# Adoption of agricultural innovations as a two-stage partial observability process

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## Abstract

In this paper, we reconsider the appropriateness of certain statistical analyses in innovation adoption studies and suggest that partial observability models may sometimes be more useful. The proposed models allow for a flexible specification of the process of adoption from one stage to two stages, facilitate the modelling of non-adopters and remedy the violation of the assumption of full information. An application to the adoption of organic cultivation in Greece demonstrates the relative merits of the proposed analysis.
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## 1. Introduction

A vast amount of economic literature on innovation and technology adoption in agriculture ends up by estimating a dichotomous adoption decision in terms of adoption or non-adoption. Such studies examine the effects of various factors on the probability to adopt, and their findings have important implications for the design of policies for the dissemination and diffusion of innovations. Static adoption studies often ignore the fact that most decision making processes concerning innovation adoption involve a multistage procedure of organisational change which affects the technical and social systems of economic actors. This is usually due to the fact that the mechanism for observing adoption is restricted, for practical reasons, to recording the final decision of 'whether or not to adopt', and is not

the outcome of any intermediate stages or decisions leading to the final result.

Studies of static adoption may be divided into two broad categories with reference to the conceptual paradigm and statistical procedures used for modelling the decision making process underlying adoption. The first category includes those studies that model the adoption-decision process as a single-stage (usually binary) decision process. The second category includes those studies that attempt to model the adoption-decision process as a two or multistage (usually a two-stage) decision process. The aim of this paper is problem solving for the first category of adoption studies: the definition and solution of the very practical problems that stem from the treatment of the simple adoption outcome (adoption–non-adoption) as a univariate binary response.

We suggest that, in many cases, the adoption observation is due to a partially defined observational mechanism and thus it should be treated as such by

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existing econometric techniques. A partially defined observational mechanism can assume a two-stage adoption-decision process (second category of adoption models) applied on a single binary observation of the adoption decision (first category of adoption models). Thus, the contribution of this paper with reference to the existing literature is the provision of a hybrid model for static adoption studies with which a two-stage adoption-decision process may be assumed even if only one adoption stage (single stage) is observed. The present paper does not provide a new theoretical framework for the study of technology adoption in agriculture. We revisit a standard agricultural economics problem; apply, for the first time, to this kind of problem a standard econometric procedure; and derive results that contribute to an improved understanding of adoption processes. Our approach may be useful in a more appropriate experimental design of adoption studies.

## 2. Individual adoption: definition, assumptions and violations

Numerous articles have been published on agricultural technology adoption in the last 30 years, ranking the 'adoption issue' high on the economics research agenda. Feder et al.'s (1985) survey paper on adoption, a milestone in the economics of adoption literature, cites more than 70 papers directly related to adoption studies in agriculture. Feder et al. (1985), define individual adoption, i.e. adoption at the level of the individual farm or firm, as the degree of use of a new technology in the long-run equilibrium when the farmer (or, in general, the rural entrepreneur) has full information about the new technology and its potential. The degree of use of a new technology may provide a quantitative measure of the extent of adoption when the new technology is divisible, i.e. when this can be divided to measurable units. For non-divisible innovations the extent of individual adoption is necessarily dichotomous (use–non-use or zero-one in quantitative terms).

The above definition of adoption assumes that first, all subjects of an adoption study are fully informed about the new technology and its potential and second, the study is carried out once long-run equilibrium has been attained. Under such circumstances, the

zero (non-use) generating process for both divisible and non-divisible technologies, is a clear rejection of the new technology by a fully aware entrepreneur in the long-run. Such an adoption response is modelled using a probit or logit specification for non-divisible technologies or using a tobit or other appropriate specification for divisible technologies. However, studies where such strict assumptions are met are rare.

