

[3]There are some empirical evidence of the positive impact of using smart meter 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 photo is hidden for the dissemination of the article but his face was visible in the questionnaire.

[7]Randomization tests on the nine treatments are done and 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 is an environmental challenge and a shortfall for agriculture.

1. In that context, is water management important to you? (*“Yes, totally”*, *“Rather yes”*, *“Rather no”*, *“Totally not”*)

2. Would you be willing to commit to better management of the water resource? (*“Yes, totally”*, *“Rather yes”*, *“Rather no”*, *“Totally not”*)

In territories that are already equipped, smart meters allow for better management of water resources thanks to the precision and frequency of the records. 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 sector.

"Since we have installed smart meters in our sector, this has allowed us to significantly reduce counting losses for our local farmers’ association, we have gone from 15% to 20% of annual losses to 3% today, which is about 15 000 euros of revenue for the association. Indeed, not only the smart meters are 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 (per treatment)

		Nudges			
		No nudge	Cocktail	Testimony	Total
Conditional subsidy	Threshold 25%	50.5%	47.6%	45.1%	47.8%
	Threshold 50%	55.1%	48.1%	49.7%	50.8%
	Threshold 75%	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.300xThresh.25%		0.128			-0.0102
		(0.101)			(0.131)
Subs.300xThresh.75%		0.0382			0.0137
		(0.100)			(0.130)
Subs.600xThresh.25%		0.0295			-0.0869
		(0.081)			(0.107)
Subs.600xThresh.75%		0.0456			0.0319
		(0.079)			(0.105)
SQxThresh.25%			-0.112*		-0.144
			(0.057)		(0.087)
SQxThresh.75%			-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
ll	-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.300xThresh.25%		-0.547			-0.779***
		(0.443)			(0.274)
Subs.300xThresh.75%		0.765***			0.787***
		(0.297)			(0.283)
Subs.600xThresh.25%		0.674***			0.547*
		(0.241)			(0.305)
Subs.600xThresh.75%		-0.588**			-0.510
		(0.294)			(0.337)
SQxThresh.25%			-0.445		1.106***
			(0.419)		(0.356)
SQxThresh.75%			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
ll	-5875.8	-5870.6	-5874.6	-5872.5	-5863.9

Standard errors in parentheses

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