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Abstract

In this article we investigate the role of information spillovers in promoting irrigation technology adoption and diffusion. In particular, we investigate the effect of different channels of information spillovers, namely informal social learning and formal extension services, while acknowledging that this effect is a function of farm-specific spatial, environmental and socio-economic characteristics, the latter including the efficient identification of the farmers' influential peers. For doing so, we develop a theoretical model of irrigation technology adoption and diffusion, which we then empirically apply using duration analysis on a micro-dataset of olive producing farms in Crete. Because unobserved variables are potentially relevant for quantifying the effect of information provision (formal and informal) we use observable indicators in a factor analytic model to proxy the unobserved latent variables used in our econometric estimation of the duration model. To the best of our knowledge, this is the first paper that brings together, both theoretically and empirically, three strands of the adoption and diffusion literature: (i) the literature on social learning, (ii) the literature on extension services, while (iii) proposing an econometric approximation of the involved unobserved variables that crucially contribute in the identification of informational cascades among rural population. The paper concludes with policy recommendations based on our empirical results, which suggest that both formal and informal information spillovers are strong determinants of technology adoption and diffusion.

Keywords: irrigation technology adoption and diffusion; informational spillovers; social learning; extension services; factor analytic model, duration analysis; olive farms.
JEL Codes: *C41*, *O16*, *O33*, *Q25*.

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1 Introduction

Modern irrigation technology is often cited as central to increasing water use efficiency and reducing the use of scarce inputs, while maintaining current levels of farm production, particularly in semi-arid and arid agricultural areas. The analysis of adoption and diffusion patterns of modern irrigation technologies has been at the core of several empirical studies in both developed and developing countries around the world (among others Dinar, Campbell and Zilberman (1992), Dridi and Khanna (2005), Koundouri, Nauges and Tzouvelekas (2006) and the references cited therein). These empirical studies provided clear evidence that economic factors like water price, cost of irrigation equipment, crop prices, but also farm organizational and demographic characteristics like size of farm operation, educational level and experience of household members, together with environmental conditions (*e.g.*, soil quality, precipitation), do matter to explain adoption and diffusion of modern irrigation technologies. This empirical research has provided quite useful results towards improving our understanding of the driving forces of modern irrigation technology adoption and diffusion. However, another strand of the technology diffusion literature in agriculture argues that the above economic, structural, demographic and environmental factors cannot explain accurately the diffusion patterns as they are conditional on what farmers know about the new technology at any given point in time (Foster and Rosenweig (1995), Besley and Case (1997), Munshi (2004), Bandiera and Rasul (2006) and Conley and Udry (2010)). In modern agriculture, farmers are informed about the existence and effective use of any new farming technology mainly through *formal* communication with extension personnel (from either private, under fee, or public extension agencies) and from their *informal* social interaction and exchange of information with other farmers.

Several studies pinpointed extension agents as the primary source of information about the existence and merits of any new farming technology including irrigation techniques (for a thorough discussion see Gisselquist, Nash and Pray (2002), Rivera and Alex (2003), World Bank (2006) and Larsen, Kim and Theus (2009)). Because the cost of passing the information on the new technology to a large heterogeneous population of farmers may be high, extension agents usually target specific farmers who are recognized as being *peers* exerting a direct or indirect influence on the whole population of farmers in their respective areas (Birkhaeuser, Evenson and Feder 1991). Farmers may also observe, exchange information, and learn from individuals with whom they have close social ties and with whom they share common professional or/and personal characteristics (education, age, religious beliefs, farming activities etc.); the latter being called *homophilic* neighbors in Rogers' (1995) terminology. It is now well recognized in the literature that informational spillover about the effective use of the new technology may speed up technology adoption rates in rural areas.

Although the distinction made by Rogers defines *homophilic* population as the reference group influencing individual choices and the spread of information, this is not always the case. Farmers may also follow or trust the opinion of those that they perceive as being successful in their farming operation, even though they occasionally share quite different characteristics. For instance, a young farmer with low experience will rather follow and trust more experienced farmers either from their own social network or from outside. Therefore, what determines the influential reference group for an individual farmer in the sense of affecting his/her decisions about the profitability of new technologies is not straightforward but is instead a combination of several factors. Another important dimension of effective informational provision is the spatial distribution of peers and farmers' reference group. In large geographical areas with a low density of farmers, formal communication channels may be less successful in promoting technology diffusion than in small areas with close geographical proximity among farmers.

Although there is a lot of literature on technology adoption, the literature on the separate impacts of information transmitted via extension agents and *neighbors*, is thin. This is indeed the result of challenging issues of attribution and identification, and, relevant to these challenges, limited data availability. Measuring the extent of social learning and identifying its role in technology diffusion is difficult for two major reasons. First, the set of *neighbors* from whom an individual can learn is difficult to define. We believe that a significant contribution to this literature should provide advancements with regards to definition and identification of *peers*. As discussed before we need to go beyond the simplistic definition of *peers* as (physical) neighbors identified (only) through physical distance. Second, distinguishing learning from other phenomena (for example, interdependent preferences and technologies, related unobserved shocks) that may give rise to similar observed outcomes is problematic (Manski, 1993).

Along these lines, our article aims to quantitatively measure the importance of both formal and informal communication channels in modern irrigation technology diffusion for a sample of 265 randomly selected olive-growing farms in Crete, Greece. In this paper we argue, in accordance with the theoretical literature, that *peers* are farmers with whom a particular farmer interacts. We use original information collected through our survey on characteristics of the *peer* group (age, education, etc.) in conjunction with factor analysis, to build factors that best represent the unobserved variables that are potentially relevant for quantifying the effect of information spillovers, both via extension visits and social learning.[1] We then use the estimated factor scores in the hazard function and estimate a duration model in order to predict diffusion rates of modern irrigation technology. The use of a duration model allows us to determine the diffusion curve of modern irrigation technology and to provide insights on the impact of social learning (formal or informal) on this diffusion process. In arid and semi-arid areas where water resources are scarce, adoption of modern more efficient irrigation technologies is vital for the sustainability of farming activities. This study sheds new light on factors affecting individual perceptions and on the process of social learning. Our findings should help identifying appropriate policy measures to promote a faster diffusion of more effective irrigation technologies.

In section 2 we develop the theoretical model of adoption and diffusion of modern irrigation

[1] Bandiera and Rasul (2006), Conley and Udry (2010) and Weber (2012) use the same conceptual approach to overcome identification problems.

technology and in section 3 we present the econometric model using duration analysis. In section 4, we discuss the data and we describe the empirical version of the econometric model. In section 5 we present the informational variables used and the factor analytic model utilized to build factors that best represent each one of the unobserved variables that are potentially relevant for quantifying the effect of information provision in the diffusion of drip irrigation technologies. In section 6 we discuss the estimation results and the last section discusses some relevant policy recommendations born out from our study and concludes the paper.

2 Theoretical Model

In this section we develop a model that describes the farmer's decision process regarding new technology adoption. This model is useful as background framework for simultaneous study of: (a) formal learning from extension services before and after adoption, (b) informal learning from peers, before and after adoption, and (c) learning-by-doing after adoption.

We assume that farm's j technology is represented by the following continuous twice-differentiable concave production function:

$$y_j = f(\mathbf{x}_j^v, x_j^w, A_j) \tag{1}$$

where y_j denotes crop production, $\mathbf{x}_j^v$ is the vector of variable inputs used in farm production (labor, pesticides, fertilizers, etc.), x_j^w represents irrigation water, and A_j denotes a farm technology index. Crop production is sensitive to the quantity of irrigation water used: we assume that if the quantity of irrigation water applied is lower than the threshold x_{min}^w the quality of the crop will be too low for the farmer to sell it on the market. The farmer is thus facing a risk of low (or negative) profit in case of water shortage.

Farmers have the option to invest in a modern, more efficient irrigation technology (*e.g.*, drip or sprinklers). Using a modern irrigation technology instead of the conventional one would allow the farmer to produce the same level of output (y) using the same quantity of variable inputs $\mathbf{x}^v$ and a lower quantity of irrigation water (x^w). The increased irrigation effectiveness of the modern technology is here described through a change in the technology index, *i.e.*, from A^0 with the conventional technology to A^* with the modern technology.[2] We assume that the maximum irrigation effectiveness is reached when the farmer operates adequately the modern irrigation technology, which corresponds to $A = A^*$. We also assume that the maximum irrigation effectiveness cannot be reached with the traditional irrigation technology ($A^* > A^0$).

