Information Transmission in Irrigation Technology Adoption and Diffusion: Social Learning, Extension Services, and Spatial Effects

Margarita Genius, Phoebe Koundouri, Céline Nauges, and Vangelis Tzouvelekas

In this article, we investigate the role of information transmission in promoting agricultural technology adoption and diffusion through extension services and social learning. We develop a theoretical model of technology adoption and diffusion, which we then empirically apply, using duration analysis, on a micro-dataset consisting of recall data covering the period 1994–2004 for olive-producing farms from Crete, Greece. Our findings suggest that both extension services and social learning are strong determinants of technology adoption and diffusion, while the effectiveness of each of the two informational channels is enhanced by the presence of the other.

Key words: extension services, irrigation water, olive-farms, social learning, technology adoption, diffusion.

JEL codes: C41, O16, O33, Q25.

Modern irrigation technology is often cited as being central to increasing water use efficiency and reducing the use of scarce inputs, while also maintaining current levels of farm production, particularly in semi-arid and arid agricultural areas. Indeed, the analysis of adoption and diffusion patterns of modern irrigation technologies is at the core of several empirical studies in both developed and developing countries (Dridi and Khanna 2005; Koundouri, Nauges, and Tzouvelekas 2006, and the references cited therein). These empirical studies provide clear evidence that economic factors (e.g., water price, cost of irrigation equipment, crop prices), farm organizational and demographic characteristics (e.g., size of farm operation, educational level and experience of household members), and environmental conditions (e.g., soil quality, precipitation) help explain the adoption and diffusion of modern irrigation technologies.

Another strand of the literature on agricultural technology diffusion argues that the abovementioned factors cannot accurately explain diffusion patterns, as they are conditional on what farmers know about the new technology at any given point in time (Besley and Case 1993; Foster and Rosenzweig 1995; Conley and Udry 2010). In modern agriculture, farmers are mainly informed about the existence and effective use of any new farming technology through extension personnel (from either private, under fee, or public extension agencies), and from their social interaction with other farmers. We contribute to this literature by theoretically modeling and then quantitatively measuring the impacts of information transmission via extension agents and social networks (i.e., interaction with other farmers) on irrigation technology adoption and diffusion among a population of farmers.

Several studies have pinpointed extension agents as being the primary source of information about the existence and merits of any new farming technology, including irrigation techniques (e.g., Rivera and Alex 2003;

Margarita Genius is an assistant professor in the Department of Economics, Faculty of Social Sciences, University of Crete, Greece. Phoebe Koundouri is an associate professor in the Department of International and European Economic Studies, Athens University of Economics and Business, Athens, Greece, and a senior research fellow in the London School of Economics and Political Science, Grantham Research Institute on Climate Change and the Environment, UK. Correspondence may be sent to: pkoundouri@aueb.gr. Céline Nauges is an Australian Research Council fellow in the School of Economics, The University of Queensland, Australia. Vangelis Tzouvelekas is an associate professor in the Department of Economics, Faculty of Social Sciences, University of Crete, Greece.

We would like to acknowledge the financial support of the European Union project FOODIMA: Food Industry Dynamics and Methodological Advances (Contract No. 044283).

Amer. J. Agr. Econ. 96(1): 328–344; doi: 10.1093/ajae/aat054
Published online August 7, 2013

World Bank 2006). The costs of informing a large heterogeneous population of farmers about a new technology may be high. Thus, extension agents usually target specific farmers who are recognized as peers (that is, farmers with whom a particular farmer interacts). These peers are then expected to exert a direct or indirect influence on the whole population of farmers in their respective areas (Birkhaeuser, Evenson, and Feder 1991).[1]

Even without the intervention of extension agents, farmers learn from their social interactions with other farmers. In Rogers' (1995) terminology, farmers learn from their "homophilic neighbors," and that is, individuals with whom farmers have close social ties and share common professional or/and personal characteristics (education, age, religious beliefs, farming activities, etc.). Moreover, farmers may also follow or trust the opinion of those that they perceive to be successful in their farming operation, even though they occasionally share quite different characteristics.

Measuring the extent of information transmission through extension agents and/or social interaction and identifying its role in technology adoption and diffusion is difficult for two major reasons. First, the set of peers from whom an individual can learn is difficult to define (a thorough discussion of the issues faced when empirically defining and measuring network attributes can be found in Maertens and Barrett [2013]). Second, distinguishing learning from other phenomena (for example, interdependent preferences and technologies or related unobserved shocks) that may give rise to similar observed outcomes is problematic (Manski 1993). For a comprehensive overview of articles that attempt to empirically identify the impact of social networks on technology adoption (mostly in developing countries), see Foster and Rosenzweig (2010).

In this paper we study the diffusion of modern irrigation technology among a population of farmers in the presence of extension agents and social networks. We first describe the farmers' technology adoption decision in a theoretical setting, allowing for knowledge accumulation (about the new technology) through three channels: extension services, social networks (before and after adoption), and learning-by-doing (after adoption). We study the decisions of farmers to invest in a new irrigation technology that would improve irrigation effectiveness (represented in what follows as a shift in the production technology). The expected efficiency gains are uncertain for the farmer at the time the decision to adopt the new technology is made, but we assume that this uncertainty can be reduced through contact with extension services and other farmers. After adoption, the farmer can still accumulate knowledge by using the technology. At each time period the farmer decides whether to adopt the technology by comparing its cost (which is assumed to decrease over time) with the expected benefit of adoption, which itself depends on the information received from extension services and peers.

This theoretical model allows us to identify relevant variables to be considered in the econometric model describing the diffusion of irrigation technology among a group of farmers using data from a sample of 265 randomly selected olive-growing farms in Crete, Greece. In our empirical model, the definition of social network combines information on the characteristics of farmers' peers (age and educational level) with data on the physical distances between them.[2] We use these data in conjunction with factor analysis to build factors that best represent the unobserved variables that are potentially relevant for quantifying the effect of information transmission, both via extension agents and social learning.