Several studies indicate that a good deal of the sampled population does not possess the necessary information and level of awareness concerning the new technology. Several examples are given below. A lack of producer information regarding the profitability of adopting improved practices may be a reason why widespread adoption of best management practices for water quality improvement has not occurred (Feather and Amacher, 1994). Saha et al. (1994) show that for emerging technologies, the percentage of farmers who have not even heard of the innovation may be large (16% in their sample) and suggest appropriate econometric procedures for handling this problem of incomplete information diffusion. Persistent barriers to the adoption of organic agriculture in Sweden and the United States include, among other factors, limited availability of and access to production and market information (Lohr and Salomonsson, 2000). In fact, almost 21% of the sampled farmers noted that they were not able to derive adequate technical and economic advice for adopting organic cultivation. In addition, the long-run may never be attained given the constant flow of overlapping innovations and the fact that most adoption studies are carried out in a reasonably short period since the innovation's first appearance, and certainly not once long-run equilibrium has been attained.

Thus, zeros may be generated by at least two distinct processes. First, due to a violation of the full information assumption, zeros may be generated by observations that are not informed at all or do not possess sufficient information to allow them to enter an evaluation process. Second, due to the fact that long-run equilibrium has not been attained, zeros may be generated by observations that are aware of the new technology but have not yet exercised their option of adopting it. In that sense, zeros may be generated by observations possessing strong risk aversion or by observations that embed into their personal valuation of the new technology future expectations of lower

adoption costs or higher profits and thus postpone the option of exercising adoption. In this paper, however, we do not directly address the implications of violating the long-run equilibrium assumption.

If we assume that the aforementioned arguments concerning violation of the basic assumptions of the definition of adoption are correct, then at least two distinct processes may generate zero observations. The implications for statistical analyses involving the estimation of univariate probit or logit models for non-divisible technologies or the estimation of tobit models for divisible technologies are significant. If only informed observations are presented with the opportunity of becoming adopters, an underlying sample selection process will occur introducing a specification bias. The specification of univariate models assumes that all zero observations possess the same chance of becoming adopters while, in fact, some zero observations do not have a chance of becoming adopters at all. In practice, this implies that the same covariates are allowed to exercise the same impact on both processes, generating zero observations in a given sample.

The following section demonstrates the application of a partially observable, i.e. an assumed but not observed, two-stage model of adoption.

## 3. A partially observed two-stage model of adoption

Any adoption decision is preceded by an information acquisition period frequently called an awareness or learning period. Saha et al. (1994), use a rather limited definition of awareness, according to which a producer has 'heard of', i.e. is only nominally acquainted with a technological innovation. However, this operational definition of awareness is used in the framework of an emerging technology. In this paper, 'awareness' is defined as the process by which producers decide to expend effort on collecting additional information about the potential of an innovation to increase the net present value of their profits. In this stage of the adoption process, a producer's acquired information determines his/her ability to evaluate the impact of adoption on his/her own economic activity. The producer's optimal information level may be the outcome of an underlying utility maximisation

problem, subscripts suppressed, as

$$I^* \equiv I(x) \tag{1}$$

where $I^*$ is the optimal level of information and $x$ a vector of the producer's demographic, economic and enterprise specific characteristics. Saha et al. (1994) have posited such an information collection stage assuming that a producer is aware of an innovation if the level of acquired information is greater than a certain threshold information level $I^T$

$$I^*(x) > I^T \tag{2}$$

or

$$Y^{A*} \equiv I^*(x) - I^T > 0 \tag{3}$$

Eq. (3) may be expressed as a linear model

$$Y^{A*} \equiv \beta x + \varepsilon^A \tag{4}$$

where $\beta$ is a vector of parameters to be estimated and $\varepsilon^A$ is an error term related to the level of awareness, the superscript A standing for awareness. In practice, $Y^{A*}$ is not observed. However, it may be assumed that there is an indicator variable denoted $Y^A$ which equals 1 if the producer is aware of the innovation, and 0 if he/she is not. In other words

$$Y^A = \begin{cases} 1, & \text{if } Y^{A*} \geq 0, \quad \beta x \geq -\varepsilon^A \\ 0, & \text{if } Y^{A*} < 0, \quad \beta x < -\varepsilon^A \end{cases} \tag{5}$$

