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Adoption of modern irrigation technologies in the presence of water theft and corruption: evidence from public irrigated areas in Medjez-el-Bab

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ABSTRACT

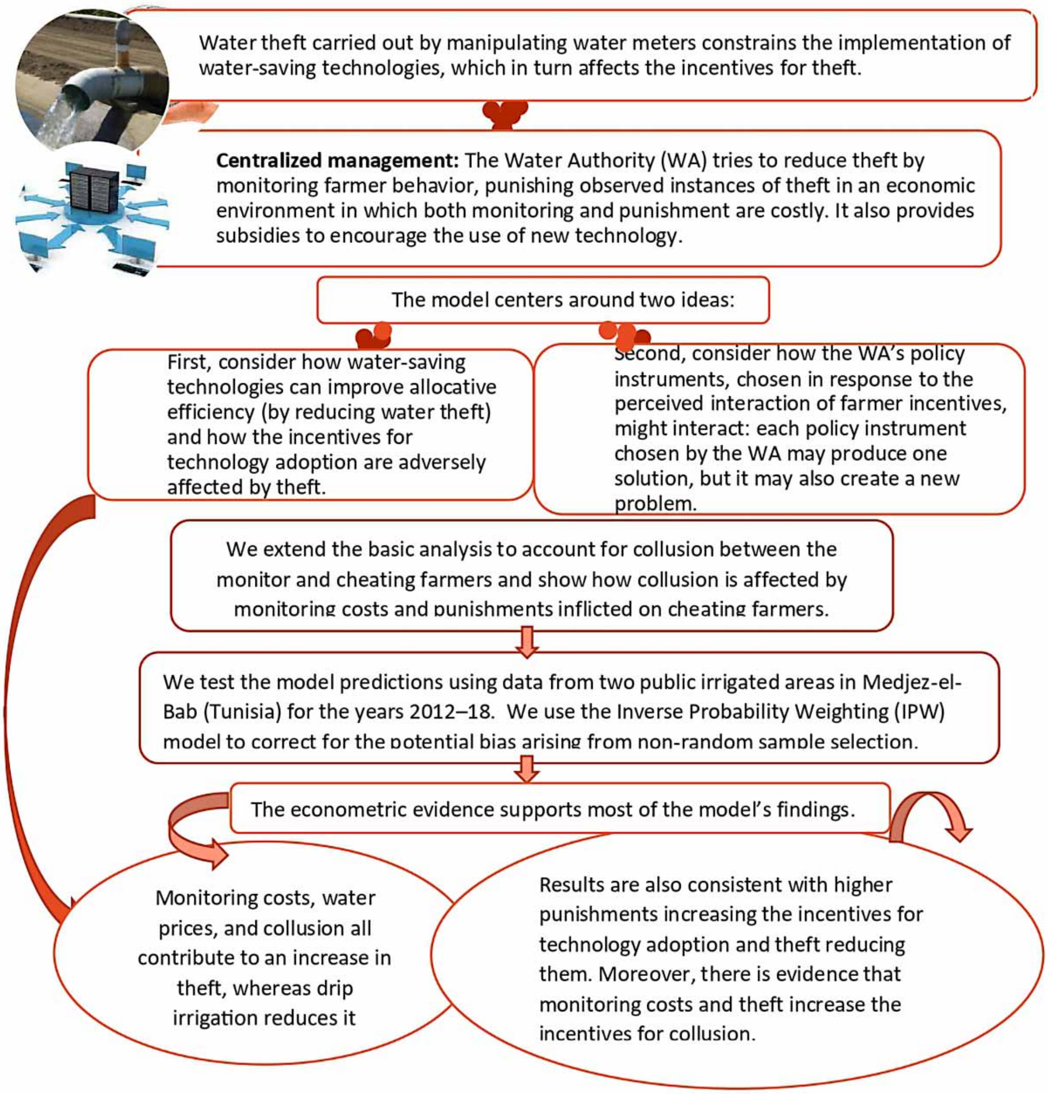
Water theft carried out by manipulating water meters constrains the implementation of water-saving technologies, which themselves affect the incentives for theft. Using a theoretical model of centralized management, we show that theft is more likely when water prices and monitoring costs are high and punishment levels are weak. Adoption of water-saving technologies is more likely when monitoring costs are low and water prices are high, though only within the range of low to medium prices. The basic analysis is extended to allow for collusion between cheating farmers and the monitor. In the model, we show that collusion is more likely when punishments are weak. We test the model predictions, using data from Tunisia for the years 2012–18, relying on instruments that proxy for unobservable monitoring costs. We use the inverse probability weighting (IPW) method to correct for the potential bias arising from non-random sample selection. Although the econometric evidence supports the majority of the theoretical findings, various economic, socioeconomic, physical, and geographical factors can counteract or supplement these effects.

Key words: Centralized water management, Collusion, Inverse probability weighting, Tunisia, Water-saving technology, Water theft

HIGHLIGHTS

- The adoption of water saving-technologies under moral hazard (the farmer's intake is her private information).
- The interaction of regulatory instruments designed to reduce the moral hazard behaviour of farmers and those to encourage technology adoption, in the sense that instruments aimed at mitigating moral hazard issues also affect technology adoption incentives and vice versa.
- Collusion between farmers and monitors and how this collusive behaviour influences the incentives for technology adoption.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Irrigation water is one of the most ill-managed resources, especially in the developing world. Methods of allocating water are sensitive to issues including scarcity, informational and environmental problems, institutional and political settings, and the presence of externalities, making it necessary to design allocation mechanisms accordingly. Pricing mechanisms and the adoption of water-saving technologies have received growing attention as major irrigation demand management tools. However, their implementation may be constrained by problems, including asymmetric information with regard to farmer intakes, which may be endogenous to decisions on pricing and technology adoption.

When farmers are in a position to steal water, typically by manipulating water meters,[1] pricing policies may not only fail to encourage conservation, but they may even increase the incidence of theft itself. In the presence of theft, optimal pricing rules need to be adjusted, and prices will typically be lower than in its absence: it is worth tolerating some allocative inefficiency in water use in return for a lower incidence of theft (Mattoussi & Seabright, 2014). This finding raises a relevant question on whether water theft is also a constraint on the adoption of water-saving technologies.

In this study, we examine how water allocative efficiency can be improved in the face of moral hazard through interlinkage[2] (Braverman & Stiglitz, 1982; Ghatak & Pandey, 2000). Specifically, can water allocative efficiency (by reducing water theft) be improved with the use of water-saving technologies?

We develop a model of centralized management where the Water Authority (WA) designs a policy scheme to reduce theft and encourage technology adoption. The WA tries to reduce theft by monitoring farmer behaviour and punishing observed instances of theft in an economic environment in which both monitoring and punishment are costly. Adopting the new technology incurs a fixed cost, and farmers may choose to not adopt it if the perceived gains from adoption do not outweigh the costs. Then, the WA is compelled to design subsidy schemes to encourage such adoption.

The model centres around two novel ideas: First, how do the incentives for adopting water-saving technologies interact[3] with those for water theft? Specifically, how theft can be reduced by the use of water-saving technologies and how the incentives for technology adoption are adversely affected by theft. Second, how the WA's policy instruments, which were chosen in response to the perceived interaction between farmer incentives, may interact: each policy instrument chosen by the WA may offer one solution, but it is also possible that it may create a new problem. We show this by comparing two settings: One in which the farmer has sufficient incentives to adopt new technology on her own and one in which she does not. We show that theft (resp. technology adoption) is more likely when monitoring costs are high (low) and punishments are weak (large). To the extent that punishments and monitoring costs affect the incentives for theft and technology adoption in the opposite direction, one should realize that theft would reduce the incentives for technology adoption.[4] We also show that technology adoption increases with the price of water, but only in the low to medium price range.

We extend the basic analysis to investigate the problem of regulatory capture when monitoring responsibility is delegated to monitors whose expertise allows them to hide information from the WA in order to collude with farmers. We show that collusion is more likely when punishments are weak. However, collusion may increase or decrease with theft and monitoring costs depending on the monitor's prior beliefs about the likelihood of being caught. To the extent that factors affecting the incentives for technology adoption, such as punishment and monitoring costs, also affect collusion, we can expect to see the likelihood of collusion empirically as a function of the incentives for technology adoption.

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[1] See Mattoussi & Seabright (2014) for the distinction between the notion of water theft here and that in the model of Azam & Rinaudo (2000).

[2] In this strand of literature, studies consider the possibility of more than one input affecting the distribution of output, and one of the inputs is contractible, while the other input is not. They show why the principal might want to subsidize or tax the contractible input to induce the agent to choose higher levels of the non-contractible input depending on whether they are complements or substitutes in production.

[3] Theft interacts with technology adoption in two ways. First, technology adoption directly affects theft by increasing the ease of detection; for example, the settings of systems as drips and sprinklers may more easily reveal the amount of water being used. Second, the expected incidence of theft may reduce the farmer's willingness to adopt new technologies; so why adopt (expensive) new technology to reduce the cost of a resource the farmer does not expect to pay for anyway.

[4] This is a partially intuitive result, given that we have shown in our model that technology adoption is affected by water price, punishment, and monitoring costs. To illustrate that theft had an impact on adoption, we have to make an extra *ad hoc* assumption (assumption 6).

Testing hypotheses about the determinants of theft, technology adoption, and collusion is a major empirical challenge since the various incentives reinforce each other or interact in a competing way. This would undoubtedly raise endogeneity problems in our empirical analysis. Our procedure is to use theory to focus attention on the underlying determinants of farmer's behaviour. Then, the theory then guides our search for proxies for unobserved variables and instruments for observed but endogenous variables that enable us to identify the appropriate causal relationships in data from Tunisia for the years 2012–18. Datasets have a problem with missing values due to non-response. We use the inverse probability weighting (IPW) model to adjust for disproportionate non-response and restore the representativeness of the sample.

We find that a variable that plausibly proxies for monitoring costs can influence theft and technology adoption, in the sense that higher monitoring costs make theft easier and technology adoption less likely to occur. The econometric findings are consistent with the hypotheses that water price increases theft, and both prices and punishments increase the incentives for technology adoption. There is also support for the positive effect of monitoring costs on theft and collusion. Moreover, collusion increases theft, which in turn reduces the incentives for technology adoption. Nevertheless, other economic, socioeconomic, physical, personal, and geographical factors are also relevant for farmer decisions, and some of these factors are considered here.

The article is structured as follows. In Section 2, we review the relevant literature. Section 3 sets out our model. We start with the analysis of the asymmetric information setting, in which we stated three propositions describing the interaction between farmer incentives for theft and technology adoption, as well as between policy instruments in response to the perceived interaction between the farmer's incentives.

Comparative statics are derived in Section 4. In Section 5, we extend the basic analysis to allow for collusion between cheating farmers and the monitor. We use propositions derived in previous sections to make predictions that can be tested empirically. Section 6 describes our data and tests theoretical predictions, and Section 7 concludes.

2. LITERATURE REVIEW

Our study partially relates to the research on the introduction of innovations that save on water use or limit the undesirable environmental effects of agricultural production. There is extensive literature aimed at explaining the process of adoption of modern irrigation technology. According to these studies, the main determinants of adoption are the cost of the technology (Abdulai *et al.*, 2011; Daia *et al.*, 2015), water costs (Foltz, 2003; Raffaele & Severini, 2009), age (Torkamani & Shajari, 2008; Chuchird *et al.*, 2017), education (Huffman, 2001; Herath & Takeya, 2003; Staal *et al.*, 2003), gender (Doss & Morris, 2001; Ndiritu *et al.*, 2014), farmer's risk aversion (Torkamani & Shajari, 2008), type of water source (Caswell & Zilberman, 1985), farm size (Negri & Brooks, 1990; Schuck *et al.*, 2005; Jara *et al.*, 2012), quality of cultivated land (Caswell & Zilberman, 1986; Dinar & Zilberman, 1991; Green *et al.*, 1996), farmer's experience, labour force availability, (land) tenure arrangements (Bahduri, 1973; Bhaduri & Nodir, 2015; Salazar & Rand, 2016), policy subsidies, government support (Dinar, 1992), access to information, training, on-farm demonstration (Rezadoost & Allahyari, 2014; Zhang *et al.*, 2019), membership in an extension service (Abdulai *et al.*, 2005; Blanke *et al.*, 2007; Salazar & Rand, 2016), government promotion, labour and learning costs associated with the technology usage (Daia *et al.*, 2015), water storage problems and problems with destructive wildlife (Friedlandera *et al.*, 2013), degree of water scarcity (Ruttan & Hayami, 1984; Blanke *et al.*, 2007), production risk (Koundouri *et al.*, 2006; Torkamani & Shajari, 2008; Salazar & Rand, 2016), liquidity constraints (Foltz, 2003; Salazar & Rand, 2016), and input and output prices (Feder *et al.*, 1985; Caswell *et al.*, 1990; Feder & Umali, 1993).