In the next section we develop the theoretical model of adoption and diffusion of modern irrigation technology. Following that, we describe our data and explain the construction of informational variables. In the following section we present the econometric model using duration analysis together with the factor analytic model. We then present the empirical results for our sample of olive-growers, and the last section concludes the paper with some policy recommendations.

[1] According to BEF, initially public extension services provision was designed to target the most influential farmers in rural areas that can effectively pass the necessary information for new technology adoption in order to keep to cost of extension services low.

[2] An important dimension in the transmission of information is the spatial distribution of farmers' reference group. In large geographical areas with a low density of farmers, information diffusion, through both extension agents and social learning, may be less successful in promoting technology adoption than in small areas with close geographical proximity among farmers. Conley and Udry (2010) and Weber (2012) use the same conceptual approach to overcome identification problems discussed in Manski (1993).

Theoretical Model

We develop a model that describes the farmer's decision making process regarding new technology adoption. This model is useful as a background framework for the simultaneous study of: (a) learning from extension services before and after adoption; (b) 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:

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

where y_j denotes crop production, $\mathbf{x}_j^v$ is the vector of variable inputs (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 thus faces a risk of low (or negative) profits in the case of a 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 a 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, that is, from A^0 with the conventional technology to A^* with the modern technology.[3] We assume that the maximum irrigation effectiveness is reached when the farmer operates the modern irrigation technology adequately, which corresponds to $A = A^*$, while 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., $x^w < x_{min}^w$), which would be detrimental to the crop. We assume that the consequences of adopting the new technology are not fully known by the farmers. First, 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^*).

We presume that the farmer can reduce this uncertainty through two channels: *i*) farmers can build knowledge about the new technology and the expected benefits of its adoption before actually adopting it through interactions with extension services or/and interactions with other farmers (and particularly with early adopters); and *ii*) farmers can improve the performance of the new technology after adoption through self-experience (or learning-by-using).

In our 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; that is, one scenario for each potential adoption time, τ, where $\tau > s$. We set the time horizon to a fixed T, which implies that $s \in \{0, 1, 2, \ldots, T-1\}$ and $\tau \in \{s+1, \ldots, T\}$. We also assume that the required equipment for the new technology has a finite life expectancy, denoted by T_e. 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 $\{\tau, \tau+1, \tau+2, \ldots, T\}$.

[3] 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.

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 $A_j < A^*$.

To summarize, up to period s, the farmer gathers information about the new technology from extension visits and/or by learning from peers. At the end of s, the farmer uses this information 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 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 that is known to them at period t. We assume that this cost decreases over time, that is, $\partial c_{j,t}/\partial t < 0$.

We denote by p, w^w, and $\mathbf{w}^v$ the expected discounted crop, irrigation water, and variable input prices, respectively, which are assumed by the farmer to remain constant over time. Right 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:

$$(2) \qquad \pi_j\left(p, \mathbf{w}^v, w^w, A_j\right) = \max_{\mathbf{x}^v, x^w}\{pf(\mathbf{x}_j^v, x_j^w, A_j) - \mathbf{w}^v\mathbf{x}_j^v - w^w x_j^w\}$$

where $\pi_j(p, \mathbf{w}^v, w^w, A_j)$ is a sublinear (positively linearly homogeneous and convex) profit function in p, $\mathbf{w}^v$, and w^w. This function is non-decreasing in crop price and the 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 during a period $\tau \leq t$, then her conditional discounted profit function (expected profits given the time, τ, of adopting a new technology) will be given by (after dropping subscript j for convenience):

$$(3) \qquad \pi_{s,\tau,t}\left(p, \mathbf{w}^v, w^w, A_s(t,\tau)\right) = \max_{\mathbf{x}^v, x^w}\{pf(\mathbf{x}_{s,\tau,t}^v, x_{s,\tau,t}^w, A_s(t,\tau)) - \mathbf{w}^v\mathbf{x}_{s,\tau,t}^v - w^w x_{s,\tau,t}^w\}.$$

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 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 $\tau + T_e \geq t \geq \tau$.[4] This does not imply that the technology index will in fact remain constant, as learning from others 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: $\pi_{s,s+1,s+1}(p, \mathbf{w}^v, w^w, A_s(s+1, s+1))$. Then, each farmer chooses to adopt the new technology by maximizing his/her temporally aggregated discounted profits over τ:

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

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, and T is large enough to imply that the

[4] 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 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 expectation 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 (late-adopters probably 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.

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. A farmer in year s considers 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 $\tau + T_e - 1 \leq T$,

$$(5)\qquad \begin{aligned}&[\tau - 1 - s\\ &\quad + (T - (\{\tau + T_e - 1\} \wedge T)) \vee 0]\pi\\ &\quad + (\{\{\tau + T_e - 1\} \wedge T\} - \tau + 1)\pi_s\\ &= [\tau - 1 - s + T - \tau - T_e + 1]\pi\\ &\quad + [\tau + T_e - 1 - \tau + 1]\pi_s\\ &= [T - (s + T_e)]\pi + T_e\pi_s\end{aligned}$$

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 the new technology will be optimally adopted at least for the period $\tau_1^* = T - T_e + 1$, and:

$$(6)\qquad \max_{\tau + T_e \leq T} V^s_{s,\tau,T} = V^s_{s,\tau_1^*,T} = V^s_{s,T-T_e+1,T}.$$

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

$$(7)\qquad \max_{1 \leq k \leq T-s} V^s_{s,s+k,T}$$

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

$$(8)\qquad V^s_{s,s+k,t} = (k-1)\pi + (T - s - k + 1)\pi_s - c_{s,s+k}$$

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

$$(9)\qquad \Delta V^s_{s,k+1} := V^s_{s,s+k+1,T} - V^s_{s,s+k,T} = \pi - \pi_s + c_{s,s+k} - c_{s,s+k+1}.$$