If there is evidence, for example in the case of emerging technologies, that a significant proportion of the sampled population is completely ignorant of the innovation, then the awareness stage may be broken down into two stages and the whole adoption process in three stages. In that case, the hurdle associated with the first stage of awareness may refer to whether the producer knows of the innovation and the second stage may refer to the level of information collected by the producer, a level which will allow him/her to evaluate and assess the innovation. In emerging technologies it is probable that the first stage (first hurdle), is fairly high and the use of two stages for the awareness process is meaningful. In more established technologies, however, the first stage may be omitted as it will not cause significant specification bias due to the fact that producers are at least aware of the innovation. In the present work we assume that all producers have heard of the innovation and so awareness collapses only to one stage, that of information collection.

Once the producer is aware of an innovation and has acquired an adequate level of information concerning the financial and regulatory terms of adoption, or he is in the awareness formation process, he evaluates the economic/financial option of adoption. The evaluation stage may be theoretically modelled under a framework of either maximised expected utility or maximised expected profits. An analysis based on maximised expected utility has the merit of making explicit the idea that the expected utility is conditional on information acquired by the producer and facilitates goals beside profit. On the other hand, an analysis based on expected profits makes explicit reference to profits, costs and revenues, as the main driver underlying the evaluation decision making process. In the present analysis we proceed under an expected profits maximisation framework which, is spite of being narrower than the expected utility framework, is closely connected to the application concerning the adoption of organic cultivation that we present in the following section. The adoption of organic cultivation is highly dependent on transaction costs related to certification and the product's market price. If we denote by $\pi_p$ the subjective estimate of the expected present value of the enterprise's future stream of net benefits under the present operation, and by $\pi_f$ the subjective estimate of the expected present value of the enterprise's future stream of net benefits under the operation of the adopted innovation, then the producer's expectation of the net present value of the net benefits differential is:

$$E(\pi_f - \pi_p) = \gamma z + \varepsilon^O \tag{6}$$

where $z$ is a vector of the enterprise's and the producer's financial characteristics, $\gamma$ vector of parameters to be estimated and $\varepsilon^O$ an error term related to the innovation's option valuation, the superscript O standing for option. We define the qualitative variable that indexes the decision of a producer to exercise the option, i.e. to adopt the innovation, as

$$Y^O = \begin{cases} 1, & \text{if } E(\pi_f - \pi_p) \geq 0, \quad \gamma z \geq -\varepsilon^O \\ 0, & \text{if } E(\pi_f - \pi_p) < 0, \quad \gamma z < -\varepsilon^O \end{cases} \tag{7}$$

The majority of empirical studies do not record (observe) any variables that can be used as a proxy for either the outcome of the information acquisition process (Eq. (5)) or of the outcome of the option valuation process (Eq. (7)). What we usually observe is

a qualitative variable indexing whether the innovation has been adopted or not, as

$$Y = Y^A Y^O = \begin{cases} 1, & \text{if the innovation is adopted} \\ 0, & \text{if the innovation is not adopted} \end{cases} \tag{8}$$

The case of $Y = 1$ will occur if $Y^A = Y^O = 1$, while the case of $Y = 0$ may be due to either inadequate awareness and information ($Y^A = 0$), or in the case of the producer's being aware, to an unwillingness to exercise the option ($Y^O = 0$). Eq. (8) defines a partial observation mechanism of innovation adoption based on information acquisition and the option valuation of the innovation under consideration. Failing to recognise the partial observability mechanism in Eq. (8) and fitting the model as a univariate probit model will result in misleading conclusions due to specification bias. The proposed two-stage adoption process may also facilitate consideration of other economic problems related to technology adoption. In the case of small rural firms or farms, the first stage may concern access to credit because of credit rationing and the second stage may concern valuation once credit has been acquired.