Key elements related to institutional factors associated with credit services, training, on-farm demonstrations, and extension services, which all play a role in adoption decisions. Farmers are more reluctant to invest in costly new technology due to financial constraints, particularly limited access to credit markets (Foltz, 2003; Salazar & Rand, 2016). Appropriate government backing and policy subsidies may override these financial considerations (Dinar, 1992; Zhang *et al.*, 2019). In addition, there are risks associated with new technology, including the cost of the technology (Abdulai *et al.*, 2011; Daia *et al.*, 2015) and learning costs incurred by the necessity of adapting new technologies to the local conditions in order to get the most benefit from them (Foster & Rosenzweig, 1995; Daia *et al.*, 2015). More exposure to appropriate information through various communication channels increases farmers' skills and knowledge about the usage of the technology. The information to which the farmer is exposed might come from training in agricultural water management, on-farm demonstrations organized by the extension service or other agencies (Zhang *et al.*, 2019), and from extension services (Abdulai *et al.*, 2005; Blanke *et al.*, 2007; Salazar & Rand, 2016).

Economic factors, including water costs and output prices, affect adoption decisions in that farmers are more inclined to invest in water-saving technologies when they have to face the full cost of their water use (Foltz, 2003; Raffaele & Severini, 2009). However, these technologies would not be adopted if output prices were not high enough to overcome the high sunk costs associated with adoption (Feder *et al.*, 1985; Caswell *et al.*, 1990; Feder & Umali, 1993).

In relation to farmers and farm characteristics, human capital, including age and education, is a potential factor in the adoption of new technology. More educated farmers are more inclined to adopt the technology, as they should easily understand its application and benefits (Huffman, 2001; Herath & Takeya, 2003; Staal *et al.*, 2003). Adoption has a negative correlation with age. Older farmers, who are less educated in general than younger farmers, are less likely to invest in technology (Torkamani & Shajari, 2008). Chuchird *et al.* (2017) found that older farmers preferred traditional irrigation technology due to its ease of use, while their younger counterparts were more inclined to adopt modern irrigation technology, probably due to their familiarity with mechanization (the motorized machinery and pumps).

Empirical studies suggest gender-linked differences in the adoption of new technologies (Doss & Morris, 2001; Ndiritu *et al.*, 2014), owing to socioeconomic inequalities and hurdles for female farmers. Furthermore, farmers' preferences towards risk seem to affect their adoption decisions. Farmers that are more risk-averse with respect to their water use are more inclined to adopt modern irrigation methods, which allow them to save water while also decreasing production risk by reducing production yield variability (Torkamani & Shajari, 2008). A factor that may explain a relationship between farm size and adoption decisions is the existence of fixed transaction costs and information acquisition costs associated with the new technology. As these costs increase, the critical farm size that makes the adoption profitable also increases. This suggests that new technologies are less likely to be adopted by small farmers (Negri & Brooks, 1990; Schuck *et al.*, 2005; Jara *et al.*, 2012).

Tenure arrangements that characterize the relationships between landlords on the one hand and tenants and rental contract holders on the other, may affect the adoption choice. Short-term rental contract holders and small tenants may have fewer incentives to invest in new technologies because they will not reap the long-term benefits of such an investment (Bahduri, 1973; Bhaduri & Nodir, 2015).

Labour availability is another often-mentioned variable that may influence adoption decisions. One of the major purposes of farm mechanization is to alleviate labour bottlenecks. As new technology is labour-saving, its adoption might be encouraged by labour shortage (Bhaduri & Nodir, 2015).

Environmental factors seem to play a significant role in adoption decisions. New irrigation methods have numerous advantages in rural zones with limiting environmental conditions such as the degree of water scarcity and poor soil quality. Irrigation prices would rise, as a resource became scarcer, driving farmers to cut water use by switching to water-saving technologies (Ruttan & Hayami, 1984; Blanke *et al*., 2007). New irrigation systems lower the water-holding capacity of land with poor soil quality (Caswell & Zilberman, 1986; Dinar & Zilberman, 1991; Green *et al*., 1996). Furthermore, increasing the consistency and flexibility of water sources boosts adoption rates as a means of improving productivity and quality of production through more uniform and accurate irrigation (Caswell & Zilberman, 1985).

Furthermore, technical issues such as water storage and damage caused by destructive animals (which can range from complete system destruction by marauding elephants to system hardware loss due to chewing by vermin (rats and other rodents) or hyenas) are the primary reasons for drip system disadoption in Sub-Saharan Africa (Friedlandera *et al*., 2013).

One key factor that has received little attention in the literature is the role of production risk in shaping the incentives for adopting new technology (Foster & Rosenzweig, 2010). Three exceptions are Koundouri *et al.* (2006), Torkamani & Shajari (2008), and Salazar & Rand (2016). Production risk increases the adoption of new technology as a risk-decreasing input, because the technology may possibly minimize reliance on rainfall and water availability, which provides improved yield stability (Koundouri *et al*., 2006; Torkamani & Shajari, 2008). However, Salazar & Rand (2016) found that production risk causes a shift from non-irrigation to the adoption of traditional technology that supports decreasing-risk properties of irrigation, while their findings on modern irrigation technologies are inconsistent with previous studies' findings on new technology's ability to hedge against production risk.

Despite the relevance of asymmetric information problems for water management, only a few studies examine the application of such concepts to irrigation water in general and to the adoption of water-saving technologies in particular. To the best of our knowledge, only Dridi & Khanna (2005) explored the role of informational problems in shaping the incentives for adopting water-saving technologies, and their results suggest that adverse selection issues reduce such incentives. The authors also show that allowing for water trade has the potential to mitigate some of the inefficiencies due to adverse selection without inducing further budgetary strain on the regulator, while inducing more modern technology adoption.

Our study differs from existing literature on the adoption of modern irrigation technology in several ways. First, the largest body of the literature has focused on analysing adoption decisions under perfect information, except for Dridi & Khanna (2005). Second, neither of these research has examined the incentives for adoption in the face of moral hazard when the farmer's water consumption is her private information. Third, neither of these studies analysed how regulatory instruments designed to reduce the moral hazard behaviour of farmers and those to encourage technology adoption might interact, in the sense that instruments aimed at mitigating moral hazard issues also affect technology adoption incentives and vice versa. Fourth, neither of the previous research has addressed the problem of collusion between farmers and monitors and how this collusive behaviour influences the incentives for technology adoption.

3. THE MODEL

Our model is a deliberately simplified structure designed to capture some features of real-world irrigation water management while abstracting from others. We take as given these features without enquiring into their optimal properties, and use them to determine how the agents operating within them would attempt to optimize, and whether they do so efficiently subject to their constraints. In particular, we shall consider a logistic production function, which according to several studies in botany including (McMartin, 1979; Gregeorczyk, 1994; De Souza *et al*., 2012; Wardhani & Kusumastuti, 2013) adequately describes the pattern of most plants' growth. In this, a period of fast growth can change to one of slow growth at a defined point where saturation begins (the inflection point), and growth stops at maturity.

Consider a risk-neutral farmer who produces homogeneous farm good using water as an input. The yield (y) response to water (q) can be described by the relation $y = g(q;\beta)$. Here, $g(.;\beta)$ is a *logistic* function[5] (a detailed discussion of this specification with graphic representations through three figures appear in the Supplementary Appendix).

$$g(q;\,\beta) = \frac{1}{d + e^{-\beta q}} \tag{1}$$

where $0 < d < 1$ and β is a technological parameter taking on two values $\{\bar{\beta}, \underline{\beta}\}$ with $\bar{\beta} > \underline{\beta}$. Here, $\bar{\beta}$ represents old technology (such as furrow and flooding irrigation) and $\overline{\beta}$ represents new technology (such as drips and sprinklers). New technology incurs a fixed cost C_T and the cost of the old technology is normalized to 0. The (private) cost incurred by the farmer for using water, measured in units of output, is c per unit of water. In addition, the farmer pays a linear price t per unit of water used, which is set by the Ministry of Agriculture. The farmer can choose the quantity of water that maximizes her net return from water application, equal to $g(q;\,\beta) - (c+t)q$ and $g(q;\,\bar{\beta}) - (c+t)q - C_T$ when old and new technologies are used, respectively. The profit-maximizing quantity of water for technology β equates the marginal value product of water[6] to the marginal cost of generating such a quantity:

$$q(\beta){:}g_q(q;\,\beta) = c + t \tag{2}$$

3.1. Asymmetric information[7]

In this section, water use and technology adoption are unobservable to the WA and hence cannot be contracted for[8]. The farmer who is equipped with an individual water meter can send a report, $q^r(\beta)$, which may differ from the true quantity $q(\beta)$ when technology β is used. We denote the amount of water stolen as $a(\beta) = q(\beta) - q^r(\beta)$, and assume that there are no rewards for over-reporting. In what follows, a few assumptions necessary to the analysis are listed.

Assumption 1: The WA can commit, before the farmer chooses her actual and reported water uses, to monitoring level m at cost $\psi(m)$, which is increasing and strongly convex[9] (i.e., $\psi'''(m) > 0$ in addition to $\psi''(m) > 0$) and satisfies $\psi(0) = 0$.

Assumption 2: Monitoring cannot be conditioned on the farmer's report[10] and must be the same for all reports. If the farmer is not monitored, she pays the mandated fee associated with her report, $tq^r(\beta)$. Otherwise, she may be

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[5] A more general production function does not provide clear insights into whether new technology saves water consumption when compared to older technology because there is no explicit expression of water use in equilibrium (and thus the level of theft) that allows for meaningful comparison and analysis.

[6] We implicitly assume that the farm good price is normalized to 1.

[7] In the absence of asymmetric information, and abstracting from any shadow cost of public funds that might imply Ramsey pricing considerations, the WA can implement the first-best efficient outcome by setting t equal to γ (here, γ represents the full public cost of resource provision, including operation and maintenance costs, investment costs, extraction externalities associated with pumping from a shared aquifer, and any shadow cost associated with water scarcity).
New technology is socially beneficial in the first best world only when efficiency gains outweigh adoption costs; that is, $W^{FB}(\bar{\beta}) - W^{FB}(\underline{\beta}) \geq C_T$, where $W^{FB}(\beta) = g(q^{FB}(\beta);\,\beta) - (c+\gamma)q^{FB}(\beta)$.

[8] While it seems plausible to assume that water use cannot be contracted for, the case for technology adoption is less strong and needs more justification. The type of technology used can be verified through visits to farmers' lands. This might be highly expensive, especially if there are a lot of farmers growing a wide variety of crops and employing various irrigation systems.

[9] The strong convexity of ψ is driven by the complexity and difficulty of assessing the true farmer's intake. In addition, from a technical standpoint, this assumption may ensure an interior solution to the problem.

[10] Unlike the tax evasion literature (where it is quite plausible to condition auditing on individuals' reports since individuals' incomes are fixed and lower reports well indicate higher evasion rates), in our model, farmers use different water levels, and therefore several scenarios can be

discovered stealing with a probability $P(m,a(\beta);\beta)$, which increases with monitoring and with her level of theft. To simplify the exposition, the probability $P(.)$ is assumed to be commonly known and takes the form

$$P(m, a(\beta), \beta) = \kappa(\beta) m \max[\alpha(\beta), 0], \quad (3)$$

where $\kappa(\beta) > 0$ (we assume, henceforth, that it is sufficiently small to generate an interior solution, which is realistic).

Assumption 3: When the farmer is detected stealing, her true intake is established without error and she pays $tq^r(\beta)$ plus a punishment measured in terms of the time length for which water is cut off from her. This time is proportional to her level of theft. Punishment takes the form

$$\bar{f} = f \max\{\alpha(\beta), 0\}, \quad (4)$$

where f is positive and greater[11] than t.

Assumption 4: Inflicting punishment f is costly, we denote by $\phi(f)$ the associated cost that can be either pecuniary or manifest in nature when the farmer resists closing her meter(s). $\phi(f)$ is increasing and strongly convex[12] (i.e., $\phi'''(f) > 0$ in addition to $\phi''(f) > 0$), and satisfies $\phi(0) = 0$.

Assumption 5: New technologies such as drips and sprinklers may make it easier to detect theft and perform monitoring. Two kinds of anecdotal evidence make us think this is a plausible assumption. First, many farmers can be observed using water in ways that seem inconsistent with their facing full prices (for example, placing rotating sprays at the corners of fields, where only one-quarter of the emitted water falls on the land being irrigated). Second, placing drips far away from the plant lines or seeing salt residue around plant roots indicates that carelessness is involved. Following a learning phase of how new technologies work, their use involves less effort and time and may increase the farmer's flexibility to irrigate at any time, particularly when activity is less intensive (i.e., at dawn or late in the night). On the one hand, irrigation at specific (low-activity) time windows may increase the likelihood of theft since inspections are expected to be less frequent. On the other hand, this may increase the monitor's ability to detect theft. To abstract the benefits of new technologies, we define a monitoring advantage parameter and a new monitoring cost as $\lambda\psi(m)$, with $0 \le \lambda \le 1$.

Assumption 6: $\overline{\kappa} > \underline{\kappa}$. New technologies increase the ease of detection (the same arguments as in assumption 5 hold here).

Assumption 7: $c + \gamma \le (\bar{\beta}/4d)$, where $0 < d < 1$. This states that both new and old technologies are privately profitable. The farmer decides which technology to use by comparing the utility level generated by each of them.