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

We now 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:

$$(10)\qquad c_{s,s+k} = (1 + a_s e^{-\delta_{c,s}(k-1)})c_s^*$$

where $a_s, \delta_{c,s} > 0$. Note that $c_{s,s+k}$ is a decreasing value of k, and converges to c_s^*, the asymptotic discounted equipment cost for farmer j at time s, as $k \to \infty$. Note also that setting $k = 1$, we obtain $c_s^* = c_{s,s+1}/(1 + a_s)$. Therefore, (10) becomes:

$$(11)\qquad c_{s,s+k} = \frac{(1 + a_s e^{-\delta_{c,s}(k-1)})}{1 + a_s} c_{s,s+1}.$$

Plugging (11) into (8) we obtain:

$$(12)\qquad V^s_{s,s+k,T} = (k-1)\pi + (T - s - k + 1)\pi_s - \frac{(1 + a_s e^{-\delta_{c,s}(k-1)})}{1 + a_s c_{s,s+1}}.$$

We also observe that:

$$(13)\qquad \frac{\partial V^s}{\partial k} = \pi - \pi_s + \frac{a_s \delta_{c,s} c_{s,s+1}}{1 + a_s} e^{-\delta_{c,s}(k-1)}.$$

The second order partial derivative in k is:

$$(14)\qquad \frac{\partial^2 V^s}{\partial k^2} = -\frac{a_s \delta_{c,s}^2 c_{s,s+1}}{1 + a_s} e^{-\delta_{c,s}(k-1)} < 0.$$

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

$$(15)\qquad \left.\frac{\partial V^s}{\partial k}\right|_{k=1} \leq 0 \Leftrightarrow \pi_s \geq \pi + \delta_{c,s} \frac{a_s c_{s,s+1}}{1 + a_s}.$$

An equivalent expression of condition (10) uses the fact that a_s is determined by the relationship between the asymptotic discounted cost c_s^* and current cost $c_{s,s+1}$, because $a_s = \frac{c_{s,s+1}}{c_s^*} - 1$. Specifically, each farmer chooses to adopt the new technology right after period s if:

$$(16) \quad \pi_s - \delta_{c,s}\left(c_{s,s+1} - c_s^*\right) \geq \pi.$$

The quantity $c_{s,s+1} - c_s^*$ approximately represents the expected excess discounted cost from choosing between whether to adopt the new technology at time $s+1$, namely, as soon as possible, or postponing the adoption for a very long period, namely, for a period where the rate of decrease of the equipment cost is practically zero.

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, which is itself driven by different paths of knowledge accumulation across the farming population. 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 ($x^w_{\min}$) 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 environmental conditions on the farm such as soil type and aridity index.

Survey Design and Data Description

Our data come from a survey carried out on the Greek island of Crete during the 2005–06 cropping period as part of the European Union (EU)-funded Research Program FOODIMA.[5] The Agricultural Census published by the Greek Statistical Service was used to select a random sample of 265 olive-growers located in the four major districts of Crete (Hellenic Statistical Authority 2001). Farmers were asked to recall the exact time they had adopted 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, 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. Thus, 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. Table 1 displays the descriptive statistics and definitions of the variables used in the present study. Of the 265 farms in the sample, 172 (64.9%) had adopted drip irrigation technology between 1994 and 2004. The variable of interest in the forthcoming empirical application is the length of time between the year of drip irrigation technology introduction (1994) and the year of adoption; the mean adoption time in our sample is 4.68 years (see the temporal distribution of adoption times in figure 1).

Variable Definitions

The choice of the independent variables to be used in the empirical irrigation technology diffusion model is dictated by the profitability condition in (16): apart from installation cost, heterogeneity in the timing of adoption is explained by heterogeneity in the technology index. Water-efficiency and farm profitability at each time t, depend on farm and household characteristics (farm size, age, education level) and the two information variables, contacts with extension services and contacts with peers (or social learning). The threshold ($x^w_{\min}$) that defines the minimum level of irrigation water required for the crop to be marketable is another source of heterogeneity: this threshold is assumed to depend on farms' environmental conditions such as soil type and aridity index, and structural features like tree density on farm plots. Finally, we include the price of olive-oil (farm gate price) in the duration model, as well as the price of irrigation water since both have a direct impact on a farm's profitability.

The installation cost of drip irrigation technology (*Cost*) includes the cost of designing the new irrigation infrastructure, the materials (i.e., pipes, hydrometers, drips),

[5] The *FOODIMA* project (EU Food Industry Dynamics and Methodological Advances) was 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 at www.eng.auth.gr/mattas/foodima.htm.

Table 1. Definitions and Summary Statistics of the Main Variables

Variable	Name	All Farms	Adopters	Non-Adopters
Number of farms		265	172	93
Time to adoption (in years)	T_{adopt}	–	4.68	–
Farm Characteristics				
Farmer's age (in years)	*Age*	53.9	49.9	61.3
Farmer's education (in years of schooling)	*Educ*	6.3	8.1	2.9
Farm size (in stremmas)	*Fsize*	21.8	22.6	20.2
Tree density (in trees per stremma)	*Dens*	13.6	14.7	11.5
Installation cost (in Euros per stremma)	*Cost*	129.3	125.8	135.8
Irrigation water price (in cents per m^3)	w_W	20.6	25.7	11.2
Olive oil price (in Euros per kg)	p_O	2.80	2.38	3.56
Profit moments				
1st moment	M_1	1.132	1.422	0.596
2nd moment	M_2	0.569	0.702	0.323
3rd moment	M_3	0.582	0.738	0.293
4th moment	M_4	3.566	4.073	2.629
Aridity index	*Ard*	0.982	1.152	0.668
Altitude (in meters)	*Alt*	341.8	167.6	664.1
Soil type (in % of farm land)				
Sandy and limestone	$Soil_{sl}$	56.6	62.8	55.2
Marls and dolomites	$Soil_{md}$	43.4	37.2	54.8
Information Variables				
Stock of adopters	*Stock*	31.3	35.4	23.6
Stock of homophilic adopters	*HStock*	12.6	15.0	8.1
Stock of indicated homophilic adopters	*RStock*	4.6	5.4	3.2
Distance between the farmer and				
other adopters	*Dista*	49.4	44.3	58.7
homophilic adopters	*HDista*	17.4	15.2	21.6
indicated homophilic adopters	*RDista*	10.1	8.9	12.5
Number of on farm extension visits				
to the farm	*Ext*	6.4	8.7	2.2
to homophilic farmers	*HExt*	3.3	4.8	0.6
to indicated homophilic farmers	*RExt*	2.0	2.9	0.2
Distance of extension outlets				
from the farm	*Distx*	111.2	87.6	154.9
from homophilic farmers	*HDistx*	52.3	34.9	84.3
from indicated homophilic farmers	*RDistx*	23.6	17.0	35.6