The modern technology not only improves irrigation effectiveness but also allows the farmer to hedge against the risk of drought (and consequently the risk of low profit) in the sense that using a more efficient irrigation technology reduces the risk of a lack of irrigation water (*i.e.*,

[2] The technology index, in the context of irrigation, is best interpreted as a water-efficiency index, the latter being the ratio of the amount of water used by the crop (sometimes called 'effective water') to the total amount of irrigation water used on the field (sometimes called 'applied water' and denoted by x_j^w in model (1)); see Caswell and Zilberman (1986) for related discussions on irrigation effectiveness.

$x^w < x^w_{min}$) that would be detrimental to the crop. We assume that the consequences of adoption in the new technology are not known with certainty by the farmers: farmers using a traditional irrigation technology may not be able to precisely quantify the expected water efficiency gains from switching to a modern irrigation technology and second, if a farmer switches to the modern irrigation technology, it may require some time before the new technology is operated at its best (*i.e.*, before the water-efficiency index A reaches its maximum A^*). In this article we consider that the farmer can reduce this uncertainty through two channels: *i*) farmers can build knowledge about the new technology and expected benefits of its adoption before actually adopting it through interactions with extension services or/and interactions with other farmers (and in particular early adopters), and *ii*) farmers can improve operation of the new technology after adoption through self-experience (or learning-by-using).

In the developed framework the farmer decides whether or not to adopt by forming expectations about the efficiency of the new technology. We denote by s each production period at the end of which the farmer will decide whether to adopt the new technology. Each farmer j accumulates information on the new technology until the end of period s and forms expectations about aggregate discounted future returns for a set of adoption scenarios; one scenario for each potential adoption time, τ, where $\tau > s$. We set the time horizon to a fixed T, which implies that $s \in \{0, 1, 2, ...T-1\}$ and $\tau \in \{s+1, \ldots T\}$. We also assume that the required equipment for the use of the new technology has a finite life expectancy, denoted by T_e. Then, we denote by A^*_j the maximum efficiency index for farmer j when the new technology is adopted, and by $A_{j,s}(t, \tau)$ the expected, at time s, efficiency index for time period t, under the assumption that the new technology is adopted at time τ. The time variable t takes values in $\{\tau, \tau+1, \tau+2, ..., T\}$. For every s, it holds that $\partial A_{j,s}/\partial t \geq 0$ and $\partial A_{j,s}/\partial \tau \geq 0$, where the inequality is strict for $t > \tau$ and $A_j < A^*$.

In a nutshell, up to period s the farmer gathers information about the new technology from extension visits and/or social learning from peers. At the end of s, the farmer uses this information in order to form expectations about future production (and hence profit) for every t until T. Then, based on these expectations she decides whether to adopt or not in period $s+1$. If she decides not to adopt in $s+1$, she continues to gather additional information about the new technology until the end of $s+1$ and, once again, based on this information she forms expectations about future profits with and without adoption. The process is repeated until adoption takes place or until $s = T$. Finally, farmers who invest in the modern irrigation technology must incur some fixed cost (c) of purchasing the equipment which is known to them at period t. We assume that this cost decreases over time, *i.e.*, $\partial c_{j,t}/\partial t < 0$.

Let us now denote by p, w^w and $\mathbf{w}^v$ the expected discounted crop, irrigation water, and variable input prices which are assumed, by the farmer, to remain constant over time. Then, just after period s, if farmer j does not decide to adopt the new technology until period t, her expected discounted profit function for period t will be

$$\pi_j\left(p, \mathbf{w}^v, w^w, A_j\right) = \max_{\mathbf{x}^v, x^w} \{pf(\mathbf{x}_j^v, x_j^w, A_j) - \mathbf{w}^v \mathbf{x}_j^v - w^w x_j^w\}$$

where $\pi_j\left(p, \mathbf{w}^v, w^w, A_j\right)$ is a sublinear (positively linearly homogeneous and convex) in p, w^v, and w^w profit function. It is non-decreasing in crop price and irrigation technology index, and non-increasing in variable input and irrigation water prices. If, on the other hand, farmer j assumes that she will have already adopted the new technology at a period $\tau \leq t$, then her conditional discounted profit function (expected profits given the time, τ, of adoption of new technology) will be given by (after dropping subscript j for convenience)

$$\pi_{s,\tau,t}\left(p, \mathbf{w}^v, w^w, A_s(t,\tau)\right) = \max_{\mathbf{x}^v, x^w} \{pf(\mathbf{x}_{s,\tau,t}^v, x_{s,\tau,t}^w, A_s(t,\tau)) - \mathbf{w}^v \mathbf{x}_{s,\tau,t}^v - w^w x_{s,\tau,t}^w\}.$$

In this model, we make the simplifying assumption that before actually adopting and while forming expectations about the level of the technology index, the farmer assumes that this index will remain constant throughout the period after adoption. In other words, when forming expectations, the farmer assumes that the technology index $A_s(t,\tau)$ is equal to A_s for all $\tau + T_e \geq t \geq \tau$.[3] This does not imply that the technology index will in fact remain constant, as learning from others (both formal and informal) and learning-by-doing might occur after adoption.

To simplify the notation we denote each farmer's discounted expected profit for period $s+1$, given her current knowledge by: $\pi_{s,s+1,s+1}\left(p, \mathbf{w}^v, w^w, A_s(s+1,s+1)\right)$. Then, each farmer chooses to adopt the new technology by maximizing over τ his/her temporally aggregated discounted profits:

$$\begin{aligned}
V_{s,\tau,T} &:= \sum_{t=s+1}^{\tau-1} \pi - c_{s,\tau} + \sum_{t=\tau}^{\{\tau+T_e-1\}\wedge T} \pi_s + \sum_{t=1+(\{\tau+T_e-1\}\wedge T)}^{T} \pi \\
&= (\tau - 1 - s)\pi - c_{s,\tau} + ((\{\tau + T_e - 1\} \wedge T) - \tau + 1)\,\pi_s \\
&\quad + ((T - (\{\tau + T_e - 1\} \wedge T)) \vee 0)\,\pi \\
&= [\tau - 1 - s + (T - (\{\tau + T_e - 1\} \wedge T)) \vee 0]\,\pi \\
&\quad + (\{\{\tau + T_e - 1\} \wedge T\} - \tau + 1)\,\pi_s - c_{s,\tau} \qquad (2)
\end{aligned}$$

where $a \wedge b = \min\{a,b\}$, $a \vee b = \max\{a,b\}$, $c_{s,\tau}$ is the discounted expected equipment cost at time s. The latter is a decreasing function of τ, while T_e is the life expectancy of the equipment for the

[3]This assumption is not very strong: the farmer considers that the technology efficiency index will remain constant after adoption mainly because she does not have enough information to predict the evolution of the technology efficiency after adoption (which is a complex function of learning from others and learning-by-doing). The model could be extended to allow for the farmers anticipating learning-by-doing. However, we believe that incorporating these effects on expectations formation is unrealistic and will unnecessarily complicate the model. Specifically, such an extension would need to incorporate assumptions about farmer-specific learning curves, which will differ between adopters based on initial adoption time (probably late adopters learn faster) and farmer-specific socio-economic characteristics (such as education and experience). Such an extension does not alter the learning processes of our model, neither before, nor after adoption, but it does make the first order conditions less clear.

application of the new technology, and T is large enough to imply that the contribution of peers' knowledge in A has reached (approximately) the highest possible level. The last sum of the right hand side is considered to be zero if $\tau + T_e \geq T$, which implies that $1 + (\{\tau + T_e\} \wedge T) > T$. Note that $c_{j,s,s+1}$ represents the current equipment cost just after period s for farmer j.

The trade-off that the farmer faces can be described as follows. Consider a farmer in year s who thinks about investing in the modern technology. Delaying investment by one year would entail some benefit because the farmer could purchase the modern irrigation technology at a reduced cost ($c_{s,\tau} > c_{s,\tau+1}$). However delaying adoption by one year would also come at a cost: the farmer will still produce in year t with the conventional technology (and bear a higher risk of water shortage). There is thus a loss in expected profit induced by delaying adoption of the modern irrigation technology.