Assumption 8: $\bar{\phi}(c+\gamma) > \phi(\mathrm{Ind}/\beta)$, where $\bar{\phi} \equiv (\bar{g}_q)^{-1}$ and $\underline{\phi} \equiv (\underline{g}_q)^{-1}$. This means that for both new and old technologies, the second partial derivative of the production function is negative; that is, $g_{qq}(q, \beta) < 0$, for $\beta \in \{\underline{\beta}, \bar{\beta}\}$. The analysis is restricted to the second phase of the plant's growth (where saturation begins and growth slows) because it is the longest and most significant phase in the growth process. Furthermore, from a

envisaged. Farmers with varied amounts of theft can file the same report. Farmers can steal the same amount of water but file different reports, and even more, farmers who file lower reports may steal less water than those who file higher reports.

[11] The punishment rate f is assumed to be greater than t because otherwise the farmer will always have an interest in stealing everything. The net return of theft is equal to $(t - \kappa mfa)a$, with the probability $\kappa ma < 1$. If $f < t$, one obtains $\kappa maf < f < t$, and theft is strictly beneficial. This essentially implies that the net return is maximized when the farmer steals everything.

[12] The strong convexity of ϕ is driven by the increased difficulty of enforcing stringent punishments. In this context, the nature of punishment damages harvest (s). The more the severity of the crop the farmer will lose, and hence, the greater her resistance to punishment implementation.

technical standpoint, the production function is concave at this stage, which may ensure the existence of a solution.

The WA may wish to subsidize the farmer for adopting new technology by the amount $S(\alpha) = \alpha C_T$, where $\alpha \in [0,1]$ is the subsidization rate.

Let $\Sigma = \{m, f, \alpha\}$ be the set of regulatory instruments used by the WA (taking the price of water for given). Treating the WA's mechanism parametrically, the farmer derives the utility

$$u(q, q^r; \Sigma, \underline{\beta} \equiv \underline{u}(q, q^r; \Sigma) = g(q) - cq - tq^r - \underline{\kappa} mf\,(q - q^r)^2, \tag{5}$$

if she uses old technology, and the utility

$$u(q, q^r; \Sigma, \bar{\beta} \equiv \bar{u}(q, q^r; \Sigma) = \bar{g}(q) - cq - tq^r - \bar{\kappa} mf\,(q - q^r)^2 - C_T + S(\alpha), \tag{6}$$

if she switches to new technology.

The social welfare function associated with the use of new technology is the sum of the farmer and water supplier surpluses, $\bar{u}(q, q^r; \Sigma)$ and $[tq^r - \gamma q - (1 + \eta_s)S(\alpha) - \lambda\psi(m) - \varphi(f)]$, where $\eta_s \geq 0$ is the transaction cost of subsidy implementation. Specifically, this function is

$$\bar{W}(\Sigma) = \bar{g}(q) - (c + \gamma)q - \bar{\kappa} mf(q - q^r)^2 - (1 + \eta_s \alpha)C_T - \lambda\psi(m) - \varphi(f) \tag{7}$$

where $\eta_s \alpha C_T$ is the social cost of technology adoption.

The order of events in this game is that the WA sets m, f, and α, then every farmer chooses whether to adopt new technology and chooses the quantity of water to use, q and to report, q^r. Once monitoring takes place the technology used becomes publicly observable, subsidies, if any, are paid and payoffs are realized. In what follows, we focus on the subgame perfect equilibrium and solve the model by straight backward induction. In stage 2, for a given technology, β the farmer chooses $q^*(\beta)$ and $q^{r*}(\beta)$ to maximize her expected payoff, that is:

$$\max_{(q, q^r)} u(q, q^r; \Sigma, \beta)$$

whose first-order conditions with respect to q and q^r are given, respectively, by:

$$g_q(q^*(\beta); \beta) = c + 2\kappa(\beta) mf[q^*(\beta) - q^{r*}(\beta)] \tag{8}$$

and

$$t = 2\kappa(\beta) mf[q^*(\beta) - q^{r*}(\beta)]. \tag{9}$$

Rewriting (9) gives the optimal level of theft:

$$\alpha^*(\beta) = \frac{t}{2\kappa(\beta) fm} \tag{10}$$

Obviously, this level is not directly influenced by water productivity but only by such variables as monitoring, water pricing, and punishments. Water use is, of course, affected by productivity, but theft is the difference between actual water use and the reported one. Clearly, an increase in punishment and monitoring reduces theft. However, the impact of water prices is ambiguous as they affect theft directly in a theft-increasing manner and indirectly through their influence on monitoring and punishments.

It immediately follows from the optimal level of theft undertaken by a farmer (10) and assumption (6) that new technology does reduce theft because it increases the ease of detection, that is:

$$\bar{\alpha}^* < \underline{\alpha}^* \tag{11}$$

One may then expect policy instruments chosen in response to a perceived interaction between theft and technology adoption to interact. Monitoring and punishments, primarily designed to reduce theft, may influence the incentives for technology adoption as well.

We denote by $u^*(\Sigma, \beta) \equiv u(q^*, q^{r*}; \Sigma, \beta)$ the farmer's maximum utility associated with the use of technology β when she faces the WA's scheme, Σ. By using (9) and (10), we rewrite the inequality that makes the farmer better off by switching to new technology, $\bar{u}^*(\sum) \geq \underline{u}^*(\sum)$ as

$$G(t) - L(m, f, t) \geq (1 - \alpha)C_T \tag{12}$$

where $G(t)$ represents *efficiency gains* in water use generated by the new technology,

$$G(t) \equiv [\bar{g}(\bar{q}^*) - (c + t)\bar{q}^*] - [\underline{g}(\underline{q}^*) - (c + t)\underline{q}^*] > 0 \tag{13}$$

$L(m, f, t)$ represents the farmer's *utility cost*[13] associated with reduced opportunities for theft from switching to new technology,

$$L(m, f, t) \equiv \frac{1}{4}\left(\frac{1}{\underline{\kappa}} - \frac{1}{\bar{\kappa}}\right)\frac{t^2}{fm} > 0 \tag{14}$$

The existing literature has always assumed that new technologies are socially desirable, and we follow this tradition here. At stage 1, the WA anticipates the farmer's behaviour when designing its policy scheme Σ and optimally solves

$$\bar{\Sigma}^* \in \arg\max_{\Sigma} \bar{W}(\Sigma)$$
$$\text{s.t.} \quad \bar{u}^*(\Sigma) \geq \underline{u}^*(\Sigma) \; (P_{\text{new}})$$

We analyse the WA's problem in two economic situations: when the farmer makes strictly higher profits by adopting new technology on her own and when she does not.

3.1.1. Technology adoption is privately profitable

When constraint (12) is strictly satisfied, it can be omitted in the problem (P_{new}). We can then show:

Proposition 1: Suppose that assumptions (6), (7), and (8) hold and constraint (12) is slack. Then, the second-best policy scheme is such that $\alpha_0^* = 0$ and (m_0^*, f_0^*) solves

$$m_0^*: \frac{t^2}{4\bar{\kappa} f_0 m_0^2} = \lambda \psi(m_0) \tag{15}$$

[13] $L(m, f, t)$ is the difference between the expected benefit from theft associated with the old technology and that associated with the new one: $L(m, f, t) \equiv B_n(m, f, t, \underline{\beta}) - B_n(m, f, t, \bar{\beta})$, where $B_n(m, f, t, \beta) = [t - \kappa(\beta) m a^*(\beta) f] a^*(\beta)$. Rearranging this expression gives equation (14) in the text.

and

$$f_0^*: \frac{t^2}{4\bar{\kappa} m_0 f_0^2} = \varphi'(f_0) \tag{16}$$

Proof: See the Supplementary Appendix.

The WA does not use subsidies and relies entirely on monitoring and punishment because it only faces the problem of *water theft*. Proposition 1 says that some monitoring and punishment are always required in equilibrium. However, because these two instruments are costly, the optimal response of the WA is to tolerate some theft in order to save on its regulatory instrument costs.

3.1.2. Technology adoption is privately unprofitable

Here, we solve for the WA's problem, when constraint (12) binds. Proposition 2 summarizes the solution.

Proposition 2: Suppose that assumptions (6), (7), and (8) hold, then the WA uses the policy scheme $\{m_1^*, f_1^*, \alpha_1^*\}$ which solves

$$m_1^*: \frac{t^2 z}{4 m_1^2 f_1} = \lambda \psi'(m_1) \tag{17}$$

$$f_1^*: \frac{t^2 z}{4 m_1 f_1^2} = \varphi'(f_1). \tag{18}$$

and

$$\alpha_1^* = 1 - \frac{G(t) - L(m_1^*, f_1^*, t)}{C_T} > 0, \tag{19}$$

where

$$z = \left[(1-\eta_s)\frac{1}{\bar{\kappa}} + \eta_s \frac{1}{\underline{\kappa}}\right] > 0$$

Proof: See the Supplementary Appendix.

Comparing the WA's optimal schemes in terms of monitoring and punishment in the binding setting (described by Equations (17) and (18)) and in the non-binding one (described by Equations (15) and (16)) sheds light on the potential interaction between regulatory instruments. As these two settings do not give explicit expressions of monitoring (m_1 and m_0) and punishments (f_1 and f_0), we resort to the particular quadratic functions, $\psi(m) = (1/3)bm^3$ and $\varphi(f) = (1/3)\omega f^3$, where $b > 0$ and $\omega > 0$ denote monitoring and punishment enforcement transaction costs, respectively.

Lemma 1: Suppose that assumptions (6), (7), and (8) hold, then, we have

$$m_0^* = \left(\frac{t^6 \omega}{64 \kappa^{-3} \lambda^4 b^4}\right)^{\frac{1}{15}} \quad \text{and} \quad m_1^* = \left(\frac{t^6 z^3 \omega}{64 \lambda^4 b^4}\right)^{\frac{1}{15}} \tag{20}$$

$$f_0^* = \left(\frac{t^4 \lambda b}{64 \kappa^{-3} \omega^4}\right)^{\frac{1}{15}} \text{ and } \quad f_1^* = \left(\frac{t^4 z^3 \lambda b}{64 \omega^4}\right)^{\frac{1}{15}}; \tag{21}$$

$$\alpha_0^* = 0 \quad \text{and} \quad \alpha_1^* > 0; \tag{22}$$

and

$$m_1^* > m_0^*, f_1^* > f_0^* \quad \text{and} \quad \alpha_1^* > \alpha_0^* \tag{23}$$

Proof: See the Supplementary Appendix.

Increased monitoring and punishment reduce theft while also encouraging technology adoption. Alternatively, more effective subsidy schemes are required to encourage the adoption of water-saving technologies, thereby indirectly reducing the incentives (and need) for theft.

4. COMPARATIVE STATICS

To obtain explicit solutions, where possible, we assume that monitoring and punishment costs take the following quadratic forms, $\psi(m) = (1/3)bm^3$ and $\varphi(f) = (1/3)\omega f^3$, where $b > 0$ and $\omega > 0$. First, we explore the impact of water prices, monitoring costs, and punishment on the equilibrium level of theft. As one intuitively expects, theft increases with water prices and monitoring costs and decreases with punishments:

$$\frac{\partial \bar{a}^*}{\partial t} = \frac{1}{10\bar{\kappa} m_1^* f_1^*} > 0 \tag{24}$$

$$\frac{\partial \bar{a}^*}{\partial b} = \frac{1}{10b\bar{\kappa} m_1^* f_1^*} > 0 \tag{25}$$

$$\frac{\partial \overline{a}^*}{\partial f} = -\frac{1}{2\overline{\kappa}(f_1^*)^2 m_1^*} < 0 \tag{26}$$

Second, we study the relationship between monitoring costs, punishments, and the net benefit from using new technologies, $G(t) - L(m, f, t)$.

$$\frac{\partial}{\partial b}(G(t) - L(m, f, t)) = -\frac{1}{15b}\left(\frac{1}{\underline{\kappa}} - \frac{1}{\bar{\kappa}}\right)\frac{t^2}{fm^3} < 0 \tag{27}$$

$$\frac{\partial}{\partial f}(G(t) - L(m, f, t)) = \frac{1}{4}\left(\frac{1}{\underline{\kappa}} - \frac{1}{\bar{\kappa}}\right)\frac{t^2}{f^2 m} > 0 \tag{28}$$

The higher the punishment (monitoring costs), the less (more) farmers have to lose in opportunities of theft from switching to new technology, and thus, the higher (lower) the net benefit from adoption.

Finally, we investigate the impact of water prices on the incentives for technology adoption, which is not straightforward, as both efficiency gains and utility costs to the farmer from adoption increase with water prices, as shown, respectively, by:

$$\frac{\partial G(t)}{\partial t} = -(\bar{q}^* - \underline{q}^*) > 0, \tag{29}$$

$$\frac{\partial L(m, f, t)}{\partial t^2} = \left(\frac{1}{\underline{\kappa}} - \frac{1}{\bar{\kappa}}\right)\frac{t}{2fm} > 0. \tag{30}$$

This implies that the overall impact of water prices on $G(t) - L(m, f, t)$ will depend on the curvature of functions G and L. Whereas function L is convex for t:

$$\frac{\partial L(m, f, t)}{\partial t^2} = \frac{3}{50fm}\left(\frac{1}{\underline{\kappa}} - \frac{1}{\bar{\kappa}}\right) > 0, \tag{31}$$

Function $G(.)$ is concave for t:

$$\frac{\partial^2 G(t)}{\partial t^2} = \frac{1}{\underline{g}_{qq}(\underline{q}^*)} - \frac{1}{\bar{g}_{qq}(\bar{q}^*)} < 0. \tag{32}$$

Proof: See the Supplementary Appendix.