Notes: All data refer to the year of adoption. Monetary values have been deflated prior to econometric estimations.

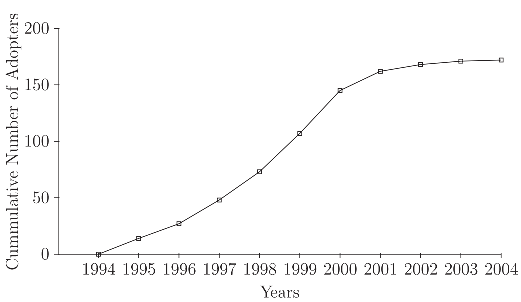

Figure 1. Diffusion of drip irrigation among Cretan olive farms

and the cost of constructing it in the field (labor cost). For adopters, the installation cost corresponds to the cost of installing the new equipment in 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) is 129.3 Euros on average over the whole sample, 125.8 Euros for adopters, and 135.8 Euros for non-adopters.

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). The expected impact of age on the timing of adoption is ambiguous since age is highly correlated with experience. On the one hand, farming experience, which provides increased knowledge about the environment in which decisions are made, is expected to positively affect the adoption of modern irrigation technologies. 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 education (*Educ*), while the average age of the household head was 53.9 years (*Age*). Farmers who adopted modern irrigation technologies were younger and more educated in our sample (49.9 and 8.1 years, respectively) than their non-adopting counterparts (61.3 and 2.9 years, respectively).

The expected impact of farm size (*Fsize*) 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 lower irrigation cost by switching to a modern irrigation technology (Putler and Zilberman 1984). Apart from farm size, tree density (*Dens*) also affects irrigation effectiveness and hence, willingness to adopt modern irrigation techniques (Moriana et al. 2003). Farms with orchards that are characterized by high tree density should have an incentive to adopt modern irrigation technologies faster to more effectively use irrigation water. Farmers who adopted the modern irrigation technology operate farms with an average size of 22.6 stremmas (one stremma equals 0.1 ha), and an average tree density of 14.7 per stremma, in the year of adoption. On the other hand, non-adopting farms are smaller on average (20.2 stremmas) and have lower tree density (11.5 trees per stremma).

Adoption of irrigation technology may also be influenced by some environmental characteristics that may affect irrigation effectiveness. We include in the diffusion model an aridity index (*Ard*), the altitude of the farm (*Alt*), and two soil dummies as a proxy for soil quality. The aridity index and the altitude of the farm 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 network of 36 local meteorological stations located throughout the island (Stallings 1968). A higher altitude is more likely to be associated with lower temperatures and therefore less stressed olive-trees. Finally, farms were classified according to two different soil types based on their water holding capacity: sandy and limestone soils ($Soil_{sl}$) exhibit a lower holding capacity than marls and dolomites soils ($Soil_{md}$). The majority of farms in the sample cultivate olive-trees in sandy and limestone soils (56.6%).

To control for economic conditions we include the price of olive oil (p_O) and the price of irrigation water (w_W), both as reported by the farmers. The crop price highly depends on the quality of olive oil and thus exhibits a significant variation across olive growers. The average olive oil price was 2.80 Euros per kilogram for the whole sample, and varied between 2.38–3.56 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 25.7–11.2 Euro cents per m^3 for adopters and non-adopters, respectively. Both prices were converted to constant prices using the producer price index published by the Greek Ministry of Agriculture (Hellenic Statistical Authority 2006).

Additionally, 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. Hence, risk-averse olive growers might consider adopting drip irrigation technology to hedge against risk during periods of water shortage or high water prices. To capture the impact of this uncertainty on farmers' adoption decisions we follow Koundouri, Nauges, and Tzouvelekas (2006), and utilize 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 from the year of adoption, we estimated the following linear profit function (corresponding standard errors appear in parentheses):

$$(17)\quad \pi_i = \underset{(0.423)}{2.341} + \underset{(0.104)}{0.657}\, p_{Oi} - \underset{(0.098)}{0.321}\, w_{Li} - \underset{(0.054)}{0.107}\, w_{Fi} - \underset{(0.032)}{0.076}\, w_{Wi} - \underset{(0.021)}{0.034}\, w_{Pi} + \underset{(0.125)}{0.431}\, x_{Ai} + u_i$$

where i denotes farmers, p_O is the farm gate price of olive oil, w_j is the price of the j^{th} variable input (i.e., labor, fertilizers, irrigation water, and pesticides), x_A is the acreage under olive tree cultivation, and u is a usual *iid* error term.[6] The residuals were 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). Descriptive statistics of the calculated first four moments (M_1, M_2, M_3, M_4) of the profit distribution are shown in table 1.

The Measurement of Information Transmission

Each farmer provided information about the number of extension visits on his farm prior to the year of adoption, together with some key characteristics (age and educational level) of his peers (or reference group), that is, farmers with whom he exchanges information about his farming operation. We use these data together with data on farm location to assess the impact of the two channels of information transmission identified in our theoretical model: extension services and contacts with other farmers.