If we assume that $Y^A$ and $Y^O$ are simultaneously determined then we deal with a concurrently determined two-stage adoption process. Assuming that the variances of $\varepsilon^A$ and $\varepsilon^O$ have been normalised to equal unity and their correlation is $\rho$, the log-likelihood function of a sample of $n$ observations is given by Poirier (1980) as

$$L(\beta, \gamma, \rho) = \sum_{i=1}^{n} Y_i \ln[F(\beta'x, \gamma'z; \rho)] \\ + (1 - Y_i) \ln[1 - F(\beta'x, \gamma'z; \rho)] \tag{9}$$

where $F(\cdot)$ denotes the bivariate standard normal distribution. If we assume that $Y^A$ and $Y^O$ are sequentially determined, then $\rho = 0$ and the log-likelihood function is given by Abowd and Farber (1982) as

$$L(\beta, \gamma) = \sum_{i=1}^{n} Y_i \ln[\Phi(\beta'x)\Phi(\gamma'z)] \\ + (1 - Y_i) \ln[1 - \Phi(\beta'x)\Phi(\gamma'z)] \tag{10}$$

where $\Phi(\cdot)$ denotes the univariate standard normal distribution.

In the simple univariate probit model estimated in only one stage, the marginal effects, showing the

percentage change in probability caused by a marginal increase in one of the independent variables, are estimated as

$$\frac{\partial P\,(Y=1)}{\partial x} = f(x'\beta)\beta \tag{11}$$

where $f(\cdot)$ is the standard normal p.d.f., $x$ the vector of variables in the univariate probit model and $\beta$ the vector of estimated coefficients. Abowd and Farber (1982) show how to estimate the marginal effects of changes in explanatory variables on the probability that a farmer has acquired an adequate level of information in a sequential model of partial observability as

$$\frac{\partial P(Y^{\mathrm{A}}=1)}{\partial x} = f(x\beta)\beta \tag{12}$$

where $x$ is the vector of variables in the first stage of the partially observed model and $\beta$ the vector of the estimated coefficients for that stage. The marginal effects on the probability to exercise the adoption option, given that the farmer is informed, are

$$\frac{\partial P(Y^{\mathrm{O}}=1|Y^{\mathrm{A}}=1)}{\partial z} = f(z'\gamma)\gamma \tag{13}$$

where $z$ is the vector of variables in the second stage of the partially observed model and $\gamma$ the vector of estimated coefficients for that stage. The marginal effects on the combined probability to adopt are estimated as

$$\begin{aligned}
&\frac{\partial P(Y=Y^{\mathrm{A}}Y^{\mathrm{O}}=1)}{\partial x} \\
&= \frac{\partial P(Y^{\mathrm{A}}=1)}{\partial x} P(Y^{\mathrm{O}}=1|Y^{\mathrm{A}}=1) \\
&\quad + \frac{\partial P(Y^{\mathrm{O}}=1|Y^{\mathrm{A}}=1)}{\partial z} P(Y^{\mathrm{A}}=1)
\end{aligned} \tag{14}$$

When the technology is divisible, a similar analysis may be applied. In Eq. (7) we may assume that the dependent variable $Y^{\mathrm{O}}$ takes zero values if the option to adopt is not exercised, or positive values if the option is exercised to a certain, measurable, extent. The latter may refer to quantities (or percentages) of production under the new technology, or in the case of agricultural technologies, to the area or the herd size (or the corresponding percentages) on which the new technology is applied. The simultaneous consideration of the awareness Eq. (5) and the option Eq. (7) leads to a solution similar to the double-hurdle model with or without dependent errors. A review of the literature on the adoption of divisible technologies shows that almost all studies use the tobit specification which attributes zero observations to corner solutions instead of using a double-hurdle like model of adoption.

In the application following this section, we consider the adoption-decision process of a non-divisible technology following a two-stage sequential pattern, the first stage being an acquaintance with the technology and the second the decision to invest in it. The application is indicative and aims at demonstrating the comparative advantages of using a partially observable sequential model instead of a simple univariate probit model.