Equations (31) and (32) and constraint (12) say that the marginal net benefit from using water-saving technologies is maximized for an intermediate water price:

$$t = \bar{t}, \text{ where } \bar{t} \leq \gamma. \tag{33}$$

This means that for a range of *low to intermediate* prices (i.e., when $t \in (0, \bar{t})$), the incentives for technology adoption increase with the price of water and decrease otherwise.

5. EXTENSION: REGULATORY CAPTURE

We allow the monitor to *collude* with the farmer. The monitor can obtain information about the farmer's theft. The farmer may bribe the monitor to hide such information from the WA. To keep the model tractable, we assume that a monetary equivalent of US\$1 received by the monitor[14] costs US\$$(1+\rho)$ to the farmer. We consider a three-tier hierarchy of farmer, monitor, and WA. All parties are risk-neutral.

1. *The farmer*: When the farmer is caught stealing, she is willing to pay the monitor a bribe $B = t(\bar{q} - \bar{q}^r)$ to take her side. Here, $t(\bar{q} - \bar{q}^r)$ is the farmer's maximum gain from theft. The bribe costs $(1+\rho)B$ to the farmer and has a value of $B/(1+\rho)$ for the monitor. The WA may discover collusion with the probability v, in which case the farmer is liable for theft by, $f(\bar{q} - \bar{q}^r)$ (occurring with the probability $v\bar{\kappa}m(\bar{q} - \bar{q}^r)$). Collusion can occur only if the two parties benefit from the retention of information. The monitor's stake in collusion is $B/(1+\rho)$, whereas the farmer's stake in collusion is $t(\bar{q} - \bar{q}^r)$. The farmer maximizes her utility function.

$$\max_{(\bar{q}-\bar{q}^r)} [\bar{g}(\bar{q}) - c\bar{q} - t\bar{q}^r - v\bar{\kappa}mf(\bar{q} - \bar{q}^r)^2 - (1-v)(1-\rho)t(\bar{q} - \bar{q}^r) - (1-\alpha)C_T] \tag{34}$$

2. *The monitor:* She is paid[15] $w(m) = wm$ for her monitoring activity. When the monitor accepts a bribe, there is a chance that she will be caught with the probability v, in which case she will be inflicted with the punishment, F. The monitor's problem is:

$$\max_{m} V(m) = wm + (1-v)\frac{t(\bar{q} - \bar{q}^r)}{1+\rho} - vF - \lambda\psi(m) \text{ (P2)}$$

3. *The WA:* It picks $\{f, F, \alpha\}$ that maximizes the social welfare function, which is the sum of the surpluses of the farmer and monitor, as well as the surplus of the water supplier, which is equal to the income from water

[14] Equivalently, the monitor attributes a monetary value of $1/(1+\rho)$ per dollar to the farmer's collusive action. The shadow price of transfer ρ reflects that transfers are not fully efficient (a bribe exposes the parties to the possibility of legal sanctions).

[15] The linearity of the monitor's income in keeping with monitoring is quite plausible since in practice monitors usually receive wages for their activity.

proceeds $t\bar{q}^r$ plus the expected punishment from the monitor $v(1-\delta)F$ (δ reflects the transaction cost of implementing punishments on a corrupt monitor). From this, we subtract the cost of providing water $\gamma\bar{q}$, the payment to the monitor wm, the cost of punishing the farmer $\varphi(f)$, the subsidy given to the farmer αC_T, and the social cost associated with adoption $\eta_s \alpha C_T$.

$$W(f, F, \alpha) = \left\{ \begin{array}{l} \bar{g}(\bar{q}) - (c+\gamma)\bar{q} - v\bar{\kappa}mf(\bar{q}-\bar{q}^r) \\ +(1-v)\left[\dfrac{1}{1+\rho} - (1+\rho)\right] t(\bar{q}-\bar{q}^r) - (1+\eta_s \alpha)C_T \\ -v\delta F - \varphi(f) - \lambda\psi(m) \end{array} \right\} \tag{35}$$

The punishment inflicted on the corrupted monitor should erode her stake from collusion, that is,

$$F \geq \frac{t(\bar{q}-\bar{q}^r)}{1+\rho} \tag{36}$$

The WA chooses $\{f, F, \alpha\}$ so as to maximize $W(f, F, \alpha)$ subject to constraints (12) and (36).

Collusion can occur only if the transaction cost of collusion is not very high. That is,

$$\rho < \frac{v}{(1-v)} \tag{37}$$

As a starting point, we use the collusion-free regulation as a benchmark. Formally, optimization problems correspond to the above programs, from which we conceal the bribe term, transaction costs (ρ and δ), and punishment inflicted on the monitor. Furthermore, constraint (36) is omitted and probability $v = 1$. Lemma 2 characterizes the solution (indexed with the superscript CFR, representing collusion-free regulation, versus superscript C, representing the collusive setting).

Lemma 2: Suppose that assumptions (6), (7), and (8) hold, then:

1. The optimal punishment inflicted on the farmer is implicitly given by

$$f^{CFR} : \frac{t^2 z}{4f^2 m} = \varphi'(f), \tag{38}$$

where $z = (1-\eta_s)\dfrac{1}{\kappa} + \eta_s \dfrac{1}{\kappa}$

2. The optimal subsidy rate is

$$\alpha^{\mathrm{CFR}} = 1 - \frac{G(t) - L(m^{\mathrm{CFR}}, f^{\mathrm{CFR}}, t)}{C_T} > 0 \tag{39}$$

3. The optimal monitoring is implicitly given by

$$m^{\mathrm{CFR}} : w = \lambda\psi(m). \tag{40}$$

4. The optimal level of theft undertaken by a farmer is

$$a^{\mathrm{CFR}} = \frac{t}{2\bar{\kappa}m^{\mathrm{CFR}} f^{\mathrm{CFR}}} \tag{41}$$

Proof: See the Supplementary Appendix.

Now we explore the collusive setting. The results are summarized by Proposition 3.

Proposition 3: Suppose that assumptions (6), (7), (8), and (41) hold, then:

1. The optimal punishments and subsidy used by the WA, $\{f^C, F^C, \alpha^C\}$ satisfy

$$f^c\!:\left\{\begin{array}{c}\left\{\begin{array}{c}\dfrac{[1-(1+\rho)(1+v)]t^2}{2v\bar{\kappa}m^C f^2}\left(\dfrac{[1-(1+\rho)(1+v)]}{2}+\dfrac{v\delta}{(1+\rho)}\right)\\ -(1+v)\left[\dfrac{1}{(1+\rho)}-(1+\rho)\right]-(1+\eta_s\alpha)C_T-\theta\dfrac{\partial}{\partial f}L(m^C,f,t)\end{array}\right\}\\ +\dfrac{[1-(1+\rho)(1+v)]t^2}{2v\bar{\kappa}m^{C2}f}\left(\begin{array}{c}\dfrac{[1-(1+\rho)(1-v)]}{2}-(1-v)+\dfrac{1}{1+\rho}-(1+\rho)\\ +\dfrac{v\delta}{(1+\rho)}\lambda\psi'(m^C)-\theta\dfrac{\partial}{\partial m}L(m^C,f,t)\end{array}\right)\dfrac{\partial m^C}{\partial f}\end{array}\right\}=\varphi'(f) \tag{42}$$

$$F^c=\frac{[1-(1+\rho)(1-v)]}{2(1+\rho)v\bar{\kappa}m^c f^c} \tag{43}$$

and

$$\alpha^c=1-\frac{G(t)-L(m^c,f^c,t)}{C^T}>0 \tag{44}$$

2. The optimal monitoring is implicitly given by

$$m^c\!:w-\frac{(1-2v)}{(1+\rho)}\frac{[1-(1+\rho)(1-v)t^2]}{2v\bar{\kappa}m^2 f}\lambda\psi(m) \tag{45}$$

3. The optimal level of theft undertaken by each farmer is

$$a^c=\frac{[1-(1+\rho)(1-v)]t}{2v\bar{\kappa}m^c f^c} \tag{46}$$

Proof: See the Supplementary Appendix.

Comparing optimal monitoring (40) and (45) reveals that less monitoring is required in setting C when collusion is less likely to occur, and higher monitoring is needed otherwise. Monitoring not only reduces the incentives for theft (incentive effect), but it may also enable the monitor to benefit from collusion (rent-seeking effect). These effects are conflictual as reducing theft reduces the monitor's stakes from collusion. When the risk of being caught is low ($v<(1/2)$), the monitor performs less monitoring, resulting in cost savings while increasing the opportunities for theft, raising the stakes from collusion. Here, the rent-seeking effect is dominant. Conversely, when the risk of being caught is high ($v>(1/2)$), more monitoring is performed, which reduces theft along with the stakes from collusion. Here, the incentive effect tends to dominate.

Using the envelope theorem, we explore the impact of punishment inflicted on the farmer[16] on the equilibrium monitoring level:

$$\frac{\partial m^c}{\partial f} = -\frac{\left[\dfrac{(1-2v)[1-(1-v)(1+\rho)]\left(\dfrac{t^2}{2v\bar{\kappa}m^2f^2}\right)}{(1+\rho)}\right]}{\dfrac{d^2V(m)}{dm^2}} \begin{cases} >0 \text{ if } v<\dfrac{1}{2} \\ <0 \text{ if } v>\dfrac{1}{2} \end{cases} \tag{47}$$

where $\dfrac{d^2V(m)}{dm^2} = -\lambda\psi''(m) < 0$.

when discovering collusion is less likely ($v < (1/2)$), monitoring and punishment are complements and can be substituted otherwise. In both cases, a lower punishment is required in setting C, because it reduces costs while increasing the scope for theft and the stakes from collusion. This acts as a disincentive for the WA to inflict harsh punishments.

Establishing whether collusion increases or decreases theft is not straightforward. However, economic intuition suggests that collusion is expected to increase theft, as the ability to bribe the monitor may allow the farmer to avoid punishment while reaping additional profits from stealing (at a minimum level[17] $(f-t)a^C > 0$). However, because the bribe given to the monitor increases with theft, the farmer may wish to reduce theft in order to lower the bribe.

5.1. Summary of empirical hypotheses

The model's predictions are as follows.

Determinants of theft

(a) Theft increases with water prices and monitoring costs.
(b) Theft decreases with punishment inflicted on a farmer and technology adoption.
(c) Theft may increase or decrease with collusion.

Determinants of technology adoption

(a) Adoption decreases with monitoring costs and theft.
(b) Adoption increases with punishment inflicted on a farmer and water prices (in a relevant range of low to medium prices).
(c) The incentives for adoption have a hump-shaped relationship with water prices.

Determinants of collusion

(a) Collusion decreases with punishment inflicted on a farmer.
(b) Collusion may increase or decrease with monitoring costs (resp. theft).

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[16] Let $M(.,.)$ be the function of two arguments α and m:$M(\alpha, m^C) = \alpha^C - 1 + \dfrac{G(t) - L(m^C, f^C, t)}{C^T} = 0$.
The implicit theorem function yields the first partial derivative of the equilibrium monitoring, m^C with respect to the subsidy, α:

$$\frac{\partial m^C}{\partial \alpha} = \frac{\frac{\partial}{\partial \alpha}M(\alpha, m)}{\frac{\partial}{\partial \alpha}M(\alpha, m)} = -\frac{C_T}{\dfrac{-\partial L(m, f, t)}{\partial m}} = \frac{-C_T}{\dfrac{[v^2 - [(1-v)\rho]^2]t^2}{4v^2m^{2f}}\left(\dfrac{1}{\underline{\kappa}} - \dfrac{1}{\bar{\kappa}}\right)} < 0.$$

[17] This follows from the assumption that punishment rate f is greater than t.

6. TESTING THE MODEL

6.1. Data

This section tests our theoretical predictions using data from two public irrigated areas in Medjez-el-Bab (Tunisia[18]) for the period 2012–18. Almost all the data was jointly provided by the farmers, the government water agency of Medjez-el-Bab (the Agricultural Regional Development Commission (ARDC)) in charge of running[19] these irrigated areas and the cell of agricultural development (CAD) of Béja the governorate where Medjez-el-Bab is located. All data is at the farmer level, except for high groundwater table measures, drip system diffusion patterns, proximity of a farmer's land to the 'Medjerda' river, and paedological characteristics such as soil type, which were collected at the plot level. Water theft and corruption data, as well as water prices, are the sole variables reported by the ARDC. The CAD, on the other hand, reports only information on water consumption for each crop per hectare and the strategy used to estimate these norms.

The survey was carried out in two public irrigated areas of Medjez-el-Bab a small town in the North West of Tunisia, characterized by a semi-arid climate and receiving moderate and erratic rainfall averaging 412 millimeters per year, mainly concentrated between December and March. Farmers, therefore, rely heavily on water sources controlled by government water agencies for the remainder of the year. The primary source for irrigation is the dam of 'Sidi Salem[20]', fed by the largest river in Tunisia, the 'Medjerda'.