Farmers receive information from extension services directly (through visits by extension agents), and indirectly through their contacts with other farmers targeted by extension agents. The second channel, identified as social learning in our model, corresponds to information received from farmers who have already acquired experience with the new technology. We argue that the strength of these two communication channels depends on the geographic distance between the farmers and extension agencies, and between the farmers and their influential peers.

We thus identify four unobserved (or latent) variables that are potentially relevant for quantifying the effect of information provision on the diffusion of drip irrigation technologies: the total number of adopters in the respondent's reference group; the average distance of the respondent's farm to his reference group; overall exposure to extension services (direct and indirect), and the average distance of the farmer's reference group (including himself) to extension agencies. The first two latent variables are used to capture social learning, whereas the last two variables represent the effect of extension provision. We use observable indicators in a factor analytic model to proxy these four (unobserved) latent variables.

For the first variable (total number of adopters in the respondent's reference group), we consider the following three observable indicators: *i*) the stock of adopters in the sample from the year the farmer adopted the modern irrigation technology (*Stock*); *ii*) the stock of homophilic adopters (*HStock*); *iii*) the stock of homophilic adopters as identified by the farmer himself (*RStock*). Following Rogers (1995) we define homophilic farmers as farmers belonging to the same age group and having similar education levels. Age groups cover six years: for example, if a farmer is 38 years old, farmers aged 35 to 41 will be considered homophilic. For education levels we considered a 2-year range. The indicator (*RStock*) is computed as the stock of adopters among those farmers who have the same age and education level as the ones identified by the farmer as belonging to his reference group.

Data on the location of the farms are then used to calculate the following road distances (in kilometers) to proxy the second latent variable (the distance of the farmer to adopters in his reference group): *i*) the average distance to adopters (*Dista*); *ii*) the average distance to homophilic adopters (*HDista*); *iii*) the average distance to homophilic adopters as identified by the farmer himself (*RDista*).

As for the overall exposure to extension services (third latent variable), we consider the following three observable indicators: *i*) the total number of on-farm extension

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

visits prior to the year of adoption (*Ext*); *ii*) the number of on-farm extension visits to homophilic farmers (*HExt*); *iii*) the number of on-farm extension visits to homophilic adopters as identified by the farmer himself (*RExt*).

Finally, spatial differences in information provision by extension agencies (fourth latent variable) have been proxied by the following three road distance indicators: *i*) the distance of the respondent to the nearest extension agency (*Distx*); *ii*) the average distance of homophilic farmers to the nearest extension agency (*HDistx*); *iii*) the average distance of homophilic adopters, as identified by the farmer himself, to the nearest extension agency (*RDistx*). Table 1 presents the descriptive statistics for these twelve observable indicators.

Econometric Model

Following Karshenas and Stoneman (1993) and Abdulai and Huffman (2005), we model the optimal time of drip irrigation technology adoption using duration analysis.[7] 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 had not occurred before, and given the specific characteristics of individual farmers and the environment in which they operate. Under the assumption that duration follows a Weibull distribution,[8] the hazard function is written as follows:

$$(18) \quad h(t, z_{it}, \alpha, \beta) = \alpha t^{\alpha-1}(\lambda_{it})^{\alpha}$$

where α is the shape parameter. The above parametric specification implies that the hazard rate either increases monotonically with time if $\alpha > 1$, falls monotonically with time if $\alpha < 1$, or is constant if $\alpha = 1$. The hazard function $h(t)$ describes the rate at which individuals will adopt the technology in period t, conditional on not having adopted prior to t, which in the present study represents the empirical counterpart of the optimality condition in (16). We specify $\lambda_{it} = \exp(-z_{it}\beta)$, where the vector z_{it} includes variables that determine farmers' optimal choice, and β are the corresponding unknown parameters. Some of these variables only vary across farmers (e.g., soil quality and altitude), whereas other vary across farms and time (e.g., cost of acquiring the new technology). Under the Weibull distribution, the mean expected adoption time is calculated as:

$$(19) \quad E(t) = \left(\frac{1}{\lambda_{it}}\right)\Gamma\left(1 + \frac{1}{\alpha}\right)$$

where $\Gamma(r) = \int_0^{\infty} x^{r-1}\exp(-x)dx$ is the Gamma function. Accordingly, the marginal effects of the k^{th} continuous explanatory variable on the hazard rate and on the mean expected adoption time are calculated as follows:

$$(20) \quad h'_{z_k}(t, z_{it}, \alpha\beta) = -h(t, z_{it}, \alpha\beta)\frac{\partial(z_{it}\beta)}{\partial z_k}\alpha$$

$$\text{and} \quad E'_{z_k}(t) = \frac{\partial(z_{it}\beta)}{\partial z_k}E(t).$$

Among other variables, the vector z_{it} includes the four latent variables discussed in the previous section. We use factor analysis to proxy these four variables using the twelve observable indicators described above. Dropping subscripts for convenience, we denote the latent components by $\boldsymbol{\xi}$ and the vector of the twelve observable indicators by $\mathbf{x}$. The relationship between observed and latent variables is given by:

$$(21) \quad \mathbf{x} = \boldsymbol{\mu} + \boldsymbol{\Gamma\xi} + \mathbf{v}$$

where $\mathbf{v}$ is a (12×1) random vector with zero mean and variance-covariance matrix given by $\boldsymbol{\Psi} = \text{diag}(\psi_1^2 \ldots \psi_{12}^2)$, $\boldsymbol{\xi}$ is a (4×1) random vector, also with a zero mean and variance-covariance matrix $\mathbf{I}$, $\boldsymbol{\Gamma}$ is a (12×4) matrix of constants, and μ is a vector of constants corresponding to the mean of $\mathbf{x}$.

