TSE WP working paper series

09-032

Research Group: *Environmental Economics and Natural Resources*

April, 2009

The Effect of Production Uncertainty and Information Dissemination of the Diffusion of Irrigation Technologies

PHOEBE KOUNDOURI, CÉLINE NAUGES AND VANGELIS TZOUVELEKAS

Ecole d'économie de Toulouse (TSE) - Manufacture des Tabacs
Aile Jean-Jacques Laffont - 21, allée de Brienne - 31000 TOULOUSE
Tél : +33 (0) 5 61 12 85 89 - Fax : +33 (0) 5 61 12 86 37 - **www.TSE-fr.eu** - contact@TSE-fr.eu

Toulouse School of Economics

THE EFFECT OF PRODUCTION UNCERTAINTY AND INFORMATION DISSEMINATION ON THE DIFFUSION OF IRRIGATION TECHNOLOGIES

PHOEBE KOUNDOURI, CELINE NAUGES and VANGELIS TZOUVELEKAS

ABSTRACT - In this paper we study the diffusion of modern irrigation technologies among a population of farmers, with a particular focus on risk and information dissemination through network and imitation effects. The major contribution of our work is to extend the traditional (theoretical) model of diffusion to account for production risk and the value of information about the new technology. This model is then applied to a sample of 385 farms located in Crete, Greece, to describe diffusion of modern irrigation technologies. Our results indicate that risk aversion plays a significant role and that farmers who are more sensitive to the risk of extreme events will adopt the modern irrigation technology earlier. Knowledge, experience and information dissemination are found to reduce time before adoption of the new technology, while farmers tend to learn more from and/or imitate farmers that are *homophylic* to them with respect to their education level, age and farm specialization.

KEYWORDS: *duration model, irrigation technology, imitation effects, production uncertainty, risk preferences.*

JEL CLASSIFICATION: *C41, D81, Q12*

This research has been partly supported by Specific Targeted Research Sixth Framework Project *EU Food Industry Dynamics and Methodological Advances-FOODIMA* under contract number 044283.

INTRODUCTION

Adoption of advanced irrigation technologies has been the major contributor to the reduction in irrigation water use in many regions and countries suffering from water scarcity. Therefore, understanding the determinants of irrigation technology investment and adoption rates is necessary for the design of agri-environmental policies towards sustainable water use. It is important for farmers, manufacturers of irrigation equipment, and regulators to understand the conditions under which a specific technology (*i.e.*, drip, sprinklers) is desirable and likely to be adopted as well as the factors that affect its diffusion process. Analyzing adoption and diffusion patterns of irrigation technologies have been at the core of several empirical studies including those by Caswell and Zilberman (1985), Dinar and Zilberman, Dinar, Campbell and Zilberman, Dinar and Yaron, Dridi and Khanna and, Koundouri, Nauges and Tzouvelekas. In contrast with the epidemic models of diffusion initiated by Griliches and Mansfield, this body of the literature argues that adoption and diffusion patterns are the result of explicit maximizing behaviour of a population of heterogeneous farmers. In most cases, economic factors (water price, cost of irrigation equipment, crop prices, etc.) but also farm organizational characteristics and environmental conditions, do matter to explain adoption and diffusion of modern irrigation technologies.

However, in the case of long-lasting technologies like modern irrigation infrastructure, farmers are faced with a decision which is costly to reverse and requires appropriate future planning. These investments change both variable and fixed costs, often require equity or debt financing, may alter the scale of production and can require more intensive on-farm management to ensure positive economic returns.[1] Sahal and Thirtle and Ruttan, summarizing the diffusion literature, argue that the epidemic models of diffusion mistakenly ignore the multidimensional process reflected in aggregate adoption rates. Individual farmers may exhibit different patterns of adoption through time due to: (i) the existing information set and their capacity to absorb and process that information, (ii) their risk preferences and perceptions - farmers may be willing to adopt irrigation technologies in order to hedge against risk during years of water shortage, as the same farm output can be sustained with less irrigation water-, (iii) the degree of technical compatibility between the innovation and farm's existing production technology, (iv) factors exogenous to the farm such as market conditions, government policy and the general economic environment.[2]

Along these lines, and using the theoretical underpinnings of technology adoption suggested by Dinar, Campbell and Zilberman and Caswell and Zilberman (1986), we extend the theoretical model developed by Koundouri, Nauges and Tzouvelekas, describing *adoption* of modern irrigation technology. More precisely, we model the process of technology *diffusion* accounting for production risk and the value of information about the new technology. The empirical application is made on a sample of 385 farms located in the island of Crete, Greece, and surveyed during the 2005-06 cropping period. Information on the exact time of adoption of drip irrigation technologies allows us to study factors affecting the length of time to adoption using a duration model. Duration analysis allows investigation of the timing of technology adoption, by modeling the conditional probability of adoption at a particular time period, given that adoption has not occurred before. In order to account for farmers' risk preferences, we incorporate the first four sample moments of profit in the diffusion model, along the lines of Kim and Chavas, and Koundouri, Nauges and Tzouvelekas. Another contribution of this paper is to investigate (empirically) the role of network and imitation effects on technology diffusion among a population of heterogeneous farmers.

In Section 2, we present the theoretical model of diffusion of modern irrigation technology under production risk and in section 3 we describe the corresponding econometric model. In section 4, we discuss the data and the specification of the diffusion model and in section 5 we discuss the estimation results. In section 6 we conclude the paper.

THEORETICAL MODEL

Let's assume that farms utilize a vector of conventional inputs $\mathbf{x_c}$ (*e.g.*, land, capital, labor) together with irrigation water x_w to produce a single output y through a technology described by a well-behaved (*i.e.*, continuous and twice differentiable) production function satisfying all the regular neoclassical properties (*i.e.*, positive and diminishing marginal productivities),

$$y = f\left(\mathbf{x_c}, \tilde{x}_w; d, k\right) \tag{1}$$

where k is the irrigation technology index,[3] d is an aridity index capturing weather conditions,[4] and $\tilde{x}_w$ is the amount of *effective* irrigation water applied to the plant. Following Caswell and Zilberman (1986) we define a measure of *irrigation effectiveness* (x_w^e) as the ratio of effective water ($\tilde{x}_w$) to applied irrigation water (x_w), *i.e.,*[5]

$$x_w^e = \tilde{x}_w / x_w \tag{2}$$

and

$$\tilde{x}_w = x_w^e \cdot x_w \tag{3}$$

Irrigation effectiveness is influenced by three decisive factors (Dinar, Campbell, and Zilberman): the water holding capacity of the soil (q), the prevailing weather conditions (d), and the method of water application (k) (*i.e.*, irrigation technology). Hence, relation (3) can be expressed as a general function of the form:

$$\tilde{x}_w = g\left(x_w; q, d, k\right) \tag{4}$$

Higher soil's water holding capacity is expected to increase irrigation water efficiency so the following relationships should hold: $g'_q > 0$ and $g''_{qq} \leq 0$.[6] High precipitation increases soil moisture, and thus irrigation effectiveness, as less water is applied to the crop. High temperatures increase yield but at the same time also increase evaporation. This positive relationship holds up to a given point ($\bar{d}$) which is unique to each field and/or plant. After that point a further increase in temperature reduces yield. Thus, we expect $g'_d > 0$ and $g''_{dd} \leq 0$ for $d \leq \bar{d}$ and $g'_d < 0$ and $g''_{dd} \geq 0$ for $d > \bar{d}$. Finally, it is reasonable to assume that capital intensive irrigation technology enhances irrigation effectiveness, while it also affects the composition of input quantities used in crop production (e.g., fertilization through irrigation system). Hence, we assume that $g\left(x_w^1, q, d; k^1\right) > g\left(x_w^0, q, d; k^0\right)$ with k=1, 0 being the modern and traditional irrigation technology, respectively.[7] Modern irrigation technologies can be interpreted as land quality augmenting since they enhance soil's water retention capacity. However, the gain in irrigation effectiveness associated with the change in irrigation technology is likely to decline with soil quality and increase with adverse weather conditions.