## 4. Application

The data is based on a face-to-face survey of Greek currant producers undertaken in the spring of 1998 in the framework of a European-wide research project. Producers of black Korinthian currants have been provided with the option of adopting organic production techniques under European Union Regulation 2092 since 1991 (European Commission, 1991). Adopting organic currant cultivation implies a thorough re-organisation of the whole production process, involving new sources for inputs, new cultivation techniques, and totally different markets for output. Adoption of organic cultivation is a non-divisible process, as it is extremely difficult for farmers to maintain on the same farm both conventional and organic modes of production. Furthermore, adoption of organic cultivation in Greece involves considerable transaction costs for administration, certification and compliance monitoring that is undertaken by the producer (Falconer, 2000). A random sample of 250 currant producers eligible for adopting organic cultivation techniques resulted in 239 usable questionnaires. The final sample contains 73 farmers that have been certified as organic producers and 166 conventional producers. The Regulation that provides details for the application of the organic aid scheme is complicated and, thus, information acquisition is a crucial stage in the adoption process. The evaluation stage depends upon expected costs (including transaction and administrative costs) and benefits, and the ability

of the farmer to define his/her option by performing precise estimations of such financial elements.

Previous adoption studies and especially studies carried out in Greece have shown that appropriate proxies related to farm and farmer characteristics may be used as explanatory variables in the first and/or second stage of adoption. The farmer's age and level of education are human capital variables frequently used as proxies to indicate the ability to acquire and process information (Damianos and Skuras, 1996a). A dummy variable indicating prior adoption of European Union aid schemes in the currant sector has been included (Saha et al., 1994). The farm's distance from main urban centres reflects spatial variability in production costs (Dimara and Skuras, 1998). The size of the farm's currant plantation is a general proxy of the expected costs and benefits after the adoption of organic cultivation, and has been successfully used in previous studies examining the factors influencing conversion to organic agriculture (Lohr and Salomonsson, 2000). Total farm income, prior to adoption, divided by total cultivated area (including all crops) is used as a broad proxy for overall farming efficiency. The last three variables are included only in the second stage of the adoption process. Definitions and summary statistics of the variables used in the estimation equations are presented in Table 1.

The data collected by this research contained a wide range of variables concerning farm and farmer characteristics, the farmer's perception of quality production, the farmer's attitudes towards organic production and especially in relation to environmental conservation and health risk reduction, and the farmer's relation to rural development institutions and organisations of agricultural extension and information dissemination of the variables concerning farmer and farm household characteristics, the number of dependent children, and the total time devoted to agricultural activities (part vs. full time farming) have been found to be statistically significant in studies examining the need to offer and adopt new rural development instruments in Greece (Dimara and Skuras, 1999) and the development of alternative farm enterprises in Greece (Damianos and Skuras, 1996b). Of the variables concerning farm characteristics, the number of different crops and the farm's size measured in labour units have been found to influence the farm's integration to the agri-food system in Greece (Barlas et al., 2001). Many of these variables were tested in the adoption models presented below but were found to be either statistically non-significant or highly correlated with other variables. For example, farmers' attitudes towards environmental conservation was not found to be statistically significant in any of the models, and the size of the farm measured in labour units was highly correlated with the size of the farm measured in hectares.

Table 2 provides the maximum likelihood estimates of the univariate probit model against the sequentially determined partial observability model presented in Eq. (10) and fitted using LIMDEP (Greene, 1998). Both models have a significant amount of explanatory power. The univariate probit model achieves the highest total percentage of correct predictions but the partial observability model achieves a higher percentage of correctly predicted adopters. The univariate probit model is a constrained version of the sequential partial observability model in which all parameters except the constant of the $\beta$ vector in Eq. (10) are