The factor analytic model represented by equation (21) is estimated using a principal components method with varimax rotation. The estimated factor loadings are presented in table 2.[9] Factor 1 will be labeled as "Stock of adopters in the reference group" (ξ_1) since the main variables contributing to this factor are the ones related to the stock of adopters. The heaviest loadings for factor 2 come from the variables related to the

[7] For more details about duration models, see Greene (2003, 791–797).

[8] 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.

[9] For more details about factor analysis, the reader is referred to Krzanowski (2000).

Table 2. Factor Analytic Model: Estimation Results

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

Note: For variable definitions, see table 1.

average distance to adopters, so factor 2 can be interpreted as the "Average distance to the stock of adopters in the reference group" (ξ_2). Variables related to the number of extension visits are the main contributors to factor 3, and the corresponding factor is thus labeled "Exposure to extension" (ξ_3). Finally, the variables related to the average distance to extension services display the heaviest loadings for factor 4, thus allowing us to conclude that factor 4 represents the "Average distance to extension" (ξ_4). Note that because all pair-wise correlations between the 12 observed indicators are significant at the 0.01 level (results not presented but available upon request), all indicators are used to predict each of the four latent variables. Under the assumption of multivariate normality of x_i and ξ_i, one can easily obtain estimates of the factors scores $\xi_{mi}, m=1,\ldots,4$, for the i^{th} respondent based on estimating $E(\xi_{mi}|x_{is})$, with s denoting the twelve observable variables.

Estimated factor scores are used in the duration model, together with the other independent explanatory variables (farm and farmers' characteristics). To explore the potential substitutability or complementarity between the two communication channels (extension services and social learning), we also include the interaction term $\hat{\xi}_1\hat{\xi}_3$ in our empirical model. The final specification for λ_{it} is given by:

$$(22)\quad \lambda_{it} = \exp(-\beta_0 - \beta_1 Age_{it} - \beta_2 Age_{it}^2 - \beta_3 Educ_{it} - \beta_4 Educ_{it}^2 - \beta_5 Cost_{it} - \beta_6 Fsize_{it} - \beta_7 Dens_{it} - \beta_8 w_{Wit} - \beta_9 p_{Oit} - \beta_{10} Ard_{it} - \beta_{11} Alt_i - \beta_{12} Soil_{sl,i} - \sum_{k=1}^{4}\delta_k M_{kit} - \sum_{m=1}^{4}\zeta_m \hat{\xi}_{mit} - \zeta_5 \hat{\xi}_{1it}\hat{\xi}_{3it}).$$

We estimate a proportional hazard model in which some of the regressors (the four latent variables) are predicted in a first-stage model. Several procedures have been proposed in the literature for estimating proportional hazard models with missing covariates (e.g., Kalbfleisch and Prentice 2002). Using regression calibration, $E\left[\exp\left(-\sum_j \beta_j z_j^o - \sum_k \delta_k M_k - \sum_m \zeta_m \xi_m - \zeta_5 \xi_1 \xi_3\right)\right]$ can be approximated by:

$$\exp\left(-\sum_j \beta_j z_j^o - \sum_k \delta_k M_k - \sum_m \zeta_m E\left[\xi_m | z_j^o, M_k, x_s\right] - \zeta_5 E\left[\xi_1\xi_3 | z_j^o, M_k, x_s\right]\right)$$

with z_j^o denoting the observed explanatory variables in λ_{it}, M_k denoting the four profit moments, ξ_m denoting the latent variables,

Table 3. Maximum Likelihood Parameter Estimates of the Hazard Function

		Model A.1		Model A.2	
Variable	Parameter	Estimate	*t*-ratio	Estimate	*t*-ratio
Constant	β_0	1.5617	1.8077	1.4303	1.5633
Farmer's age	β_1	−0.0168	−2.4766	−0.0106	−1.3404
Farmer's age-squared	β_2	0.0001	2.1568	0.0001	1.1931
Farmer's education	β_3	0.0182	1.1456	0.0347	2.2150
Farmer's education-squared	β_4	−0.0010	−1.5354	−0.0021	−3.0807
Installation cost	β_5	0.0089	1.0786	0.0099	1.1629
Farm size	β_6	−0.0048	−0.3848	−0.0117	−0.8617
Tree density	β_7	−0.0127	−3.7991	−0.0109	−2.9231
Water price	β_8	−0.0164	−10.892	−0.0205	−13.694
Crop price	β_9	0.0596	1.8796	0.0658	1.8465
Aridity index	β_{10}	−0.0389	−1.1718	−0.0412	−1.3601
Farm altitude	β_{11}	0.0006	3.3071	0.0005	2.9544
Sandy and limestone soils	β_{12}	−0.0002	−0.0075	0.0265	0.7475
1st profit moment	δ_1	−0.0943	−2.5987	−0.1132	−2.7071
2nd profit moment	δ_2	−0.1752	−2.4884	−0.1611	−1.8807
3rd profit moment	δ_3	0.0292	0.9414	0.0770	1.6685
4th profit moment	δ_4	−0.0024	−0.3167	−0.0125	−1.0554
Stock of adopters	ζ_1	−0.0509	−1.9745	–	–
Distance between adopters	ζ_2	0.0299	1.6498	–	–
Exposure to extension	ζ_3	−0.0531	−2.7988	–	–
Distance from extension outlets	ζ_4	−0.0238	−1.6691	–	–
(Adopters)X(Extension)	ζ_5	−0.0554	−3.5119	–	–
Shape 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	

and x_s denoting the twelve observed indicators used in the factor analysis. Hence, estimates of $E[\xi_m|z_j^o, M_k, x_s]$ can be used in the hazard rate when $\boldsymbol{\xi}$ 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, that is, $E[\xi_m|z_j^o, M_k, x_s] = E[\xi_m|x_s]$, the estimated factor scores can be used in the hazard function.