Note that while $\tau + T_e - 1 \leq T$,

$$\begin{aligned} & [\tau - 1 - s + (T - (\{\tau + T_e - 1\} \wedge T)) \vee 0]\, \pi + (\{\{\tau + T_e - 1\} \wedge T\} - \tau + 1)\, \pi_s \\ = \ & [\tau - 1 - s + T - \tau - T_e + 1]\, \pi_j + [\tau + T_e - 1 - \tau + 1]\, \pi_s \\ = \ & [T - (s + T_e)]\, \pi + T_e \pi_s \end{aligned}$$

which does not depend on the date of adoption τ. Therefore, since $c_{s,\tau}$ is a decreasing function of τ, each farmer estimates that new technology will be optimally adopted at least for the period $\tau_1^* = T - T_e + 1$, and

$$\max_{\tau + T_e \leq T} V^s_{s,\tau,T} = V^s_{s,\tau_1^*,T} = V^s_{s,T-T_e+1,T}$$

This fact implies that new technology will not be adopted before period $T - T_e + 1$. Therefore, the initial problem is simplified to

$$\max_{1 \leq k \leq T-s} V^s_{s,s+k,T} \ , \tag{3}$$

where $s \geq T - T_e$. Then, we have

$$V^s_{s,s+k,t} = (k-1)\, \pi + (T - s - k + 1)\, \pi_s - c_{s,s+k}, \tag{4}$$

which implies that the rate of change of $V^s_{s,s+k,s+T_e}$ as a function of k is

$$\Delta V^s_{s,k+1} := V^s_{s,s+k+1,T} - V^s_{s,s+k,T} = \pi - \pi_s + c_{s,s+k} - c_{s,s+k+1} \tag{5}$$

Therefore, any change on $\Delta V^s_{s,k+1}$ is a result only of a change in $\Delta c_{s,k+1} := c_{s,s+k+1} - c_{s,s+k}$.

Now it is time to introduce a simplified assumption on the rate of decrease of the equipment cost. We assume that at any point in time, s, farmer j assumes a rate of decrease for the discounted equipment cost as follows,

$$c_{s,s+k} = (1 + a_s e^{-\lambda_{c,s}(k-1)}) c_{0,s}, \tag{6}$$

where $a > 0$ and $0 < \lambda_{c,s}$. Note that $c_{0,s} = c_{s,s+1}/(1 + a_s)$. Therefore, (6) becomes

$$c_{s,s+k} = \frac{(1 + a_s e^{-\lambda_{c,s}(k-1)})}{1 + a_s} c_{s,s+1} \tag{7}$$

Plugging (7) in (4) we obtain

$$V^s_{s,s+k,T} = (k-1)\,\pi + (T - s - k + 1)\,\pi_s - \frac{(1 + a_s e^{-\lambda_{c,s}(k-1)})}{1 + a_s} c_{s,s+1} \tag{8}$$

We observe that

$$\frac{\partial V^s}{\partial k} = \pi - \pi_s + \frac{a_s \lambda_{c,s} c_{s,s+1}}{1 + a_s} e^{-\lambda_{c,s}(k-1)}$$

The second order partial derivative in k is

$$\frac{\partial^2 V^s}{\partial k^2} = -\frac{a_s \lambda^2_{c,s} c_{s,s+1}}{1 + a_s} e^{-\lambda_{c,s}(k-1)} < 0$$

Therefore, after period s, farmer j decides to adopt new technology starting from period $s + 1$ only if

$$\left.\frac{\partial V^s}{\partial k}\right|_{k=1} \leq 0 \Longleftrightarrow \pi_s \geq \pi + \lambda_{c,s} \frac{a_s c_{s,s+1}}{1 + a_s} \tag{9}$$

An equivalent expression of condition (9) uses the fact that a_s is determined by the relationship between the final discounted cost $c_{0,s}$ and current cost $c_{s,s+1}$, because

$$a_s = \frac{c_{s,s+1}}{c_{0,s}} - 1 \tag{10}$$

Specifically, each farmer chooses to adopt the new technology right after period s if

$$\pi_s - \lambda_{c,s}\,(c_{s,s+1} - c_{0,s}) \geq \pi \tag{11}$$

Note that in this model the optimal time of adoption depends on output and input prices (through the profit functions), the water-efficiency index, and the cost of installing the technology. Heterogeneity in the timing of adoption is explained by heterogeneity in the technology index, itself driven by different paths of knowledge accumulation across the population of farmers. In the forthcoming empirical application we assume that the water-efficiency index at each time t depends on farmers' characteristics (age, experience in farming, education level), contacts with extension services, and contact with peers. The threshold (w_{min}) that defines the minimum level of irrigation water required for the crop to be marketable is another source of heterogeneity: this threshold will depend on farms' environmental conditions such as soil type and aridity index.

3 Econometric Model

Following Karshenas and Stoneman (1993), Kerr and Newell (2003) and Abdulai and Huffman (2005), we model the optimal time of drip irrigation technology adoption using duration analysis. A duration model of irrigation technology adoption and diffusion is based on formulating the problem in terms of the conditional probability of adoption at a particular period, given that adoption has not occurred before and given the specific characteristics of individual farmers and the environment in which they operate. In addition to the intuitive appeal of framing the technology adoption decision in this way, duration models provide a convenient framework for incorporating data on explanatory variables that change over time and other elements of the dynamic process of technological change (*i.e.*, informational cascades including *learning-from-others* and *learning-by-doing*). Estimating the effect of informational variables and other determinants of technology adoption that change over time (e.g., installation costs, crop and irrigation water prices) is in fact central to our empirical research interest.

Under the assumption that duration, T, is a positive random variable with a continuous probability density function, $f(t)$, the cumulative distribution function is given by $F(t) = \int_0^t f(s)ds = P(T \leq t)$. The probability $P(T > t)$ defines the survival function: $S(t) = 1 - F(t) = 1 - \int_0^t f(s)ds = \int_t^\infty f(s)ds$, which represents the probability of survival (in our case, survival of the old technology) beyond a certain point in time. 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. 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:

$$h(t) = \lim_{\Delta \to 0} \left(\frac{F(t + \Delta) - F(t)}{\Delta S(t)} \right) = \frac{f(t)}{S(t)}$$

which is the empirical counterpart of the optimality condition in (11). In empirical work, it is common to specify the hazard function as the product of the baseline hazard, which is assumed to be common to all individuals and to depend only on time and some unknown parameters α, and a component which depends on adopters' characteristics, λ_{it}: $h(t, z_{it}, \alpha, \beta) = h_0(t, \alpha) \cdot \lambda_{it}$, where $\lambda_{it} = exp(-z_{it}\beta)$ can be seen as the empirical counterpart of the arbitrage condition as defined in the previous section. The vector z_{it} includes variables that are supposed to enter the arbitrage condition determining farmers' optimal choice, and β are the corresponding parameters to be estimated. These variables can vary only across time (*e.g.*, cost of acquiring the new technology), vary only across farmers (*e.g.*, farm size, soil quality and weather conditions) or vary across both dimensions (*e.g.*, farmer's age).

The choice of a specific structure for $h_0(t, \alpha)$ is subject to the peculiarities of each case study. Here, following the relevant literature, we assume that the random variable T follows a *Weibull* distribution, which is flexible in the sense that it accommodates hazard rates that increase or decrease exponentially with time.[4] Following Greene (2003, p.794), the hazard function under a *Weibull* distribution takes the following form:

$$h\left(t, z_{it}, \alpha, \beta\right) = \lambda_{it}\alpha(\lambda_{it}t)^{\alpha-1} \tag{12}$$

where, α 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 $\alpha = 1$.[5]

Under the *Weibull* distribution, the set of unknown parameters 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 as:

$$LnL\left(\alpha, \beta\right) = \sum_{i=1}^{N} d_i lnh\left(t, z_{it}, \alpha\beta\right) + \sum_{i=1}^{N} lnS\left(t, z_{it}, \alpha\beta\right)$$

where, $d_i = 1$ if the i^{th} spell is not censored and $d_i = 0$ if censored. In the context of the *Weibull* distribution, the mean expected survival (*i.e.*, adoption) time is calculated as:

$$E(t) = \left(\frac{1}{\lambda_{it}}\right)\Gamma\left(1 + \frac{1}{\alpha}\right)$$

where $\Gamma(r) = \int_0^\infty x^{r-1}exp(-x)dx = (r-1)!$ (the last equality holding if r is a positive integer) is the *Gamma* function, and the marginal effects of the k^{th} continuous explanatory variables on the hazard rate and on the mean expected survival time are calculated from:

$$h'_{z_k}\left(t, z_{it}, \alpha\beta\right) = -h\left(t, z_{it}, \alpha\beta\right)\frac{\partial(z_{it}\beta)}{\partial z_k}\alpha \tag{13}$$

and

$$E'_{z_k}(t) = \frac{\partial(z_{it}\beta)}{\partial z_k}E(t) \tag{14}$$

4 Data Description and Model Specification

The data used in this study come from a detailed survey undertaken in the Greek island of Crete on the adoption and diffusion of major farming technologies among olive growers. The survey was undertaken within the context of the Research Program *FOODIMA* financed by the European

[4]Karshenas and Stoneman (1993) suggested that the choice of a baseline hazard structure seems to make little difference as far as parameter estimates and inferences are concerned.

