Information Acquisition and Adoption of Organic Farming Practices: Evidence from Farm Operations in Crete, Greece

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Abstract

The objective of the paper is to model the degree of organic farming adoption as well as the importance of technical information acquisition in the adoption decision process. In doing so, a trivariate ordered probit model is specified and implemented in the case of organic farming adoption in Crete, Greece. The results suggest that the decisions of information acquisition and adoption are indeed correlated and different farming information sources play a complementary role. Policies required to encourage organic farming adoption should be primarily structural while the provision of technical information is more crucial than conversion subsidies if total organic adoption is to be pursued.

1. Introduction

The adoption of technological innovations in agriculture has been studied intensively since Griliches (1957) pioneering work on the adoption of hybrid corn in the USA. Excellent surveys of the existing literature are provided by Feder, Just and Zilberman (1985) and by Feder and Umali (1993), while Besley and Case (1993) provide a detailed methodological framework of modeling technological adoption in developing countries. The majority of the existing applied research has been concerned with answering the question what determines whether a particular farmer adopts or rejects an innovation in both a static and a dynamic analytical framework (most recent studies include Dinar, Campbell and Zilberman, 1992; Doss and Morris, 2001; Lapar and Pandey, 1999; amongst others). Another strand of this literature has been concerned with the adoption

decision as a dynamic process spanning over time (e.g., de Souza, Young and Burton, 1999; Ghadim and Pannell, 1999, Pietola and Oude Lansink, 2001), or the patterns of new technology diffusion (e.g., Batz, Peters and Janssen, 1999).

However, a relative dearth of empirical research in developing country's agriculture seems to exist on the perceivable link between the farmer's decision to adopt innovations and his decision to gather information concerning both the available new technologies and farming practices in general. The role of information is of major importance in technological innovations emphasized by a number of studies (Hiebert, 1974; Linder, 1980; Feder and O'Mara, 1982; Hornik, 1982; Feder and Slade, 1984). Costly and inadequate information services may restrict farmers' innovativeness. The final decision of an individual farmer to adopt a new technology primarily depends on his/her ability to acquire, process and decode the information related both with farming practices and the technological innovation itself (Rogers and Shoemaker, 1971; Kilhstrom, 1976; Jensen, 1982; Stoneman and David, 1986). Information accumulation improves farmer's knowledge on farming practices which in turn reduces uncertainty and therefore induces new technology adoption by risk-averse operators.

On the other hand, farmers' choice to adopt or not a particular innovation, affects his decision to gather technical information from various sources. A farmer who is interested in applying a new technology (e.g., farming practices) has a clear incentive to search for relevant information either through the information network that he/she has established during the years involved in farming or by actively seeking for new information sources. However, as noted by Kihlstrom (1976), producers' decision for information gathering is more complicated when information is available in increasing degree of reliability at increasing cost. The latter suggests that adoption and information acquisition decisions are correlated and the impact of the determinants of these decisions may differ with the channels of information dissemination (Wozniak, 1993; Gervais, Lambert and Boutin-Dufrense, 2001). It follows that the decisions to adopt (or not) new technologies and acquire relevant information are not separable and therefore, the intimate link between the two decisions should be explicitly introduced, in empirical analysis. Within this analytical framework, the objective of the present study is to model the degree

of technology adoption as a process jointly determined with the process via which farmers seek for technical information from various sources.

We apply our empirical model to the case of farmers adopting organic farming practices in Crete, Greece. Organic farming offers an interesting case of an alternative (to conventional farming) new technology. This mode of farming has been actively promoted in the context of the Common Agricultural policy (CAP) of the European Union (EU) during the last decade. The respective EU policies (summarized in EU Regulation 1257/1999) are basically subsidy-driven. Lampkin and Padel (1994) summarizing financial support programmes in various European countries, found that most of these countries adopted a direct subsidy scheme that requires complete conversion of at least a portion of a farm's land and continued organic production. They concluded that conversion subsidies had increased significantly organic farming sector throughout Europe the last years.

Indeed financial incentives such as direct subsidies, where the central government "shares" in the risk of adoption, are common and effective means for overcoming farmer's adverse perceptions. These types of incentives are however costly, especially if adoption depends primarily on farmer's perceptions about future yields. A promising and equally effective way to promote technological adoption in farming sector is the provision of informational incentives that revise producer's perceptions about the profit (or cost)-effectiveness of new farming practices. Although fixed initial costs are incurred, informational incentives may be less costly than financial incentives in the long-run as information spreads throughout the rural communities. In addition, as Stoneman and David (1986) have shown, although both information and subsidy policies speed up adoption and diffusion of new technologies, subsidy policies may yield welfare losses in the form of income transfers from other sectors of the economy.

Recently, Lohr and Salomonsson (2000) analyzing the EU policies concerning organic farming found that market services and information sources rather than subsidies are more effective in encouraging organic adoption throughout the EU. In addition, other studies (Oude Lansink, Pietola and Backman, 2002; Tzouvelekas, Pantzios and Fotopoulos, 2001a; 2001b) have shown that the application of organic farming methods by EU farmers is in general, inefficient (i.e., they do not explore fully the potential of the

given technology). The majority of producers appear rather cautious regarding organic adoption as they do not have the knowledge required; ignore the risks involved; and, more importantly they do not know how to use sources of general farming information which could enlighten them on the prospects of such alternatives. It follows that the farmer's attitude towards actively seeking (or not) information about his professional activities is of major importance for his organic adoption decision.

We model the farmer's organic adoption and farming information-gathering decisions by means of a structural model based on a multivariate probit specification. Specifically, a recursive simultaneous trivariate ordered probit model is implemented using cross-sectional data from a survey of farm operations in the Greek island of Crete. The following section describes the theoretical framework of our analysis on technological adoption and information acquisition processes, while section 3 presents the econometric model. Data and the estimation results are presented in section 4 while policy recommendations derivable from our findings and summary remarks are offered in the last two sections.

2. Theoretical Framework

We assume that the adoption of organic farming is closely related to the ways in which farmers obtain technical information regarding farming practices in general. We distinguish between *active* and *passive* sources of farming-related information gathering (Feder and Slade 1984; Jensen, 1982; Wozniak, 1993; Gervais, Lambert and Boutin-Dufrense, 2001). The former refer to the case wherein the farmer acquires farming-related information via periodical contacts with public or private extension agents while the latter refer to the case wherein the farmer acquires farming information incidentally from various information media (e.g., newspapers, television and radio; visits to agricultural product fairs and shows; sporadic attendance of seminars, meetings or demonstrations; merchandisers of input supplies; and so on). It is further assumed that both sources of information gathering entail either paid or imputed (the opportunity cost of labor) cost.