Empirical Results

The maximum likelihood parameter estimates of the hazard function, along with their corresponding t-statistics, are shown in table 3. Consistent standard errors for these parameters were obtained using the stationary bootstrapping technique of Politis and Romano (1994). The dependent variable in the diffusion model is the natural logarithm of the length of time (T_{adopt}, measured in years) from first availability of the drip irrigation technology (1994) to when the farmer adopted it (up to 2004). In this framework a negative coefficient implies a negative marginal effect on duration before adoption, that is, faster adoption.

To examine the robustness of our results we also estimated the hazard function, excluding the four latent variables (model A.2). Parameter estimates of the reduced model, together with their corresponding t-ratios, are also presented in table 3. All key explanatory variables in both models are found to be statistically significant. The signs of the 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 is more adequate for explaining variability in farmers' adoption times. Predicted mean adoption times are not statistically different: 5.76 in the full model, and 5.74 in the reduced model.

The shape parameter of the Weibull hazard function is statistically significant and well above unity in both models. According to Karshenas and Stoneman (1993), this implies the existence of what they call epidemic effects. In summary, these effects relate to endogenous learning being a process of self-propagating information about the new technology that grows with the spread of a technology. Karshenas and Stoneman (1993) identify three potential 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 absent from Karshenas and Stoneman's (1993) empirical model; and (c) the reductions in uncertainty resulting from extensive use of the new technology. The latter seems to be more relevant in our empirical study and could capture, in a broader sense, learning-by-doing effects as implied by our theoretical model.

Using the parameter estimates from table 3, we calculated the marginal effects of the explanatory variables on the hazard rate and average expected time to adoption of drip irrigation technology using (20) (see table 4). 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 years). Surprisingly, the distance from extension outlets has a negative marginal effect on mean adoption time, implying that the further the farm is from the extension outlet, the shorter is the time before adoption. However, this counterintuitive result can be explained by extension agents primarily targeting farmers in remote areas (since these farmers are less likely to visit extension outlets).

Information transmission not only takes place through extension services but also between farmers themselves: a larger stock of adopters in the farmer's reference group induces faster adoption (−0.293 years), while a greater distance between adopters increases time before adoption (0.172 years). The impact of social learning is comparable to the impact of information provision 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). However, unlike with exposure to extension, geographical proximity is an important factor influencing information transmission among the farmers.

Finally, the interaction term between the two channels of information transmission is found to be statistically significant and negative (see table 3). This result indicates that extension services and intra-farm communication channels are complementary for information provision to olive growers. This finding might be explained by the nature of the transmitted information. Irrigation technologies, like many other farming innovations, are not fully embodied in a set of artefacts like manuals or blueprints (Evenson and Westphal 1995), and the performance of any irrigation technology is sensitive to local conditions (environmental, cultural, demographic, etc). Therefore, passing on information cannot be done using rules of thumb mainly utilized by extension personnel, but instead also requires strong social networks between olive-growers already engaged in learning-by-doing. The complementarity between the two communication channels used to enhance irrigation technology diffusion among olive-growers in Crete indicates 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 individual farmers' adoption behavior. First, we find that the time prior to adopting drip irrigation technologies 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 the adoption of modern irrigation technologies. The marginal effect of a farmer's age on adoption time is −0.010 years (see table 4). On the other hand, time until adoption increases with education whenever one's education level is less than nine years (elementary schooling). For those farmers who have more than nine 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.

Risk attitudes are also found to be important determinants of the adoption behavior of Cretan olive-growers. The first two

Table 4. Marginal Effects on the Hazard Rate and Mean Adoption Time

	Model A.1		Model A.2	
Variable	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
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
1st profit moment	0.831	−0.543	0.798	−0.650
2nd profit moment	1.544	−1.009	1.136	−0.925
3rd profit moment	−0.258	0.168	−0.543	0.442
4th profit moment	0.021	−0.014	0.088	−0.072
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	–	–

Notes: Marginal effects are computed at the mean of explanatory variables. For dummy variables, they are computed as the difference between the quantity of interest when the dummy takes the value of 1, and when it takes a zero value.

empirical moments of the profit distribution (i.e., expected profit and profit variance) are highly significant, whereas the third and fourth moments approximating skewness and kurtosis of profit distribution are not statistically significant (see table 3). These results indicate that a higher expected profit and a higher variance of profit induce faster adoption rates. These findings confirm that olive growers in Crete are risk averse and adversely affected by a high variability in returns. Adopting modern irrigation technology allows these farmers to reduce production risk in periods of water shortage, which confirms earlier findings by Koundouri, Nauges, and Tzouvelekas (2006). The role that risk preferences play in the 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 do not take 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.[10]

We also find evidence that adverse weather conditions, as proxied by a farm's low elevation and aridity index, induce faster irrigation technology adoption, although the magnitude of the effect is small. This may indicate that farmers who can exert better control over the quantity of water used for production purposes see the innovative irrigation technology as insurance against adverse (drier) weather conditions. Neither soil type nor farm size have an impact on the timing of adoption (see table 3). However, our results show that olive farms with high tree densities adopt 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 adoption time by speeding up the diffusion rates of new irrigation technology (0.145 and −0.95, respectively). On the other hand, a higher crop price delays adoption rates (marginal effect is 0.343 years), because farmers have reduced incentives to change irrigation practices as a means of increasing the farm's expected returns. Finally, installation costs do not affect diffusion of the new technology:

[10] This empirical finding is specific to our study on olive-growers. Other studies in the agricultural sector found evidence of down-side risk aversion, for example, Antle (1987) and Garrido and Zilberman (2008).

the corresponding parameter estimate is positive but not statistically significant (though the *t*-statistic is greater than one).

Conclusions and Policy Implications

In this article we developed a theoretical model to empirically identify the importance of knowledge accumulation through both extension services and social learning in the adoption of modern irrigation technologies among olive growers. Our theoretical and empirical models, together with the developed econometric approach, are general enough to have global relevance and applicability. Indeed, our approach can be applied in various agricultural settings and can produce results that inform one's basic understanding of the ways in which learning processes (both through extension services and social learning) impact farmers' choices. Our approach allows us to identify these learning processes, the variables that influence them, and their respective effects on farmers' adoption decisions.