Following Dinar, Campbell and Zilberman, farmer's joint decision of an irrigation water application rate and irrigation technology assuming profit-maximizing behavior can be solved via a two-stage procedure. First, farmers choose the optimal amount of irrigation water together with conventional inputs for each technology (traditional and modern) and subsequently choose the irrigation technology yielding the highest profits. Obviously if none of the technologies yields positive profits, farmers will not operate at all. In addition, we assume that farmers are not myopic in a sense that they can form expectations concerning all conjectures of their future profit flows.[8]

Furthermore, since farm production is affected by weather conditions we assume that farmers incur production risk. This risk is commonly represented by a random variable $\tilde{\varepsilon}$, whose distribution is exogenous to farmer's actions. Following Koundouri, Nauges and Tzouvelekas, this is the only source of risk we consider, as output and factor prices are assumed non-random (*i.e.*, farmers are assumed to be price-takers in both the input and output markets).

Hence if farmers are risk-averse with irrigation technology k (k= *0, 1*), the profit function is written as follows:

$$\pi^k = py^k - w_w^k x_w^k - \mathbf{w_c^{k'}} \mathbf{x_c^k} - c^k \tag{5}$$

where $y^k = f\left(\tilde{x}_w^k, \mathbf{x_c^k}; d, k\right)\tilde{\varepsilon}$ and $\tilde{x}_w^k = g\left(x_w^k; q, d, k\right)$, c^k is the fixed cost of production associated with the given state of irrigation technology $\left(k = 0,1\right)$; p is the output price which is known to farmers with certainty;[9] $\mathbf{w_c^k} \in \Re_{++}$ is the vector of strictly positive conventional factor prices, and w_w^k is the unit cost of irrigation water.

Farmers initially produce using a traditional irrigation technology (*i.e.*, furrow), but they have the option to invest in a more efficient technology (*i.e.*, drip). If they switch technologies, they must incur an irreversible investment cost, which may include the cost of designing a complete irrigation system and investing in the new infrastructure (*e.g.*, pipes, filters, fertilization equipment) as well as the cost related with training both themselves and hired workers to use the new irrigation equipment. So, we assume that adoption of the new technology implies a change in the fixed cost of production, $c^1 > c^0$ (*e.g.*, new fertilization equipment) and might change the marginal cost of water $\left(w_w^1 \neq w_w^0\right)$.[10] Adoption of modern irrigation technology is assumed to be irreversible, as it might not be easy to re-sale the equipment. These arguments imply that a positive value of additional information might exist (Jensen; Dixit and Pindyck). In other words, imperfect knowledge about the new irrigation technology can lead to a strategic incentive to delay adoption (Foster and Rosenzweig).

If we assume that the cost of acquiring the new drip irrigation technology at time *t* is known to the farmers, and the adoption decision is a discrete choice, then each farmer maximizes expected profits and chooses the time of adoption, *τ,* which solves the following dynamic optimization problem (Kerr and Newell):

$$\max_{\tau}\ \psi\left(t\right)=\max_{\tau}\int_{0}^{\tau}E\left[U\left(\pi^{0}\left(t\right)\right)\right]e^{-\rho t}dt+\int_{\tau}^{\infty}E\left[U\left(\pi^{1}\left(t\right)\right)\right]e^{-\rho t}dt\ \text{-}\ \left[C\left(\tau\right)+I\left(\tau\right)\right]e^{-r\tau} \qquad (6)$$

where $\psi\left(t\right)$ are the total benefits obtained by farmers under both irrigation technologies, $U\left(\cdot\right)$ is an increasing, concave and twice differentiable *von Neumann-Morgenstern* utility function, $C\left(\tau\right)$ is the cost of equipment for the new irrigation technology at the year of adoption, $I\left(\tau\right)$ represents the value of information also at the year of adoption, ρ is the risk-adjusted discount rate since farm production is subject to weather risk, and *r* is the risk-free discount rate. Farmers will adopt at year *τ* the new irrigation technology if it is not more profitable to wait until a later period because of falling investment costs. The first-order condition of the maximization problem in (5), known as the *arbitrage* condition, implies:

$$\psi'\left(\tau\right)=V\left(\tau\right)-r\left[C\left(\tau\right)+I\left(\tau\right)\right]+C_t'\left(\tau\right)+I_\tau'\left(\tau\right)\geq 0 \qquad (7)$$

where $V(\tau) = E\left[U\left(\pi^1(\tau)\right)\right] - E\left[U\left(\pi^0(\tau)\right)\right]$ are the expected gross benefits of adopting drip irrigation technology at time τ. The arbitrage condition is sufficient if the acquiring cost is non-increasing and convex, and the expected gross benefits of adoption are non-decreasing with respect to time. Specifically, the second-order sufficient condition implies that:

$$\psi''(t) = V_t'(t) - r\left[C_t'(t) + I_t'(t)\right] + C_{tt}''(t) + I_{tt}''(t) \geq 0 \qquad (8)$$

Conditions (7) and (8) are likely to hold as water availability is decreasing over time and the technology-acquiring cost generally decreases at a decreasing rate over time, eventually reaching a constant level. Hence, the general pattern implied by relation (7) is convex. In addition, in order for adoption to take place in finite time, these conditions imply that adoption must be profitable:

$$\psi(\tau) = \int_{\tau}^{\infty} V(\tau) e^{-\rho t} dt - \left[C(\tau) - I(\tau)\right] e^{rt} > 0 \qquad (9)$$

ECONOMETRIC MODEL

We model the diffusion of drip irrigation technology using duration analysis following Karshenas and Stoneman, Kerr and Newell and Abdulai and Huffman. The duration model that will be developed below can be seen as the empirical counterpart of the arbitrage condition as defined in (7).

Duration analysis builds on the so-called survival function, *S(t)*, and hazard function, *h(t)*. The survival function describes the probability of survival (in our case, survival of the old technology) beyond a certain point in time, *t*. The hazard function, *h(t)*, describes the probability of abandoning the old technology or the probability of adopting the new technology in the next "instant", given that the old technology has survived up to time *t*.

Let us assume that T is a positive random variable with a continuous probability distribution function (pdf), *f(t)*. The cumulative distribution function is written

$$F\left(t\right)=\int_{0}^{t} f(s)ds = P\left(T \leq t\right). \tag{10}$$

We are interested in the probability $P\left(T > t\right)$ which defines the survival function:[11]

$$S\left(t\right)=1-F\left(t\right)=1-\int_{0}^{t} f\left(s\right)ds=\int_{t}^{\infty} f\left(s\right)ds. \tag{11}$$

The hazard function or hazard rate *h(t)* describes the rate at which individuals will adopt the technology in period *t*, conditional on not having adopted before *t*. Said differently, given that the old technology has survived until time *t*, the hazard rate will indicate how likely the farmer is to abandon it and adopt the new technology in the next interval Δt: $P\left(t \leq T \leq t+\Delta t \middle| T \geq t\right)$. The hazard function, *h(t)*, corresponds to the limit of the latter probability when the time interval $\Delta t \to 0$:

$$h\left(t\right)=\lim_{\Delta\to 0}\left(\frac{P\left(t \leq T \leq t+\Delta \middle| T \geq t\right)}{\Delta}\right)=\lim_{\Delta\to 0}\left(\frac{F\left(t+\Delta\right)-F\left(t\right)}{\Delta S\left(t\right)}\right)=\frac{f\left(t\right)}{S\left(t\right)}. \tag{12}$$

In empirical work, it is common to specify the hazard function as the product of two components: the baseline hazard, $h_0(t)$, which is assumed to be common to all individuals and to depend only on time, and a component which depends on adopters' characteristics ($\mathbf{z_i}$) in an exponential manner (to ensure a positive hazard). The hazard function is thus written:

$$h\left(t,\mathbf{z_i},\beta\right)=h_0\left(t\right)\exp\left(\mathbf{z_i'}\beta\right) \tag{13}$$

where $\mathbf{z_i}$ is a set of explanatory variables and $\boldsymbol{\beta}$ a vector of parameters to be estimated. The vector $\mathbf{z_i}$ should include variables that are supposed to enter the arbitrage condition (7). These variables can either vary only across time (*e.g.*, price of innovation), vary only across farmers (*e.g.*, farm size, soil quality) or vary across both dimensions (e.g., farmer's age).[12]

