Technology Adoption Under Production Uncertainty: Theory and Application to Irrigation Technology

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We propose a theoretical framework to analyze the conditions under which a farmer facing production uncertainty (due to a possible water shortage) and incomplete information, will adopt a more efficient irrigation technology. A reduced form of this model is empirically estimated using a sample of 265 farms located in Crete, Greece. The empirical results suggest that farmers choose to adopt the new technology in order to hedge against production risk. In addition, we show that the farmer's human capital also plays a significant role in the decision to adopt modern more efficient irrigation equipment.

Key words: human capital, information value, irrigation technology adoption, production uncertainty.

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Introduction

Irrigation water is a scarce resource for the agricultural sector in many regions and countries. Common procedure in past rural policy schemes was the development of adequate irrigation infrastructure in order to guarantee the supply of irrigation water as the demand for agricultural products continued to increase. However, these expansionary policies, which entailed a significant investment cost, have resulted in increased consumption of irrigation water by the agricultural sector and in increased physical scarcity of the resource. Water scarcity has become a concern for the policy makers and competitive water users, and agriculture in particular appears to be at the core of the water shortage problem. The use of modern irrigation technologies has been proposed as one of several possible solutions.

Several studies have attempted to analyze on-farm adoption of irrigation technologies using the engineering notion of irrigation water efficiency defined by Whinlesey, McNeal and Obersinner (i.e., the ratio of water stored in the crop root zone to the total water diverted for irrigation). Moreover, by technically and economically evaluating irrigation technologies, some combinations of water savings and yield increase were found to be necessary in order to induce farmers to adopt water conserving technologies (*e.g.*, Coupal and Wilson; Santos; Droogers, Kite and Murray-Rust; Arabiyat, Segarra and Johnson). Despite the fact that these studies are quite appealing in analyzing the changes and the diffusion of irrigation technologies in the farming sector, they lack economic intuition.

On the other hand, in the context of technological adoption models initiated by Zvi Griliches pioneering work on adoption of hybrid corn in the US, the analysis of farmers' decisions to adopt technological innovations took a different direction.[1] Much of this research has been concerned with the socio-economic, demographic and structural factors that determine the farmer's choice to adopt (or not) irrigation technologies, and with the patterns of diffusion of the innovation through the population of potential adopters over time.[2] Despite numerous studies in this area, the results of applied research are often contradictory with regards to the importance and influence of any given variable used to analyze farmers' decisions. Among the various socio-economic, structural or demographic variables used in these studies, risk has been recognized as a major factor influencing the rate of adoption of any kind of innovation (Jensen, 1982; Just and Zilberman). Uncertainty associated with the adoption of any kind of agricultural technology has two features: first, the perceived riskiness of future farm yield after adoption and second, production or price uncertainty related to farming itself.

Several authors have empirically investigated technology adoption and diffusion taking into account farmers' perceptions about the degree of risk concerning future yield (*e.g.*, Tsur, Sternberg and Hochman; Saha, Love and Schwart). In particular, Saha, Love and Schwart identify those factors that affect technology adoption and its intensity, under incomplete information dissemination and output uncertainty. Their results emphasize the role of information (and thus, improvements in farmer's human capital) in the adoption of emerging technologies. Nevertheless, they explicitly assume that in the absence of adoption, farmers' profits are non-random and therefore in their theoretical framework they assume that neither the riskiness of the new technology nor the farmer's attitude towards risk affects adoption decisions. It seems therefore that there exists a relative dearth of research on the perceived link between a farmer's decision to adopt innovations and production or price uncertainty related to agricultural production. A notable exception is the work by Yaron, Dinar and Voet who attempted to analyze the effect of price uncertainty on the degree of innovation exhibited by family farms in the Nazareth region of Israel, by including in their adoption model a proxy of farmer's risk tolerance towards output price variability. Furthermore, in a different context, Kim and Chavas investigate the dynamic effects of technological progress (as measured by a time trend) on risk exposure, through the calculation of conditional moments of yield and profit from a panel data on corn production from Wisconsin. Their results indicate that technological progress contributes to reducing exposure to risk (as well as downside risk) over time, although these effects vary across space.

The present paper contributes to the relevant literature by testing how production risk and incomplete information affect the probability that a farmer adopts a new and more efficient irrigation technology. Specifically, we extend the Saha, Love and Schwart theoretical framework by explicitly introducing risk into adoption versus non-adoption decisions. In arid and semi-arid regions where water is a primary and scarce input, farm expected production levels (and therefore profits) become random because they are functions of exogenous climatic conditions. Hence risk-averse farmers might consider adopting a water-efficient irrigation technology (i.e., a irrigation equipment which enables the use of *less* water for the production of the *same* level of output) in order to reduce the production risk they face during periods of water shortage. First, we derive a structural model defining the conditions for adoption, when the farmer is risk averse and has incomplete information about the new technology. Then, the reduced form of this model is estimated using a randomly selected sample of 265 farms located in the island of Crete, Greece for the 1995-96 cropping period.

A complete analytical framework for investigating adoption decisions should ideally describe the time pattern of factors such as information gathering, learning by doing, or accumulating resources, that may affect farmer's decision (Feder, Just and Zilberman; Sunding and Zilberman). Indeed, dynamic processes that result in changes to these variables would help in explaining why individuals choose different adoption dates (Karshenas and Stoneman). Such dynamic representations are well suited when one needs theoretical guidance for specification of an adoption model to be applied on a cross-section of individuals followed over several periods of time.[3] However, when only a cross-section of farmers or firms is available, one can only try to explain why, at the time the survey was conducted, the farmer or the firm chose to use the new technology or not.[4] The common approach is then to model the individual's decision in a static framework and to use binary choice models to explain adoption or non-adoption.[5] Our article belongs to the latter group of models as our data contains information about the choice of a single cross-section of farmers to adopt or not a new and recently available irrigation technology. Our contribution resides in the analysis of two sources of risk (production risk and uncertainty related to the use of a new technology) in the model of adoption.