Our empirical results suggest how these processes, now identified for the case study under consideration, can be better integrated into relevant policy making. To sum up, both extension services and intra-farm communication channels are found to be strong determinants of technology adoption and diffusion, while the effectiveness of each type of information channel is enhanced by the presence of the other. This means that the provision of extension services will be more effective than intra-farm communication for speeding up the adoption process in areas where there is already a critical mass of adopters. Moreover, the 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. At the same time, the nature of extension provision should be redesigned to take into account its complementarity with farmers' social networks.

Water and crop prices also affect technology adoption and diffusion. Hence, efficient pricing of agricultural inputs and outputs should become an explicit target of any reformed agricultural policy. In addition to a farmer's characteristics (education, age), climate variables (aridity, altitude) are found to be important drivers of a farmer's technology adoption decisions and resulting technology diffusion, and as such both should be incorporated into 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 access to more information than they are unable to process, and thus extension services could assist them in this task.

At the same time, our results highlight the importance of accommodating the correct understanding of risk preferences when evaluating policy formation in the agricultural sector. That is, when policy makers consider policy options that affect input and technology choices, they should consider the level of farmers' risk-aversion to correctly predict the technology adoption and diffusion effects, as well as the magnitude and direction of input responses (Groom et al. 2008). Indeed, accurately predicting these effects and farmers' responses will also help accurately predict the magnitude of policy-induced welfare changes, as well as assist in the efficient provision of agricultural insurance policies.

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—especially the transition to decoupled farm payments, instability in world agricultural commodity prices, and contradictory 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 light of the current financial and economic crisis. On November 18, 2010, the European Commission published a paper on the future of the CAP.[11] The reforms contained in the paper aim 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

[11] See http://ec.europa.eu/agriculture/cap-post-2013/communication/com2010-672_en.pdf.

results can provide fruitful input to this reform, especially with regards to developing socioeconomic tools and policies aiming at incentivizing efficiency-enhancing technology adoption, over time and across space, under uncertainty.

References

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

Antle, J.M. 1987. Econometric Estimation of Producers' Risk Attitudes. *American Journal of Agricultural Economics* 69: 509–522.

Besley, T., and A. Case. 1993. Modeling Technology Adoption in Developing Countries. *American Economic Review* 83: 396–402.

Birkhaeuser, D., R.E. Evenson, and G. Feder. 1991. The Economic Impact of Agricultural Extension: A Review. *Economic Development and Cultural Change* 39: 610–650.

Carroll, R.J., D. Ruppert, and L.A. Stefanski. 1995. *Nonlinear Measurement Error Models*. London: Chapman and Hall.

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

Conley, T.G., and C.R. Udry. 2010. Learning about a New Technology: Pineapple in Ghana. *American Economic Review* 100: 35–69.

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

Evenson, R., and L. Westphal. 1995. Technological Change and Technology Strategy. In *Handbook of Development Economics*, ed. J. Behrman and T.N. Srinivasan, 2209–2299. Amsterdam: North Holland.

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

Foster, A.D., and M.R. Rosenzweig. 2010. Microeconomics of Technology Adoption. *Annual Review of Economics* 2: 395–424.

Garrido, A., and D. Zilberman. 2008. Revisiting the Demand for Agricultural Insurance: The Case of Spain. *Agricultural Finance Review* 68: 43–66.

Greene, W.H. 2003. *Econometric Analysis*, 5th International Edition. Upper Saddle River, NJ: Prentice Hall.

Groom, B., P. Koundouri, C. Nauges, and A. Thomas. 2008. The Story of the Moment: Risk Averse Cypriot Farmers Respond to Drought Management. *Applied Economics* 40: 315–326.

Hellenic Statistical Authority. 2001. Agricultural Census. Athens: HSA Publications.

Hellenic Statistical Authority. 2006. Producer Price Indexes in Agriculture. Athens: HSA Publications.

Huffman, W.E., and S. Mercier. 1991. Joint Adoption of Microcomputer Technologies: An Analysis of Farmers' Decisions. *Review of Economics and Statistics* 73: 541–546.

Kalbfleisch, J.D., and R. Prentice. 2002. *The Statistical Analysis of Failure Time Data*. New Jersey: Wiley-Interscience.

Karshenas, M., and P. Stoneman. 1993. Rank, Stock, Order, and Epidemic Effects in the Diffusion of New Process Technologies: An Empirical Model. *Rand Journal of Economics* 24: 503–528.

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

Krzanowski, W.J. 2000. *Principles of Multivariate Analysis: A User's Perspective*. New York: Oxford University Press.

Maertens, A., and C.B. Barrett. 2013. Measuring Social Networks' Effects on Agricultural Technology Adoption. *American Journal of Agricultural Economics* 95: 353–359.

Manski, C.F. 1993. Identification of Endogenous Social Effects: The Reflection Problem. *Review of Economic Studies* 60: 531–542.

Moriana, A., F. Orgaz, M. Pastor, and E. Fereres. 2003. Yield Responses of a Mature Olive Orchard to Water Deficits. *Journal* *of the American Society of Horticultural Science* 128: 425–431.

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

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

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

Rivera, W.M., and G. Alex. 2003. *Extension Reform for Rural Development*. Washington, DC: World Bank.

Rogers, E.M. 1995. *Diffusion of Innovations*, 4th Edition. New York: Free Press.

Stallings, J.L. 1968. Weather Indexes. *Journal of Farm Economics* 42: 180–186.

Weber, J.G. 2012. Social Learning and Technology Adoption: The Case of Coffee Pruning in Peru. *Agricultural Economics* 43: 1–12.

World Bank. 2006. *Enhancing Agricultural Innovation: How to Go Beyond the Strengthening of Research Systems*. Washington, DC: Agriculture and Rural Development Division, The World Bank.