The first area, 'Medjez-el-Bab – Mattisse – Sidi Nasser' and the second one, 'El Heri – Grish – Griaat' are equipped with irrigation infrastructure covering nearly 3,791 and 2,905 hectares, respectively. These areas exhibit similar topographical characteristics and cropping patterns; their landscapes are mostly flat, with less than 15% consisting of hills and valleys. Currently, typical winter crops are wheat, olives, and vegetables, with wheat being the most important in terms of cultivated surface (72.3%) for the first area and (65%) for the second one. Tomatoes, potatoes, peppers, and fruits such as apples, peaches, pears, and almonds are common summer crops; tomato is the most widely cultivated crop, accounting for 31.3% of the cultivated surface in the first area and 22.2% in the second.

We choose to focus on these two areas because of their economic and social importance. They contribute for 33.56% of the total surface area of 19,954 hectares in Béja (the governorate rated second in Tunisia's North West in terms of public irrigated lands).

They account for over 40% of the agricultural production in the governorate's public irrigated fields, with summer crops like tomatoes, watermelon, and potatoes being the first more relevant annual crops in the governorate in terms of surface and occupying the first position when production value is taken into account. Fruit tree crops come in second place in terms of cultivated surface and production. Apart from their economic relevance, these two areas are important from a social perspective due to the fact that they demand great amounts of labour, mainly during the harvest season, which represents more than 50% of the agricultural labour in Medjez-el-Bab (CAD of Béja, 2018).

The key question for investigation is what determines theft, diffusion of water-saving technologies (drips), and collusion. The difficulties in testing such predictions are that key variables such as theft and collusion, and some of the likely determinants of theft (such as monitoring) are not observable, at least by the econometrician.

[18] A country that faces growing water scarcity. Government policies for the last three decades have promoted irrigated cropping patterns at the expense of dryland.

[19] The government water agency (ARDC) provides irrigated areas with water, deals with the operation and maintenance of irrigation infrastructure, replaces equipment, monitors farmers to reduce theft, tackles leakages, and collects water proceeds.

[20] The largest Tunisian dam with a storage capacity of about 700 million cubic meters.

Besides, there is a potential endogeneity problem in our key variables: theft, collusion, and drip that we should correct for, as standard regression analysis of observational data (including OLS and probit) can break down under several circumstances and thus produce biased estimates.

In our key variables, we may have all types of endogeneity[21], including simultaneous endogeneity, which occurs when the causality runs in both directions. Economic intuition suggests a bidirectional causal relationship between theft and technology adoption in our analysis: farmers who expect to freely divert water by stealing may have weaker incentives to adopt costly water-saving technologies; conversely, farmers who use technologies that save water may be less inclined to involve in the risky activity of theft. Furthermore, a bidirectional causal association between theft and collusion is quite to exist, as farmers who expect to steal water may bribe the monitor to avoid penalties. Furthermore, higher theft rates call for more corruption to escape punishment.

In practice, monitoring brings only *evidence* of the occurrence of theft, not its amount.[22] Theft, as such, is not observable; what the ARDC observes is the reported water. The ARDC is then required to estimate actual water use,[23] which it does using norms established by the CAD. Norms[24] are based on the pilot-scale cultivation process. Various cultures are grown under a full range of conditions, including plot surface, crop variety, soil type, season, irrigation system, climate conditions, inputs used, and so on. The ARCD estimates water consumptions using these norms and information on the farmer's cultivation activity (including cropping pattern, land surface for each crop and soil type, irrigation systems) and then cross-checks their findings with CAD experts. To ensure that what we report about the ARDC process indeed holds, we estimate these levels ourselves using the ARDC strategy.

Since corruption is clandestine, it is virtually impossible to come up with precise objective measures of it. The key problem we have faced in investigating corruption is that no reliable evidence can be brought about monetary bribes unless parties involved in the corrupted activity confess. If even possible, it begs a relevant question on who is more corrupt, the one who confesses bribing or the one who does not. One way to overcome this problem was to restrict attention to identifying corrupted farmers, and data of this kind was provided by the ARDC, whose identification strategy is the following: From the initial sample, the ARDC dropped farmers who were reported stealing (because they are unlikely[25] to have bribed monitors). The remaining set includes farmers who did not steal and those involved in bribery. The ARDC identified each of these two categories using data on the (estimated) rates of theft, with corrupted farmers being those with positive (estimated) rates of theft.

Our dataset includes information provided by farmers about their personal characteristics such as gender, age, and education, as well as socioeconomic characteristics such as off-farm income, harvest losses in previous years, and whether they hold a prestigious social position. Farmers also reported the percentage of their land equipped with drip irrigation systems and whether they have received extension services at least once. We also gathered information about farm paedological characteristics, such as the percentage of land with red soil, and agro-ecological characteristics, such as high groundwater table measures. Our information also includes data on the price of water, as well as levels of water theft and whether a farmer has been declared corrupted.

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[21] There are three sources for endogeneity: measurement errors, omitted variables, and simultaneous causality.

[22] The monitor's task is to report water use indicated by a farmer's meter and to check whether the meter has indeed been manipulated. If so, the evidence of manipulation will be established with certainty.

[23] We also estimate the individual theft levels.

[24] Norms are revised when necessary to take into account any changes in these effects, which vary over time.

[25] The monitor can only report two things to the WA: the farmer's report and whether or not her meter has been manipulated, so if the monitor discovers evidence of manipulation and decides to report it to the WA, the farmer is labelled a cheating farmer and will be punished based on her (estimated) level of theft as determined by the WA. This essentially means that the monitor's only option for falsification is to conceal the evidence of manipulation, as she is unable to underreport the farmer's level of theft (simply because she does not observe it). So, why should a farmer who has been declared stealing ever pay a bribe to the monitor when she will have to pay the full penalty for her water theft once declared stealing?

In this study of a population of 300 farmers equipped with individual water meters, 275 farmers were selected because they were involved in irrigation during the survey, but only 245 of them participated (89.091%). We have a problem with missing data due to non-response. In addition to the 30 non-participants who did not provide responses to the survey, 31 participants responded to certain of the survey questions but failed and/or refused to provide answers for particular items, leaving us with 214 farmers ('complete cases' (CC)) with complete data for all variables in the analysis.

Non-response is problematic if, collectively, respondents are systematically different from non-respondents in some or all characteristics related to the survey key variables. In our sample, non-respondents differ from respondents with respect to some of the model's key variables, such as water theft (a detailed discussion of the method appears in the Supplementary Appendix). The statistics provide evidence for the presence of a non-response bias and show that non-response is non-random; thereby, a selection correction procedure may be needed. This is why in the empirical application we account for sample selection and apply the IPW model to restore the representativeness of the sample. The complete cases (CC) data is of an unbalanced panel type, covering 6 years from 2012 to 2018 for 212 farmers and 5 years from 2013 to 2018 for the remaining two farmers.

6.2. Description of key variables

We start this section by clarifying the way in which we propose to measure monitoring costs. Given that monitoring levels are not directly observable, we need to find a suitable[26] proxy measure.

DISTANCE: The length of the main road's portion (in kilometers) separating the entrances[27] of the farmer's plot of land irrigated and the ARDC of Medjez-el-Bab.

This is likely to increase monitoring costs because it reduces the ability of monitors to observe the behaviour of farmers. Monitoring costs cannot by themselves be used as excluded instruments for endogenous variables as theory predicts that monitoring costs determine collusive behaviour, the use of drip technology, and the level of theft conditional on the incentives for collusion and technology adoption. We nevertheless investigate whether monitoring costs also directly influence the incentives for collusion and technology adoption in Subsections 6.4.2 and 6.4.3. Table 1 illustrates summary statistics. In the definition of empirical variables below, a farmer, in the case of a family farm, is meant to be the *primary* farmer who takes all decisions about irrigation activity. Our empirical variables are defined as follows:

AGE: The age of a farmer.

ALTERNATIVE REVENUE: scores 0 when a farmer's sole source of revenue is irrigation. It scores 1 when the farmer receives an average monthly revenue of between 200 and 500 Tunisian Dinars (TD) (from having animals, receiving remittances from family, and/or having various assets) in addition to her irrigation earnings. It scores 2 when revenue is between 500 and 700 TD. It scores 3 when revenue is between 700 and 1,200 TD, 4 when revenue is between 1,200 and 3,000 TD, and 5 when revenue exceeds 3,000 TD.

ALTERNATIVE SOURCE: The distance (in kilometers) between a farmer's land and the 'Medjerda' river.

CORRUPTION: Scores 1 if a farmer gives a bribe to a monitor; and 0 otherwise.

DISTANCE TO LARGE CITY: The distance (in kilometers) between a farmer's childhood town or hamlet and the nearest large city with public infrastructure such as schools, public hospitals, water systems, bridges, roads, and other public structures.

DRIP: The percentage of a farmer's land equipped with drips.

EDUCATION: The number of a farmer's years of schooling.

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[26] Even though this proxy could be the best available given data limitations, we are aware of its weaknesses. For example, its rigidity as an instrument in the government's hands (as it may ignore various expenses related with monitoring) may reduce the flexibility of the government policy directed to control water theft.

[27] Entrances are officially determined by municipalities where the irrigated area and the ARDC are located.

Table 1 | Summary of descriptive statistics.

Variable	Unit of measure	Observation	Weight	Mean	Std. Dev.	Min.	Max.
AGE	Year	1646	2,190.57307	53.04906	11.58133	23	78
ALTERNATIVE REVENUE	Index	1441	1,815.18679	2.19277	1.2845	0	5
ALTERNATIVE SOURCE	Kilometer	1468	1,907.10378	1.9352	1.03063	0	5
COMPLETECASE	Binary variable	1646	2,190.57307	0.75056	0.432817	0	1
CORRUPTION	Binary variable	1646	2,190.57307	0.66482	0.4722	0	1
DISTANCE	Kilometer	1468	1,907.10378	9.02554	3.573536	3	16
DISTANCE TO LARGE CITY	Kilometer	1438	1,866.27329	8.831018	4.843987	0	18
DRIP	Percentage	1646	2,190.57307	0.5116	0.19236	0.09	1
EDUCATION	Year	1444	1,870.18731	11.19768	4.61804	2	22
EXTENSION SERVICES	Binary variable	1468	1,907.10378	0.585154	0.49286	0	1
FATHER EDUCATION	Year	1445	1,1871.83037	9.343581	3.671285	1	20
GENDER	Binary variable	1646	2,190.57307	0.807	0.3947	0	1
INTERVIEWED BY A FEMALE	Binary variable	1646	2,190.57307	0.60205	0.685107	0	11
MARITAL HISTORY	Index	1646	2,190.57307	1.97789	1.1485	0	5
MATHER EDUCATION	Year	1445	1,871.83037	9.301129	3.519663	1	20
NEIGHBOURD ACCOMMODATIONS	Percentage	1646	2,190.57307	0.18417	0.10038	0	0.5
	Days (for which a cheating farmer who is caught stealing is denied access to water feeding the irrigated area) per 1,000 m^3 of water stolen by the cheating farmer	1646	2,190.57307	1.59707	1.1887	0	22
Pr	Probability	1646	2,190.57307	0.7514	0.2107	0.0615	0.9982
PR	Square of probability	1646	2,190.57307	0.60897	0.24934	0.00378	0.996
PRICE	Tunisian dinar per cubic meter of water reported by the farmer	1646	2,190.57307	0.134335	0.00694	0.126	0.146
PRICE squared	Square of the unit of PRICE	1646	2,190.57307	0.0181	0.00188	0.0158	0.0213
PRIVILEGE	Binary variable	1456	1,889.45076	0.618628	0.48589	0	1
RED SOILS	Percentage	1646	2,190.57307	0.5101	0.25966	0	1

(*Continued*.)

Table 1 | Continued

Variable	Unit of measure	Observation	Weight	Mean	Std. Dev.	Min.	Max.
REVENUE SHOCK	Percentage	1396	1,743.99428	0.2565	0.15428	0	1
TYPE OF ACCOMMODATION	Index	1646	2,190.57307	2.1108	1.2218	0	6
SIZE OF HOUSEHOLD	Individual	1646	2,190.57307	8.8992	3.5747	0	16
WATER LOGGING	Meter	1468	1,907.10378	4.26214	1.8347	0.4	8
WATER THEFT	Percentage	1646	2,190.57307	0.38714	0.18903	0	0.90
Wt	Weight	1646	2,190.57307	2.0099	3.10016	1.0018	16.2603
YEAR	Year	1646	2,190.57307	3.5175	1.7115	1	6
CODE	Code	1646	2,190.57307	859.4983	477.6078	1	1629

Source: Compilation of variables and calculations made by the authors.

EXTENSION SERVICES: Scores 1 when a farmer has contact with extension agents; and 0 otherwise.

FATHER EDUCATION: The number of years of schooling of a farmer's father.

GENDER: Scores 1 if a farmer is male; and 0 otherwise.

MOTHER EDUCATION: The number of years of schooling of a farmer's mother.

PRICE: The price per cubic meter of water charged by Tunisia's Ministry of Agriculture (in TD). In practice, the Ministry of Agriculture sets tariffs that barely cover the costs of operating and maintaining the water delivery system, let alone the infrastructural costs (Ministry of Agriculture of Tunisia). The price changes because of the fluctuating operation and maintenance costs.

PRIVILEGE: Scores 1 if a farmer holds a prestigious social position (such as being a member of parliament, a minister, a university professor, a banker, and the head of a firm) and/or has political ties, and/or is a member of one of the county's most powerful families (such as being one of the county's wealthiest families and being a political family); and scores 0 otherwise.