In essence we depart from existing studies which regard innovation adoption as a process consisting of sequential phases. To be more explicit, Saha, Love and Schwart (1994) argue that in the case of emerging technologies, we should distinguish the first

phase (the information-collection phase) wherein a farmer becomes aware of ('hears about') a new innovation and gathers information. Conditional on his hearing about the innovation, the farmer decides in the second phase whether or not to adopt. In the third phase, which need not be temporally distinct from the second, the farmer decides the degree (intensity) at which he will adopt the new innovation. In cases involving a great deal of farmers who have not even heard about the innovation examined (i.e. emerging technologies), the first phase may be viewed as comprising two sub-stages: in the first the farmer becomes nominally aware of (i.e., 'hears of') the innovation while in the second he collects relevant information to assess the innovation. However, if it can be realistically assumed that all farmers are aware of an innovation, which is clearly the case of organic farming, the first phase may be reduced only to the information collection process.

In this context, we posit that the farmer's adoption decision (to turn organic) is affected, among others, by his general information acquisition process. According to human capital theory, efficiency of the adoption decisions is hypothesized to be related to characteristics that indicate allocative skills of farm operators. These allocative skills are assumed to be acquired or learned rather than innate. Information gathering, among others, is expected to enhance allocative skills and to increase the efficiency of adoption decisions. Better informed farmers about the general performance and peculiarities of new technologies will have more accurate assessments of future yields and profitability and thus will make more efficient adoption decisions. On the other hand, imperfect information concerning new technologies may bring risks with regard the adoption of this new technology that arise the possibility of committing errors (Stigler, 1961; Huffman, 1977; Rahm and Huffman, 1984; Huffman and Mercier, 1991; Lin, 1991).

Under this hypothesis we can reasonable assume that the process of information acquisition precedes farmer's decision to adopt or not the new technology. Farmers have established a network, through years that they are involved in farming, via which they are used to collect information concerning farming practices in general. The extent to which this information gathering process is adequate in reducing risk, affects their final decision to adopt or not the new technology.

The farmer's optimal information level is the outcome of an underlying utility maximization problem:

$$I_i^* \equiv f(x_i) \tag{1}$$

where I^* is the optimal information level for farm i and x_i is a vector of farm's i relevant economic and demographic characteristics. A farmer may be viewed as being well informed about farming activities as well as of the innovation (i.e., organic farming) if the level of collected farming information exceeds a certain threshold I^T, that is, if

$$I^*(x_i) > I^T \quad \text{or} \quad Y^{INF*} \equiv I^*(x_i) - I^T > 0 \tag{2}$$

The above equation may be further expressed as a linear model of the form:

$$Y_i^{INF*} \equiv f(x_i; \beta) + u_i \tag{3}$$

where superscript INF stands for information, β is a parameter vector and, u_i is the respective error term. As Y^{INF*} is not observed practically, an indicator Y^{INF} may be assumed to exist which equals 1 if the farmer is collecting farming information, and 0 if he does not. That is,

$$Y_i^{INF} = \begin{cases} 1 & \text{if} \quad f(x_i; \beta) + u_i \geq 0 \\ 0 & \text{if} \quad f(x_i; \beta) + u_i < 0 \end{cases} \tag{4}$$

Although the information acquisition process is distinguished from the technological adoption decision, the farmer's perception regarding the future yields is conditional upon the acquired information level, Y^{INF*}. Based (among others) on the information acquired, the farmer evaluates the economic/financial aspect of the innovation (*i.e.*, he decides whether or not to adopt). This adoption decision may be formalized in terms of maximized expected profits. Thus, if π^C denotes the farmer's expected present value of the future stream of net benefits under the current state of technology he uses, and π^N denotes the expected present value of the future stream of net benefits if the innovation is

adopted, then the farmer's expected present value of the difference of these net benefits can be expressed as a linear function of the form

$$\underset{INF}{E}\left(\pi_i^N - \pi_i^C\right) = g(\mathbf{s}_i; \zeta) + v_i \tag{5}$$

where E is the expectation operator conditioned on farmers' information level, ζ is a parameter vector, $\mathbf{s}_i$ is a matrix of the farm's i structural and demographic characteristics, and v_i the vector of the respective error term.

As the expected present value-difference above is not observed practically, an indicator Y^A may be assumed to exist which equals 1 if the farmer decides to adopt the innovation, and 0 if he does not. That is,

$$Y_i^A = \begin{cases} 1 & if \quad g(\mathbf{s}_i, INF; \zeta) + v_i \geq 0 \\ 0 & if \quad g(\mathbf{s}_i, INF; \zeta) + v_i < 0 \end{cases} \tag{6}$$

Note that the case of $Y^A=1$ may occur regardless the value of Y^{INF}. However, the unobservable factors included in information gathering equation (4) above may be well influential in the adoption decision and *vice versa*. In order to address this issue both information gathering and adoption equations should be jointly estimated allowing for correlation between the two equations' error terms (u_i and v_i, respectively).

Regarding technology adoption, farmers often choose to adopt only parts of an innovation rather than the whole package (Yaron, Dinar and Voet, 1992); or they opt to apply the new technology only to one part rather than the whole farm (Leathers and Smale, 1991; Feder, 1982; Saha, Love and Schwart, 1994). In the case of organic farming, it is common practice for farmers to convert only a portion of the farm (or only one of the farm activities) to organic[1]. Therefore a useful criterion regarding organic farming adoption is the intensity (or degree) of adoption with respect to the size of the farm operation. For the purpose of our analysis we distinguish organic farming adoption into *partial* (when organic techniques are applied only to a portion of the farm's total acreage) and *total* (when the whole farm is converted to organic).

3. Econometric Model

Given the preceding theoretical framework, we consider that all farmers are aware of the innovation *i.e.*, organic farming. This is a rather realistic assumption since the EU institutional framework[2] that formally introduced organic farming has been in place since 1991. Then, we model organic farming adoption via a three-equation system allowing for two types of information acquisition. More exactly, we specify a system of three equations describing respectively the farmer's decisions to (i) acquire farming information via *periodical contacts* with public or private extension agents (ii) actively acquire farming information *sporadically* from other media sources and (iii) adopt *partially*, *totally* or *not* organic farming methods based, among others on decisions (i) and (ii).

In essence, given the correlation between u_i and v_i mentioned above, we consider a recursive simultaneous trivariate choice model with one of the choices being ordered. The three joint choices refer to information acquisition via extension (Y^{EXT}), information acquisition via other sources (Y^{INF}) and organic farming adoption (Y^A); moreover, organic adoption is viewed as an ordered choice to capture partial land, total land and non-adoption decisions.