In contrast with the previous literature, we propose a more flexible representation of uncertainty by using moments of the profit distribution as determinants of farmer's decision regarding adoption of new irrigation technology. We build on the Antle (1983; 1987) and Antle and Goodger theoretical framework. The empirical analysis provides fresh insights into the link between production risk and technology adoption. In particular, we show that the probability of adoption increases for farmers who experience higher variance of profit, and for farmers that face the risk of extreme outcomes. The latter effect is approximated by the fourth moment of profit, which captures behavior in the tails of the profit distribution (i.e. outlier activity). On the whole, both of these effects indicate that farmers are willing to adopt in order to hedge against production risk. We also demonstrate that improvements in the farmer's human capital (i.e., education level, extension services, farming information accumulation) generally increase the probability that the farmer adopts the new irrigation technology.

These results provide guidance to policy makers contemplating the introduction of economic instruments, in order to create incentives for adoption of water conservation technologies. In particular, they indicate that policy makers should incorporate into the relevant cost-benefit analysis, the expected benefits that farmers derive from the reduction in their production risk which will be provided by adoption. Moreover the results show that, in addition to the use of economic instruments for creating incentives that induce faster diffusion of new water-efficient technologies, the provision of technology-related information has the same effect by reducing the quasi option value associated with adoption. Hence, the policy maker may use information-provision to induce faster diffusion of adoption among farmers.[6] Although the quantitative results derived in this study are somewhat specific to the region under consideration, the policy recommendations that follow apply equally to any rural region where the shortage of irrigation water is an issue (in arid and semi-arid areas of Southern Europe and the US, as well as other areas).

The rest of the article is organized as follows. In section 2 we present the theoretical framework used to analyze the farmer's decision in the presence of production risk and incomplete information about the new technology. In section 3 we describe the data used in the estimation of the empirical model and introduce the relevant estimation procedure. In section 4 we present and analyze the empirical results, while in section 5 we conclude by deriving some policy recommendations.

Theoretical model

We assume that farmers are risk-averse and utilize a vector of conventional inputs $\mathbf{x}$ together with irrigation water x_w, to produce a single output q through a technology described by a well-behaved (i.e., continuous and twice differentiable) production function $f(\cdot)$. Let p denote output price and $\mathbf{r}$ the corresponding vector of input prices. The farmer is assumed to incur production risk as crop yield might be affected by climatic conditions. This risk is represented by a random variable ε, whose distribution $G(\cdot)$ is exogenous to the farmer's actions. This is the only source of risk we consider, as prices p and $\mathbf{r}$ are assumed non-random[7] (i.e., farmers are assumed to be price-takers in both the input and output markets).

Irrigation water input is assumed to be essential in the farm production process. Efficiency in water use, which is dependent on the utilized irrigation technology, is captured by incorporating a function $h(\alpha)$ in the production function. Farmers are heterogeneous in the sense that irrigation water efficiency depends on farm management and other farmer characteristics incorporated in vector α. The production function will thus be written as $q = f\left[h(\alpha)x_w, \mathbf{x}\right]$.

Allowing for risk aversion, the farmer's problem is to maximize the expected utility of profit, i.e.,

$$(1) \qquad \max_{\mathbf{x},x_w} E\left[U(\varpi)\right] = \max_{\mathbf{x},x_w} \int \left\{U\left[pf\left(\varepsilon, h(\alpha)x_w, \mathbf{x}\right) - r_w x_w - \mathbf{r}'\mathbf{x}\right]\right\} dG(\varepsilon)$$

where $U(\cdot)$ is the *von Neumann-Morgenstern* utility function. Given that p and r_w are non-random, the first-order condition for irrigation water input choice is given by the following relation:

(2a) $$E\left[r_w U'\right] = E\left\{p \frac{\partial f\left(\varepsilon, h(\alpha) x_w, \mathbf{x}\right)}{\partial x_w} U'\right\} \Leftrightarrow$$

(2b) $$\frac{r_w}{p} = E\left\{\frac{\partial f\left(\varepsilon, h(\alpha) x_w, \mathbf{x}\right)}{\partial x_w}\right\} + \frac{cov\left[U'; \partial f\left(\varepsilon, h(\alpha) x_w, \mathbf{x}\right) / \partial x_w\right]}{E\left[U'\right]}$$

where $U' = \partial U(\varpi)/\partial \varpi$. For a risk-neutral farmer, the ratio of input price to output price, r_w/p, equals the expected marginal product of the irrigation water input, namely the first term in the right hand-side of relation (2b). However, when the farmer is risk-averse, the second-term in the right-hand side of (2b) is different from zero and measures deviations from the risk-neutrality case. More precisely, this term is proportional and is opposite in sign to the marginal risk premium with respect to the irrigation water input.

Let us now incorporate into the above general model, the farmer's decision whether or not to adopt a new, more efficient irrigation technology. This decision can be modeled as a binary choice, where the farmer can choose to adopt (A=1) or not (A=0) an innovative irrigation technology. This innovative technology is assumed to increase water use efficiency, i.e., $h^1(\alpha) > h^0(\alpha)$ for $0<\alpha<1$.If the farmer uses the new technology, less water will be necessary to produce the same level of output. In other words, the adoption of the new technology will reduce production risk during years of water shortage in the agricultural sector, induced by adverse climatic conditions. Under conditions of certainty with regards to the use of the new equipment, i.e., future costs and benefits are perfectly known at the time of adoption, adopting the new technology implies a fixed cost $\left(I^1 > 0 \text{ } and \text{ } I^0 = 0\right)$and might change the marginal cost of water $\left(r_w^1 \neq r_w^0\right)$. Denote $\mathbf{x^1}$ $\left(\mathbf{x^0}\right)$ the optimal input choices if the new technology is adopted (non-adopted). The farmer will adopt the new and more efficient irrigation technology if the expected utility with adoption is greater than the expected utility without adoption, i.e.,

$$E\left[U\left(\varpi^{1}\right)\right]-E\left[U\left(\varpi^{0}\right)\right]>0 \tag{3}$$