PUNISHMENT RATE: The number of days on which a farmer is denied access to irrigation, expressed per 1,000 cubic meters of water stolen.

RED SOILS: The percentage of a farmer's land with red soil.

REVENUE SHOCK: The percentage of a farmer's harvest losses in the previous year. It is the ratio of losses measured per hectare in the total surface irrigated. These losses are related to factors including natural catastrophes that have struck the farmer's harvest (such as floods and/or crop diseases) and poor marketing distribution channels.

WATER LOGGING: A measure of a high groundwater table. It measures the aquifer inflow (in meters) as a result of poor drainage.

WATER THEFT: The differential between the *estimated* water used by a farmer and that indicated by her water meter, expressed as a percentage of the *estimated* water used by the farmer.

6.3. Estimation procedure

We propose here the instrumental variables regression model to deal with the potential endogeneity of some of our main variables. The method is deemed appropriate by analysts to deal with all types of endogeneity (Reiersøl, 1945; Sargan, 1958; White, 1982). It is appealing because of its rigor, flexibility, transparency, and amenability to empirical testing (Bascle, 2008), especially when the difficult challenge of identifying high-quality instruments is solved.

We believe that this is the case here, as we may well have all sources of endogeneity cumulated. Furthermore, the relative wealth of our data, which includes a relatively large number of exogenous variables (which account for 42% of total variables in the analysis), may provide a greater scope for identifying valid and strong instruments to adequately address endogeneity issues.

6.4. Results

Here, we report the determinants of theft, using various regressions including instrumental variables estimations, to deal with the endogeneity of technology adoption and collusion. We then report more detailed econometric evidence about the determinants of technology adoption and collusive behaviour.

6.4.1. Estimation of water theft

Here, we discuss the determinants of theft, particularly the theoretical predictions that theft increases with water prices and monitoring costs and decreases with punishments. We also investigate how theft is affected by the opportunities for collusion and the use of water-saving technologies. We regress *WATER THEFT* on the following variables: *PRICE*, *DISTANCE*, *PUNISHMENT RATE*, *CORRUPTION*, *DRIP*, *EDUCATION*, *ALTERNATIVE SOURCE*, and *REVENUE SHOCK*.

Table 2 illustrates two OLS (results of the CC and IPW analyses) and three 2SLS estimation regressions (with clustering on farmers) to explore the possible endogeneity of some determinants of theft. The most likely variable to suffer from endogeneity is *DRIP*: farmers who expect to steal their water may be less inclined to invest in costly technologies to save on resource use. This would bias upward the OLS parameter estimate since a causal association of high drip system adoption with low rates of theft would be reinforced by a reverse-causal association of high rates of theft with low adoption rates. A variable that might be endogenous for different reasons is *CORRUPTION*. Higher rates of theft call for higher bribes to avoid punishments inflicted on cheating farmers.

To explore these possibilities, our instrumenting strategy is as follows: Beginning with *CORRUPTION*, we use the idea that relevant personal characteristics, captured by the variable *GENDER*, may be associated with higher corruption rates. Our use of this variable is inspired by earlier evidence collected by several authors (Dollar *et al.*, 2001; Swamy *et al.*, 2001; Schulze & Frank, 2003; Seligson, 2006) that women are less likely to condone corruption compared to men since women can be more risk-averse than men and/or may have higher social norms regarding bribery than men and/or may experience greater social pressures against 'taboo' corrupt behaviours. We use another control, *PRIVILEGE*, as a positive proxy for collusion enforcement: monitors are more fearful of reneging on agreements with individuals with powerful social and political relationships.

Second, we control for *DRIP* using a geographical variable that influences the productivity of the technology. *RED SOILS* are those with lower water retention, so drips save more water. We consider another control, *AGE*. Older individuals may have imperfect knowledge about the usage of new technology, probably due to their unfamiliarity with mechanization (Chuchird *et al.*, 2017) and/or maybe more conservative and less willing to take risks in general (Donkers *et al.*, 2001; Dohmen *et al.*, 2011, 2018; Bonsang & Dohmen, 2015), and in particular, the risks[28] associated with new technologies.

Another variable likely to suffer from endogeneity is *EDUCATION*. Our use of this variable is inspired by the literature on the negative impact of education on crime (Lochner, 2004; Lochner & Moretti, 2004; Hjalmarsson, 2008). According to this strand of literature, education may make individuals more risk-averse and may teach them to be more patient. This is very likely to reduce the likelihood of committing crimes, as more risk-averse and/or forward-looking individuals would place greater weight on any expected punishment associated with their criminal activities. We instrument for *EDUCATION* using a farmer's parents' education (captured by two

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[28] The risks of water-saving technologies stem from costs related to its usage, which include the technology cost, as well as labour and learning costs (Daia *et al.*, 2015).

Table 2 | Determinants of WATER THEFT – ordinary least squares (OLS) and instrumental variables estimates.

Specification/Instrumented variable for 2SLS	Equation (2.1) *OLS of CC*	Equation (2.2) *OLS of IPW*	Equation (2.3)[a] *2SLS (DRIP)*	Equation (2.4)[b] *2SLS (DRIP + COR)*	Equation (2.5)[c] *2SLS (DRIP + COR + EDU)*
Independent variable					
ALTERNATIVE SOURCE	−0.0175 (0.00457)***	−0.0164 (0.00477)***	−0.0039 (0.00526)	−0.0047 (0.0054)	−0.0037 (0.0055)
CORRPUTION (COR)	0.084 (0.0068)***	0.08017 (0.0076)***	0.071 (0.0083)***	0.0509 (0.0206)**	0.0536 (0.0208)***
DISTANCE	0.0163 (0.00117)***	0.01589 (0.00128)***	0.01287 (0.0017)***	0.0136 (0.0019)***	0.01347 (0.00193)***
DRIP	−0.184 (0.02189)***	−0.189 (0.02336)***	−0.3756 (0.0496)***	−0.3854 (0.04905)***	−0.3868 (0.0488)***
EDUCATION (EDU)	−0.0018 (0.00058)***	−0.0019 (0.000649)***	−0.001178 (0 .00069)*	−0.001069 (0.00071)	−0.0017 (0.0008)**
PUNISHMENT RATE	0.0228 (0.00459)***	0.02237 (0.00547)***	0.02214 (0.0051)***	0.0234 (0.0054)***	0.02327 (0.0054)***
PRICE	4.993 (0.351)***	4.8289 (0.478)***	4.217 (0.489)***	4.2435(0.4929)***	4.25037(0.4887)***
REVENUE SHOCK	0.0588 (0.01885)***	0.0768 (0.0213)***	0.0582 (0.02033)***	0.05686 (0.02046)***	0.0528 (0.0199)***
CONSTANT	−0.4199 (0.055)***	−0.3949 (0.07389)***	−0.212 (0.085)**	−0.205 (0.086)**	−0.1996 (0.0858)**
R^2	0.7242	0.7012	0.6817	0.6779	0.6779
Hansen *J*-statistics (% significance)	–	–	0.231 (0.6305)	0.397 (0.8198)	0.151 (0.9271)
Durbin–Wu–Hausman test (% significance)	–	–	15.882 (0.0001)	20.072 (0.0000)	25.286 (0.0000)
No. of observations	1376	1376	1376	1370	1370

Note: Heteroscedasticity-Robust standard errors (clustered on farmers) are in parentheses; *, **, and *** denote variables significant at 10, 5, and 1%, respectively.
Source: Authors' calculations.
[a]The excluded instruments are AGE and RED SOILS.
[b]The excluded instruments are as in (2.3) plus GENDER and PRIVILEGE.
[c]The excluded instruments are as in (2.4) plus FATHER EDUCATION.

variables: *FATHER EDUCATION* and *MOTHER EDUCATION*) and a variable capturing the proximity to schools (Card, 1993). Parents' education has been extensively used in the literature as more educated parents are the most likely to have more educated children (Haveman & Wolfe, 1995; Holmlund *et al.*, 2010). The variable *DISTANCE TO LARGE CITY* can be used as a positive proxy for educational infrastructure and/or proximity to schools and may be associated with lower education levels.

A word of caution is in order: Although we find the exclusion restrictions plausible, we cannot rule out *a priori* that the proposed instruments do in fact affect theft directly. Moreover, even though these instruments are arguably relevant, we may suspect that correlations are only weak. This is why we pay particular attention to the statistical tests of over-identification restrictions and weak instruments that we report in all specifications below.

Equations (2.3), (2.4), and (2.5) from Table 2 report the results of these instrumental variables estimations. We first instrument for *DRIP*, then for *DRIP* and *CORRUPTION*, and finally for both of these variables, as well as for *EDUCATION*.

Overall, the results provide a striking confirmation of our hypotheses about the determinants of theft, even when we control for the endogeneity of collusion and technology adoption. All equations show that theft increases with the price of water, the incidence of collusion, and the distance of the farmer's plot of land from the government water agency, ARDC, and decreases with the use of drip systems. Results also show various controls for which the theory provides no unambiguous predictions. The coefficient on *ALTERNATIVE SOURCE* is negative, as expected, as the proximity to the river may give the farmer increased opportunities to freely divert water from it, which would reduce her incentives (and need) for theft. *REVENUE SHOCK* is associated with water theft in a theft-increasing direction. This index captures the broad characteristics of the farmer's revenue shock and can thereby be considered as a proxy measure of her liquidity constraints. This would increase the farmer's incentives for theft to reduce the cost of water. The negative coefficient on *EDUCATION* is along expected lines.

Our findings also show that our concerns about endogeneity are justified, though more for some variables than for others. The coefficient on *DRIP* doubles in absolute magnitude compared to the OLS estimate, suggesting that there is a reverse causality effect of theft that tends to reduce *DRIP*. The Durbin–Wu–Hausman test on this variable alone rejects exogeneity at less than a 1% confidence level. The coefficient on *CORRUPTION* is somewhat smaller, indicating that the causal association of high rates of theft with high corruption rates is almost compensated by the reverse-causal association of high corruption rates with higher levels of theft. A Durbin–Wu–Hausman test on this variable alone (not reported) rejects exogeneity at less than an 8% level. The joint test of exogeneity on *DRIP* and *CORRUPTION* together, as well as a similar test on all three variables, are both clearly rejected. Finally, the instruments comfortably pass the Hansen test of over-identifying restrictions and the Kleibergen-Paap rk test of weak instruments, as shown in equations (2.3), (2.4), and (2.5) and (3.3), (3.4), and (3.5) in Tables 2 and 3, respectively. Table 3 shows the instrumented variables' first-stage IV estimations in the estimation of *WATER THEFT*.

6.4.2. Adoption of drip

Here, we report the results of our estimates of the determinants of *DRIP*. Our model predicts that adoption will increase with water prices at a decreasing rate. It also increases with punishments and decreases with monitoring costs and theft. In testing these predictions, we use an approach based on personal characteristics recorded by two variables, *EDUCATION* and *AGE*. Education may capture the higher awareness of the benefits of drips, as well as the ease of understanding and using these devices (Staal *et al.*, 2003). The arguments behind the control for age differences are discussed in the previous section.

We control for extension services since the implementation of modern irrigation technology requires more knowledge about environmental conditions, for example, evaporation conditions, to achieve efficiency in water use (Abdulai *et al.*, 2005). We also control for paedological and agro-ecological characteristics, including soil texture and high groundwater table levels (measured by the variables *RED SOILS* and *WATER LOGGING*), which affect the productivity of the technology. Finally, we control for factors influencing the ability of farmers to provide necessary investment. We regress *DRIP* on the following variables: *DISTANCE*, *PUNISHMENT RATE*, *PRICE*, *AGE*, *EXTENSION SERVICES*, *EDUCATION*, *RED SOILS*, *WATER LOGGING*, and *ALTERNATIVE REVENUE*.

Table 3 | First-stage IV estimates of the instrumented variables in the estimation of WATER THEFT (Equation 2.3, Equation 2.4, and Equation 2.5).