[5]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 $\alpha = 3.4$ the *Weibull* distribution resembles closely the *normal* distribution whereas for $\alpha \to \infty$, the *Weibull* distribution asymptotically approaches the *Dirac delta* function.

Commission.[6] The final sample consists of 265 randomly selected olive producing farms located in the four major districts of Crete during the 2005-06 cropping period. Using the Agricultural Census published by the *Greek Statistical Service*, olive farms in Crete were classified according to their size and farming activities. Then, with the assistance of extension agents from the *Regional Agricultural Directorate* of Crete a random sample of olive farms was selected. Given the significance of the olive sector for the regional economy and the state of water resources in the island, special attention was placed on modern irrigation technologies.[7] To that end, farmers were asked to recall the exact time of adoption of modern irrigation technologies (*i.e.*, drip or sprinklers) together with some key variables related to their farming operation on the same year (*i.e.*, production patterns, input use, average yields, gross revenues, water use and cost, structural and demographic characteristics). A pilot survey run at the beginning of the project showed that none of the surveyed farmers had adopted drip irrigation technology before 1994. So in the final survey interviewers asked recall data for the years 1994-2004 (2004 being the last cropping year before the survey was undertaken). All information was gathered using questionnaire-based field interviews undertaken by the extension personnel from the *Regional Agricultural Directorate* of Crete.

The dependent variable in our duration model in (12) is the length of time between the year of drip irrigation technology introduction (1994) and the year of adoption. Out of the 265 farms in the sample, 172 (64.9%) have adopted drip irrigation technology between 1994 and 2004. The mean adoption time is 4.68 years in our sample (see the temporal distribution of adoption times in Figure 1). Our final choice of the independent variables included in the empirical irrigation technology diffusion model is dictated by the profitability condition in (11): apart from installation cost, heterogeneity in the timing of adoption is explained by heterogeneity in the technology index, itself driven by different paths of knowledge accumulation across the population of farmers. We further assume that the water-efficiency index and farm profitability at each time t depends on farm and household characteristics (farm size, age, education level), contacts with extension services, and contact with peers (*i.e.*, informational incentives). The threshold (w_{min}) that defines the minimum level of irrigation water required for the crop to be marketable is another source of heterogeneity: this threshold will depend on farms' environmental conditions such as soil type and aridity index and structural features like tree density on farm plots. Finally, we include in the duration model the price of olive oil (the farm gate price) as well as the price of irrigation water, both entering farm's profitability levels.

The installation cost of drip irrigation technology includes the cost of designing the new irrigation infrastructure, the investment cost (*i.e.*, pipes, hydrometers, drips) and the cost of deployment in the field (*i.e.*, labor cost). For adopters, installation cost corresponds to the (recalled) cost of

[6]The *FOODIMA* project (EU Food Industry Dynamics and Methodological Advances) is financed within the 6^{th} 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.

[7]Since the early nineties water sustainability has become a major issue for regional authorities as the quite flourishing tourism industry also absorbs significant amount of islands' water resources.

installing the new equipment during the year it was adopted. For non-adopters the value of installation cost refers to the last year of the survey (2004). The installation cost per stremma (one stremma equals 0.1 ha) for the whole sample of farms was 129.3 euros on average, 125.8 euros for adopters and 135.8 euros for non-adopters (Table 1).[8]

Concerning the two human capital variables (*i.e.*, farmer's age and education) we expect more educated farmers to adopt modern irrigation technologies faster since the associated payoffs from any innovation are likely to be greater (Rahm and Huffman, 1984). Educated farmers do read technical bulletins more than their less educated counterparts and highly educated farmers might be less likely to make allocative errors in applying any farming innovation including irrigation technologies (Gervais, Lambert and Boutin Dufrense, 2001). The expected impact of age on the timing of adoption is ambiguous since age is highly correlated with experience. Therefore its effect can be considered as the composite effect of farming 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 of modern irrigation technologies positively. On the other hand, younger farmers with longer planning horizons may be more likely to invest in new irrigation technologies as they foresee longer future profits arising from efficient water use. In both cases, if farmers are not faced with significant capital constraints and take future generations' welfare into account, the primary effect of age is likely to increase the likelihood of adopting irrigation innovations faster (Huffman and Mercier, 1991). According to our survey, farmers in our sample received 6.3 years of formal education, while the average age of the household head is 53.9 years. Farmers who adopted modern irrigation technologies are younger and more educated in our sample (49.9 and 8.1 years, respectively) that their non-adopters counterparts (61.3 and 2.9 years, respectively).

The expected impact of farm size on adoption time is also ambiguous. Larger farms may have a greater potential to adopt modern irrigation technologies because of the high costs involved in irrigation water. On the other hand, larger farms may have less financial pressure to search for alternative ways to improve water effectiveness and hence irrigation cost by switching to a modern irrigation technology (Perrin and Winkelmann, 1976; Putler and Zilberman, 1984). In general, given that drip irrigation technology is risk-decreasing, if farmers' preferences exhibit decreasing relative risk-aversion, then large farms tend to switch faster to the new technology than smaller farms and *vice-versa* (Just and Zilberman, 1983). Apart from farm size, tree density also affects irrigation effectiveness and hence, willingness to adopt modern irrigation techniques (Moriana *et al.*, 2003; Pereira, Green and Villa Nova, 2006). In olive orchards with low tree density water efficiency using traditional furrow irrigation is much higher than those with high tree density. Hence, farms having orchards characterized by high tree density should have an incentive to adopt modern irrigation technologies faster in order to improve irrigation water use effectiveness. Farmers who adopted the modern irrigation technology operate farms with an average size of 22.6 stremmas and an average tree density of 14.7 per stremma, in the year of adoption (Table 1). On the other hand, non-

[8]All monetary values reported by individual farmers were deflated *prior* to econometric estimation.

adopting farms are smaller on average (20.2 stremmas) and have lower tree density (11.5 trees per stremma).

Next, and as suggested by our theoretical framework, adoption behavior for irrigation technology diffusion may also be influenced by some environmental characteristics that may affect irrigation effectiveness. We include in the diffusion model an aridity index, the altitude of the farm, and two 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, defined as the ratio of the average annual temperature over total annual precipitation, is calculated for the year of adoption in each adopting farm using data provided by the 36 local meteorological stations located throughout the island (Stallings, 1968). Since the value of the aridity index is identical for some farms that are located in the same area and adopted drip irrigation on the same year, we also include the altitude of farm's location as an additional variable. Higher altitude is more likely to be associated with lower temperatures and therefore less stressed olive trees. As shown in Table 1, the average value of the aridity index is 0.982, whereas the average altitude is 341.8 meters. Finally, farms were classified according to two different soil types based on 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 sandy and limestone soils (56.6%).

To control for economic conditions faced by olive growers, we include the price of olive oil sold and the price of irrigation water (as reported by the farmers), since they directly influence farm profitability levels. Crop price highly depends on the quality of olive oil and thus exhibits a significant variation across olive growers. On average, olive oil was priced at 2.80 euros per kilogram varying between 2.38 and 3.56 euros for adopters and non-adopters, respectively (Table 1). Irrigation water is supplied by regional water authorities under different price schemes that reflect the local cost of extraction. Therefore the price of irrigation water also exhibits significant variation with the average ranging between 25.7 and 11.2 euro cents per m^3 for adopters and non-adopters, respectively (see Table 1). Both prices were converted to constant prices using the producer price index published by the *Greek Ministry of Agriculture*.