where

$$\max_{\mathbf{x^1},x_w^1} E\left[U\left(\varpi^{1}\right)\right]=\max_{\mathbf{x^1},x_w^1}\int\left\{U\left[pf\left(\varepsilon,h^{1}\left(\alpha\right)x_w^{1},\mathbf{x^1}\right)-r_w^{1}x_w^{1}-\mathbf{r}'\mathbf{x^1}-I^{1}\right]\right\}dG\left(\varepsilon\right) \tag{4}$$

and

$$\max_{\mathbf{x^0},x_w^0} E\left[U\left(\varpi^{0}\right)\right]=\max_{\mathbf{x^0},x_w^0}\int\left\{U\left[pf\left(\varepsilon,h^{0}\left(\alpha\right)x_w^{0},\mathbf{x^0}\right)-r_w^{0}x_w^{0}-\mathbf{r}'\mathbf{x^0}-I^{0}\right]\right\}dG\left(\varepsilon\right) \tag{5}$$

are, respectively, the expected utility under adoption and non-adoption. Thus, for the risk-averse farmer, the first order condition for water input corresponding to the case of adoption is given by:

$$\frac{r_w^1}{p}=E\left\{\frac{\partial f\left(\varepsilon,h\left(\alpha\right)x_w^1,\mathbf{x^1}\right)}{\partial x_w^1}\right\}+\frac{cov\left[U';\partial f\left(\varepsilon,h\left(\alpha\right)x_w^1,\mathbf{x^1}\right)/\partial x_w^1\right]}{E\left[U'\right]} \tag{6}$$

and for the case of non-adoption:

$$\frac{r_w^0}{p}=E\left\{\frac{\partial f\left(\varepsilon,h\left(\alpha\right)x_w^0,\mathbf{x^0}\right)}{\partial x_w^0}\right\}+\frac{cov\left[U';\partial f\left(\varepsilon,h\left(\alpha\right)x_w^0,\mathbf{x^0}\right)/\partial x_w^0\right]}{E\left[U'\right]}. \tag{7}$$

As the new technology is more water-efficient we would expect risk-averse farmers who bear higher profit uncertainty to have a higher probability of adoption, in order to hedge against the risk of adverse climatic conditions.

Assume now that future profit flows after adoption, are not known with certainty due either to ignorance of the exact performance of the new irrigation technology or to the higher probability of committing errors in the use of this technology. Moreover, buying the new irrigation technology entails sunk costs (there is a fixed cost of investment and some irreversibility in the decision; it might not be easy to re-sale the equipment). These arguments imply that additional information might possess a positive value (Dixit and Pindyck). Farmers may prefer to delay adoption in order to get more information on the new equipment. Consequently, an additional premium may enter the condition of adoption. The farmer will adopt *iff*:

(8)
$$E\left[U\left(\varpi^{1}\right)\right]-E\left[U\left(\varpi^{0}\right)\right]>VI$$

where $VI \geq 0$ represents the value of new information for the representative farmer, which should depend on the fixed cost of investment, the level of uncertainty related to the use of the new technology and the farmer's own characteristics.

Data and Estimation Procedure

Data Description

The dataset used in this study is extracted from a broader dataset, collected via a survey on the structural characteristics of the agricultural sector in Crete. This survey was financed by the Regional Directorate of Crete as part of the Regional Development Program 1995-99 (Liodakis). The sample is a cross-section of 265 randomly selected farms located in the four major districts of Crete: Chania, Rethymno, Heraklio and Lasithi, during the 1995-96 cropping period.[8] The survey provides detailed information about production patterns, input use, average yields, gross revenues, structural characteristics and the number of farms that had adopted modern irrigation technologies. In the sample, 87 out of 265 farms (32.8%) had adopted modern irrigation technologies at the time they were surveyed. These technologies vary from simple sprinklers applied mainly to tree crops, to greenhouse integrated systems that control the irrigation of an entire plantation. Descriptive statistics of the variables are provided in Table 1 for both adopters and non-adopters.

The adopting farms are of a smaller size (45 stremmas or 4.5 ha on the average) and with lower capital stock (2,634 euros). Although farms adopting new irrigation technologies have lower profits compared with their non-adopters counterparts (17,087 and 20,673 euros, respectively), they exhibit higher average profitability per stremma (380.1 and 370.2 euros/stremma respectively). Finally, the average irrigation water use per stremma is 2.8 and 3.3 m^3 for adopters and non-adopters respectively. Statistical testing (using a simple *t*-test[9]) confirms that there are indeed significant differences between the two sub-samples except in the case of capital stock.

In Table 1 we also present information on the socio-economic and structural characteristics of the farms surveyed. From the data presented, it is evident that older farmers, who are in general less educated than their younger counterparts, are not so eager to adopt new technologies. The average age and educational level of farmers that adopted modern irrigation technologies is 36 years of age and 11 years in schooling, respectively, whereas for farmers using traditional technologies the corresponding values are 56 and 6 years. Statistical testing confirms that there are indeed statistically significant differences between adopters and non-adopters at the 1% level.

Furthermore, farms with higher debts and subsidies are more likely to have adopted new irrigation technologies. It is also interesting to note that the average debt for adopting farms is 2,921 euros, whereas the corresponding figure for farms which are using traditional irrigation practices is only 893 euros. A careful inspection of the dataset, however, reveals that this difference is not associated with the adoption of innovative irrigation technologies. The majority of adopters cultivate mainly annual crops (including those under greenhouses), and receive loans at the beginning of the cropping season in order to finance their operation. Hence, although statistical testing confirms the existence of a difference between the two sub-samples, this finding should not be misinterpreted.