The early literature on technology adoption has posed that the diffusion of technological innovations is the result of a process similar to the spread of a disease, with adoption rates depending on the interaction between adopters and potential adopters (Griliches; Mansfield). Karshenas and Stoneman assumed that these *epidemic effects* in diffusion are captured by the baseline hazard which is time dependent.[13]

We choose to specify a parametric form for the baseline hazard $h_0\left(t\right)$.[14] For the purposes of the present analysis we assume that the random variable *T* follows a *Weibull* distribution.[15] The *Weibull* distribution is flexible in the sense that it accommodates hazard rates that increase or decrease exponentially with time. The hazard function under a *Weibull* distribution takes the following form:

$$h\left(t,\mathbf{z}_{\mathrm{i}},\beta\right)=\alpha t^{\alpha-1}\lambda_i \text{ with } \lambda_i \equiv exp\left(\mathbf{z}_{\mathrm{i}}^{'}\beta\right) \tag{14}$$

where $\alpha > 0$ is the shape parameter. The hazard rate either increases monotonically with time if $\alpha > 1$, falls monotonically with time if $\alpha < 1$, or is constant if $\alpha = 1$.[16] The latter case indicates that there are no epidemic effects in the diffusion process.

Under the assumption that *T* follows a *Weibull* distribution, the set of unknown parameters $\left(\alpha,\beta\right)$ can be estimated by maximum likelihood techniques. Since, at the time of the survey, not all farmers have adopted the modern technology, the likelihood has to account for right-censoring of some observations. The log-likelihood is written:

$$Ln\, L(\alpha,\beta) = \sum_{i=1}^{N} d_i \; ln\, f\left(t,\mathbf{z_i},\alpha,\beta\right) + \sum_{i=1}^{N}\left(1-d_i\right) ln\left[1-F\left(t,\mathbf{z_i},\alpha,\beta\right)\right] \tag{15}$$

or

$$Ln\, L(\alpha,\beta) = \sum_{i=1}^{N} d_i \; ln\, h\left(t,\mathbf{z_i},\alpha,\beta\right) + \sum_{i=1}^{N} ln\, S\left(t,\mathbf{z_i},\alpha,\beta\right) \tag{16}$$

where $d_i = 1$ if the ith spell is not censored and $d_i = 0$ if censored. In the context of the *Weibull* distribution, we have: $h\left(t,\mathbf{z_i},\beta\right) = \lambda_i \alpha t^{\alpha-1}$ and $S_i\left(t,\mathbf{z_i},\beta\right) = exp\left(-\lambda_i t^{\alpha}\right)$ with $\lambda_i \equiv exp\left(\mathbf{z_i'}\beta\right)$. The mean expected survival (*i.e.*, adoption) time is calculated as:

$$E\left(t\right) = \left(\frac{1}{\lambda_i}\right)^{1/\alpha} \Gamma\left(1+\frac{1}{\alpha}\right) \tag{17}$$

with $\Gamma\left(n\right) = \left(n-1\right)!$ being the *Gamma* function, and the marginal effects of the explanatory variables on the hazard rate and on the mean expected survival time are calculated from:

$$h'_{z_k}\left(t,\mathbf{z_i},\alpha,\beta\right) = h\left(t,\mathbf{z_i},\alpha,\beta\right)\beta_k \tag{18}$$

and

$$E'_{z_k}\left(t\right) = -\frac{\beta_k}{\alpha} E\left(t\right) \tag{19}$$

DATA DESCRIPTION AND MODEL SPECIFICATION

The data used in this study come from a detailed survey undertaken in the Greek island of Crete about the adoption and diffusion of drip irrigation technologies. The survey was undertaken within the context of the Research Program *FOODIMA* financed by the European

Commission under the 6th Framework Program.[17] The final sample consists of 385 randomly selected olive producing farms located in the four major districts of Crete namely, Chania, Rethymno, Heraklio and Lasithi during the 2005-06 cropping period.[18] Detailed information about production patterns, input use, average yields, gross revenues, and structural characteristics of the surveyed farms were obtained via questionnaire-based, field interviews. Farmers were asked the exact time of adoption of drip irrigation technologies during the last twelve years (*i.e.*, 1994-2005). Also farmers were asked to recall data on some key variables including family size, irrigation water use, land tenancy, farm specialization and size, extension outlets, total debts and off-farm income.[19] Summary statistics for these variables together with those gathered from secondary sources are reported in Table 1. From the total of 385 farms in the sample, 250 (64.9%) have adopted drip irrigation technologies during the 1994-2005 period. The intertemporal distribution of adoption times is presented in Figure 1.

Our final choice of the variables to be included in the irrigation technology diffusion model is dictated by the arbitrage condition in (7) and by the definition of irrigation effectiveness in (4). The first decisive factor concerning individual adoption times as underlined by relation (7) is the cost of installation of drip irrigation equipment. This cost includes the cost of design for the new irrigation infrastructure, the cost of investment in the new equipment (*i.e.*, pipes, hydrometers, drips) and the cost of installation on field. Table 1 shows that installation cost per stremma (one stremma equals 0.1 ha) was on the average €130 varying from a minimum of €98 to a maximum of €185 during the period analyzed (monetary values reported by individual farmers were deflated prior to estimation). The rate of change of the installation cost was found to be decreasing on average by 10.1% annually (in Figure 2 the price index of installation cost per stremma for drip irrigation exhibits a decreasing trend from 1.8 in 1994 to 0.8 in 2005).

The second important component arising from the arbitrage condition in (7) concerns the informational incentives that may change producers' perception about the profit-effectiveness of new irrigation technologies. Although fixed initial costs are incurred, informational incentives may be less costly than financial incentives in the long-run as information spreads throughout the rural communities. To understand what lies behind that, it is useful to make use of Rogers (1995, p.12) distinction between the *hardware* and the *software* aspects of new technologies. The hardware is the object that embodies the technology, while the software is the information needed to use it effectively. Although some of the software can be transmitted impersonally through retailers or user's manuals, much of the software of a particular technology is built up based on the experience of using it. And without good software knowledge, many potential users of the new irrigation technologies will not adopt the new technology, although they are aware of its existence. In our empirical model, we proxy this software information spread, by the number of on-farm visits by extension personnel (private and public). In both developed and developing countries agriculture, much of software knowledge is transmitted through extension agents.[20]

However, to pass on software knowledge, potential users need to be able to communicate directly with current users who have accumulated experience with the new technology, besides the passage of information by extension agents. That is, software knowledge may often follow a *word of mouth* information diffusion process in which previous users are the main source of information. This means that the conditions for adoption of drip irrigation improve with the passage of time as cumulative rural experience on the new technology makes learning from others more effective. Hence the mass of information available to a potential adopter is a function not only of time and on-farm extension visits, but also of the density of adopters in the area or village at the time of deciding whether to adopt or not.

This raises an important concern about the intra-farm communication and the transmission of software knowledge. Obviously the flow of information between farmers is not homogeneous and therefore the stock of adopters in rural areas may not speed up the diffusion rate. Usually, farmers tend to exchange information and imitate farmers with whom they share common characteristics (religious beliefs, education, age, etc). Using Rogers' terminology it is more likely that farmers imitate and gather information from their *homophylic* neighbors. When the population of farmers is *heterophylic*, differences between farmers can impede the process of communication or, more likely, the process of persuasion.

In order to capture these distinct effects of information dissemination among rural communities, we introduce in the diffusion model two different variables: a village level variable reflecting the cumulative extent of drip irrigation adoption within each village in the year prior to making a decision, and the stock of *homophylic* adopters in the village (see Table 1b). Given our data availability, we define *homophylic* farmers based on education level, age and farm specialization. Farms were classified into four quartiles using these variables and *homophylic* farmers were defined as those belonging to the same quartile according to all variables. Finally, as implied by arbitrage condition in (7), we take into account changes in this information dissemination process through years, considering the rate of change in the stock of both *homophylic* and total adopters and on-farm extension visits in each year for every village.