Finally, since our analysis refers to a semi-arid area of the Mediterranean basin, farmers face some uncertainty in terms of water availability. As a consequence they may face production risk in the sense that expected production and profit levels may become random as they are both functions of exogenous climatic conditions (Saha, Love and Schwart, 1994). Hence, risk-averse olive growers might consider adoption of drip irrigation technology in order to hedge against risk during periods of water shortage or high water prices. In order to capture the impact of this uncertainty on farmers' adoption decision we follow Koundouri, Nauges and Tzouvelekas (2006) in utilizing moments of the profit distribution as determinants of adoption. Using recall data on olive-oil revenues, variable inputs (labor, fertilizers, irrigation water, pesticides), and fixed (land) input categories provided by farmers in the year of adoption, we estimated the following linear profit function for olive-growers in the island (corresponding standard errors in parentheses):

$$\pi_i = \underset{(0.423)}{2.341} + \underset{(0.104)}{0.657} p_{Oi} - \underset{(0.098)}{0.321} w_{Li} - \underset{(0.054)}{0.107} w_{Fi} - \underset{(0.032)}{0.076} w_{Wi} - \underset{(0.021)}{0.034} w_{Pi} + \underset{(0.125)}{0.431} x_{Ai} + u_i$$

where p_{Oi} is the farm gate price of olive oil, w_{ji} is the price of the j^{th} variable input (*i.e.*, labor, fertilizers, irrigation water, and pesticides), x_{Ai} is the acreage under olive trees cultivation, and u_i is a usual *iid* error term.[9] The residuals have been used to estimate the k^{th} central moments ($k = 1, \ldots, 4$) of farm profit conditional on variable and fixed input use (Koundouri, Nauges and Tzouvelekas, 2006, p. 664). Descriptive statistics of the estimated first four moments of the profit distribution are shown in Table 1.

5 Informational Variables and the Factor Analytic Model

As for informational variables, we distinguish between formal and informal communication channels that are likely to affect individual adoption decisions. The first channel is linked to communication sources emanating from extension services. A farmer's exposure to extension agencies includes not only his/her direct contacts with extension agents but also contacts between extension agents and the farmers' influential *peers*. The second channel is related to the farmer's interactions with other farmers who have already acquired experience with the new technology. We consider that the likelihood of a farmer adopting the irrigation technology depends on the adoption behavior of farmers who interact with him/her or, in other words, on the existing stock of adopters in a farmer's group of influential farmers. Moreover we assume that the strength of the above mentioned channels will depend on the geographical distance between the farmers and extension agencies, and between the farmers and their influential *peers*.

Although each farmer in our sample provided information about the number of extension visits on his farm *prior* to the year of adoption together with some key characteristics of his reference group (within which he/she exchanges information about his farming operation), this is not sufficient to identify the full impact of formal and informal communication channels on individual adoption behavior. Indeed, we have four unobserved (or latent) variables that are potentially relevant for quantifying the effect of information provision (formal and informal) in the diffusion of drip irrigation technologies: *i*) the total number of adopters in the respondent's reference group, *ii*) the average distance of the farmer to his reference group, *iii*) the overall exposure to extension services and, *iv*) the distance of the farmer's reference group (including himself) to extension services. Because these variables cannot be observed, we suggest using observable indicators in a factor analytic model to *proxy* the unobserved latent variables. Specifically, we apply factor analysis to build factors that will best represent each of these four latent variables.[10]

[9] We have also tried to fit a linear quadratic or a more flexible *translog* specification but unfortunately econometric estimates were not satisfactory.

[10] Woittiez and Kapteyn (1998) face a similar problem in their study of female labor supply, where they postulate

For the first latent variable (the total number of adopters in the respondent's reference group) we consider the following three observable indicators:

1. The *stock of adopters* in the sample during the year the farmer adopted modern irrigation technology. Using the reported year of adoption by individual respondents, we calculated the total number of adopters in the sample for each year during the 1994-2004 period. These values have been used to define the stock of adopters in the year each respondent adopted modern irrigation technology.

2. The *stock of homophilic adopters*. Given our data availability and Rogers (1995) definitions, we defined *homophilic* farmers as those having the same age and education level. Using information on farmer's age and educational level for the year of adoption reported in the questionnaires and the stock of adopters, we calculated the *homophilic* stock of adopters for each respondent. Age groups cover six years: for example, if a farmer is 38 years old, farmers aged 35 to 41 will be considered as *homophilic*. As for education, we consider a two-year range.

3. The *stock of farmers' indicated homophilic adopters*. In running the survey, farmers were asked to provide some basic characteristics (age and educational level) of other farmers in the area with whom they regularly exchange information about their farming operations in an attempt to identify intra-farm communication. Using this information and respondents' age and educational levels, we calculated the stock of adopters in the reference group for each individual respondent in the year of adoption.

Once the different adopters' groups have been defined and measured, we used the location of the farm to calculate the following road distances (in kilometers) that were utilized to proxy the second latent variable, the distance of the farmer to the adopters in his reference group: (i) the average distance to the stock of adopters, (ii) the average distance to the stock of *homophilic* adopters and, (iii) the average distance to the stock of farmers' indicated *homophilic* adopters.

As for formal information channels, namely direct and indirect contacts with extension personnel, we consider the following three observable indicators:

1. The *number of extension visits on farm* to capture the direct effect of informational provision. Farmers were asked to recall data on the number of extension visits (public or private) in their farm for each year during the 1994-2004 period. This information was used to calculate the cumulative number of extension visits on farm up to adoption year.

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that the number of hours a person chooses to work may depend on the number of hours the members of their reference group choose to work. They also proposed to use observable indicators on the reference group in a factor analytic model to *proxy* their unobserved latent variable.

2. The *number of extension visits on homophilic farms* to capture the indirect effect of informational incentives among similar farmers. This indicator has been calculated using the above definition of *homophilic* farmers and data on extension visits for each respondent.

3. The *number of extension visits on farmers' identified homophilic farms* to capture any potential heterogeneity in the indirect effect of information provision by extension personnel. The different reference groups for each individual have been defined as for the stock of adopters.

Finally, spatial differences in formal information provision (fourth latent variable) have been proxied by the following three distance indicators: (i) the distance of the respondent to the nearest extension agency (private or public), (ii) the average distance of *homophilic* farmers to the nearest extension agency and, (iii) the average distance of farmers' identified *homophilic* farms to the nearest extension agency. Again all distances were measured as road distances in kilometers. Table 1 presents the descriptive statistics for these twelve observable indicators.

The pair-wise correlations between the twelve observed indicators are presented in Table 2. Even though correlations between some indicators are low they are all statistically significant, therefore all indicators are used in the definition of each latent variable. Denoting by $\mathbf{x}$ the vector of the twelve indicator variables and by ξ the vector of the four latent variables, we assume that the relationship between the manifest (or observed) and latent variables is given by,

$$\mathbf{x} = \mu + \mathbf{\Gamma}\xi + \mathbf{v} \tag{15}$$

where, $\mathbf{v}$ is a (12x1) random vector with zero mean and variance-covariance matrix given by $\mathbf{\Psi} = diag\left(\psi_1^2 \ldots \psi_{12}^2\right)$, ξ is a (4x1) random vector also with zero mean and variance-covariance matrix $\mathbf{I}$, $\mathbf{\Gamma}$ is a (12x4) matrix of constants and μ is a vector of constants corresponding to the mean of $\mathbf{x}$.

Equation (15) is a factor analysis model consisting of twelve manifest variables and four factors which can be estimated using a number of commercial software packages. Principal components method with *varimax* rotation has been used to estimate the factor loadings which are presented in Table 3. The main variables contributing to factor 1 are the ones related to the stock of adopters and factor 1 is thus labeled as *stock of adopters in the true reference group*. The heaviest loadings for factor 2 are those for the variables related to the average distance to adopters; so factor 2 can be interpreted as *average distance to the stock of adopters in true reference group*. The main contributors to factor 3 are the variables related to the number of extension visits ; the corresponding factor is labeled *exposure to extension*. Finally, the variables related to the average distance to extension services display again the heaviest loadings for factor 4, allowing us to conclude that factor 4 represents the *average distance to extension*.