Similarly, the level of received subsidies is almost three times higher for farms that adopted innovative irrigation technologies compared to the corresponding level of subsidies paid to non-adopters; i.e., 1,194 and 444 euros for adopters and non-adopters, respectively (the corresponding *t*-statistic is well above the critical value at the 1% level of significance). Although subsidies refer mainly to direct income transfers from CAP (Common Agriculture Policy) and are thus are unrelated to the farmer's adoption behavior, it seems that they provide farmers with the financial backing necessary for investing in new technologies. Another interesting point that arises from the data presented in Table 1, refers to the exposure of farmers to extension services (private or public), and their access to general farming information. Specifically, farmers adopting new irrigation technologies are visited by extension agents on average nine times during the cropping year, whereas farmers relying on traditional irrigation technologies are visited only two times on average. Furthermore, farmers that adopt new technologies absorb better farming related information from various sources (i.e., newspapers, television and radio, visits to agricultural product fairs and shows, sporadic attendance of seminars, meetings or demonstrations and so on).[10] The corresponding *t*-test is well above the critical value at the 1% level of significance. Finally, as was anticipated, farms enjoying less favorable environmental conditions seem to be first among the adopters of new irrigation technologies. Farms facing higher average annual temperature and/or lower annual precipitation are more likely to have adopted new irrigation technologies.

The Estimation Procedure

Relation (8) above implies that the condition of adoption requires the following inequality to hold:

(9) $$E\left[U\left(\varpi^{1}\right)\right]-E\left[U\left(\varpi^{0}\right)\right]-VI>0\,.$$

At the time of the survey we observe farmers in a unique situation (adoption or non-adoption), and hence we cannot estimate this structural equation. Instead, we estimate a reduced-form of this equation and we focus on the impact of risk to explain the adoption decision. First, in order to avoid specifying a functional form for the probability function of profit $\varpi(\cdot)$, the distribution of risk $G(\cdot)$ and, farmer's risk preferences (i.e., the utility function $U(\cdot)$), we use a moment-based approach, which allows a flexible representation of the production risk (see Antle, 1983, 1987; Antle and Goodger). Production risk and thus profit uncertainty are accounted for in the adoption model by using the sample moments of the profit distribution as explanatory variables of farmer's decision. Our dataset has the great advantage of gathering information on farmers who had *just* adopted the new irrigation technology. Specifically, farmers were surveyed at the time the decision to adoption/not adopt was made. Thus, the profit function has not yet been affected by the adoption decision and for this reason, moments of profit can be assumed exogenous to farmers' decision. Second, as explained earlier, there exists an additional source of risk that derives from uncertainty on future profit flows, which is introduced into the production process through the use of the new equipment.

The cost of this uncertainty is represented by a premium (*VI*) in the above equation, indicating the value of seeking additional information. In our empirical model, the role of information on the adoption decision will be measured through the following proxy variables that determine the farmer's human capital: the *education* level of the head of the household, the general *active farming information* gathering and, the number of *extension visits*. All three variables are assumed to be positively correlated with farmer's information level on the new equipment. According to human capital theory, innovative ability is closely related to these variables,[11] since these characteristics are associated with the resource allocation skills of farm operators (Nelson and Phelps; Schultz; Huffman, 1977). Information gathering, regardless of whether it refers to the innovation itself or not, is expected to enhance resource allocation skills, and to increase the efficiency of adoption decisions. A farmer with a high level of resource allocation skills will make more accurate predictions of future yields and profitability and will thus make more efficient adoption decisions (Stigler; Huffman, 2001). Similarly, imperfect information concerning new technologies may bring risks associated with innovation adoption that may raise the possibility of committing errors.

The estimation procedure follows two steps. First we compute the first four sample moments of the profit distribution of each farmer, namely the mean, variance, skewness and kurtosis coefficients. Second, we incorporate the estimated moments in a traditional discrete choice model, along with other farmer's characteristics and the variables related to the farmer's information, in order to analyze how production risk and information affects the decision to adopt a technological innovation. The first four moments of the profit distribution are derived following a sequential estimation procedure (see Kim and Chavas for a detailed description of the procedure).[12] In the first step, profit is regressed on the contemporaneous input variables to provide an estimate of the "*mean*" effect. The model[13] has the following general form:

(10) $$\varpi_i = \varphi\left(x_{wi}, \mathbf{x_i}, \mathbf{z_i}; \boldsymbol{\beta}\right) + u_i$$

where $i = 1, \ldots N$ denotes individual farmers in the sample, ϖ is the profit per hectare, $\mathbf{x}$ is the vector of variable inputs (labor, intermediate inputs), x_w is irrigation water input, $\mathbf{z}$ is the vector of extra shifters including farmer's characteristics (farmer's age and farmer's supplementary revenue unrelated to farming activities), and farm-specific characteristics (geographical location[14] and aridity). u is the usual *iid* error term. Under expected profit maximization the explanatory variables are assumed to be exogenous and thus the OLS estimation of (10) provides consistent and efficient estimates of the parameter vector $\boldsymbol{\beta}$. Then, the j^{th} central moment of profit $\left(j = 2, \ldots, m\right)$ conditional on input use is defined as:

$$\mu_j\left(\bullet\right) = E\left\{\left[\varpi\left(.\right) - \mu_1\right]^j\right\} \tag{11}$$

where μ_1 represents the mean or first moment of profit. Thus, the estimated errors from the mean effect regression $\left(\widehat{u} = \varpi - \varphi\left(x_w, \mathbf{x}, \mathbf{z}; \widehat{\boldsymbol{\beta}}\right)\right)$ are estimates of the first moment of the profit distribution. The estimated errors $\widehat{u}$ are then squared and regressed on the same set of explanatory variables:

$$\widehat{u}_i^2 = g\left(x_{wi}, \mathbf{x_i}, \mathbf{z_i}; \boldsymbol{\delta}\right) + \tilde{u}_i \, . \tag{12}$$

The application of OLS on (12) provides consistent estimates of the parameter vector $\boldsymbol{\delta}$ and the predicted values $\hat{\widehat{u}}_i^2$ are consistent estimates of the second central moment of the profit distribution (i.e., the variance) (Antle, 1983). We follow the same procedure to estimate the third and fourth central moments, by using the estimated errors raised to the power of three and four, respectively, as dependent variables in the estimated models.[15] The four estimated moments are then incorporated into a discrete model of technology adoption along with farmer's structural and demographic characteristics.