The structure of the model is as follows (see Maddala, 1983, pp. 122-123):

$$Y_i^{EXT} = \begin{cases} 1 \ if \quad \beta_0 + \sum_j \beta_j x_{ji} + u_i \geq 0 \ (if \ farmer \ contacts \ extension \ agents) \\ 0 \ if \quad \beta_0 + \sum_j \beta_j x_{ji} + u_i < 0 \ (otherwise) \end{cases} \qquad (7a)$$

$$Y_i^{INF} = \begin{cases} 1 \ if \ \delta_0 + \sum_k \delta_k z_{ki} + e_i \geq 0 \ (if \ farmer \ uses \ other \ sources \ of \ information) \\ 0 \ if \ \delta_0 + \sum_k \delta_k z_{ki} + e_i < 0 \ (otherwise) \end{cases} \qquad (7b)$$

$$Y_i^A = \begin{cases} 2 \ if \ \sum_l \zeta_l s_{li} + \gamma_1 Y_i^{EXT} + \gamma_2 Y_i^{INF} + v_i \geq \alpha_2 \ (full \ land \ adoption) \\ 1 \ if \ \alpha_1 \leq \sum_l \zeta_l s_{li} + \gamma_1 Y_i^{EXT} + \gamma_2 Y_i^{INF} + v_i < \alpha_2 \ (partial \ land \ adoption) \\ 0 \ if \ \sum_l \zeta_l s_{li} + \gamma_1 Y_i^{EXT} + \gamma_2 Y_i^{INF} + v_i < \alpha_1 \ (no \ adoption) \end{cases} \qquad (7c)$$

where, $i=1, 2, ..., n$ are the farm operations, x_{ji}, z_{ki} and s_{li} are the explanatory variables assumed to affect the information acquisition and adoption decisions, α_1 and α_2 are the threshold levels of the ordered choice equation which need to be estimated (the third equation contains no constant term in order to ensure identification of the threshold parameters) and u_i, e_i, v_i are random disturbances that follow a trivariate normal distribution with zero mean and variance covariance matrix, given by:

$$
M = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{bmatrix} \tag{8}
$$

The above specification has been chosen to emphasize two important points of our approach. On the one hand, in our framework information acquisition of any type can shift the probability of partial and total adoption; therefore variables Y^{EXT}, Y^{INF} are included in equation (7c) but Y^A does not appear in equations (7a) nor (7b), thus making the system recursive. On the other hand, we consider a simultaneous equations model that allows for the three decisions to be correlated or dependent (under our normality assumption the two concepts coincide). Note that if the three decisions were to be independent we would still have the two media variables entering equation (7c) but we could estimate each equation separately.

We can estimate the parameters of the system of equations given in (7a), (7b) and (7c) by the ML method after specifying the twelve (12) cell probabilities that appear in it as a function of a trivariate normal distribution function. The simulation based Geweke-Hajivassiliou-Keane (GHK) algorithm can be used to compute the corresponding cell probabilities and their derivatives (Hajivassiliou, McFadden and Ruud, 1996).

For each one of the cells we can define an indicator function d_m that takes value 1 if the observation falls in that cell and 0 otherwise. If $i=1, 2, ..., n$ stands for individual farms and $m=1, 2, ..., 12$ for the twelve cell probabilities we have:

$$
C_1 = \left\{ i : Y_i^{EXT} = 1, Y_i^{INF} = 1, Y_i^A = 0 \right\} \qquad d_{1i} = \begin{cases} 1 \text{ if } i \in C_1 \\ 0 \text{ otherwise} \end{cases} \tag{9a}
$$

$$C_2 = \left\{ i : Y_i^{EXT} = 1, Y_i^{INF} = 0, Y_i^A = 0 \right\} \qquad d_{2i} = \begin{cases} 1 \text{ if } i \in C_2 \\ 0 \text{ otherwise} \end{cases} \qquad (9b)$$

$$C_3 = \left\{ i : Y_i^{EXT} = 0, Y_i^{INF} = 1, Y_i^A = 0 \right\} \qquad d_{3i} = \begin{cases} 1 \text{ if } i \in C_3 \\ 0 \text{ otherwise} \end{cases} \qquad (9c)$$

$$C_4 = \left\{ i : Y_i^{EXT} = 0, Y_i^{INF} = 0, Y_i^A = 0 \right\} \qquad d_{4i} = \begin{cases} 1 \text{ if } i \in C_4 \\ 0 \text{ otherwise} \end{cases} \qquad (9d)$$

similarly, C_5 to C_8 and d_{5i} to d_{8i} are defined as above for the case in which $Y_i^A = 1$, while C_9 to C_{12} and d_{9i} to d_{12i} correspond to the case $Y_i^A = 2$ (the analytical expressions of the twelve cell probabilities are given in Appendix 1).

Let $A = (\alpha_1, \alpha_2)'$, $B = (\beta_j, \delta_k, \zeta_1)'$, $\Gamma = (\gamma_1, \gamma_2)'$ and $P = (\rho_{12}, \rho_{13}, \rho_{23})'$ then given the probabilities of the twelve cells defined above, the log-likelihood function can be written as:

$$L(A, B, \Gamma, P) = \sum_{i=1}^{n} \sum_{m=1}^{12} d_m \ln[P(i \in C_m; A, B, \Gamma, P)] \qquad (10)$$

The parameter estimates of the system of equations defined in (7a) through (7c) indicate only the direction of the effect of each explanatory variable on the response probabilities of the information acquisition and technological adoption. The exact effect of each explanatory variable on the individual probabilities of the three response variables requires computing the marginal effects of the regressors. A brief description of the expressions needed to compute the marginal effects is given in Appendix 2. These marginal effects can be easily converted into the respective probability elasticities.

4. Data and Estimation Results

Data Description

The data used in this study are part of a broader survey on the structural characteristics of the agricultural sector in Crete financed by the Regional Directorate of Crete in the context of the *Regional Development Program 1995-99* (Liodakis, 2000). The sample

consists of 237 randomly selected multi crop farms[3] located in the four major districts of Crete, namely Chania, Rethymno, Heraklio and Lasithi, during the 1995-96 period. The sampling procedures used to select farms was stratified purposive. Since our objective was to carry out an in-depth analysis of adoption behavior, farms were divided into two strata namely adopters and non-adopters according to the size of their holdings. Adopters were defined as farmers who have converted at least one parcel of their land to organic and had crop production during the year prior to survey.

In order to the reduce the effect of environmental variation, non-adopting farms were selected from the same villages and where possible were farms with their holdings adjacent to the adopting farms.[4] A structural questionnaire was used for the field interviews that provide detailed information about production patterns, input use, average yields, gross revenues, structural characteristics. Interviews were conducted together with government officials from the Regional Agricultural Directorates of Crete engaged in organic farming conversion. Concerning the factors assumed to affect farmer's information acquisition and decision processes these are classified into four categories, namely, personal characteristics, economic variables, institutional factors and environmental conditions. Summary statistics of the variables used in the empirical analysis are shown in Table 1.

Farmer's age is assumed to affect both information acquisition and technological adoption. Age is highly correlated with experience and therefore its effect can be considered as the composite effect of farming experience and planning horizon. Experience in turn provides increased knowledge about the environment in which decisions must be made. Thus, experience may serve as a substitute for information or at least may modify the decision set for which information is sought. On the other hand, the impact of farmer's age on technological adoption is less clear; longing farming experience is expected to affect positively adoption, younger farmers on the other hand, with greater planning horizons may be more likely to invest in new technologies (Lapar and Pandey, 1999).