Under the assumption of multivariate normality of $\mathbf{x}$ and ξ, the expected value of the latent vector for a given value of the vector of manifest variables is given by (Krzanowski, 2000):

$$E[\xi|\mathbf{x}] = \mathbf{\Gamma}' \left(\mathbf{\Gamma}\mathbf{\Gamma}' + \mathbf{\Psi}\right)^{-\mathbf{1}} (\mathbf{x} - \mu)$$

Therefore an obvious estimator of the factor scores ξ_i for the i^{th} respondent is given by

$$\hat{\xi}_{\mathbf{i}}' = \hat{\mathbf{\Gamma}}' \left(\hat{\mathbf{\Gamma}} \hat{\mathbf{\Gamma}}' + \hat{\mathbf{\Psi}} \right)^{-\mathbf{1}} (\mathbf{x_i} - \hat{\mu})$$

Our analysis is based on a proportional hazard model, where some of the regressors are not observed (our latent variables defined above) but instead we observe some indicators that can help us predict the missing explanatory variables. Many of the proportional hazard models used in the literature including the *Weibull* used in the present article assume that the conditional hazard rate in (12) can be written as:

$$h\left(t|\mathbf{z},\xi;\alpha,\mathbf{b}\right) = \alpha t^{\alpha-1}\left(exp\left(-\left(\mathbf{z}'\mathbf{b}_1 + \xi'\mathbf{b}_2\right)\right)\right)^{\alpha} = \alpha t^{\alpha-1} exp\left(-\left(\mathbf{z}'\mathbf{b}_1^* + \xi'\mathbf{b}_2^*\right)\right) \tag{16}$$

where $\mathbf{b}_j^* = \alpha \mathbf{b}_j, j = 1,2$, $\mathbf{z}$ is the matrix of farm-specific economic, demographic, structural and environmental characteristics discussed in the previous section and ξ are the four latent variables that are not observed. Several procedures have been proposed in the literature for the proportional hazards model with missing covariates (see for example Kalbfleisch and Prentice, (2002)). *Regression Calibration* uses the fact that $E\left[exp\left(-\left(\mathbf{z}'\mathbf{b}_1^* + \xi'\mathbf{b}_2^*\right)\right)\right]$ can be approximated by $exp\left(-\mathbf{z}'\mathbf{b}_1^* - E\left[\xi|\mathbf{z},\mathbf{x}\right]\mathbf{b}_2^*\right)$ and therefore estimates of $E\left[\xi|\mathbf{z},\mathbf{x}\right]$ could be used in the hazard rate when ξ is not available (Carroll, Rupert and Stefanski, 1995). By further assuming that conditional on the twelve indicators, the four latent variables are uncorrelated with the observed explanatory variables $\mathbf{z}$, *i.e.*, $E\left[\xi|\mathbf{z},\mathbf{x}\right] = E\left[\xi|\mathbf{x}\right]$, we can use the estimated factor scores from the factor analytic model in the hazard function.

6 Empirical Results and Policy Implications

The maximum likelihood parameter estimates of the hazard function in (16) along with their corresponding t-statistics are shown in Table 4. 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. In order to examine the robustness of our approach in measuring informational spillovers, we have also fitted econometrically the hazard function without the four latent informational variables (Model A.2): $h\left(t|\mathbf{z},\xi;\alpha,\mathbf{b}\right) = \alpha t^{\alpha-1}\left(exp\left(-\mathbf{z}'\mathbf{b}_1^*\right)\right)^{\alpha}$. Parameter estimates of the reduced model together with their corresponding t-ratios are also presented in Table 4. All the key explanatory variables in both models are found statistically significant.

Comparing the two model specifications, the signs of estimated parameters are remarkably stable between models, nevertheless the reduced model underestimates the effects of age and tree density on mean adoption time while it overestimates the effect of education, crop price and mean profit. Moreover, both the *Akaike* and the *Bayesian* information criteria indicate that the full model (ModelA.1) is more adequate in explaining variability in farmers' adoption times. Predicted mean adoption times also do not statistically differ, 5.76 and 5.74 in the full and reduced model, respectively. The shape parameter of the *Weibull* hazard function is statistically significant and well above unity in both models suggesting the existence of epidemic effects in irrigation technology adoption. According to Karshenas and Stoneman (1993) these epidemic effects relate to endogenous learning as a process of self-propagation of information about the new technology that grows with the spread of that technology. More explicitly, they identify three sources for these effects: (a) the pressure of social emulation and competition, which is not highly relevant for farming business (b) the learning process and its transmission through human contact, which our model captures explicitly via the latent information variables, and (c) the reductions in uncertainty resulting from extensive use of the new technology, which are relevant in farming and capture *learning-by-doing* effects, as modelled in the theoretical section of this paper. In a nutshell, our empirical model provides evidence on the existence of epidemic effects, which capture *learning-by-doing* and imply an acceleration of the rate of adoption as time passes.

Using the parameter estimates from Table 4 we calculated the marginal effects of the explanatory variables on the hazard rate and mean expected adoption time of drip irrigation technology using relations (13) and (14) (see Table 5). Our results indicate that exposure to extension services has a strong positive and very significant effect on the hazard rate and that it considerably reduces adoption time (marginal effect estimated at -0.306), which confirms the hypothesis that formal information dissemination reduces time before adoption of the new technology. Surprisingly the distance from extension outlets results in a negative parameter estimate and hence marginal effect on mean expected time, implying that the further the farm from the extension outlet, the shorter the time before adoption. Looking carefully into the data set, this counterintuitive empirical result can be explained by the targeting of farmers in remote areas by extension services. Farmers closer to extension outlets are more likely to be informed about new farming technologies either from their interaction with market agents or by simply visiting extension outlets. Therefore, extension services are mainly directed to farmers located far away from market centers to counterweight the lack of informational incentives. These results provide support for subsidizing extension services. Moreover, spatial dispersion of extension outlets could also be designed away from market centers in a way that allows, for example, minimization of the average distance between outlets and *peer* farms in remote areas.

Informational spillovers occur not only through formal channels, but also between farmers themselves: a larger stock of adopters in the farmer's reference or influential group induces faster adoption (-0.293 years), while a larger distance between adopters increases time before adoption (0.172 years), which confirms that social interaction between farmers is a significant factor driving the diffusion of irrigation technologies. Unlike with exposure to extension, geographical proximity is an important factor determining informational incentives among the population of farmers. Mean adoption times are reduced significantly in small high populated rural areas due to intra-farm communication and exchange of information. On the other hand, the stock effect of adoption behavior clearly enhances the diffusion of modern irrigation technologies among Cretan olive growers. The passage of information among farmers is proved equally important with that initiated by extension personnel (mean marginal effects on adoption times are -0.293 and -0.306 for the stock of adopters and exposure to extension services, respectively).

Finally, concerning the relationship between informational variables, the

interaction term between the two channels of information provision resulted in a statistically significant negative parameter estimate. This result indicates that formal and informal communication channels are complementary in information provision to olive growers. According to Evenson and Westphal (1995) if a technology is characterized by tacitness or circumstantial sensitivity,[11] the passage of information cannot be made using rules of thumb mainly utilized by extension personnel, but instead it also requires strong social networks from growers engaged in learning-by-doing. In these instances informational channels are complements to each other, which implies that extension agents may pass the new technology's "hardware" aspects (the equipment that embodies the technology) while farmers are getting familiar with the new technology's "software" aspects (how to use the technology effectively) through their social networks. In our case study, although a single crop is cultivated in a small geographical, tacitness and circumstantial sensitivity may derive from varying environmental conditions (aridity, soil type, altitude) and farmer's characteristics (risk attitudes, education, age). The complementarity between the two communication channels in enhancing irrigation technology diffusion among olive growers in Crete, points to the need of redesigning the extension provision strategy towards internalizing the structure and effects of farmers' social networks.

Our results also indicate that human capital variables (age and education) have a significant impact on adoption behavior of individual farmers. First, we find that the time of adoption of drip irrigation technologies is significantly shorter for old farmers. Duration time decreases with age up to 60 years and then follows an increasing trend, which is an indication that both planning horizon and farming experience have a combined effect on adoption of modern irrigation technologies. The marginal effect of farmer's age on adoption time is -0.010 years (see Table 5). On the other hand, farmer's education level is positively related with adoption times up to a certain level of schooling and then follows a decreasing trend. More precisely duration time increases with education whenever education level is less than nine years (elementary schooling). For those farmers who have more than 9 years of education, higher educational levels lead to faster adoption rates implying that only highly educated farmers are more likely to benefit from modern technologies. These results identify education and age criteria on which a subsidy-based adoption-inducing policy can

[11] A farming technology is tacit, if it is not fully embodied in a set of artefacts like manuals or blueprints. For instance, modern irrigation technologies do not evenly apply in all crops and areas with the same manner that can be described uniformly by any manual. The performance of any irrigation technology exhibits circumstantial sensitivity, if it is sensitive to the local conditions (environmental, cultural, demographic, etc) that affect its use by individual farmers.

be structured.