	Equation (2.3)	Equation (2.4)		Equation (2.5)		
Instrumented variable	***DRIP***	***DRIP***	***COR***	***DRIP***	***COR***	***EDU***
Independent variable						
AGE	−0.0015 (0.0003)***	−0.0016 (0.0003)***	−7.16e − 06 (0.00107)	−0.0017 (0.00028)***	0.00006 (0.0011)	−0.027 (0.0051)***
ALTERNATIVE SOURCE	0.0485 (0.00438)***	0.04913 (0.0044)***	−0.0523 (0.0136)***	0.0467 (0.0044)***	−0.0528 (0.0138)***	−0.1186 (0.0885)
CORRPUTION (COR)	−0.0373 (0.00863)***	–	–	–	–	–
DISTANCE	−0.0143 (0.00123)***	−0.0163 (0.00126)***	0.0281 (0.0043)***	−0.0168 (0.00127)***	0.0283 (0.00427)***	−0.1255 (0.02007)***
FATHER EDUCATION	–	–	–	0.0068 (0.00106)***	−0.00086 (0.0033)	1.047 (0.0205)***
EDUCATION (EDU)	0.0053 (0.00089)***	0.0048 (0.0009)***	−0.00147 (0.00257)	–	–	–
GENDER	_	−0.00588 (0.0088)	0.3701 (0.0322)***	−0.0085 (0.00887)	0.3704 (0.0323)***	−0.3957 (0.1643)**
PUNISHMENT RATE	−0.0122 (0.00635)*	−0.015 (0.0068)**	0.0638 (0.01589)***	−0.0153 (0.0069)**	0.0637 (0.0158)***	0.007 (0.045)
PRIVILEGE	–	0.01274 (0.007)*	0.0983 (0.0234)***	0.01496 (0.00706)**	0.0959 (0.02306)***	0.967 (0.1436)***
PRICE	−2.168 (0.475)***	−2.229 (0.4758)***	2.7957 (1.5346)*	−2.246(0.469)***	2.771(1.532)*	5.35407(9.246)
RED SOILS	0.236 (0.01578)***	0.2406 (0.0166)***	−0.1329 (0.0435)***	0.238 (0.0165)***	−0.1303 (0.0429)***	−1.055 (0.259)***
REVENUE SHOCK	−0.099 (0.0238)***	−0.1024 (0.0239)***	0.0862 (0.0829)	−0.09607 (0.0239)***	0.0897 (0.083)	−0.2895 (0.3947)
CONSTANT	0.801 (0.0634)***	0.8139 (0.0639)***	−0.2636 (0.2304)	0.821(0.0633)***	−0.2737 (0.2301)	3.8413 (1.2478)***
Weak identification test (Kleibergen-Paap rk Wald *F* statistic)	113.298	42.579	42.579	32.891	32.891	32.891
F statistic (excluded instruments)	$F(2,1374) = 113.30$	$F(4,1368) = 70.65$	$F(4,1368) = 47.48$	$F(5,1368) = 67.16$	$F(5,1368) = 38.76$	$F(5,1368) = 776.43$

Note: Heteroskedasticity-Robust standard errors (clustered on farmers) are in parentheses; *, **, and *** denote variables significant at 10, 5, and 1%, respectively.
Source: Author's calculations.

In addition, we test the hypothesis that theft influences the incentives for technology adoption. We do this by including the variable *WATER THEFT* but as it may be endogenous, we control for it using *ALTERNATIVE SOURCE*, *AGE*, and *EDUCATION* as instruments, but in equation (4.3)[b] from Table 4, we replace *EDUCATION*[29] by the farmer's father's education level, which is a more clearly exogenous variable, and which is a significant predictor of education. Similarly, we test the hypothesis that corruption may affect the incentives for technology adoption. Corrupted farmers may be more reluctant to adopt (expensive) new technology to save on a resource that they do not expect to face the full cost of use. Table 4 illustrates these results. All the underlying specifications allow for a quadratic effect of water price to test for the inverted-U-shaped relationship between drip and water prices.

Results from Table 4 show that the coefficient on *PUNISHMENT RATE* is positive (as expected) and significant in all 2SLS specifications. The coefficient on *DISTANCE* is negative and highly significant in the OLS specification and the 2SLS specifications where we control for *EDUCATION* (resp. *CORRUPTION*) alone (not reported). The coefficient on *CORRUPTION* is negative (though insignificant) in the OLS specification. The negative coefficient on *AGE* (though significant only in the OLS regression) is along expected lines. This is consistent with the findings of Chuchird *et al*. (2017), which suggest that older farmers are more receptive to traditional irrigation technology due to its ease of use, while their younger counterparts prefer to use modern irrigation technology, probably because of their familiarity with mechanization (the motorized machinery and pumps). The positive coefficient on *EDUCATION* is expected as more educated farmers should easily understand the usage of new technologies and apply them more efficiently throughout the adoption process (Staal *et al*., 2003). The coefficient on *ALTERNATIVE REVENUE* is consistently positive and highly significant in most specifications. This variable controls for differences in external off-farm income sources. The more financial resources farmers have from off-farm activities, the more funds they may afford to invest in drip. This is in line with the empirical findings of Gerhart (1975), Rochin & Witt (1975), Perrin (1976), and Lee (2005) on the relevance of external off-farm income sources in financing the purchase of a fixed-investment type innovation, including modern irrigation technologies.

The positive coefficient on *RED SOILS* is expected. Drip systems save more water on red soils since they have lesser water retention. The positive coefficient for *WATER LOGGING* is along expected lines, as high inflows increase threats of saline water from the aquifer, which would lower land quality. The productivity of drip systems would be higher than any traditional irrigation method since drip would lower the water-holding capacity of this land. This is in line with previous studies finding that new technologies are more likely to be used in locations with relatively low land quality (Caswell & Zilberman, 1986; Dinar & Yaron, 1990; Green *et al*., 1996).

Extension services positively affect adoption as expected. This is in line with Abdulai *et al*. (2005) and Zhang *et al*. (2019), among others. The key explanations are that these services are a potential source for information on how to efficiently use new technology through on-farm demonstrations they may organize for farmers and information on how to adapt new technology to farms' local conditions.

Furthermore, when we instrument for variables with a potential problem of endogeneity, such as water theft, the coefficients of the linear and quadratic terms of *PRICE* become positive and negative, respectively, and they become significant at less than a 5% confidence level, suggesting that the impact of *PRICE* on drip can be even stronger than it is if it were not for the fact that higher prices also encourage theft. Besides, these findings support the inverted-U-shaped link between *DRIP* and *PRICE*.

[29] Which may not be quite appropriate as an instrument for *WATER THEFT* since *EDUCATION* itself may have a potential problem of endogeneity.

Table 4 | Determinants of DRIP – ordinary least squares (OLS) and instrumented estimates.

Specification/ Instrumented Variable for 2SLS	Equation (4.1) *OLS of CC*	Equation (4.2) *OLS of IPW*	Equation (4.3)[a] *2SLS (WTH)*	Equation (4.4)[b] *As 4.3*	Equation (4.5)[c] *2SLS (WTH + COR)*	Equation (4.6)[d] *2SLS (WTH + COR + EDU)*
Independent variable						
AGE	−0.00165 (0.00025)***	−0.00138 (0.00025)***	–	–	−0.00034 (0.00051)	−0.0004 (0.00047)
ALTERNATIVE REVENUE	0.01015 (0.0027)***	0.00967 (0.0029)***	0.0116 (0.0043)***	0.01162 (0.0042)***	0.0102 (0.00419)**	0.0135 (0.00425)***
CORRUPTION (COR)	−0.0104 (0.00766)	−0.01216 (0.0077)	0.1161 (0.0259)***	0.1112(0.024)***	0.0864 (0.0353)**	0.0986 (0.0375)***
DISTANCE	−0.0107 (0.00132)***	−0.01086 (0.0013)***	0.019 (0.0056)***	0.01785 (0.00514)***	0.018 (0.0066)***	0.0141 (0.0058)**
EDUCATION (EDU)	0.0059 (0.00077)***	0.00603 (0.0008)***	–	–	–	0.0008 (0.00138)
EXTENSION SERVICES	0.1169 (0.0073)***	0.1164 (0.0073)***	0.0605 (0.0142)***	0.0626 (0.01358)***	0.0648 (0.01603)***	0.0721 (0.0134)***
PUNISHMENT RATE	−0.0109 (0.00486)**	−0.0105 (0.00537)*	0.0353 (0.01025)***	0.0335 (0.0096)***	0.0331 (0.0116)***	0.0288(0.0102)***
RED SOILS	0.2073 (0.0156)***	0.2034 (0.0161)***	0.0461 (0.0276)*	0.0512 (0.0261)**	0.055 (0.0317)*	0.0799 (0.0303)***
WATER LOGGING	0.0054 (0.00218)**	0.0063 (0.00226)***	0.0132 (0.00343)***	0.0129 (0.00336)***	0.0132 (0.00343)***	0.0102 (0.0034)***
PRICE	−24.355 (19.829)	−25.653 (20.3904)	104.806 (37.4438)***	99.973 (35.918)***	95.367 (37.495)**	81.869 (35.855)**
PRICE squared	84.679 (72.728)	89.568 (74.808)	−361.885 (135.492)***	−345.2077 (130.234)***	−329.151 (135.045)**	−281.5667 (129.608)**
WATER THEFT (WTH)	−0.224 (0.0387)***	−0.221 (0.0401)***	−1.667 (0.228)***	−1.6136 (0.206)***	−1.559 (0.262)***	−1.4446 (0.2386)***
CONSTANT	2.251 (1.346)*	2.319 (1.382)*	−6.876 (2.568)***	−6.534 (2.459)***	−6.193 (2.584)**	−5.258 (2.4572)**
R^2	0.7126	0.6992	0.2125	0.2490	0.2836	0.3358
	–	–		1.261 (0.5324)	0.030 (0.8621)	2.721 (0.2565)

(*Continued.*)

Table 4 | Continued

Specification/ Instrumented Variable for 2SLS	Equation (4.1) *OLS of CC*	Equation (4.2) *OLS of IPW*	Equation (4.3)[a] *2SLS (WTH)*	Equation (4.4)[b] *As 4.3*	Equation (4.5)[c] *2SLS (WTH + COR)*	Equation (4.6)[d] *2SLS (WTH + COR + EDU)*
Hansen *J*-statistics (% significance)			0.609 (0.7375)			
Durbin–Wu–Hausman test (% significance)	–	–	116.279 (0.0000)	116.338 (0.0000)	80.439 (0.0000)	68.287 (0.0000)
No. of observations	1420	1420	1420	1421	1429	1334

Note: Heteroskedasticity-Robust standard errors (clustered on farmers) are in parentheses; *, **, and *** denote variables significant at 10, 5, and 1%, respectively.
Source: Authors' calculations.
[a]The excluded instruments are ALTERNATIVE SOURCE, AGE, and EDUCATION.
[b]The excluded instruments are as in (4.3) minus EDUCATION plus FATHER EDUCATION.
[c]The excluded instruments are as in (4.3) minus EDUCATION and AGE plus GENDER and PRIVILEGE.
[d]The excluded instruments are as in (4.5) plus REVENUE SHOCK and DISTANCE TO LARGE CITY.

Our concerns about endogeneity are justified for most variables. There is a sharp downward bias in the coefficient of *WATER THEFT*, suggesting the existence of a reverse causal effect that tends to reduce theft. A Durbin–Wu–Hausman test on this variable alone rejects exogeneity at less than a 1% level. When we control for *EDUCATION* alone, its coefficient becomes somewhat higher than the OLS parameter estimate. This upward bias in the coefficient of education confirms the causal association of high education levels with high adoption rates. The test of exogeneity on this variable (not reported), as well as the joint test of exogeneity on *WATER THEFT* and *CORRUPTION* and the same test on all three variables, comfortably pass the Durbin–Wu–Hausman test. Finally, the excluded instruments pass the Hansen test of over-identifying restrictions and the Kleibergen-Paap rk test of weak instruments, as shown in equations (4.3), (4.4), and (4.5) and (5.3), (5.4), and (5.5) in Tables 4 and 5, respectively. Table 5 shows the instrumented variables' first-stage IV estimates in the DRIP estimation.

6.4.3. Corruption

Here, we investigate the determinants of *CORRUPTION*. Our model predicts that corruption decreases with punishments inflicted on cheating farmers and may increase or decrease with monitoring costs. We test these predictions using variables that capture personal characteristics (*GENDER* and *AGE*) as well as factors that influence the enforcement of a monitor-farmer side informal contract (*PRIVILEGE*).

Because both corruption and theft are criminal acts, and engaging in either of them is a rule-breaking activity, controlling for age differences in the analysis of corruption depends on the same justifications presented for its inclusion in the regression of theft. We also account for factors that influence the farmers' ability to provide the necessary investment to engage in bribery. Our independent variables are the following: *DISTANCE*, *PUNISHMENT RATE*, *AGE*, *ALTERNATIVE REVENUE*, *GENDER*, and *PRIVILEGE*.

In addition, we test the hypothesis that theft influences corruption. This is done by including the variable *WATER THEFT*, which we control for using *ALTERNATIVE SOURCE* because it is a good predictor of theft. We also test the hypothesis that *DRIP* affects corruption. As a water-saving device, drip would reduce the farmers' need for theft, lowering their chance of being detected and facing a penalty. This would make them less likely to get involved in bribery. Given that the variable *CORRUPTION* may suffer from endogeneity, we need to control for it. Table 6 provides average marginal effects for PROBIT and instrumental variables for PROBIT estimates. We first control for *DRIP* and then for both *DRIP* and *WATER THEFT*.

Table 5 | First-stage IV estimates of the instrumented variables in the estimation of DRIP (Equation (4.3), Equation (4.4), Equation (4.5), and Equation (4.6)).