Table 1

Definition and descriptive statistics of explanatory variables

| Variable name | Mean | S.D. | Definition |
|---|---|---|---|
| Awareness | 0.38 | 0.40 | A non-observed variable predicting a producer to be 'aware' as shown in Eq. (5) |
| Age | 53.64 | 15.95 | Age of the household's head and manager |
| Education | 0.63 | 0.48 | Dummy variable, equals 1 if producer has more than primary education (6 years of formal education), zero otherwise |
| Prior adoption | 0.37 | 0.48 | Dummy variable, equals 1 if producer adopted European Union currants schemes in the past, zero otherwise |
| Distance | 9.97 | 7.02 | Proximity of the farm to main urban centres in km |
| Size | 16.23 | 10.51 | The size of currant plantations in stremma (10 strema = 1 ha) |
| Efficiency | 0.36 | 0.35 | Average agricultural income from all cultivations prior to adoption in million Greek Drachmas per stremma |

*Note*: descriptive statistics for the awareness variable are based on correctly predicted cases.

Table 2
Estimated coefficients and marginal effects from the univariate and partial observability model

| Variable | Univariate probit | | Partially observed sequential model Eq. (10) | | |
|---|---|---|---|---|---|
| | Coefficient estimates $Y$ | Marginal effects Eq. (11) | Coefficient estimates | | Marginal effects Eq. (14) |
| | | | $Y^A$ | $Y^O$ | |
| Constant | −1.176 (−2.265) | | 1.831 (2.087) | 5.475 (0.001) | |
| Age | −0.007 (−1.035) | −0.003 | −0.052 (−3.111) | 0.041 (2.504) | −0.020 (−2.753) |
| Education | 0.752 (3.665) | 0.237 | 1.918 (4.152) | −9.063 (−0.010) | 0.636 (3.892) |
| Prior adoption | 0.695 (3.671) | 0.242 | 0.051 (0.150) | 1.770 (4.063) | 0.021 (4.087) |
| Distance | 0.002 (1.172) | 0.008 | – | −1.753 (−4.311) | −0.012 (−4.113) |
| Size | 0.008 (0.818) | 0.003 | – | 0.041 (2.286) | 0.015 (2.307) |
| Efficiency | 0.312 (1.076) | 0.122 | – | 1.740 (2.212) | 0.067 (2.011) |
| log likelihood | −125.728 | | −112.619 | | |
| $\chi^2$ (d.f.) | 42.706 (6) | | 74.959 (10) | | |
| Percentage of correct predictions (all) | 75.73 | | 54.81 | | |
| Percentage of correct predictions (adopters) | 43.84 | | 71.23 | | |

Note: numbers in parentheses next to the coefficients are asymptotic t-ratios. For dummy variables the marginal effects are analysed as discrete or relative changes when the respective dummy takes its two different values 0 and 1, respectively.

equal to zero, and the constant is set to some arbitrary large positive number (Abowd and Farber, 1982). The maximum log-likelihood value of the sequential partial observability model is −112.6, compared with a log-likelihood value of −125.7 in the univariate probit model. The likelihood ratio test statistic of 26.2 is sufficient to reject the univariate probit model since the critical value of a $\chi^2$ distribution with four degrees of freedom at the 0.005 level of significance is 14.9.

The effect of certain variables on the adoption decision shows the additional information gained once a partial observability model is used. The producer's age is assumed to influence both the information and valuation process. In the univariate probit model, age has a non-significant, negative coefficient. In the partial observability model the coefficients for age are statistically significant but in the information acquisition phase the sign is negative and in the evaluation phase the sign is positive. The combined marginal effect for age shown in Table 2 is negative, implying that for a farmer who is a year older than the average age in the sample, and with all other variables at their sample means, the probability that organic cultivation will be adopted decreases by 2%. In other words, the sequential partial observability model reveals the contradictory action of age in the underlying processes leading to the adoption decision.

Education and prior experience with European Union schemes are both significant in the univariate probit model but are significant only in the information acquisition and valuation phases, respectively, in the sequential partial observability model. The marginal effects in the univariate probit model show that with all other variables held constant at their sample means, the probability that organic cultivation is adopted is 23.7% higher for a farmer with more than basic education. The respective combined marginal effect in the sequential partial observability model is 63.6%. The marginal effects for prior experience with European Union schemes in the univariate probit model show that prior experience increases the probability that organic cultivation will be adopted by 24.2%. In the sequential partial observability model, the respective change is only 2.1%.