Risk attitudes are also found to be important determinants of adoption behavior of Cretan olive growers. Parameter estimates of the sample profit moments turned to highly statistically significant values for the first two of them (*i.e.*, expected profit and profit variance). The third and fourth moments approximating skewness and kurtosis of profit distribution are not statistically significant (see Table 4). These results indicate that the higher the expected profit the greater the probability that a farmer decides to adopt modern irrigation technology faster, as he/she expects to be able to afford the cost of new water saving technologies. Moreover, the greater the variance of profit the greater will be the probability to adopt new irrigation technologies sooner. These findings confirm that olive growers in Crete are risk averse and adversely affected by a high variability in returns. The adoption of the modern irrigation technology allows these farmers to reduce production risk in periods of water shortage, which confirms earlier findings of Koundouri, Nauges, and Tzouvelekas (2006). The role that risk preferences play in adoption decision is quite important: the marginal effect of the profit variance on mean adoption time is -1.009 years. Finally the insignificance of the third and fourth moments of the profit distribution indicate that farmers are not taking downside yield uncertainty into account when deciding whether to adopt new irrigation technology. In other words, irrigation technology does not seem to affect exposure to downside risk. The results presented in this paragraph highlight the importance of accommodating a correct understanding of risk preferences in the evaluation of policy formation in the agricultural sector. That is, when policy-makers consider policy options affecting input and technology choices, they should take into account the level of farmers' risk-aversion and the fact that the farmers exhibit no down-side risk-aversion, in order to correctly predict the technology adoption and diffusion effects, as well as the magnitude and direction of input responses (Groom *et al.*, 2008). Accurate predictions of these effects and responses, will enable accurate prediction of the magnitude of the policy-induced welfare changes, as well as efficient provision of agricultural insurance policy.

We also find evidence that adverse weather conditions, as proxied by farm's altitude and aridity index, induce faster irrigation technology adoption, although the magnitude of the effect is small. This may indicate that farmers who can exert a better control on the quantity of water used for production purposes see the innovative irrigation technology as an insurance against adverse (here drier) weather conditions. This result should also be integrated in future revisions of the agricultural input and insurance policy. Neither soil type nor farm size have an impact on the timing of adoption (see Table 4). However, our results show that olive farms with high tree density are adopting the new efficient irrigation technology faster than farms engaged in more extensive olive tree cultivation. The marginal effect of tree density on mean adoption time is -0.073 years.

The price of olive oil and the price of irrigation water have an important impact on adoption rates. An increase of one euro cent in the water price has a very significant effect on both the hazard and the mean time, speeding up the diffusion of new irrigation technology (0.145 and -0.95, respectively). On the other hand, a higher crop price delays adoption rates as farmers are less motivated to change irrigation practices as means of increasing farms expected returns. Mean adoption time is increased by 0.343 years when the price of olive oil is getting higher. Finally, installation costs do not affect diffusion of the new technology: the corresponding parameter estimate is positive but not statistically significant (the t-statistic though is greater than one). Intuitively, a higher water price speeds up the diffusion of water efficient irrigation technology, whereas a higher crop price delays adoption rates as farmers are less motivated to change irrigation practices as means of increasing farms' expected returns. These results highlight the importance of efficient pricing of water resources in order to transmit the correct scarcity signals to the farmers and incentivize its efficient use as an input in agricultural production. Efficient water pricing is also one of the major targets of the implementation of the *EU Water Framework Directive*. Moreover, our results point to the need for an efficient crop product market, which again enters the farmer-specific cost-benefit analysis, which informs the farmer's decision on technology adoption.

7 Concluding Remarks

Our theoretical and empirical models, together with the developed econometric approach, are general enough to have worldwide relevance and applicability. Our approach can be applied in varying agricultural setting and produce results that inform basic understanding of the ways in which learning processes (both formal and informal) about new agricultural technologies can be used to bring benefits to individual farmers in an agricultural community and as a result increase private and social welfare. In particular, our approach allows identification of these learning processes, identification of the variables that influence them and identification of their respective effects on farmers' adoption decision and profitability. These information can be integrated in relevant policies towards incentivizing welfare increasing technology adoption. Such policies are particularly policy relevant nowadays, given EU agricultural policy reform and almost worldwide tight government budgets.

Our discussion in Section 6 suggests how these processes, now identified for the case-study under consideration, can be better integrated in relevant policy making. To sum up, both formal and informal informational channels, are found to be strong determinants of technology adoption and diffusion while the effectiveness of each type of informational channel is enhanced by the presence of the other. This means that the provision of extension services will be more effective speeding up the adoption process in areas where there is already a critical mass of adopters. Water and crop prices also affect technology adoption and diffusion, hence efficient pricing of agricultural inputs and outputs should become an explicit target of the reformed agricultural policy. Farmer's characteristics (risk attitudes, education, age) and environmental variables (aridity, soil type, altitude) are also found to be important drivers of farmers' technology adoption decisions and resulting technology diffusion and as such should be integrated in relevant policies. For instance in the case of education, our results show that there is a threshold level of education after which additional schooling enhances faster adoption, but the opposite happens before this threshold. This could be due to the fact that as farmers become more educated but still remain below the threshold level, they have more access to information that they are unable to process and thus extension services could assist them in this task.

Greece is among the biggest beneficiaries of the Common Agricultural Policy (CAP) and it continues to defend a large CAP budget and a strong first pillar. In Greece, CAP reforms and especially the transition to decoupled farm payments, instability in world agricultural commodity prices and contradicting agricultural policy signals, are the major causes of changing farming practices. Technology diffusion efforts are strongly influenced by a piecemeal policy framework and institutional rigidities. These need to change if Greek agriculture is to adopt a sustainable path, especially in the light of the current financial and economic crisis. On the 18 November 2010, the European Commission published the Communication Paper on the future of the CAP.[12] The reform aims at making the European agricultural sector more dynamic, competitive, and effective in responding to the Europe 2020 vision of stimulating sustainable growth, smart growth and inclusive growth. Our results can provide fruitful input to this reform.

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Tables and Figures

Figure 1: Diffusion of Drip Irrigation by Cretan Olive Farms

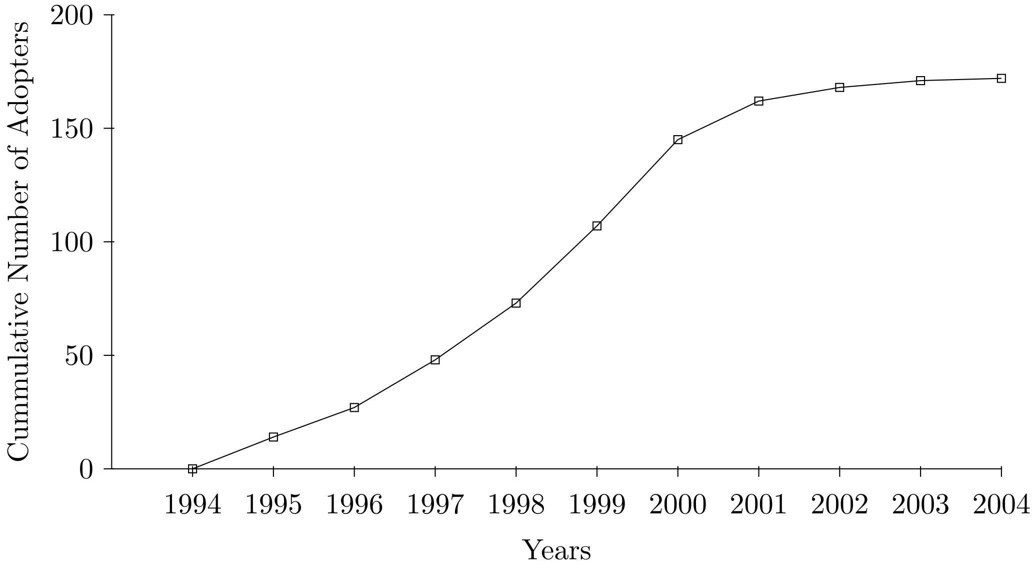

Table 1: Definitions and Summary of the Variables

Variable	All Farms	Adopters	Non Adopters
Number of Farms	265	172	93
Duration length (in years)	–	4.68	–
Farm Characteristics			
Farmer's age (in years)	53.9	49.9	61.3
Farmer's education (in years of schooling)	6.3	8.1	2.9
Farm size (in stremmas)	21.8	22.6	20.2
Tree density (in trees per stremma)	13.6	14.7	11.5
Installation cost (in euros per stremma)	129.3	125.8	135.8
Irrigation water price (in cents per m^3)	20.6	25.7	11.2
Olive-oil price (in euros per kg)	2.80	2.38	3.56
Profit moments:			
1st moment	1.132	1.422	0.596
2nd moment	0.569	0.702	0.323
3rd moment	0.582	0.738	0.293
4th moment	3.566	4.073	2.629
Aridity index	0.982	1.152	0.668
Altitude (in meters)	341.8	167.6	664.1
Soil type (in % of farm land):			
Sandy and Limestone	56.6	62.8	55.2
Marls and Dolomites	43.4	37.2	54.8
Information Variables			
Stock of adopters	31.3	35.4	23.6
Stock of *homophilic* adopters	12.6	15.0	8.1
Stock of farmers' indicated *homophilic* adopters	4.6	5.4	3.2
Distance from the adopters	49.4	44.3	58.7
Distance from *homophilic* adopters	17.4	15.2	21.6
Distance from farmers' indicated *homophilic* adopters	10.1	8.9	12.5
No of extension visits in the area	6.4	8.7	2.2
No of extension visits in *homophilic* farms	3.3	4.8	0.6
No of visits in farmers' indicated *homophilic* farms	2.0	2.9	0.2
Distance of extension outlets:			
from farms in the area	111.2	87.6	154.9
from *homophilic* farms	52.3	34.9	84.3
from farmers' indicated *homophilic* farms	23.6	17.0	35.6

All data refer to the year of adoption as those have been recalled by individual farmers. Monetary values have been deflated prior to econometric estimations.