Recall that the farmer will choose to adopt the modern irrigation technology *iff*

$$Y_i^* \equiv E\left[U\left(\varpi_i^1\right)\right] - E\left[U\left(\varpi_i^0\right)\right] - VI > 0 \, . \tag{13}$$

Y_i^* is an unobservable random index for each farmer that defines their propensity to adopt a new irrigation technology. For purposes of estimation, denote by

(14) $$Y_{0i} = \mathbf{z}'_{0i}\boldsymbol{\alpha}_0 + \mathbf{m}'_{0i}\boldsymbol{\alpha}_0^{\mathbf{m}} + \left[\mathbf{m}\times\mathbf{k}\right]'_{0i}\boldsymbol{\alpha}_0^{\mathbf{k}} + v_{0i},$$

the indirect utility (per year) of farmer *i* if he is a non-adopter, and by

(15) $$Y_{1i} = \mathbf{z}'_{1i}\boldsymbol{\alpha}_1 + \mathbf{m}'_{1i}\boldsymbol{\alpha}_1^{\mathbf{m}} + \left[\mathbf{m}\times\mathbf{k}\right]'_{1i}\boldsymbol{\alpha}_1^{\mathbf{k}} + v_{1i},$$

the indirect utility of farmer *i* if he is an adopter.

Vector **z** is a vector of regressors including all structural and demographic characteristics, **m** is the vector of the first four profit moments that introduce uncertainty into the model and $\left[\mathbf{m}\times\mathbf{k}\right]$ denotes the vector containing the interactions between the four moments and the human capital variables. $\boldsymbol{\alpha}$ is a vector of parameters to be estimated and v is the usual error term. Based on the empirical evidence reported in the relevant literature and on the availability of data arising from our sample survey, the **z** vector of explanatory variables contains the following: (*a*) the farmer's age measured in years; (*b*) the farmer's educational level measured in years of schooling; (*c*) a dummy indicating general farming information actively gathered from other sources; (*d*) an aridity index defined as the ratio of the average annual temperature over the total annual precipitation in the area (Stallings); (*e*) the farm's total debts measured in euros; (*f*) the number of extension visits to the farm; (*g*) off-farm income measured in euros; (*h*) a dummy denoting family-owned farms; (*j*) three soil dummies distinguishing soils of different quality (i.e., clayey sandy, clayey limestones, marly limestones) and; (*i*) three locational dummies capturing interregional differences (i.e., Rethymno, Heraklio, Lasithi). Finally, the variables measuring human capital (i.e., the farmer's education level, active information gathering, and extension visits) are interacted with each of the four profit moments.

From (14) and (15), the probability of farmer i adopting modern irrigation technology is given by the following probability model:

$$\text{(16)} \qquad \begin{aligned} \Pr[Y_i = 1] &= \Pr[Y_{0i} < Y_{1i}] = \Pr\left[v_i < z_i'\alpha + m_i'\alpha^m + [m \times k]_i' \alpha^k\right] \\ &= \Phi\left[z_i'\alpha + m_i'\alpha^m + [m \times k]_i' \alpha^k\right] \end{aligned}$$

where $v_i = v_{i0} - v_{i1}$, $z_i = z_{i1} - z_{i0}$, $m_i = m_{i1} - m_{i0}$, $[m \times k]_i = [m \times k]_{i1} - [m \times k]_{i0}$, $\alpha = \alpha_1 - \alpha_0$, $\alpha^m = \alpha_1^m - \alpha_0^m$, and $\alpha^k = \alpha_1^k - \alpha_0^k$.

The binary choice model in (16) will be estimated using a Probit model, i.e. assuming that v_i is $N(0,\sigma^2)$ and that $\Phi(.)$ is the cumulative of the normal distribution.

Prior to the estimation of the model, we need to address the potential endogeneity of three variables included in model (16); farm's debts, extension visits and, off-farm income.[16] We do so by implementing a two-stage instrumental variable procedure suggested by Lee and utilized by Connelly and DeSimone. In the first-stage we specify all the above variables as functions of all other exogenous variables included in (16), plus a set of instruments.[17] In the second-stage, the observed values of these variables (i.e., farm's debts, extension visits and off-farm income) are included along with the vector of their corresponding residuals, arising from the first-stage into the model in (16) as:

$$\text{(17)} \qquad Pr[Y_i = 1] = \Phi\left(\mathbf{z}_\mathbf{i}'\boldsymbol{\alpha} + \mathbf{m}_\mathbf{i}'\boldsymbol{\alpha}^\mathbf{m} + [\mathbf{m} \times \mathbf{k}]_\mathbf{i}' \boldsymbol{\alpha}^\mathbf{k} + \tilde{\mathbf{v}}_\mathbf{i}'\boldsymbol{\alpha}^\mathbf{v}\right)$$

where, $\tilde{\mathbf{v}}_\mathbf{i}$ is the vector of the residuals obtained from the first-stage and $\boldsymbol{\alpha}^\mathbf{v}$ is the vector of the corresponding parameters. The above relation enables the consistent estimation of the parameters in the presence of possible endogenous variables in **z**. A simple *t*-test for the significance of the coefficient vector $\boldsymbol{\alpha}^\mathbf{v}$ is a test for the exogeneity of the three suspicious variables (Smith and Blundell).[18] Finally, since we incorporate estimated values (i.e., profit moments) in the probit equation, we use bootstrapping techniques to obtain consistent estimates of the corresponding standard errors in the probit model (Politis and Romano).

Estimation results

The two-stage instrumental variable parameter estimates of the probit model in (17), along with the corresponding t-statistics obtained through bootstrapping techniques, are presented in Table 2. First, McFadden's R^2 exhibits a high value (i.e., 83.29) indicating a good fit to the model. The signs of the explanatory variables in the probit model conform to our expectation that the farmers who bear more risk are more likely to adopt the new, water-saving, irrigation technology. The rejection of risk-neutrality is shown through the significance of the direct effect of three (first, second and fourth) out of the four sample moments included in the estimated adoption model.