Highly educated farmers on the other hand may acquire more easily technical information as their capacity to digest information from various sources is larger (Gervais, Lambert and Boutin-Dufrense, 2001). Indeed educated farmers do read technical bulletins

and innovative-describing leaflets more than do their less educated counterparts presumably because they find it profitable to do so. As a human capital variable, education is also expected to positively affect the efficiency of adoption. The more educated farmers are adopting quicker profitable new technologies since the associated payoffs from innovations are likely to be greater and the risk likely to be smaller (Nelson and Phelps, 1966; Schulz, 1975; Rahm and Huffman, 1984). Indeed the more educated farmers are able to discriminate between promising and unpromising ideas and hence less likely to make allocative mistakes (Welch, 1970). Thus, one would expect that farmer's education level to be positively correlated with his decision to adopt or not organic farming and information acquisition process.[5]

Farm size may also affect both information acquisition and technical adoption processes. The direction of these effects, however, is less clear. Larger farms have a greater potential to convert a part of their land to organic farming. This is partly explained by the associated high costs involved in organic conversion - developing new markets and distribution channels, financing new activities - and risk considerations.[6] On the other hand, one can assume that larger farms may have less financial pressures to search for alternative ways to improve their income either by switching to a different farming technology or by seeking for technical information (Perrin and Winkelmann, 1976; Putler and Zilberman, 1984). In addition, small farms are generally using more labor intensive technologies as they use relatively more family labor which has a low opportunity cost (Hayami and Ruttan, 1985). In that respect conversion to organic-farming may be served as a good alternative as it requires more on-farm labor than conventional farming practices.

Specialized farms have less requirements for technical assistance and thus for information gathering as their respective know how is continuously improved through years. On the other hand, production specialization may affect in either way farmer's decision to adopt technical innovations. Farmers growing a single crop are faced with a higher risk associated with future yields and thus farm income which in turn induces a lower level of adoption.

Off-farm income is hypothesized to provide financial resources for information acquisition and to create incentives to adopt new technologies as the opportunity cost of

time rises. On the other hand, the level of off-farm income may not be exogenous but influenced by the profitability of farming itself which in turn depend on adoption decisions.   However, in our survey, off-farm income arises mainly from non-farm business activities (i.e., tourism) and from employment in other non-farm sectors (i.e., public administration). Given that the skill requirements are different for these jobs farm and off-farm income may be realistically assumed as non-competitive. Thus we can assume that the level of off-farm income could be largely exogenous to adoption decisions (Lapar and Pandey, 1999; Wozniak, 1993).

Unfavorable environmental conditions in the area also increase the risk of future yields and thus decrease farmers propensity to adopt organic farming practices. On the other hand, subsidies received in the context of CAP reduce the financial pressure to the farm and thus are expected to affect positively adoption decisions.[7] This is also true of farmer's consciousness about environmental degradation. As McCann *et al.*, (1997) noted organic farmers express a greater awareness and concern for environmental problems associated with agriculture. Finally, the proximity of farm operations to urban centers is expected to affect positively passive information gathering, while the distance from extension agents and the number of extension outlets in the area are assumed to affect negatively and positively, respectively active information gathering.

Estimation Results

For the estimation of the trivariate ordered probit model we implement the GHK algorithm with 100 repetitions using *Gauss* and the ML parameter estimates of equations (7a-7c) are listed in Table 2. Focusing first on the lower part of the table it can be seen that the estimated correlation coefficients $(\hat{\rho}_{12}, \hat{\rho}_{13}, \hat{\rho}_{23})$ lend support to the hypothesis that farming information acquisition and organic farming adoption are correlated decisions. Specifically, the positive and significant interaction between the two modes of information acquisition implies that the likelihood of acquiring farming information periodically from public or private extension agents is positively related to likelihood of acquiring this information actively from other sources.

In addition, positive and significant interaction is found between each type of information acquisition and the decision to adopt organic farming methods; this suggests

that information exposed farmers are more likely to be organic adopters. Statistical testing supports further the above findings since each individual correlation coefficient is statistically significant at either 1% or 5% significance level and the hypothesis that there are no correlations between the two types of information and organic adoption $\left(H_0 : \rho_{12} = \rho_{13} = \rho_{23} = 0\right)$ is rejected at the 1% significance level.[8] Therefore information acquisition should not be treated as an exogenous variable when estimating a model for adoption. In addition, the model overall correctly predicts the 74.41% of individual probabilities.[9]

The maximum likelihood coefficient estimates of equations (7a) to (7c) are shown in the upper part of Table 2.   The majority of the estimated parameters are statically significant at least at the 5 percent level, in all three equations. As mentioned earlier these estimates have a limited interpretation due to the discrete nature of the dependent variables and therefore we need to compute the corresponding marginal effects. In the case of a continuous explanatory variable the marginal effect shows, *ceteris paribus*, the change in the probability that the dependent variable takes a specific value caused by a one-unit change in the explanatory variable,

While in the case of a dummy explanatory variable it captures the difference in the probabilities of the 2 different categories.   The marginal effects of the explanatory variables on the information acquisition dependent variables (equations 7a-7b) are shown in Tables 3 and 4, respectively. The marginal effects of the explanatory variables on the probabilities of partial and total land organic conversion (equation 7c) are presented in Tables 5 and 6 respectively. All marginal effects are computed at the mean values.

According to Table 3, the factors which primarily lead to increases in a farmer's probability to acquire farming information via periodical contacts with public or private extension agents are his Education level, followed by the number of extension outlets available to him. Specifically, the marginal effect for education suggests that, holding all other variables constant at their sample means, a farmer with one more year of education than the average level in the sample has a higher probability (by an amount of 0.147) of acquiring farming information periodically via extension. Similarly, the marginal effect of the farming extension outlets available implies that ceteris paribus farmers with access to

one more outlet than the average number of outlets in the sample have a lower probability (by an amount of 0.108) of acquiring farming information periodically.

On the other hand, the farm's specialization seems to be the factor with the largest negative influence on the extension-based information acquisition, followed by the farmer's age, the farm size, and the distance of extension outlets. Thus, the probability of acquiring farming information periodically via extension decreases by 0.036 for those farms with Herfindhal index – values one percent larger than the sample's average. Similarly, a unit-increase in the farmer's age, farm size or the farm's distance from extension outlets seems to reduce ceteris paribus the probability of acquiring farming information, by 0.097, 0.005, and 0.085, respectively. On the other hand, off-farm income does not appear to exert a significant influence on the farmer's decision to acquire extension-based information.

The influence of these determinants appears to differ with respect to the farmer's decision to actively seek farming-information via other media sources. The study of Table 4 reveals that similarly to the case of extension-based information acquisition, Education followed by information availability (as measured by the farm's proximity to urban centers where presumably the chances of exposure to all kinds of information are higher) are the two major influences increasing the probability of a farmer to acquire farming information sporadically via various media sources. Contrary however to the case of periodical information acquisition, age followed by off-farm income and farm specialization appear to be the major negative influences on the farmer's sporadic information acquisition; moreover the farm size does not appear to have any significant impact on this decision.