Next, the stochastic element in the optimal decision in (7) is not observable as it reflects individual subjective perceptions about future yields under both types of irrigation technology. However, according to the relevant literature, these perceptions may be realistically assumed to be influenced by the farmer's economic and socio-demographic characteristics which are both observable. Following this line of reasoning, the expected gross benefits from adopting drip irrigation technology at time τ can be modeled as it is presented in

(14) with **z** being a matrix of farm's socio-economic and demographic characteristics. Our choice for the elements of **z** is based on the availability and reliability of the relevant information arising from our sample survey. Based on the primary data collected we classify the factors affecting the diffusion of drip irrigation technology into three categories: farm, household and market characteristics.

First, we expect more educated farmers to adopt profitable new technologies faster since the associated payoffs from innovations are likely to be greater (Rahm and Huffman). The expected impact of age on the timing of adoption is ambiguous since age captures the effect of both experience and planning horizon. On the one hand, farming experience, which provides increased knowledge about the environment in which decisions are made, is expected to affect adoption positively. On the other hand, younger farmers with longer planning horizons may be more likely to invest in new technologies as they have to take into account future generations. Farmers in our sample received 7.72 years of formal education on average. The average age of the household head is 53.3 years, while family size is 3.78 persons on average.

The average farm size is 29.1 stremmas in our sample. The expected impact of farm size on adoption time is again ambiguous. Larger farms may have a greater potential to adopt modern irrigation technologies because of the high costs involved in irrigation. On the other hand, larger farms may have less financial pressure to search for alternative ways to improve their income by switching to a different technology (Perrin and Winkelmann; Putler and Zilberman). Also, the size of the farm is usually correlated with farmer's risk aversion, which in turn may impact the time to adoption. If farmers owning larger [smaller] farms are less [more] risk-averse, then they may be more likely to adopt a new technology that is risk-increasing [risk-decreasing]. The role of production risk and farmer's risk aversion are taken into account through the inclusion of the first four conditional moments of farm profits in the diffusion model (Kim and Chavas; Koundouri, Nauges and Tzouvelekas). The computation of the first four moments of farm profits is described in Appendix I, while Tables 1a and 1b show some basic statistics.

Since property is an element of the institutional environment, we include in our model land tenancy as an explanatory variable of irrigation technology diffusion (Braverman and Stiglitz). The potential effect of land tenure on diffusion is ambiguous. A positive relationship would be consistent with the hypothesis that greater leasing (or share-cropping) motivates farmers to work harder to meet their contractual obligations. On the other hand, a negative relationship would be consistent with agency theory, reflecting monitoring problems and adverse incentives between the parties involved that diminish business performance and hence profitable adoption decisions.

The degree of farm specialization may also affect the timing of adoption. Specialized farms have fewer requirements for technical assistance and thus for information gathering as their know-how is continually improved over time. On the other hand, farmers growing a single crop are faced with a higher risk of income loss in case of adverse events, which in turn may induce a lower probability of adoption if farmers are risk-averse. Farm's specialization is measured by the *Herfindhal* index.[21] In our sample, this index has an average value of 0.64, which indicates a high degree of specialization.

Off-farm income is hypothesized to provide financial resources for information acquisition and to create incentives to adopt new technologies as the opportunity cost of time rises. On the other hand, 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 business activities (*i.e.*, tourism) and from employment in other non-farm sectors (*i.e.*, public administration, construction work). Given that the skill requirements are different for these jobs, farm and off-farm income may be realistically assumed to be non-competitive. Thus, we can assume that the level of off-farm income could be largely exogenous to adoption decisions (we statistically examine this assumption, see last paragraph of this section).

Further, our diffusion model of drip irrigation technology incorporates farm's distance from the market and total debts of the household. The village location and remoteness from the market is likely to be an important feature influencing the probability of adoption, while total debts are utilized to test Jensen's (1986) hypothesis that increased financial obligations stimulate effort by producers to improve their performance in order to meet these obligations. In our sample, farms are located 26.22 km away from the major city in their area, whereas individual household debts are 1,587 euros on average (Table 1b).

Finally, as relation (4) implies, adoption behavior for irrigation technology may also be influenced by the environmental characteristics of the farm that affect irrigation effectiveness. Given this, we include in the diffusion model an aridity index, the altitude of the farm and four soil dummies as a proxy for soil quality. The aridity index and the altitude of farm location reflect on-farm weather conditions, whereas the soil quality dummies reflect the water holding capacity of the soil. The aridity index is defined as the ratio of the average annual temperature over total annual precipitation (Stallings). It is calculated for the whole period analyzed using data provided by the 36 local meteorological stations located throughout the island. Since the value of the aridity index is identical for some farms that are located in the same area, we also include the altitude of farm's location as an additional variable reflecting weather conditions. Higher altitude is more likely to be associated with adverse weather. As shown in the lower panel of Table 1a, the average value of the aridity index is 0.89, whereas the average altitude is 365 meters. Farms are classified according to four different soil types with respect to their water holding capacity. Sandy and limestone soils exhibit a lower holding capacity than marls and dolomites soils. The majority of farms in the sample are cultivating olive-trees in marls (35.24%), followed by limestone (28.1%), sandy soils (19.72%), and dolomites (16.92%).

To control for possible endogeneity of off-farm income, stock of adopters, stock of *homophylic* adopters, extension visits and debt, we implement a two-stage instrumental variable procedure as suggested by Lee. In the first-stage we specify all the potential endogenous variables as functions of all other exogenous variables, plus a set of instruments.[22] In the second-stage, the observed values of these variables are included along with the vector of their corresponding residuals, arising from the first-stage into the duration model. A simple *t*-test for the significance of the coefficients of the corresponding residuals is a test for the exogeneity of the suspicious variables (Smith and Blundell). Since we incorporate estimated values (*i.e.*, profit moments) in the duration model, we use bootstrapping techniques to obtain consistent estimates of the corresponding standard errors (Politis and Romano).

ESTIMATION RESULTS AND SPECIFICATION TESTS

The maximum likelihood parameter and standard error estimates of the hazard function are shown in Table 2. The dependent variable in the diffusion model is the natural logarithm of the "length of time" variable (measured in years) from first availability of the drip irrigation technology to when the farmer adopted it. In this framework, a negative coefficient estimate in the hazard function implies a negative marginal effect on duration time before adoption, that is, faster adoption. The overall fit of our model is satisfactory, since McFadden R^2 reaches 0.55. Several specification tests have been performed using the generalized likelihood-ratio (LR) test statistic (see Table 3).[23]

We reject the null hypothesis of a constant baseline hazard model: the four district-specific intercepts in the hazard function ($h\left(t, z_i, \beta\right) = \alpha_r t^{\alpha_r - 1} exp\left(\alpha_{or} + \mathbf{z}_i'\beta\right)$, where $r = 1, \ldots, 4$

stands for the four districts in the island, namely, Chania, Rethymno, Heraklio and, Lasithi) are all different from zero and positive, except for the district of Rethymno (Table 2), and jointly different from zero (Table 3). This indicates that the rate at which farmers adopt the technology varies from one district to the other, all other things being equal.

We reject the null hypothesis that the four district-specific intercepts are equal to one (H0: $\alpha_r = 1 \ \forall r$), which indicates positive duration dependence of adoption probabilities, conditional on the covariates (see Table 3), and hence the existence of epidemic effects in the diffusion process. The largest intercept is obtained for the district of Lasithi, where average annual rainfall is the lowest among all districts of the island, while the lowest intercept is obtained for Rethymno, which had the lowest average aridity index over the time period analyzed. The rate of adoption of more efficient irrigation technologies is thus found to be higher for farmers located in regions characterized by less favorable weather conditions (less rainfall).

The next hypothesis we examine is whether the baseline hazard contains sufficient information to explain diffusion patterns across farms, *i.e.* if adoption of drip irrigation technology can be described by a simple epidemic model of diffusion. The joint hypothesis that all farm-specific variables included in the hazard function are equal to zero is rejected, indicating that the adoption of drip irrigation technology by Cretan farmers cannot be explained by a process similar to the spread of a disease.