Distance has a positive but non-significant effect in the univariate probit model and a statistically significant negative effect in the sequential partial observability model. The combined marginal effect shows that the probability that organic cultivation will be adopted decreases by 1.2% for each kilometre that the sample's average farm is removed from an urban centre. Finally, the size of currant plantation and of farming efficiency are not significant in the univariate probit model but are significant in the valuation phase of the partial

Table 3
Descriptive statistics of explanatory variables by predicted categories of producer

| Variable name | Not aware: $P[Y^A = 0]$ $= P[Y^{A*} < 0] = P[\varepsilon^A < -\beta x]$ | | Aware and willing to exercise the option: $P[Y^A Y^O = 1] =$ $P[Y^A = 1] P[Y^O = 1 | Y^A = 1] = P[\varepsilon^A \geq -\beta x] P[\varepsilon^O \geq -\gamma z]$ | |
|---|---|---|---|---|
| | Mean | S.D. | Mean | S.D. |
| Age | 56.16 | 13.55 | 46.23 | 12.07 |
| Education | 0.49 | 0.50 | 0.92 | 0.14 |
| Prior adoption | 0.21 | 0.41 | 0.60 | 0.49 |
| Distance | 10.67 | 7.39 | 8.94 | 6.43 |
| Size | 14.68 | 9.48 | 17.85 | 10.61 |
| Efficiency | 0.35 | 0.33 | 0.41 | 0.41 |
| $N$ | | 149 | | 52 |

Note: descriptive statistics are based on correctly predicted cases.

observability model. The combined marginal effect of the farm's size shows that the probability that organic cultivation will be adopted increases by 15% for each hectare that the farm is larger than the sample average. The respective marginal effect for the farm's efficiency shows that the probability that organic cultivation will be adopted increases by 6.7% for each million drachmas above the average agricultural income prior to the adoption. Table 3 presents descriptive statistics for the exogenous variables by category of producer as this is predicted from the partial observability model.

In general, the aforementioned results agree with results reported by most static adoption studies carried out in Greece and elsewhere, as well as with studies of the adoption of organic cultivation, of which Rigby and Cáceres (2001) provide an updated review. However, the partial observability model provides additional information, conditional of course on the correct theoretical specification of the model and the consequent choice of variables to be included or eliminated from the two stages of the partial observability model. The theoretical specification of each of the two stages of the partial observability model may be founded on economic theory, in the same way that a bivariate static adoption model is founded. To state this more clearly, the economic foundation of a two-stage sequential partial observability model is not different from that of a bivariate probit model. Thus, we form the model and choose the proxies for a partial observability model in the same way we construct the theoretical model and choose the appropriate proxies for a two-stage full observation model. In statistical

terms, however, the omission or inclusion of variables in the two-stage sequential partial observability model may be tested with a likelihood ratio test comparing the log likelihoods of the alternative models. The inclusion or exclusion of a variable in any of the two stages affects the estimation of the marginal effects as shown in Eq. (14) due to its presence or absence in the vectors $x$ and $z$ used to estimate the marginal effects.

## 5. Conclusions

We argue that the assumption of full information embedded in the definition of adoption, is frequently violated and thus many adoption studies using probit, logit and tobit analyses for modelling the static adoption decision are mis-specified. The literature today provides two broad categories of static adoption models; those that model adoption in one stage using univariate probit models and those that model adoption in two stages using bivariate adoption models. The proposed partial observability adoption model is a hybrid model that can assume a two- or three-stage adoption process without the need to observe the outcome of each stage.