Extra information may be gained in the context of our approach with respect to the role of the factors determining both the farming information acquisition and the organic adoption decisions. The marginal effect on the adoption decision of variables that jointly determine the farmer's decision to seek information and to adopt organic production is the combination of an indirect and a direct component reflecting the variable's effect in the information acquisition and the adoption processes, respectively. Thus, the combined effect for age shown in Table 5 is negative implying that *ceteris paribus*, the probability of

a farmer who is a year older than the average age in the sample to convert partially to organic farming decreases by 0.096.

Moreover, this decrease is primarily due to the lower chance older farmers have to acquire farming information either periodically via extension or sporadically via various media. Specifically, an additional year of age (with respect to the mean age) directly reduces the probability of partial adoption by 0.036 while it also reduces this probability indirectly by 0.060 through the negative effect that age has on the likelihood that a farmer will seek farming information.

An important positive influence on the farmer's examined decision is his education. Moreover, the corresponding marginal effect appears to be almost evenly split between the increased ability of more educated farmers to acquire farming information and their ability to make adoption decisions. Next (in terms of their marginal effect–magnitudes) come the farmer's environmental awareness, and the media-based, active farming-information acquisition followed closely by the extension-based, passive information acquisition.

The sum of exogenous subsidy rates received appears to have only a mild positive impact on the probability of partial organic adoption. On the other hand, farm specialization is the factor primarily decreasing the probability of partial organic conversion followed by the farmer's age and less favorable climatic conditions (as measured by the aridity index). Moreover, the marginal effect of farm specialization is mainly determined by the decreased probability of specialized farms to seek farming-information in general either via extension or via the media. Finally, the partial organic adoption-decision appears not to be affected by farm size, off-farm income or the farm's proximity to urban areas.

These determinants influence the farmer's decision for total organic conversion in the same manner, however their relative importance (as reflected in the magnitude of their marginal effects) differs substantially. As seen in Table 6, the primary positive influences on the total-adoption decision is the farmer's decision to acquire farming information either via periodical extension contacts or via sporadic contacts with various media. Thus, farmers seeking farming information via extension (media) appear to a have a higher

probability (by 0.016) to totally convert their farms into organic than farmers who do not seek such information.

The second largest positive influence comes from the farmer's education which (as in the case of the partial-adoption decision, above) is almost equally split in magnitude between the increased likelihood of more educated farmers to make organic adoption decisions and their increased probability of acquiring farming information via extension or media contacts. The third positive influence comes from the farmer's environmental awareness followed by the farm's proximity to urban areas. On the other hand, as with the case of partial organic conversion, farm specialization is the factor primarily reducing the probability of full organic conversion.

Moreover, the negative impact of this factor is primarily due to the lower probability of specialized farmers to totally convert into organic because of their higher specialization rather than their lower ability to acquire farming information. The farmer's age, and the existence of less favorable climatic conditions (as measured by the aridity index) follow as the second largest negative influence with almost the same negative marginal effect. Farm-size and off-farm income appear not to have any considerable impact on the total adoption-decision.

5. Policy implications

Elaborating on the empirical findings presented above, we may first notice the positive correlation found between the two modes of information acquisition. This interestingly implies that (public and private) extension and other media appear to be complementary sources of farming information. Moreover, younger more educated farmers seem more likely to both acquire farming information and adopt partially or fully organic farming technology in their operations. This is a rather standard empirical finding in the adoption literature (*i.e.*, Schulz).

The farm-size appears not to affect most of the decisions examined, here. Indeed, there is no size-effect neither on the probability of information acquisition via media nor on the probabilities of adopting organic farming methods (totally or partially). Farm-size affects negatively only the farmer's decision to seek extension information: owners of larger farms seem less likely to obtain farming information via extension contacts.

Off-farm income does not influence neither the information acquisition nor the adoption decisions. It should be noted at this point that income from off-farm sources is often viewed as a means of finance for information acquisition and new technology adoption. Especially in the case of organic farming adoption, it has been argued that organic farming is an activity particularly favored by farm operators with considerable off-farm finances. The empirical findings of the present study however do not confirm such considerations.

Environmental awareness appears to have a more powerful impact on the decision for partial rather than full organic conversion. This is only natural given the higher risks associated with converting the entire farm (rather than one part) into organic. Moreover, the relative importance of this factor vis-a-vis other determinants in the farmer's conversion decision implies that environmental considerations (although present) do not seem to be the driving force behind organic technology adoption.

Subsidies received appear to play only a minor role in organic farming adoption relative to other variables. This finding is of particular importance in light of EU plans to convert a sizable portion of European farming into organic while implementing CAP measures which are almost exclusively subsidy-driven. In the early conversion stages when organic farming was marginal profitable mainly due to unsatisfactory market conditions and distribution channels the subsidies implied by structural programs had affected positively many farmer's decisions. However, through years marketing channels and new market opportunities have been better explored making thus organic farming profitable even at unsubsidized capital and input prices. Thus, gradually farmer's decisions are less dependent on the subsidy rates implied by the respective EU regulations. Favorable climatic conditions seem to be a consideration in the farmer's decision for organic technology adoption. This finding is in accordance with analogous results found elsewhere. It may be viewed as an indication of the approach farmers advocate to deal with the lower yields and higher production uncertainty of organic farming methods.

With respect to the two modes of obtaining farming information examined here, our findings indicate that both have a similar impact on the adoption decision. This implies that both modes are given almost equal importance by partial and total organic adopters. However the magnitude of this impact is distinctly different in the cases of partial and full

adoption. Thus in partial organic adoption, the farmer's ability to obtain information via extension or various media has a moderate influence in his adoption decision (vis-a-vis the influence of other determining factors). By contrast, in full organic adoption the farmer's ability to obtain information via extension or media appears to be the factor primarily shaping his adoption decision.

The policy recommendations derivable from these results may be summarized in terms of the diffusion strategies planning authorities may wish to pursue with respect to organic farming adoption. First active and passive information sources have different audiences. To enhance the return of information dissemination activities and better serve farmers needs, policies and practices of information providers should reflect the specific characteristic of potential adopters. Active information providers should target farms with low level of off-farm income less specialized in their farming activities that are close to urban centers. On the other hand, extension services can target small highly diversified farms with higher educated operators who have greater capacity for processing and decoding technical information.

Thus, if policy makers wish to encourage partial (gradual) organic adoption then policy measures should address: (i) the improvement of farmer education, (ii) the retirement of aging farm operators, (iii) the development of farming information channels (including extension services), (iv) the cultivation of environmental considerations among farmers, and (v) the encouragement of multi-output oriented farms. On the other hand, if total organic adoption (conversion of the entire farm) is to be encouraged, policy measures should primarily focus on the advancement of public and private extension services and the development of farming information channels and networks.

6. Conclusions

The present study suggests that a farmer's decision to adopt new technologies should not be studied separately from his decision to acquire farming information. To that end, we specify a structural probit model in which the farmer's decision to acquire farming information via different sources and of new technology are correlated.

We implement our model to the case of Greek organic farming adopters using a cross-sectional data-set. The empirical results show that acquisition of farming

information and organic adoption are indeed correlated decisions. Moreover, the sources via which farmers gather farming information appear to be positively related. This implies that different sources play a complementary role in the gathering of information about new farming technologies by the farmer.