Finally, three (out of five) residuals obtained from the first-stage instrumental variable regressions, are significant, indicating endogeneity of the overall 'stock of adopters', the stock of *homophylic* adopters, and number of extension visits, thus providing support for our two-stage instrumental variable estimation procedure.

The effect of risk aversion is explicitly captured by the first four sample moments of profit, but only the first and third moments are significant. A higher first moment, *i.e.,* higher expected profit, is found to increase the time to adoption, while a higher third moment, which captures downside risk, is found to reduce time to adoption.[24] Hence, the length of adoption time will be shorter for farmers who are more sensitive to extreme events. This implies that one reason for the farmers in our sample to adopt drip irrigation technologies is to hedge against the risk of particularly bad outcomes. Moreover, a higher aridity index, a higher altitude and sandy soils are found to reduce time to adoption, significantly. Higher aridity and sandy soils both increase the water requirements of crops and thus increase the production risk related to adverse climatic conditions such as droughts (Koundouri, Nauges and Tzouvelekas). These results are consistent with the previous finding regarding risk aversion: farmers with a higher aridity index and sandy soils bear a higher risk of water shortage and hence are more likely to adopt a more efficient irrigation technology. In general, the role of risk aversion in explaining *diffusion* of modern irrigation technology is in line with the findings of Koundouri, Nauges and Tzouvelekas (who studied *adoption* of irrigation technologies under risk) using earlier data on farmers from the same region.

The time to adoption of drip irrigation technologies is significantly shorter for farmers with higher level of education and for older farmers. The marginal effect of education and age on adoption time is estimated at -1.93 and -0.75 years, respectively. These results indicate that knowledge and experience, as approximated by education and age, are important factors in inducing faster adoption of efficient irrigation technologies in this region. Moreover, the impact of extension services is found to be quite strong (the marginal effect is the highest: -2.22 years), which confirms the hypothesis that information dissemination reduces time before adoption of the new technology.

The estimated coefficient of farm size is positive, which indicates that time to adoption is longer for larger farms. This result may suggest that the installation cost of the new technology is not a burden for small farms and that these farms adopt the new technology to cope against the risk of water shortage (which is likely to be higher for small farms). As expected, higher installation costs (and an increase in installation costs over time) induce an increase in the time to adoption. The marginal effect on adoption time is almost one year, while the coefficients of the four variables measuring imitation effects are significant. The negative signs of the two stocks variables confirm that the mass of adopters and the possibility of learning from others do matter in explaining diffusion of new technologies. The marginal effect of the stock of *homophylic* adopters on adoption time (-1.46 years) is about ten times the marginal effect of the total stock of adopters in the village (-0.14 years). This result indicates that farmers tend to learn more from and/or imitate farmers that are “more similar”, in our case this refers to farmers with common characteristics in terms of education level, age and farm specialization. The changes in the ‘stock of adopters’ has the opposite sign because, as time passes, more and more farmers have already adopted the new technology (i.e., the ‘stock of farmers’ increases) but, at the same time, the number of new adopters each year decreases.

The negative coefficient of the variable measuring total debt confirms Jensen’s hypothesis that increased financial obligations stimulate effort by producers to improve their performance. The negative coefficient of off-farm income is also as expected and confirms the assumption that off-farm income creates incentives to adopt more efficient technologies as the opportunity cost of time rises. Finally, family size, land tenancy, farm specialization, and distance to the market are not found significant in this model.

CONCLUSIONS AND POLICY IMPLICATIONS

In this paper we extend the traditional (theoretical) model of diffusion technology to account for production uncertainty and the value of information about the new technology, and apply it to the case of irrigation technology diffusion, on a sample of 385 farms located in Crete.

Our results indicate that the role of risk aversion in explaining diffusion of modern irrigation technology is significant and the length of adoption time will be shorter for farmers who are more sensitive to downside risk. These findings are consistent with the result that farmers with a higher aridity index and sandy soils bear a higher risk of water shortage and hence are more likely to adopt the more efficient irrigation technology. In general, the role of risk aversion in explaining *diffusion* of modern irrigation technology is in line with the findings of Koundouri, Nauges and Tzouvelekas (who studied *adoption* of irrigation technologies under risk) using earlier data on farmers from the same region. Knowledge, experience and information dissemination are found to reduce time before adoption of the new technology, while farmers tend to learn more from and/or imitate farmers that are *homophylic* to them with respect to their education level, age and farm specialization.

These results have significant policy implications with regards to creating incentives for technology adoption and regulating the pattern and timing of technology diffusion. First, the regulator must recognize that farmers face production uncertainty (mainly with respect to exogenous weather conditions), that farmers' risk preferences will affect the timing of technology adoption and that new water-conservation irrigation technologies can be used as a means for production risk management. Hence these preferences must be uncovered and integrated in relevant water-related, agricultural and environmental management policies. Second, to increase the speed of technology adoption, the policy makers should invest in campaigns and educational programs that increase the knowledge and information dissemination with regards to the specific technology under investigation. Moreover, these campaigns will have higher feedback if directed to more experienced farmers. Finally, the regulator must recognize the importance of understanding the pattern of technology diffusion, which is significantly influenced by the similarity (with regards to education, age and farm specialization) between farmers. This implies that policies/campaigns that increase the homogeneity of the farmers with regards to these characteristics will increase the speed of technology diffusion and as a result economize on the use of irrigation water.

An interesting extension of this work is to attempt to introduce in the econometric model, and estimate, dynamic imitation effects. In particular, one could follow the theoretical results by Schlag, who identifies a uniquely optimal individual rule for the imitation process (both for the social planner and the boundedly rational individual), which describes how to choose future actions. If this rule is empirically translated and incorporated in the estimated model it can inform the time-series dimension of technology diffusion and allow further refinement of technology adoption policy. Such an extension would require panel data.

REFERENCES

Abdulai, A., and W.E. Huffman. The Diffusion of New Agricultural Technologies: The Case of Crossbred-Cow Technology in Tanzania. *American Journal of Agricultural Economics*, 2005, 87: 645-659.

Braverman, A., and J.E. Stiglitz. Cost-sharing arrangements under sharecropping: Moral hazard, incentive, flexibility and risk. *American Journal of Agricultural Economics*, 1986, 68: 642-52.

Caswell, M. F., and D. Zilberman. The Choices of Irrigation Technologies in California. *American Journal of Agricultural Economics*, 1985, 67(2): 224-239.

Caswell, M., and D. Zilberman. The Effects of Well Depth and Land Quality on the Choice of Irrigation Technology. *American Journal of Agricultural Economics*, 1986, 68(4): 798-811.

David, P.A. Technology Diffusion, Public Policy and Industrial Competitiveness. In *The Positive Sum Strategy: Harnessing Technology for Economic Growth*, eds., R. Landau and N. Rosenberg, 373-391, Washington DC: National Academy Press, 1986.

Dinar, A., and D. Yaron. Adoption and Abandonment of Irrigation Technologies. *Agricultural Economics*, 1992, 6(4): 315-332.

Dinar, A., and D. Zilberman. The Economics of Resource-Conservation, Pollution-Reduction Technology Selection: The Case of Irrigation Water. *Energy and Resources*, 1991, XIII: 323-348.

Dinar, A., Campbell, M., and D. Zilberman. Adoption of Improved Irrigation and Drainage Reduction Technologies under Limiting Environmental Conditions. *Environmental and Resource Economics*, 1992, (2): 373-398.

Dixit, A.K., and R.S. Pindyck. *Investment Under Uncertainty*, Princeton N.J.: Princeton University Press, 1994.

Dridi, C., and M. Khanna. Irrigation Technology Adoption and Gains from Water Trading under Asymmetric Information. *American Journal of Agricultural Economics*, 2005, 87(2): 289-301.

Foster, A.D., and M.R. Rosenzweig. Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *Journal of Political Economy*, 1995, 103(6): 1176-1209.

Griliches, Z. Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica*, 1957, 24: 501-522.