Table 2: Correlation Matrix of the Twelve Information Indicators

Variable	*Stock*	*HStock*	*RStock*	*Dista*	*HDista*	*RDista*	*Ext*	*HExt*	*RExt*	*Distx*	*HDistx*	*RDistx*
Stock	1.000											
HStock	**0.673**	1.000										
RStock	**0.579**	**0.772**	1.000									
Dista	-0.439	-0.526	-0.572	1.000								
HDista	-0.326	-0.450	-0.478	**0.732**	1.000							
RDista	-0.254	-0.410	-0.429	**0.692**	**0.919**	1.000						
Ext	0.521	0.624	0.767	-0.585	-0.521	-0.453	1.000					
HExt	0.519	0.599	0.735	-0.573	-0.510	-0.445	**0.918**	1.000				
RExt	0.520	0.595	0.719	-0.600	-0.503	-0.451	**0.882**	**0.934**	1.000			
Distx	-0.453	-0.539	-0.534	0.521	0.472	0.428	-0.556	-0.570	-0.565	1.000		
HDistx	-0.529	-0.535	-0.489	0.448	0.447	0.373	-0.496	-0.534	-0.507	**0.791**	1.000	
RDistx	-0.459	-0.455	-0.416	0.422	0.428	0.386	-0.424	-0.430	-0.417	**0.648**	**0.842**	1.000

where *Stock* is the stock of adopters, *HStock* is the stock of *homophilic* adopters, *RStock* is the stock of farmers' indicated *homophilic* adopters, *Dista* is the distance from the stock of adopters, *HDista* is the distance from the stock of *homophilic* adopters, *RDista* is the distance from the stock of farmers' indicated *homophilic* adopters, *Ext* is the No of extension visits in the area, *HExt* is the No of extension visits in the *homophilic* farms, *RExt* is the No of extension visits in the farmers' indicated *homophilic* adopters, *Distx* is the distance of extension outlets from farms in the area, *HDistx* is the distance of extension outlets from the *homophilic* farms, *RDistx* is the distance of extension outlets from the farmers' indicated *homophili! c* adopters. All correlations are significant at the 0.01 level. Each block of bold values gives correlations within a triad of indicators.

Table 3: Estimation Results of the Factor Analytic Model for Informational Variables

Variable	Stock of Adopters (ξ_1)	Distance between Adopters (ξ_2)	Exposure to Extension (ξ_3)	Distance from Extension Outlets (ξ_4)
Stock	0.8188	-0.0873	0.2280	-0.2955
HStock	0.7729	-0.2465	0.3509	-0.2454
RStock	0.6801	-0.2574	0.6080	-0.1772
Dista	-0.2850	0.7143	-0.3478	0.2061
HDista	-0.1290	0.9022	-0.2288	0.2234
RDista	-0.0858	0.9270	-0.1767	0.1758
Ext	0.2762	-0.2554	0.8562	-0.2160
HExt	0.2311	-0.2324	0.8818	-0.2537
RExt	0.2359	-0.2489	0.8667	-0.2343
Distx	-0.1854	0.2420	-0.3565	0.7465
HDistx	-0.2519	0.1683	-0.2311	0.8847
RDistx	-0.2032	0.2051	-0.1216	0.8687

where *Stock* is the stock of adopters, *HStock* is the stock of *homophilic* adopters, *RStock* is the stock of farmers' indicated *homophilic* adopters, *Dista* is the distance from the stock of adopters, *HDista* is the distance from the stock of *homophilic* adopters, *RDista* is the distance from the stock of farmers' indicated *homophilic* adopters, *Ext* is the No of extension visits in the area, *HExt* is the No of extension visits in the *homophilic* farms, *RExt* is the No of extension visits in the farmers' indicated *homophilic* adopters, *Distx* is the distance of extension outlets from farms in the area, *HDistx* is the distance of extension outlets from the *homophilic* farms, *RDistx* is the distance of extension outlets from the farmers' indicated *homophilic* adop! ters.

Table 4: Maximum Likelihood Parameter Estimates of Alternative Specifications of the Hazard Function for the Adoption of Drip Irrigation Technology by Cretan Olive Farms

Variable	Model A.1		Model A.2	
	Estimate	t-ratio	Estimate	t-ratio
Constant	1.5617	1.8077	1.4303	1.5633
Farmer's age	-0.0168	-2.4766	-0.0106	-1.3404
Farmer's age-squared	0.0001	2.1568	0.0001	1.1931
Farmer's education	0.0182	1.1456	0.0347	2.2150
Farmer's education-squared	-0.0010	-1.5354	-0.0021	-3.0807
Installation cost	0.0089	1.0786	0.0099	1.1629
Farm size	-0.0048	-0.3848	-0.0117	-0.8617
Tree density	-0.0127	-3.7991	-0.0109	-2.9231
Water price	-0.0164	-10.892	-0.0205	-13.694
Crop price	0.0596	1.8796	0.0658	1.8465
1^{st} profit moment	-0.0943	-2.5987	-0.1132	-2.7071
2^{nd} profit moment	-0.1752	-2.4884	-0.1611	-1.8807
3^{rd} profit moment	0.0292	0.9414	0.0770	1.6685
4^{th} profit moment	-0.0024	-0.3167	-0.0125	-1.0554
Aridity index	-0.0389	-1.1718	-0.0412	-1.3601
Farm altitude	0.0006	3.3071	0.0005	2.9544
Sandy and limestone soils	-0.0002	-0.0075	0.0265	0.7475
Stock of adopters	-0.0509	-1.9745	-	-
Distance between adopters	0.0299	1.6498	-	-
Exposure to extension	-0.0531	-2.7988	-	-
Distance from extension outlets	-0.0238	-1.6691	-	-
(Stock of adopters)X(Exposure to extension)	-0.0554	-3.5119	-	-
Scale parameter (α)	9.1085	15.075	8.0932	16.420
Log-Likelihood	107.709		86.834	
Akaike Information Criterion	-0.639		-0.520	
Bayesian Information Criterion	-0.329		-0.276	
Mean Adoption Time	5.76		5.74	

Table 5: Marginal Effects of the Explanatory Variables on the Hazard Rate and Mean Adoption Time of Drip Irrigation Technology Adoption

Variable	Model A.1		Model A.2	
	Hazard Rate	Adoption Time	Hazard Rate	Adoption Time
Farmer's age	0.015	-0.010	0.007	-0.006
Farmer's education	-0.047	0.031	-0.058	0.047
Installation Cost	-0.079	0.051	-0.070	0.057
Farm size	0.043	-0.028	0.082	-0.067
Tree Density	0.112	-0.073	0.077	-0.063
Water Price	0.145	-0.095	0.145	-0.118
Crop Price	-0.525	0.343	-0.464	0.378
1^{st} profit moment	0.831	-0.543	0.798	-0.650
2^{nd} profit moment	1.544	-1.009	1.136	-0.925
3^{rd} profit moment	-0.258	0.168	-0.543	0.442
4^{th} profit moment	0.021	-0.014	0.088	-0.072
Aridity Index	0.343	-0.224	0.291	-0.237
Altitude	-0.005	0.003	-0.004	0.003
Sandy-Limestone soils	0.002	-0.001	-0.190	0.152
Stock of adopters	0.449	-0.293	–	–
Distance between adopters	-0.264	0.172	–	–
Extension services	0.468	-0.306	–	–
Distance from extension outlets	0.210	-0.137	–	–

Marginal effects are computed at the means values of explanatory variables. For the case of dummy variables, they are computed as the difference between the quantity of interest when the dummy takes the value 1 and when it takes a 0 value.