Policy insights derived in the context of our study suggest that measures to promote the adoption of organic farming techniques should be primarily structural rather than subsidy-driven. Specifically, our findings indicate that organic farming adoption would be mainly influenced by policy measures encouraging the retirement of older farmers; improving their education, environmental awareness, and information channels and networks; encouraging farm output-diversification; and advancing extension services. Moreover, the availability of extension services (public or private) appears to be pivotal if a strategy of total organic adoption (that is, conversion of the entire farm) is to be pursued.

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Table 1
Summary Statistics for Cretan Organic Farming Conversion and Information Acquisition Data

	Non-Adopters	Partial Adopters	Full Adopters
Number of Farms	118	75	44
	(49.8)	(31.6)	(18.6)
Education Level (in years)		*(percentage of farms)*	
Elementary (<6)	59.3	28.0	4.5
High School (6-9)	21.2	38.7	9.1
Higher School (9-12)	13.6	18.6	43.2
Graduate Degree (>12)	5.9	14.7	43.2
Average	7.7	10.4	13.0
Farmer's Age (in years)		*(percentage of farms)*	
<35	8.5	30.7	31.8
35-45	16.1	33.3	45.5
45-55	23.7	22.7	15.9
55-65	22.9	12.0	4.5
>65	28.8	1.3	2.3
Average	55.6	42.3	41.3
Farm Size (in stremmas, 1stremma=0.1ha)		*(percentage of farms)*	
<20	22.0	24.0	18.2
20-40	28.8	45.3	27.3
40-60	15.3	14.7	31.8
60-80	15.3	10.7	13.6
>80	18.6	5.3	9.1
Average	20.5	37.4	43.0
% of farms received extension	16.9	70.7	88.6
No of extension outlets in the area	4.5	5.0	7.5
Distance from extension outlets (in km)	44.5	42.8	38.9
% of farms received active information	11.9	49.3	72.7
% of farms close to urban centers	26.3	44.0	56.8
% of farmers with environmental awareness	16.1	41.3	79.5
Specialization (Herfindhal index[1])	0.767	0.494	0.410
Off-farm income (€/year)	640	954	980
Subsidies received (€/year)	652	1,001	1,459

[1] The Herfindhal index is defined as: $H = \sum_{p} \left(y_p^S\right)^2$ where y_p^S is the share of pth output in total farm production. A value of H close to unity indicate specialization, whereas smaller values reflect increased diversification.

Table 2

Parameter Estimates of the Trivariate Ordered Probit Model of Organic Farming Conversion in Cretan Agriculture

Parameter	Extension Contacts		Active Information		Organic Adoption	
	Estimate	t-ratio[1]	Estimate	t-ratio	Estimate	t-ratio
Constant	1.025	(5.417)	1.369	(6.205)	-	-
Farmers' Age	-0.287	(6.087)	-0.109	(1.805)	-0.098	(3.089)
Farmers' Education	0.569	(7.598)	0.316	(4.102)	0.237	(2.102)
Farm Size	-0.042	(1.756)	-0.008	(0.606)	0.007	(1.015)
Off-farm Income	0.007	(0.874)	-0.076	(2.986)	0.023	(1.117)
Aridity Index	-	-	-	-	-0.647	(7.526)
Subsidies	-	-	-	-	0.039	(1.798)
Farm Specialization	-0.268	(4.187)	-0.306	(5.036)	-0.095	(1.985)
Distance of Extension Outlets	-0.085	(1.865)	-	-	-	-
No of Extension Outlets	0.326	(1.987)	-	-	-	-
Environmental Awareness	-	-	-	-	0.041	(2.687)
Urban Area	-	-	0.092	(3.187)	-	-
Extension Contacts	-	-	-	-	0.103	(4.085)
Active Information	-	-	-	-	0.190	(5.178)
α_1	-	-	-	-	-1.325	(3.074)
α_2	-	-	-	-	-0.865	(2.857)
ρ_{12}	0.568	(3.587)				
ρ_{23}	0.369	(1.968)				
ρ_{13}	0.215	(4.069)				
$Ln(\theta)$	-102.39					
% of correct prediction	74.41%					
No of observations	237					

[1] Standard errors were obtained using block resampling techniques which entails grouping the data randomly in a number of blocks of ten farms and reestimating the model leaving out each time one of the blocks of observations and then computing the corresponding standard errors (Politis and Romano, 1994).

Table 3

The Effects of Explanatory Variables on the Probability that Cretan Farmers Seek Private

or Public Extension Contacts

Variable	Estimate	t-ratio[1]
Farmers' Age	-0.092	(2.058)
Farmers' Education	0.147	(3.685)
Farm Size	-0.005	(1.905)
Off-farm Income	0.001	(0.874)
Farm Specialization	-0.036	(3.247)
Distance of Extension Outlets	-0.085	(4.287)
No of Extension Outlets	0.108	(3.745)

[1] Standard errors were obtained using block resampling techniques which entails grouping the data randomly in a number of blocks of ten farms and reestimating the model leaving out each time one of the blocks of observations and then computing the corresponding standard errors (Politis and Romano, 1994).

Table 4

The Effects of Explanatory Variables on the Probability that Cretan Farmers Actively

Seek Information from Various Sources

Variable	Estimate	t-ratio[1]
Farmers' Age	-0.112	(1.953)
Farmers' Education	0.098	(4.587)
Farm Size	-0.002	(0.741)
Off-farm Income	-0.032	(1.869)
Farm Specialization	-0.045	(4.174)
Urban Area	0.062	(3.905)

[1] Standard errors were obtained using block resampling techniques which entails grouping the data randomly in a number of blocks of ten farms and reestimating the model leaving out each time one of the blocks of observations and then computing the corresponding standard errors (Politis and Romano, 1994).

Table 5
The Effects of Explanatory Variables on the Probability of Partial Land Organic
Conversion of Cretan Farmers

Variable	Indirect	Direct	Total[1]	
Farmers' Age	-0.060	-0.036	-0.096	(4.069)
Farmers' Education	0.045	0.069	0.114	(5.470)
Farm Size	0.005	-0.002	0.003	(0.905)
Off-farm Income	-0.009	0.005	-0.004	(0.641)
Aridity Index	-	-0.102	-0.102	(7.265)
Subsidies	-	0.008	0.008	(1.905)
Farm Specialization	-0.044	-0.018	-0.062	(4.005)
Environmental Awareness	-	0.031	0.031	(3.874)
Urban Area	0.004	-	0.004	(1.047)
Extension Contacts	-	0.087	0.087	(2.041)
Active Information	-	0.071	0.071	(2.174)

[1] In parentheses are the corresponding absolute t-ratios. Standard errors were obtained using block resampling techniques which entails grouping the data randomly in a number of blocks of ten farms and reestimating the model leaving out each time one of the blocks of observations and then computing the corresponding standard errors (Politis and Romano, 1994).