Hannon, T.H., and J.M. McDowell. The Determinants of Technology Adoption: The Case of the Banking Firm. *Rand Journal of Economics*, 1984, 15: 328-335.

Jensen, M.C. Agency Costs of Free Cash Flow, Corporate Finance and Takeovers. *American Economic Review*, 1986, 76: 233-38.

Karshenas, M., and P. Stoneman. Rank, Stock, Order, and Epidemic Effects in the Diffusion of New Process Technologies: An Empirical Model. *Rand Journal of Economics*, 1993, 24: 503-28.

Kerr, S., and R.G. Newell. Policy-Induced Technology Adoption: Evidence from the U.S. Lead Phasedown. *Journal of Industrial Economics*, 2003, 51: 317-343.

Kiefer, N. Economic Duration Data and Hazard Functions. *Journal of Economic Literature*, 1988, 26: 646-679.

Kim, K., and J.P. Chavas. Technological change and risk management: an application to the economics of corn production. *Agricultural Economics*, 2003, 29: 125-142.

Koundouri, P., Nauges, C., and V. Tzouvelekas. Technology Adoption under Production Uncertainty: Theory and Application to Irrigation Technology. *American Journal of Agricultural Economics*, 2006, 88(3): 657-670.

Lee, L.F. Simultaneous Equations Models with Discrete and Censored Variables, in C. Manski and D. McFadden (eds.), *Structural Analysis of Discrete Data: With Econometric Applications*, 1982, Cambridge MA: MIT Press.

Mansfield, E. *Industrial Research and Technological Innovation*, New York: Norton, 1968.

Owens, T., Hoddinott, J., and B. Kinsey. The impact of agricultural extension on farm production in resettlement area of Zimbabwe. *Economic Development and Cultural Change*, 2003, 51: 337-57.

Perrin, R., and D. Winkelmann. Impediment to Technical Progress on Small versus Large Farms. *American Journal of Agricultural Economics*, 1976, 58: 888-894.

Politis, D., and J. Romano. Large Sample Confidence Regions Based on Subsamples Under Minimal Assumptions. *Annals of Statistics*, 1994, 22: 2031-2050.

Putler, D.S., and D. Zilberman. Computer Use in Agriculture: Evidence from Tulare County, California. *American Journal of Agricultural Economics*, 1984, 70: 790-802.

Rahm, M., and W. Huffman. The Adoption of Reduced Tillage: The Role of Human Capital and Other Variables. *American Journal of Agricultural Economics*, 1984, 66: 405-413.

Rogers, E.M. *Diffusion of Innovations*. Free Press: New York, 1995.

Rosenberg, N. *Perspectives on Technology*. Cambridge University Press, 1976.

Sahal, D. *Patterns of Technological Innovation*. Reading MA: Addison-Wesley, 1981.

Schlag, K.H. Why Imitate, and if so How? A Boundedly Rational Appraisal to Multi-armed Bandits. *Journal of Economic Theory*, 1998, 78:130-156.

Schoengold, K., and D. Zilberman. The Economics of Water, Irrigation, and Development. *Handbook of Agricultural Economics: Volume 3*, eds. Robert Evenson and Prabhu Pingali, Elsevier Science Publishers, 2007.

Sherlund, S.M., Barrett, C.B., and A.A. Adesima. Smallholder technical efficiency controlling for environmental production conditions. *Journal of Development Economics*, 2002, 69:

85-101.

Smith, R.J., and R.W. Blundell. An Exogeneity Test for a Simultaneous Equation Tobit Model with Application to Labor Supply. *Econometrica*, 1986, 54: 679-686.

Stallings, J.L. Weather Indexes. *Journal of Farm Economics*, 1960, 42: 180-186.

Thirtle, C.G. and V.W. Ruttan. *The Role of Demand and Supply in Generation and Diffusion of Technical Change*. New York: Harwood Academic Publishers, 1987.

Tsur, Y., Sternberg, M., and E. Hochman, 1990. Dynamic Modeling of Innovation Process Adoption with Risk Aversion and Learning. *Oxford Economic Papers* 42: 336-355.

APPENDIX: COMPUTATION OF THE FOUR SAMPLE MOMENTS

The first four moments of the profit distribution are derived following a sequential estimation procedure. In the first step, profit is regressed on the contemporaneous input variables to provide an estimate of the "*mean*" effect. The model has the following general form:

$$\varpi_i = \varphi(\mathbf{x_i};\boldsymbol{\gamma}) + u_i \tag{A.1}$$

where $i = 1,\ldots N$ denotes individual farmers in the sample, ϖ is the profit per hectare, **x** is the vector of variable inputs, and extra shifters reflecting farm characteristics and, u_i is the usual *iid* error term. Specifically, vector **x** includes capital stock measured in euros, irrigation water use measured in m^3, cultivated area measured in stremmas, intermediate inputs (i.e., chemical fertilizers and pesticides) measured in euros, farmer's education level measured in years, the aridity index as a proxy of environmental conditions and on-farm extension visits.

Under expected profit maximization the explanatory variables are assumed to be exogenous and thus the OLS estimation of (A.1) provides consistent and efficient estimates of the parameter vector γ. Then, the j^{th} central moment of profit $(j = 2,\ldots,m)$ conditional on input use and farm characteristics is defined as:

$$\mu_j(\bullet) = E\left\{\left[\varpi(.) - \mu_1\right]^j\right\} \tag{A.2}$$

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

$$\widehat{u_i}^2 = g\left(\mathbf{x}_{\mathrm{i}};\boldsymbol{\delta}\right) + \tilde{u}_i \tag{A.3}$$

The application of OLS on (A.3) provides consistent estimates of the parameter vector $\boldsymbol{\delta}$ and the predicted values $\widehat{\widehat{u_i}^2}$ are consistent estimates of the second central moment of the profit distribution (*i.e.*, the variance). 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.

Figure 1. Diffusion of Drip Irrigation in Crete, Greece.

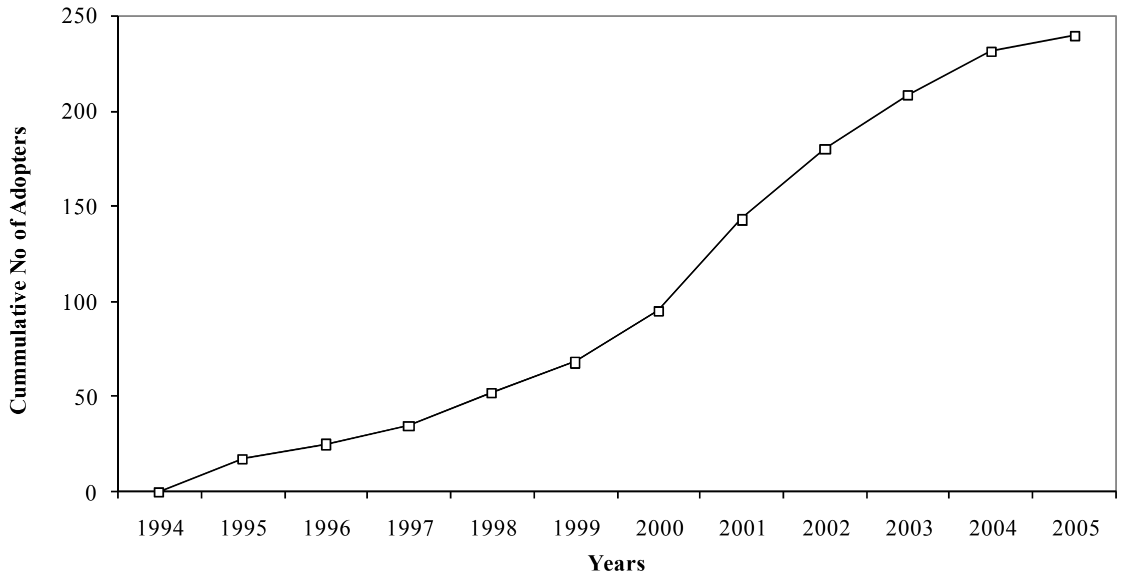

Figure 2. Cost of Installation Equipment for Drip Irrigation.