As shown in table 2, only the residuals of the extension visits equation are statistically significant, indicating that extension visits are endogenous to the farmer's decision, when they belong to the sample that has adopted an innovative irrigation technology. On the other hand, the farm's debts and off-farm income are both exogenous variables as the coefficients of the corresponding residual vectors turned out to be statistically non-significant estimates. As far as extension services (public or private) are concerned, farmers that are considering adoption of technological innovations (including irrigation technologies) are more likely to visit extension agents, in order to obtain the necessary information for adequate implementation of the new technology. Off-farm income, on the other hand, is often hypothesized to provide financial resources and to create incentives to adopt new technologies as the opportunity cost of time rises. The level of off-farm income may not be exogenous but influenced by the profitability of farming itself, which in turn depends on adoption decisions. However, in our survey, off-farm income arises mainly from non-farm activities (i.e., tourism) and from employment in other non-farm related sectors (i.e., public administration and construction work).[19] Given that skill requirements are different for these jobs, farm and off-farm income may be realistically assumed to be non-competitive in the sense that the time allocated on each occupation is fixed exogenously (Wozniak, 1993; Lapar and Pandey). Thus, off-farm income could be largely exogenous to adoption decisions, an assumption supported by statistical testing. Finally, concerning the level of the farm's debts, looking carefully at our sample survey we observe that the vast majority of debts arise from cultivation loans taken at the beginning of cropping season by farms producing mainly fresh vegetables in greenhouses. Besides, at the time of the survey, 40% of the cost of adoption was financed by structural funds of the Greek Ministry of Agriculture. Hence farms' debts are not endogenous to the decision to adopt new irrigation technologies, which is also supported by statistical testing.

Risk is found to play a prominent role in the decision to adopt a new more efficient irrigation technology. Risk associated with the environmental characteristics of the farm is found to be important. Higher aridity as well as sandy soils,[20] both increase the water requirements of crops and thus increase the production risk related to adverse climatic conditions (such as droughts). This in turn, induces farmers to adopt new technologies with greater water-saving potential. Farmers' own characteristics are also highly significant in the choice of adopting new irrigation equipment. We show that the younger and the more educated the farmer is, the higher the probability that he/she will adopt new irrigation technologies. The educational effect as well as the positive signs associated with the variables describing exposition of farmers to extension services and access to general farming information may indicate that there exists a positive value on waiting for better information (Dixit and Pindyck). In other words, the farmers who have better information (through visits, general information channels, or education) put a lower value on the option to wait and for this reason are more likely to adopt than other farmers (i.e., they have a higher probability to adopt the new technology at the time of the survey with respect to less informed farmers).

The central role of risk in farmer’s decision is highlighted through the significance of the sample moments. The first and second moments, which approximate expected profit and profit variance, are highly significant. The third moment, which approximates the skewness of profit is not statistically significant whilst the fourth moment is marginally significant at the 10% level. These results indicate that the higher the expected profit the greater the probability that a farmer decides to adopt a new irrigation technology, as he/she expects to be able to afford the adoption of new water-saving technologies. Moreover, the greater the variance of profit (and the bigger the probability of facing extreme profit values), the greater the probability to adopt new irrigation technologies. This allows farmers to reduce production (yield) risk in the periods of water shortage. This result provides evidence that farmers invest in new technologies as a means to hedge against input related production risk. Finally, the statistical insignificance of the third moment of profit indicates that farmers are not taking downside yield uncertainty into account when they decide whether to adopt a new irrigation technology. That is, while the choice of irrigation technology is relevant in dealing with production risk (as measured by the variance of yield), these results suggest that technology choice does not affect exposure to downside yield uncertainty.

Following Kim and Chavas, we can test for the nature of the exposure to downside risk. More precisely, we can test the null hypothesis that the profit distribution is symmetric, using a Wald statistic. The skewness coefficient measuring symmetry of the distribution is defined as $s=\left(\mu_3\right)^2 / \left(\mu_2\right)^2$ where μ_j is the j^{th} central moment of profit. Under the null hypothesis of symmetry (s=0), the test statistic $W=N\left(\hat{s}/6\right)$ (where N is the number of farmers), is distributed as a $\chi^2_{(1)}$. If the null hypothesis of symmetry is rejected this constitutes evidence that the distribution of profit is skewed to the left (corresponding to a significant exposure to downside yield risk). We test for symmetry at the sample mean, and at the mean of various sub-samples: the sub-sample of adopters and non-adopters; and sub-samples defined by the geographical location of farmers. In all cases but one (the sub-sample of the farmers located in Rethymno), we cannot reject the null of symmetry in the profit distribution. These results might explain the non-significance of the third sample moment in the adoption model.

Interacting the four moments of profit with education, extension visits and active information gathering allows us to test if the amount of information the farmer has accumulated (through education, extension visits and information gathering) affects farmer's response to risk. Active information gathering is found not to impact farmer's response to any of the four moments. However, a higher education level and more frequent extension visits are found to increase farmer's response to variation of the second moment of profit, and to decrease the farmer's response to changes in the fourth moment. The former effect indicates that the more educated and informed about production-related technological advances the farmer is, the more responsive he/she is to parameters that affect the variance of farm-profit. The latter effect possibly indicates that the more educated and informed the farmer is, the more likely he is to realize the difficulty of hedging against extreme events, which are difficult to predict. As a result, his probability of adopting a new technology in order to hedge against outlier activity in his profit distribution decreases.

One useful expedient when undertaking a probit analysis is to calculate the value of the derivatives at the mean values of all the independent variables in the sample. The motivation is to display the derivative for a "*typical*" element of the sample. These derivatives are reported in Table 3 and represent the marginal effect of each regressor, approximating the change in the probability of adoption at the regressors' mean. Once again, standard errors were obtained using block resampling techniques following the approach suggested by Politis and Romano. The highest effect arises from the adverse environmental conditions (i.e., aridity index) followed by the first moment of profit (i.e., expected profits), farmer's level of education and the number of extension visits. Specifically, a one per cent increase in the value of these variables will *ceteris paribus* result in an increase in the probability of adoption by 0.046, 0.043, 0.018 and 0.017 per cent, respectively.