Table 6

The Effects of Explanatory Variables on the Probability of Full Land Organic Conversion of Cretan Farmers

Variable	Indirect	Direct	Total[1]	
Farmers' Age	-0.027	-0.047	-0.074	(5.174)
Farmers' Education	0.034	0.058	0.092	(4.047)
Farm Size	0.003	-0.005	-0.002	(0.784)
Off-farm Income	-0.009	0.006	-0.003	(0.824)
Aridity Index	-	-0.092	-0.092	(6.352)
Subsidies	-	0.005	0.005	(2.163)
Farm Specialization	-0.011	-0.030	-0.041	(3.241)
Environmental Awareness	-	0.022	0.022	(2.258)
Urban Area	0.001	-	0.001	(0.698)
Extension Contacts	-	0.103	0.103	(3.325)
Active Information	-	0.092	0.092	(2.925)

[1] In parentheses are the corresponding absolute t-ratios. Standard errors were obtained using block resampling techniques which entails grouping the data randomly in a number of blocks of ten farms and reestimating the model leaving out each time one of the blocks of observations and then computing the corresponding standard errors (Politis and Romano, 1994).

Appendix 1: Expressions of the Twelve Cell Probabilities

Define the following expressions representing the vectors of means:

$$\mu_{11} = \begin{pmatrix} \beta_0 + \sum_j \beta_j X_{ji} \\ \delta_0 + \sum_k \delta_\kappa Z_{ki} \\ -\alpha_1 + \sum_l \zeta_l S_{li} + \gamma_1 + \gamma_2 \end{pmatrix} \qquad \mu_{21} = \begin{pmatrix} \beta_0 + \sum_j \beta_j X_{ji} \\ \delta_0 + \sum_k \delta_\kappa Z_{ki} \\ -\alpha_2 + \sum_l \zeta_l S_{li} + \gamma_1 + \gamma_2 \end{pmatrix}$$

$$\mu_{12} = \begin{pmatrix} \beta_0 + \sum_j \beta_j X_{ji} \\ \delta_0 + \sum_k \delta_\kappa Z_{ki} \\ -\alpha_1 + \sum_l \zeta_l S_{li} + \gamma_1 \end{pmatrix} \qquad \mu_{22} = \begin{pmatrix} \beta_0 + \sum_j \beta_j X_{ji} \\ \delta_0 + \sum_k \delta_\kappa Z_{ki} \\ -\alpha_2 + \sum_l \zeta_l S_{li} + \gamma_1 \end{pmatrix}$$

$$\mu_{13} = \begin{pmatrix} \beta_0 + \sum_j \beta_j X_{ji} \\ \delta_0 + \sum_k \delta_\kappa Z_{ki} \\ -\alpha_1 + \sum_l \zeta_l S_{li} + \gamma_2 \end{pmatrix} \qquad \mu_{23} = \begin{pmatrix} \beta_0 + \sum_j \beta_j X_{ji} \\ \delta_0 + \sum_k \delta_\kappa Z_{ki} \\ -\alpha_2 + \sum_l \zeta_l S_{li} + \gamma_2 \end{pmatrix}$$

$$\mu_{14} = \begin{pmatrix} \beta_0 + \sum_j \beta_j X_{ji} \\ \delta_0 + \sum_k \delta_\kappa Z_{ki} \\ -\alpha_1 + \sum_l \zeta_l S_{li} \end{pmatrix} \qquad \mu_{24} = \begin{pmatrix} \beta_0 + \sum_j \beta_j X_{ji} \\ \delta_0 + \sum_k \delta_\kappa Z_{ki} \\ -\alpha_2 + \sum_l \zeta_l S_{li} \end{pmatrix} \qquad (A.1)$$

and the following rectangles:

$$\begin{aligned} G_1 &= (0,\infty) \times (0,\infty) \times (-\infty,0) & G_5 &= (0,\infty) \times (0,\infty) \times (0,\infty) \\ G_2 &= (0,\infty) \times (-\infty,0) \times (-\infty,0) & G_6 &= (0,\infty) \times (-\infty,0) \times (0,\infty) \\ G_3 &= (-\infty,0) \times (0,\infty) \times (-\infty,0) & G_7 &= (-\infty,0) \times (0,\infty) \times (0,\infty) \\ G_4 &= (-\infty,0) \times (-\infty,0) \times (-\infty,0) & G_8 &= (-\infty,0) \times (-\infty,0) \times (0,\infty) \end{aligned} \qquad (A.2)$$

We can compute the probabilities for the 12 cells in the following way, where we only show the details for the first cell,

$$P\left(Y_i^{EXT} = 1, Y_i^{INF} = 1, Y_i^A = 0\right)$$

$$= P\left(u_i \geq -\beta_0 - \sum_j \beta_j X_{ji}, e_i \geq -\delta_0 - \sum_k \delta_k Z_{ki}, v_i \leq \alpha_1 - \sum_l \zeta_l S_{li} - \gamma_1 - \gamma_2\right)$$

$$= P\left(u_i + \beta_0 + \sum_j \beta_j X_{ji} \geq 0, e_i + \delta_0 + \sum_k \delta_k Z_{ki} \geq 0, v_i - \alpha_1 + \sum_l \zeta_l S_{li} + \gamma_1 + \gamma_2 \leq 0\right) \text{(A.3)}$$

$$= \int_{G_1} \phi(v - \mu_{11}, M) dv = P(G_1, \mu_{11}, M)$$

where M is defined in (8) and ϕ is the trivariate normal density with vector of means 0 and variance covariance matrix M. We can similarly define the probability of any of the 8 rectangles in the following way:

$$P(G_s, \mu_{ij}, M) = \int_{G_s} \phi(v - \mu_{ij}, M) dv, \quad s = 1, \ldots, 8. \tag{A.4}$$

Thus we have:

$$P\left(Y^{EXT} = 1, Y^{INF} = 1, Y^A = 0\right) = P(G_1, \mu_{11}, M)$$
$$P\left(Y^{EXT} = 1, Y^{INF} = 0, Y^A = 0\right) = P(G_2, \mu_{12}, M)$$
$$P\left(Y^{EXT} = 0, Y^{INF} = 1, Y^A = 0\right) = P(G_3, \mu_{13}, M) \tag{A.5}$$
$$P\left(Y^{EXT} = 0, Y^{INF} = 0, Y^A = 0\right) = P(G_4, \mu_{14}, M)$$

for the four cases corresponding to no adoption, while the four cases corresponding to partial land adoption are given by:

$$P\left(Y^{EXT} = 1, Y^{INF} = 1, Y^A = 1\right) = P(G_1, \mu_{21}, M) - P(G_1, \mu_{11}, M)$$
$$P\left(Y^{EXT} = 1, Y^{INF} = 0, Y^A = 1\right) = P(G_2, \mu_{22}, M) - P(G_2, \mu_{12}, M)$$
$$P\left(Y^{EXT} = 0, Y^{INF} = 1, Y^A = 1\right) = P(G_3, \mu_{23}, M) - P(G_3, \mu_{13}, M) \tag{A.6}$$
$$P\left(Y^{EXT} = 0, Y^{INF} = 0, Y^A = 1\right) = P(G_4, \mu_{24}, M) - P(G_4, \mu_{14}, M)$$