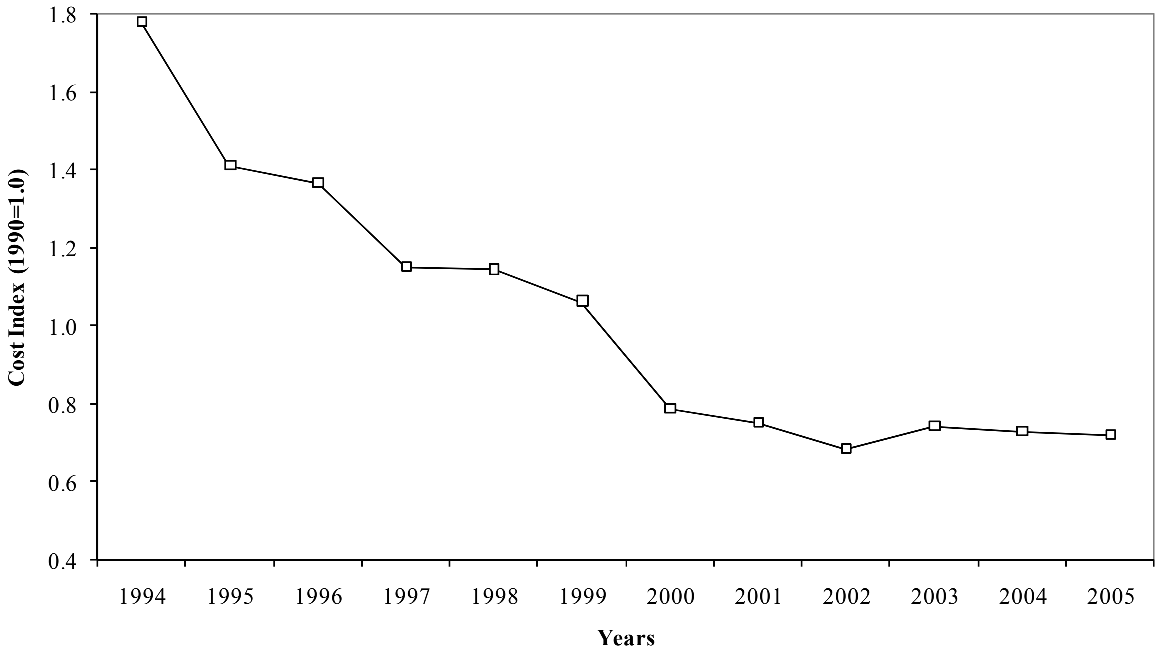

Table 1a. Definitions and Descriptive Statistics of the Variables: household, farm characteristics and environmental conditions.

Variable	Name	Mean	St Dev
Duration length (years)	*Time*	5.63	4.89
<u>*Household Characteristics:*</u>			
Education (years of schooling)	*Edu*	7.72	3.41
Age (years)	*Age*	53.3	13.1
Family size (no of persons)	*Fam*	3.78	1.43
<u>*Farm Characteristics:*</u>			
Irrigation water use (m^3)	*Water*	30.83	15.12
Land tenancy (% of rented land)	*Ten*	0.29	0.21
Capital Stock (€)	*Cap*	3,147.34	1,514.12
Specialization (*Herfindhal* index)	*Spec*	0.64	0.13
Farm output (kg)	*Out*	18,547	4,521.04
Intermediate inputs (€)	*Intm*	2,058	987.17
Farm size (stremmas[a])	*Size*	29.12	14.52
1st profit Moment	*Mom1*	2.03	0.81
2nd profit Moment	*Mom2*	0.72	0.33
3rd profit Moment	*Mom3*	0.89	0.61
4th profit Moment	*Mom4*	2.10	1.14
<u>*Environmental Conditions:*</u>			
Aridity index	*Ard*	0.89	0.34
Altitude (meters)	*Alt*	365.42	231.43
Soil Type (% of farm Land):			
Sandy	*San*	19.72	
Limestone	*Lim*	28.12	
Marls	*Mar*	35.24	
Dolomites	*Dol*	16.92	
Districts (no of farms):			
Chania	*Cha*	79	
Rethymno	*Rth*	41	
Heraklio	*Her*	84	
Lasithi	*Las*	46	

[a] one stremma equals 0.1 ha.

Table 1b. Definitions and Descriptive Statistics of the Variables: information and market characteristics.

Variable	Name	Mean	StDev
Information:			
Extension services (no of visits)	*Ext*	18.12	15.78
Rate of change in extension (%)	*ΔExt*	1.17	0.23
Market Characteristics:			
Installation cost (€ per stremma[a])	*Cost*	130.15	21.37
Rate of change in installation cost (%)	*ΔCost*	-10.12	1.32
Stock of adopters (no of farms)	*Stock*	132.67	90.09
Rate of change in stock of adopters (%)	*ΔStock*	20.76	10.21
Stock of homophylic adopters (no of farms)	*HStock*	13.45	5.23
Rate of change in the stock of homophylic adopters (%)	*ΔHStock*	3.09	2.11
Interest rate (%)	*r*	8.12	1.11
Distance from the market (km)	*Dist*	26.22	12.34
Total debts (€)	*Dbt*	1,587.11	942.36
Off-farm income (€ per year)	*Off*	987.34	678.93
Extension outlets (no of outlets)	*ExtOut*	4.62	2.87
Distance from extension outlets (km)	*ExtDist*	37.12	21.58
Tourist arrivals (thousands of persons)	*Tour*	432.12	157.01
Distance from district capital (km)	*Distc*	42.36	14.48

[a] one stremma equals 0.1 ha.

Table 2. Maximum Likelihood Parameter Estimates of Hazard Function for Adoption of Drip Irrigation Technology.

Variable	Estimate	Std Error	Variable	Estimate	Std Error
α_{Cha}	2.0158	$(0.6587)^{*}$	β_{Ext}	-0.5141	$(0.1147)^{*}$
α_{Rth}	0.9857	(0.8356)	$\beta_{\Delta Ext}$	0.1458	$(0.0705)^{**}$
α_{Her}	1.1241	$(0.4541)^{*}$	β_{Dist}	0.1105	(0.1359)
α_{Las}	2.3651	$(0.6025)^{*}$	β_{Size}	0.0751	$(0.0329)^{**}$
β_{Cost}	0.4025	$(0.1025)^{*}$	β_{Water}	-0.5085	$(0.1698)^{*}$
$\beta_{\Delta cost}$	0.0141	$(0.0066)^{**}$	β_{Ten}	-0.0066	(0.0091)
β_{Stock}	-0.0385	$(0.0195)^{**}$	β_{Spec}	0.1425	(0.1014)
$\beta_{\Delta stock}$	0.0068	$(0.0036)^{**}$	β_{Dbt}	-0.0958	$(0.0447)^{**}$
β_{Hstock}	-0.4021	$(0.2001)^{**}$	β_{Off}	-0.0135	$(0.0068)^{**}$
$\beta_{H\Delta Stock}$	0.0958	$(0.0412)^{**}$	β_{Ard}	-0.1412	$(0.0692)^{**}$
β_{Edu}	-0.4528	$(0.1458)^{*}$	β_{Alt}	-0.0662	$(0.0344)^{**}$
β_{Fam}	0.0098	(0.0103)	β_{San}	-0.1304	$(0.0625)^{**}$
β_{Mom1}	0.0745	$(0.0403)^{**}$	β_{Lim}	-0.0854	(0.1147)
β_{Mom2}	0.0421	(0.0621)	β_{Mar}	0.0625	(0.0847)
β_{Mom3}	-0.0748	$(0.0321)^{**}$	β_{Age}	-0.1745	$(0.0925)^{**}$
β_{Mom4}	-0.0085	(0.0097)			
β_{Off_Res}	0.0055	(0.0092)	β_{Ext_Res}	0.0517	$(0.0142)^{*}$
β_{Stock_Res}	-0.0147	$(0.0041)^{*}$	β_{Dbt_Res}	-0.0589	(0.0747)
β_{HStock_Res}	0.0417	$(0.0112)^{*}$			
$Ln(\theta)$		-304.187	No of observations		385
McFadden R^2		0.5547	No of adopters		250

* (**) indicate significance at the 1 (5) per cent level. Standard errors were obtained using block re-sampling techniques which entails grouping the data randomly in a number of blocks of 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). For variable definitions see Tables 1a and 1b.