		Equation (4.4)	Equation (4.5)		Equation (4.6)		
Instrumented variable	Equation (4.3) *WTH*	*WTH (as 3.3[a] minus EDUCATION plus FATHER EDUCATION)*	*WTH*	*COR*	*WTH*	*COR*	*EDU*
Independent variable							
AGE	0.00071 (0.0003)**	0.0007 (0.00029)**	0.001 (0.0003)***	−0.0003 (0.00105)	0.0008 (0.0003)***	0.000098 (0.0011)	−0.0088 (0.0027)***
ALTERNATIVE SOURCE	−0.0213 (0.0045)***	−0.0198 (0.0045)***	−0.0286 (0.0049)***	−0.0438 (0.0137)***	−0.0246 (0.0049)***	−0.0428 (0.0138)***	0.1669 (0.038)***
ALTERNATIVE REVENUE	0.00217 (0.00216)	0.00237 (0.00213)	−0.00065 (0.0024)	−0.0031(0.0087)	0.0016 (0.0025)	−0.0024 (0.00902)	−0.0385 (0.0214)*
CORRPUTION (COR)	0.0852 (0.0074)***	0.0859 (0.0074)***	–	–	–	–	–
DISTANCE	0.0182 (0.0012)***	0.0186 (0.0011)***	0.0216 (0.0013)***	0.0243 (0.0039)***	0.0201 (0.0014)***	0.0242 (0.0044)***	0.00008 (0.0102)
DISTANCE TO LARGE CITY	–	–	–	–	0.0023 (0.0007)***	0.0014 (0.00243)	−0.9226 (0.0067)***
EDUCATION (EDU)	−0.0036 (0.0006)***	–	–	–	–	–	–
FATHER EDUCATION	–	−0.0051 (0.0007)***	–	–	–	–	–
EXTENSION SERVICES	−0.0324 (0.006)***	−0.032 (0.00612)***	−0.0041 (0.0065)***	−0.1038 (0.0241)***	−0.0356 (0.0064)***	−0.1023 (0.0247)***	−0.0032 (0.0638)
GENDER	–	–	0.021 (0.0084)**	0.3707 (0.0313)***	0.0243 (0.0085)***	0.0369 (0.0324)***	0.07 (0.0709)
PUNISHMENT RATE	0.0288 (0.007)***	0.029 (0.007)***	0.0343 (0.008)***	0.0713 (0.0168)***	0.0351 (0.0092)***	0.063 (0.0159)***	0.0288 (0.0249)
PRIVILEGE	–	–	−0.0118 (0.0057)**	0.0941 (0.0227)***	−0.00215 (0.00583)	0.0975 (0.0239)***	0.163 (0.0632)***
PRICE	91.162 (18.033)***	91.191 (17.911)***	89.362 (19.067)***	−6.689 (71.771)	82.34 (20.0834)***	−7.602 (74.5326)	−42.335 (209.893)
PRICE squared	−315.067 (66.39)***	−315.24 (65.961)***	−308.386 (70.23)***	31.988 (264.0547)	−282.945 (73.87)***	38.5785 (274.091)	185.559 (776.102)

(*Continued*.)

Table 5 | Continued

Instrumented variable	Equation (4.3) WTH	Equation (4.4) WTH (as 3.3[a] minus EDUCATION plus FATHER EDUCATION)	Equation (4.5) WTH	Equation (4.5) COR	Equation (4.6) WTH	Equation (4.6) COR	Equation (4.6) EDU
RED SOILS	−0.093 (0.0139)***	−0.0909 (0.0138)***	−0.093 (0.0146)***	−0.099 (0.0445)**	−0.108 (0.0161)***	−0.1047 (0.0451)**	0.0705 (0.1306)
REVENUE SHOCK	–	–	–	–	0.0978(0.0225)***	0.1063 (0.0847)	−0.8478(0.211)***
WATER LOGGING	0.0052 (0.0017)***	0.0049 (0.0017)***	0.0064 (0.0019)***	0.0014 (0.0067)	0.0061 (0.0019)***	0.00675 (0.00686)	0.0307 (0.0164)*
CONSTANT	−6.373 (1.216)***	−6.3747 (1.2073)***	−6.2808 (1.2845)***	0.509 (4.8675)	−5.835 (1.3545)***	0.4328 (5.0598)	21.808 (14.182)
Weak identification test: Kleibergen-Paap rk Wald *F* statistic	24.111	24.111	14.375	14.375	9.587	9.587	9.587
F statistic (excluded instruments)	$F(3,1418) = 24.11$	$F(3,1419) = 29.30$	$F(3,1422) = 16.18$	$F(3,1422) = 63.46$	$F(5,1332) = 14.84$	$F(5,1332) = 35.74$	$F(5,1332) = 4422.70$

Note: Heteroskedasticity-Robust standard errors (clustered on farmers) are in parentheses; *, **, and *** denote variables significant at 10, 5, and 1%, respectively.
Source: Authors' Calculations.

In the two IVPROBIT specifications where we control for *DRIP* and both *DRIP* and *WATER THEFT*, and in the PROBIT specification where *WATER THEFT* is not accounted for (not reported), the average marginal effect of *DISTANCE* is positive and highly significant; however, including *WATER THEFT* reduces it to insignificance because distance is indeed a strong determinant of theft. The results reveal that under the PROBIT specification and the IVPROBIT specification, where we control for *DRIP* alone, the average marginal effect of *GENDER* is positive and significant, as expected. The average marginal effect of *PRIVILEGE* is positive and significant in both the PROBIT specification and the IVPROBIT specification, where we control for both *DRIP* and *WATER THEFT*. The average marginal effect of *PRIVILEGE* is positive and significant in both the PROBIT specification and the IVPROBIT specification, where we control for both *DRIP* and *WATER THEFT*.

The negative average marginal effect of *AGE* is in line with the findings of Togler & Valev (2004), who show that older people are less likely to perceive corruption as justifiable. Age has also been identified as an important determinant of other illegal activities: older people are on average more tax compliant and less likely to be involved in crime (Torgler, 2003).

Results from (6.3) and (6.4) show that our concerns about endogeneity are justified for all variables. Controlling for the endogeneity of theft and drip separately sharply increases the average marginal effect of *WATER THEFT*, suggesting that the causal association of higher rates of theft with higher corruption rates is reinforced by the reverse-causal association of increased incidence of theft with higher corruption rates. The marginal effect of *DRIP* increases when we control for *WATER THEFT* alone (not reported) and drastically decreases when we

Table 6 | Determinants of CORRUPTION – marginal effects (Univariate probit and instrumental variables for probit estimates).

Specification/Instrumented variable for IVPROBIT	**Equation (6.1)** ***PROBIT of CC***	**Equation (6.2)** ***PROBIT of IPW***	**Equation (6.3)[a]** ***IVPROBIT (DRIP)***	**Equation (6.4)[b]** ***IVPROBIT (DRIP + WTH)***
Independent variable				
AGE	−0.0042 (0.00149)***	−0.00439 (0.00159)***	–	–
ALTERNATIVE REVENUE	0.01117 (0.0122)	0.0046 (0.0126)	−0.0908 (0.037)**	0.095 (0.027)***
DISTANCE	−0.00345 (0.0058)	−0.00105 (0.0061)	0.0859 (0.0228)***	0.0947 (0.0145)***
DRIP	−0.371 (0.1019)***	−0.364 (0.1044)***	4.916 (1.1849)***	−6.602 (0.1724)***
PUNISHMENT RATE	0.0445 (0.01582)***	0.0603 (0.0167)***	0.088 (0.0482)*	0.278 (0.049)***
GENDER	0.4055 (0.03916)***	0.417 (0.0413)***	0.938 (0.188)***	0.089 (0.098)
PRIVILEGE	0.1745 (0.0307)***	0.197 (0.03216)***	0.105 (0.1438)	0.11045 (0.0664)*
WATER THEFT (WTH)	1.936 (0.143)***	1.861 (0.147)***	6.489 (0.437)***	−9.777 (0.2817)***
Log pseudo-likelihood	−499.9735	−645.656	467.4016	1856.297
Pseudo R^2	0.4493	0.4376	–	–
J over-identification test (% significance)	–	–	Equation exactly identified	Equation exactly identified
Wald test (% significance)	–	–	10.45 (0.0012)	$2.2 \times 10^{+10}$ (0.0000)
No. of observations	1429	1429	1429	1429

Note: Heteroskedasticity-Robust standard errors (clustered on farmers) are in parentheses for probit estimates (standard errors for ivprobit estimates); *; **, and *** denote variables significant at 10, 5, and 1%, respectively.
Source: Authors' Calculations.
[a]The excluded instrument is AGE.
[b]The excluded instrument are as in (6.3) plus ALTERNATIVE SOURCE.

control for both *WATER THEFT* and *DRIP*. However, this marginal effect becomes positive when we control for *DRIP* alone. The exogeneity test on *DRIP*, as well as the joint exogeneity test on *DRIP* and *WATER THEFT*, are both clearly rejected as they pass the Wald test at less than a 1% level. Finally, the instruments used are strong ones, as evidenced by equations (7.3) and (7.4) from Table 7, where the *F* statistic in each of the first-stage regressions is greater than 10. Table 7 reports the instrumented variables' first-stage IV estimations in the estimation of *CORRUPTION*.

7. CONCLUSION

Adoption of water-saving technologies is one of the main water demand management tools, which can bring benefits in the form of water conservation and increased productivity. However, its implementation may be constrained by informational problems. In this paper, we investigate the potential advantages and limitations encountered by the adoption of water-saving technologies in the presence of water theft by manipulation of water meters. In particular, we show how the farmer's incentives for theft and technology adoption interact, as well as how regulatory instruments designed in response to this perceived interaction would themselves interact. We extend the basic analysis to allow for collusion between cheating farmers and monitors, and show how collusion is affected by monitoring costs and punishment levels inflicted on cheating farmers.

Table 7 | First-stage IV estimates of the instrumented variables in the estimation of CORRUPTION (Equation (6.3) and Equation (6.4)).

Instrumented variable	Equation (6.3) *DRIP*	Equation (6.4) *DRIP*	*WTH*
Independent variable			
AGE	−0.0015 (0.0003)***	−0.00192 (0.0003)***	0.00132 (0.00035)***
ALTERNATIVE SOURCE	–	0.0671 (0.00456)***	−0.0358 (0.00535)***
ALTERNATIVE REVENUE	0.0177 (0.003)***	0.01387 (0.0035)***	−0.00039 (0.0027)
DISTANCE	−0.0156 (0.0016)***	−0.01967 (0.00131)***	0.0243 (0.00145)***
GENDER	−0.019 (0.0095)**	−0.0163 (0.01008)	0.0214 (0.0096)**
PUNISHMENT RATE	0.0056 (0.00308)*	−0.005 (0.004)	0.0323 (0.0069)***
PRIVILEGE	0.051 (0.0077)***	0.039 (0.0079)***	−0.0194 (0.0064)***
WATER THEFT	−0.493 (0.039)***	–	–
CONSTANT	0.842 (0.0223)***	0.623 ((0.0304)***	0.0783 (0.034)**
F statistic	$F(7,1422) = 353.04$	$F(7,1421) = 283.29$	F(7,1421) = 263.10
R^2	0.548	0.5375	0.5943
No. of observations	1429	1429	1429

Note: Heteroskedasticity-Robust standard errors (clustered on farmers) are in parentheses; *, **, and *** denote variables significant at 10, 5, and 1%, respectively.
Source: Authors' calculations.

Based on survey data from two public irrigated areas in Medjez-el-Bab (Tunisia) for the years 2012–18, we discuss results from IV variables regression models. The econometric evidence supports most of the theoretical predictions in that monitoring costs, the price of water, the adoption of drip technology, and the higher scope for collusion increase theft. We also find support for higher punishment levels, increasing the incentives for technology adoption and the expected incidence of theft, reducing them. Moreover, the econometric evidence lends credence to the fact that monitoring costs, punishment levels, and the use of drip systems reduce the incentives for collusion, whereas the expected incidence of theft increases them.

Besides, the empirical analysis supports the role of various economic, socioeconomic, physical, and geographical factors in explaining the various farmer incentives. The results indicate that farmers with more education, capital, and access to alternative irrigation supplies are less inclined to steal water. Furthermore, better-educated farmers, with more off-farm income opportunities, receiving extension services, and growing crops in plots of land with a higher percentage of red soils and characterized by higher groundwater table levels, are more likely to adopt new technologies. In relation to farmer characteristics, variables that control for differences in external off-farm income sources, gender, and privileged social situations play an important role in explaining the incentives for getting involved in bribery.

Overall, we believe that our findings have important implications for the success of government interventions to address concerns about enhancing water allocative efficiency in the face of moral hazard through interlinkage. Encouraging farmers to adopt water-saving technologies is a way to fight water theft and corruption. But, as theft and corruption themselves reduce adoption rates, well-designed institutional rules like monitoring and punishment can be effective at creating the right incentives for reducing them, which in turn increases the incentives for technology adoption.

Second, we found evidence in favour of pricing policies increasing adoption rates, while also increasing the incidence of theft. Our findings suggest that pricing rules should be adjusted in the presence of theft such that prices are not too high to encourage farmers to invest in water-saving systems because otherwise, farmers will be more likely to steal the resource rather than to invest in costly technologies to save it.

Finally, another key implication of our empirical findings is the important role of socioeconomic characteristics, including education and gender, in influencing the incentives for technology adoption and illicit water theft and corruption. Women are reported to be less implicated in corruption than men, and better-educated persons steal less water and adopt more new technologies.

Policymakers should encourage more educated farmers, particularly educated women to get involved in irrigated agricultural activities. This is, along with policy interventions through extension programs providing adoption-related information.

CONFLICTS OF INTEREST

The authors declare to have no conflicts of interest.

DATA AVAILABILITY STATEMENT

All relevant data are available from https://docs.google.com/spreadsheets/d/12SCvjDyiY1WyzhXaTAtG-I_-1mn1H-jq/edit?usp=sharing&ouid=103878801869438591323&rtpof=true&sd=true.

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