and for the case of full land adoption we have:

$$P\left(Y^{EXT}=1, Y^{INF}=1, Y^A=2\right)= P\left(G_5, \mu_{21}, M\right)$$
$$P\left(Y^{EXT}=1, Y^{INF}=0, Y^A=2\right)= P\left(G_6, \mu_{22}, M\right)$$
$$P\left(Y^{EXT}=0, Y^{INF}=1, Y^A=2\right)= P\left(G_7, \mu_{23}, M\right) \qquad (A.7)$$
$$P\left(Y^{EXT}=0, Y^{INF}=0, Y^A=2\right)= P\left(G_8, \mu_{24}, M\right)$$
$$\begin{aligned}&= 1 - P\left(G_1, \mu_{21}, M\right) - P\left(G_2, \mu_{22}, M\right) - P\left(G_3, \mu_{23}, M\right)\\ &\quad - P\left(G_4, \mu_{24}, M\right) - P\left(G_5, \mu_{21}, M\right) - P\left(G_6, \mu_{22}, M\right)\\ &\quad - P\left(G_7, \mu_{23}, M\right)\end{aligned}$$

Appendix 2: Computation of Marginal Effects.

The computation of the marginal effects involves computing the derivatives of the above probabilities. Let's consider first the marginal effects on $P(Y^A=1)$. The effect of a continuous regressor that appears in the 3 equations such as AGE which has coefficients $B_{AGE}=(\beta_1, \delta_1, \zeta_1)'$ (corresponding to eqs. (7a), (7b) and (7c) respectively) on $P(Y^A=1)$ can be computed as (note that this probability is the sum of the four terms in expression (A.6) and that all the probabilities on the right hand side depend on the regressors only through the vectors of means defined in (A.1)):

$$\begin{aligned}\frac{\partial P\left(Y^A=1\right)}{\partial AGE} &= B_{AGE}'\left[\nabla_\mu P\left(G_1, \mu_{21}, M\right) - \nabla_\mu P\left(G_1, \mu_{11}, M\right)\right]\\ &\quad + B_{AGE}'\left[\nabla_\mu P\left(G_2, \mu_{22}, M\right) - \nabla_\mu P\left(G_2, \mu_{12}, M\right)\right] \qquad (A.8)\\ &\quad + B_{AGE}'\left[\nabla_\mu P\left(G_3, \mu_{23}, M\right) - \nabla_\mu P\left(G_3, \mu_{13}, M\right)\right]\\ &\quad + B_{AGE}'\left[\nabla_\mu P\left(G_4, \mu_{24}, M\right) - \nabla_\mu P\left(G_4, \mu_{14}, M\right)\right]\end{aligned}$$

where for instance the expression $\nabla_\mu P(G_1, \mu_{21}, M)$ denotes the gradient with respect to the vector of means μ_{21} of the probability of rectangle G_1. This gradient has three components, each one corresponding to one of the equations in (7a), (7b), (7c).

Note that to compute the effect of a continuous regressor that does not appear in some equation then we just set the corresponding coefficient in the vector B equal to zero. The indirect (through eqs. (7a), (7b)) and direct (through eq. (7c)) effects of a continuous regressor such as *AGE* can similarly be computed by multiplying the corresponding element of the vector B_{AGE} by the corresponding element of the gradient expressions above.

The effect of a discrete regressor S has been computed as:

$$P\left(Y^A = 1 \middle| z = 1\right) - P\left(Y^A = 1 \middle| z = 0\right) \tag{A.9}$$

using the terms in expression (A.6)

Similarly the effect of the endogenous variables Y_1, Y_2 can be computed as:

$$P\left(Y^A = 1 \middle| Y^p = 1\right) - P\left(Y^A = 1 \middle| Y^p = 0\right) \tag{A.10}$$

with $p=EXT$, *INF* using the expressions in (A.6).

The procedure to compute the marginal effects on $P(Y^A=0)$ and $P(Y^A=2)$ is analogous. In addition we have computed in a similar fashion the marginal effects on $P(Y^{EXT}=1)$ and $P(Y^{INF}=1)$ of the regressors entering those equations taking into account that:

$$
\begin{aligned}
P\left(Y^{EXT} = 1\right) = & P\left(Y^{EXT} = 1, Y^{INF} = 1, Y^A = 0\right) + P\left(Y^{EXT} = 1, Y^{INF} = 0, Y^A = 0\right) \\
& + P\left(Y^{EXT} = 1, Y^{INF} = 1, Y^A = 1\right) + P\left(Y^{EXT} = 1, Y^{INF} = 0, Y^A = 1\right) \\
& + P\left(Y^{EXT} = 1, Y^{INF} = 1, Y^A = 2\right) + P\left(Y^{EXT} = 1, Y^{INF} = 0, Y^A = 2\right)
\end{aligned} \tag{A.11}
$$

and

$$P\left(Y^{INF} = 1\right) = P\left(Y^{EXT} = 1, Y^{INF} = 1, Y^A = 0\right) + P\left(Y^{EXT} = 0, Y^{INF} = 1, Y^A = 0\right)$$
$$+ P\left(Y^{EXT} = 1, Y^{INF} = 1, Y^A = 1\right) + P\left(Y^{EXT} = 0, Y^{INF} = 1, Y^A = 1\right) \qquad (A.12)$$
$$+ P\left(Y^{EXT} = 1, Y^{INF} = 1, Y^A = 2\right) + P\left(Y^{EXT} = 0, Y^{INF} = 1, Y^A = 2\right)$$

Finally, the standard errors of the marginal effects were obtained using block resampling techniques which entails grouping the data randomly in a number of blocks and reestimating the system leaving out each time one of the blocks of observations and then computing the corresponding standard errors (see Politis and Romano,1994).

Endnotes

[1] This is especially true for Greek organic adopters. The structural characteristics of Greek farm operations, namely the high degree of land fragmentation and their multi-output orientation particularly facilitate partial land organic conversion.

[2] Within the E.U. organic farming was originally institutionalized via EU Regulations 2092/91 and 2078/92.

[3] It should be noted here that our empirical results are not subject to sample selection bias as all sample participants were aware about organic farming.

[4] Given the peculiar nature of our sample survey it is evident that extra attention should be paid in generalizing our farm demographic, socioeconomic and structural characteristics for the whole agricultural sector in Crete.

[5] However, it should be noted that Dinar and Yaron (1990) found that the relationship between education level and technology adoption is positive up to a certain level and then is becomes negative.

[6] However, as noted by Just and Zilberman (1983), if the new technology is risk-increasing then larger farms tend to use less of the modern technology than smaller farms if relative risk-aversion is decreasing and vice versa.

[7] It should be noted here that only the exogenous subsidies rates foreseen within the respective common market organization and not those referring to EU Regulations 2092/91 and 2078/92 were included in our model.

[8] The corresponding Likelihood-Ratio test statistic is 41.92 with 3 d.f.

[9] The percent of correctly prediction for each one of the twelve probabilities ranges from a minimum of 45% to a maximum of 96%. The values are not reported here but available upon request.