As indicated in Table 3, the sample moments of the profit distribution, in particular mean and variance, affect the decision of the farmer to adopt a new technology thus confirming that farmers are not risk-neutral. The farmer's human capital, as measured by his education level, his access to information, and extension visits, is also found highly significant, thus reinforcing the idea that the quasi option value (or value of waiting to get better information) may play an important role in the farmer's decision.

Conclusions

In this article we develop a theoretical model to describe irrigation technology adoption by farmers facing production risk and incomplete information about new technology. The condition of adoption is derived under the assumptions of farmers' risk-aversion, and assuming that uncertainty can come from two sources: randomness in climatic conditions and uncertainty of future profit flows associated with the use of the new technology. We estimate a reduced form of this equation using a randomly selected sample of 265 farms located in Crete, Greece. The estimation procedure is developed in two steps. In the first step, we estimate the first four moments of the profit distribution and in the second step we incorporate these estimated moments in the technology adoption model. Risk is found to play a central role in farmers' decisions, first through the direct effect of the sample moments of the profit distribution in the adoption model, and second through the role of information in the decision to adopt.

These results have important policy implications. Firstly, adoption of new water-conservation irrigation technologies can be used as a means for production risk management. Secondly, if farmers are risk averse, the value of the marginal product of variable inputs exceeds their market price. This result might lead to the erroneous inference that farms are inefficient in the allocation of their variable inputs and that regulation regarding input choices is needed. Neglecting risk considerations when assessing the impact of regulation policies on input choices and expected profit could provide misleading guidance to policy makers. This should alert all policy makers contemplating regulation of stochastic production process in general, and agriculture, in particular. Thirdly, when a policy maker is contemplating the introduction of economic instruments (*e.g.*, subsidies) in order to give incentives for adoption of water-conservation technologies, he should incorporate into the relevant cost-benefit analysis the expected benefits that farmers derive from the reduction in their production risk caused by adoption. Ignoring these benefits might result in potentially welfare-enhancing policies not satisfying a cost-benefit criterion. Finally, when the effect of a new technology on future profit flows is uncertain, provision of adoption-related information induces faster diffusion among farmers, by reducing the quasi option value of adoption.

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Table 1
Summary Statistics of the Variables

Variable	Adopters		Non-Adopters	
Economic Data	mean	StDev	mean	StDev
Crop Output (in Kgs)	18,234	10,078	21,439**	11,868
Livestock Output (in Kgs)	1,542	1,288	2,504*	1,038
Land (in stremmas[1])	45	31	56*	42
Labour (in hours)	452	265	530	272
Chemical Inputs (in Kgs)	12,405	11,135	16,212**	14,104
Capital Stock[2] (in euros)	2,634	1,197	3,247	1,845
Irrigation Water (in m^3)	130	125	186*	166
Total Cost (in euros)	36,189	23,036	45,198*	32,152
Total Revenue (in euros)	53,276	35,600	65,871*	46,474
Profits (in euros)	17,087	15,088	20,673**	17,265
Farm Characteristics				
Farmer's Age (in years)	36	6	56*	11
Farmer's Education (in years)	11	3	6*	2
Farm's Debts (in euros)	2,921	1,953	893*	687
Subsidies (in euros)	1,194	328	444*	287
Extension visits (No visits)	9	7	2*	1.8
Information (1=yes, 0=no)	0.471	0.50	0.082*	0.149
Aridity Index[3]	1.188	1.8	0.603**	1.2
Soil type: (% of farms)				
Clayey sandy	10.3		41.0	
Clayey limestones	40.2		19.7	
Marly limestones	41.4		15.7	
Dolomitic limestones	8.1		23.6	
Number of Farms	87		178	

Note: [1] one stremma equals 0.1 ha; [2] capital stock was estimated using the perpetual inventory method as described in Ball *et al.*; [3] aridity index is defined as the ratio of the average annual temperature in the area over the total annual precipitation (Stallings). * (**) indicate statistically significant differences in the respective variables between the two sub-samples (i.e., adopters and non-adopters). The null hypothesis that there is no difference was tested using a simple *t*-test.

Table 2

Estimation Results for the Probability of Adopting the New Irrigation Technology

Variable	Estimate	T-ratio	Variable	Estimate	T-ratio
Constant	-3.0587	(-5.0247)	<u>Profit Moments:</u>		
Age	-0.1374	(-4.8965)	1st Profit Moment	0.2628	(2.8290)
Education	0.1954	(3.0217)	x Education	0.0748	(1.0147)
Aridity Index	0.3895	(4.9854)	x Extension Visits	0.0074	(1.8685)
Farms' Debts	0.0017	(4.7458)	x Active Information	0.0857	(0.1254)
Extension Visits	0.0952	(2.1476)	2nd Profit Moment	0.6358	(1.9658)
Active Information	0.1504	(3.4784)	x Education	0.1248	(1.9587)
Off-farm Income	-0.0426	(-2.0748)	x Extension Visits	0.1054	(2.0247)
Family Farming	-0.0472	(-2.1275)	x Active Information	-0.0505	(-0.8036)
<u>Soil Dummies:</u>			3rd Profit Moment	-0.2587	(-0.8625)
Clayey Sandy	0.2236	(2.6987)	x Education	0.1628	(1.0685)
Clayey Limestones	0.3025	(1.9674)	x Extension Visits	0.1241	(1.3258)
Marly Limestones	0.8905	(1.0748)	x Active Information	-0.1587	(-0.6544)
<u>Location Dummies:</u>			4th Profit Moment	0.0758	(1.8147)
Rethymno	0.2307	(0.2865)	x Education	-0.1785	(-1.9631)
Heraklio	0.6857	(2.0899)	x Extension Visits	-0.1354	(-2.1325)
Lasithi	0.2408	(3.1951)	x Active Information	-0.2047	(-1.3258)
Farms' $Debts_{res}$	-0.0017	(-0.1478)	Off-farm $Income_{res}$	0.0075	(0.8574)
Extension $Visits_{res}$	0.0107	(2.2857)			
% correct prediction	92.17				
McFadden's R^2	83.29				

Note: Standard errors were obtained using block resampling techniques which entails grouping the data randomly in a number of blocks of ten (10) farms and re-estimating the model leaving out each time one of the blocks of observations and then computing the corresponding standard errors (Politis and Romano).