Table 3. Model Specification Tests.

Null hypothesis	Parameter Restrictions	LR-test	Critical value (α=0.05)
1. Constant baseline hazard	$\alpha_r = 0 \ \forall r$	244.87	$\chi^2_4 = 9.49$
2. No epidemic effects	$\alpha_r = 1 \ \forall r$	35.89	$\chi^2_4 = 9.49$
3. Epidemic model of diffusion	$\beta_k = 0 \quad \forall k$	385.44	$\chi^2_{32} \simeq 44.01$

Table 4. Marginal Effects of the Explanatory Variables on the Hazard Rate and Mean Expected Adoption Time of Drip Irrigation Adoption (indicate percentage change in the hazard rate).

Variable	Hazard Rate	Adoption Time
Installation cost	-17.14	0.95
Change in installation cost	-0.69	0.05
Stock of adopters	3.12	-0.14
Change in stock of adopters	-0.49	0.03
Stock of homophylic adopters	20.15	-1.46
Change in stock of homophylic adopters	-4.87	0.35
Education	26.15	-1.93
Family size	-0.38	0.02
1^{st} Profit moment	-0.023	0.011
2^{nd} Profit moment	-0.010	0.007
3^{rd} Profit moment	0.019	-0.008
4^{th} Profit moment	0.001	0.000
Extension services	34.19	-2.22
Change in extension services	-5.08	0.36
Distance from the market	-5.17	0.32
Farm size	-4.42	0.28
Irrigation water use	28.19	-2.03
Land tenancy	0.38	-0.04
Specialization	-5.23	0.41
Total debts	5.58	-0.33
Off-farm income	0.92	-0.04
Aridity Index	9.53	-0.53
Altitude	3.82	-0.22
Sandy soils	0.08	-0.06
Limestone soils	0.02	-0.01
Marble soils	-0.01	0.001
Age	9.17	-0.75

ENDNOTES

---

[1] Dixit and Pindyck argue that favorable but irreversible technology adoption decisions require positive net present values to reflect the opportunity cost to the farm of keeping its investment options open in the future.

[2] Hannon and McDowell and David provide empirical evidence on the important role of institutions in technology diffusion.

[3] Empirical agronomic evidence suggests that irrigation technologies may well affect the use of other variable inputs in crop production such as fertilizers or labor (for instance when fertilization is applied through drip irrigation system). Therefore the irrigation technology index may be directly included in the production function. In order to keep our empirical analysis tractable, we assume irrigation technologies to be the only source of farm innovation.

[4] Sherlund, Barrett and Adesima showed that neglecting "environmental factors" leads to omitted variable bias in the estimated parameters of the production function and hence, on conventional factors' marginal productivities.

[5] According to Schoengold and Zilberman *applied* water is the total amount of water that is used by the farmer on the field, while *effective* water is the amount of water actually used by the crop.

[6] Soil is a dynamic system which acts as a reservoir and buffer against plant dehydration. Whether enough water is stored for the plant to avoid water deficiency and stress depends on several soil characteristics such as its slope, salinity, and water retention. The combination of these characteristics provide an index of the soil water holding capacity.

[7] In traditional irrigation technologies like furrow, large quantities of water are applied in a short period of time. Water is spread from the distribution pipes across fields using gravity forces that often result in a non-uniform application. On the other hand, capital intensive

modern irrigation technologies like drip apply less amount of water over longer time periods, while both capital equipment and pressure ensure a uniform distribution throughout the plot.

[8] In a similar context Rosenberg and Tsur, Sternberg, Hochman model the diffusion process as a result of a dynamic optimization procedure under the assumption that decision makers have perfect foresight regarding the effects of present decisions on future events.

[9] Since farmers do not have any kind of market power producing a variety of crops, their adoption decision rarely influences the output price.

[10] For example drip irrigation technology may involve higher pressurization cost. On the other hand, since farmers are assumed to be price takers in both output and input markets, the marginal cost of all other factors of production is not affected by their choice of irrigation technology.

[11] For an individual farm, $1-S(t)$ gives the probability that the farmer will have adopted the innovation by time *t*, but if one considers the whole population of farmers, all of whom are present at the date of innovation, it will also represent the expected diffusion of the innovation through that population of farmers, that is, the share of farmers that has adopted the innovation.

[12] Time-varying variables can follow either a continuous time path (e.g., farmer's age) or be step-functions over time (e.g. price of innovation).

[13] Karshenas and Stoneman also introduced a multiplicative *epidemic baseline hazard function*. However, recognizing that it is not econometrically possible to identify separately these functions, they implicitly assumed that the epidemic hazard is absorbed into the baseline hazard.

[14] The choice of a specific structure for $h_0(t)$ is subject to the peculiarities of each case study. The baseline hazard can be either semi-parametric, as in the Cox proportional hazard model

where explanatory variables shift the baseline hazard function, or parametric according to which a specific functional form defines the baseline hazard for all individuals over the whole period. Semi-parametric models are more flexible as no distributional assumption is required about the shape of the hazard function. However, they ignore what happens to explanatory variables in periods where no adoption occurs. On the other hand, parametric models are more efficient in their use of information provided by the data. The most widely used parametric specifications include the *logistic*, *Weibull*, *exponential*, *log-normal*, *log-logistic* and *Gompertz* probability distributions. More details on these particular probability distributions functions within duration analysis are provided by Kiefer.

[15] Although Karshenas and Stoneman suggested that the choice of a baseline hazard structure seems to make little difference as far as parameter estimates and inferences are concerned, the appropriateness of our choice will be validated next.

[16] For $\alpha = 1$ the *Weibull* distribution reduces to the exponential distribution. For $\alpha = 2$, the *Weibull* distribution becomes the *Rayleigh* distribution which has linearly increasing hazard rate as t increases. For 3.4 the *Weibull* distribution resembles closely the *normal* distribution whereas for $k \to \infty$, the *Weibull* distribution asymptotically approaches the *Dirac delta* function.

[17] The *FOODIMA* project (EU Food Industry Dynamics and Methodological Advances) is financed within the 6th Framework Programme under Priority 8.1-B.1.1 for the *Sustainable Management of Europe's Natural Resources*. More information on the *FOODIMA* project can be found in www.eng.auth.gr/mattas/foodima.htm.

[18] Using the Agricultural Census published by the Greek Statistical Service, farms were classified according to their size and activities. Then with the help of extension agents from the Regional Agricultural Directorate of Crete a randomly sample of farms was selected. In

the case that farmers were not available or not willing to provide the required information, they were replaced by similar ones from the same area.

[19] Running a pilot survey we found that nobody had adopted drip irrigation technologies before 1994. So in the final survey, interviewers were asking recall data only for that period.

[20] In a traditional sense, agricultural extension is a mechanism by which information on new technologies, and better farming practices can be transmitted to farmers (Owens, Hoddinott and Kinsey).

[21] The *Herfindhal* index was calculated as $H = \sum_i s_i^2$ where s_i is the share of crop *i* in total farm production.

[22] For the off-farm income equation, the set of instruments includes the distance from district capital in kilometers and the number of tourist arrivals in the island. For the stock of adopters and *homophylic* adopters we include the farm population in the area and the share of farms cultivating olive-trees. For on-farm extension visits, we use the number of extension outlets (public and private) in the area and the distance of the farm to the extension outlets in kilometers. Finally, for household debts, the instruments were capital stock and a dichotomous variable indicating whether farms use mechanical harvesting equipment or not.

[23] The LR test statistic is computed as: $LR = -2\{ln\, L(H_0) - ln\, L(H_1)\}$ where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and the alternative (H_1) hypothesis, respectively. The LR-test follows approximately a χ^2 distribution with degrees of freedom equal to the number of restrictions.

[24] Downside risk aversion means that when there is a choice between two output distributions with the same mean and variance, the output distribution which is less skewed to the left is preferred.