Table 3
Marginal Effects of the Explanatory Variables

Variable	Estimate	T-ratio
Age	-0.00807	(-5.8547)
Education	0.01808	(3.8698)
Aridity Index	0.04569	(3.7926)
Farms' Debts	0.00014	(5.3658)
Extension Visits	0.01674	(2.1736)
Active Information	0.00337	(3.8571)
Off-farm Income	-0.01109	(-1.9808)
Family Farming	-0.00739	(-1.8231)
Soil Dummies:		
Clayey Sandy	0.00254	(3.1369)
Clayey Limestones	0.00132	(1.9057)
Marly Limestones	0.00441	(1.1063)
Location Dummies:		
Rethymno	0.00034	(0.7517)
Heraklio	0.01308	(2.8423)
Lasithi	0.02482	(3.0534)
Profit Moments:		
1^{st} Moment	0.04308	(3.9541)
2^{nd} Moment	0.02974	(2.0412)
3^{rd} Moment	-0.00857	(-0.7325)
4^{th} Moment	0.00268	(1.9829)

Note: Standard errors were computed using bootstrapping techniques.

Endnotes

[1] Feder, Just and Zilberman, Feder and Umali and Sunding and Zilberman provide excellent surveys on the technological adoption literature. Besley and Case review extensively the existing empirical technological adoption models in the light of their consistency with an underlying theoretical model of optimizing behavior.

[2] The most indicative empirical studies analyzing irrigation technology adoption include those by Fishelson and Rymon, Dinar and Zilberman, Dinar, Campbell and Zilberman, Dinar and Yaron and, Dridi and Khanna.

[3] As pointed out by one of the referees, this type of analysis can be adequately represented by a *hazard ratio* model that formulates the problem in terms of the conditional probability of adoption at a particular time, given that adoption has not already occurred. This kind of models have been used in several applications related to technology adoption in both the agricultural and industrial sector (*e.g*., Rose and Joskow; Karshenas and Stoneman; Saloner and Shephard; Kerr and Newell; Abdulai and Huffman). Stoneman provides a detailed discussion of the relevant issues in the light of more general technological diffusion models.

[4] Besley and Case, in reviewing the empirical models used to analyze technology adoption in developing countries, suggest that the use of a simple cross-section of data is able to provide insights into the farm and farmer characteristics associated with ultimately accepting the new technology but fail to explore the adoption process itself. They suggest the use of *recall* data to address this limitation (i.e., the exact time when farmers actually adopted the new technology). Our sample survey, however, contains only farms that have adopted innovative irrigation technologies at the time of survey, and thus it is appropriate to use them in a simple probit under the assumption that all

explanatory variables are indeed exogenous (this assumption is tested in the forthcoming sections).

[5] The most indicative studies include those by Wozniak (1984; 1993), Putler and Zilberman, Huffman and Mercier and, Lin.

[6] While both information and subsidy policies speed up adoption and diffusion of new technologies, Stoneman and David have shown that subsidy policies (which are frequently used by the European Union (EU) as means of promoting technological adoption throughout Europe) may yield welfare losses in the form of income transfers from other sectors of the economy.

[7] Since farms in the sample are located in a relatively small geographic area, output and factor price variability is low (Huffman and Mercier). In addition, farmers face a minimum guaranteed price under the relevant regulation applied within the respective Common Market Organization of the Common Agricultural Policy. That is, if the market price of output, in any particular year is lower than the minimum guaranteed price, farmers will receive a lump-sum equal with the difference between market and threshold price.

[8] The island of Crete is a semi-arid area in the south of Greece and it is among the major agricultural producing regions of the country accounting for the 12% of the total national GDP, while it contributes by 6% to the total world olive-oil production and by 23% to the total EU out-of-season (i.e., in greenhouses) fruits and vegetables production. Thus, it constitutes an indicative case-study for the empirical evaluation of the adoption of new more-efficient irrigation technologies.

[9] The *t*-test used to compare the average of variable x between the sub-sample of adopters ($\overline{x}_A$) and the sub-sample of non-adopters ($\overline{x}_N$), is computed as:

$t=\frac{\overline{x}_A-\overline{x}_N}{\sqrt{\left(Var\left[x_A\right]/n_A\right)+\left(Var\left[x_N\right]/n_N\right)}}$, where $v \approx n_A+n_N-2$ is the number of the degrees of freedom, n_A and n_N is the number of adopting and non-adopting farms in the sample, respectively.

[10] Following Feder and Slade and Jensen (1988) this refers to active information gathering.

[11] Indeed additional schooling may affect the knowledge that the farmer has about how technologies might work and how to gather and analyze publications or reports containing technology-related information (Kihlstrom).

[12] Even though most distribution functions are well approximated by their first three moments, we proceed to the estimation of the fourth moment, which provides a measure of the variability of profit variance, a measure that might be relevant for the farmers' selection of production inputs.

[13] We choose a flexible functional form for $\varphi(\cdot)$ which includes inputs in levels, squares and cross-variables.

[14] We control for farm location among the four districts of Crete, namely Chania, Rethymno, Heraklio, and Lasithi.

[15] Estimation results are not reported here but are available upon request.

[16] This issue has been pointed out by one of the referees.

[17] In the farm's debts equation we have used as instruments the size of the farm operation, its capital stock and a dummy indicating farms cultivating in greenhouses; in the extension visits equation the distance of the farm from the nearest extension outlet and the number of outlets in the area; while in the off-farm income equation the distance from the nearest city and the intensity of tourism activities in the area measured as the number of tourist arrivals.

[18] This test is similar to the Hausman test for exogeneity. Similar tests have been proposed by Davidson and MacKinnon and Even.

[19] In fact the 53.4% of off-farm income arises from tourism activities, 20.4% from public administration and 26.1% from other non-farm sectors.

[20] Crop production on sandy soils is more water intensive, as they have higher absorbing capacity than other types of soil.