However, the application of partial observability models in adoption studies has two main weaknesses. First, often a technology is adopted in one stage, i.e. the assumed two or three stages collapse to one. Second, there is a deeper problem concerning identification; which factors really affect one phase but not the other? The use of partially observable models may give the impression that researchers are allowed

to experiment with different specifications until they reach a 'desired' result. The solution to this issue lies in the careful use of the literature and the use of correctly specified theoretical models, exactly as we would do if a two-stage bivariate model were constructed. Furthermore, the econometric problem of model identification may be confronted using appropriately constructed likelihood ratio or Lagrange multiplier tests examining variable omission or redundancy.

The application of partial observability models is worth trying in individual static adoption studies. Their use permits researchers to test hypotheses concerning the simultaneous versus the sequential nature of adoption process and reveals the frequently contradictory influence of certain factors on the decision making process. Such indications are important when designing new surveys or drawing conclusions for policy. The behaviour of certain variables may indicate, for example, the need to target policy dissemination measures (affecting the information acquisition phase) or financial schemes (affecting the evaluation phase) at certain parts of the entrepreneurial farm population under consideration.

In particular, the partial observability model may be useful when there is evidence that a certain part of the farming population is somehow excluded from adopting an innovation. Such circumstances may arise when certain farmers are excluded from information, advice or extension services, or when farmers are excluded from financial sources that are vital for the adoption of the innovation. The latter may be particularly valid in adoption studies where a number of smallholders are involved and credit rationing is applied. In that case, the first stage of the partial observability model may capture credit rationing and non-adoption due to farmers' exclusion from accessing financial sources, while the second stage can model adoption as a result of positive expected net value of the future stream of profits or utility.

Future research may attempt to fit three-stage sequential partial observability models for non-divisible technologies and double-hurdle models for divisible technologies. The latter should be compared with adoption models based on tobit formulations. Also, if theoretical and empirical evidence permits, a researcher might also attempt to fit the simultaneous partial observability model in Eq. (9), which, however, is computationally more difficult and, in certain cases, intractable as it involves bivariate distributions.

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## References

Abowd, J.M., Farber, H.S., 1982. Job queues and the union status of workers. Ind Labour Relations Rev. 35, 354–367.

Barlas, Y., Damianos, D., Dimara, E., Kasimis, C., Skuras, D., 2001. Factors influencing the integration of alternative farm enterprises into the agro-food system. Rural Sociol. 66, 342–358.

Damianos, D., Skuras, D., 1996a. Unconventional adjustment strategies for rural households in the less developed areas in Greece. Agric. Econ. 15, 61–72.

Damianos, D., Skuras, D., 1996b. Farm business and the development of alternative farm enterprises: an empirical analysis in Greece. J. Rural Stud. 12, 273–283.

Dimara, E., Skuras, D., 1998. Adoption of new tobacco varieties in Greece: impacts of empirical findings on policy design. Agric. Econ. 19, 297–307.

Dimara, E., Skuras, D., 1999. Importance and need for rural development instruments under the CAP: a survey of farmers' attitudes in marginal areas of Greece. J. Agric. Econ. 50, 304–315.

European Commission, Council Regulation (EEC) No. 2092/91, 1991. Organic production of agricultural products and indications referring thereto on agricultural products and foodstuffs. Official J. Eur. Commun. 34, 1–15.

Falconer, K., 2000. Farm level constraints on agri-environmental scheme participation: a transactional perspective. J. Rural Stud. 16, 379–394.

Feather, P., Amacher, G., 1994. Role of information in the adoption of best management practices for water quality improvement. Agric. Econ. 11, 159–170.

Feder, G., Just, R.E., Zilberman, D., 1985. Adoption of agricultural innovations in developing countries: a survey. Econ. Dev. Cultural Change 31, 255–298.

Greene, W., 1998. LIMDEP Version 7.0. Econometric Software Inc., Bellport, New York, 925 pp.

Lohr, L., Salomonsson, L., 2000. Conversion subsidies for organic production: results from Sweden and lessons from the US. Agric. Econ. 22, 133–146.

Poirier, D.J., 1980. Partial observability in bivariate probit models. J. Econ. 12, 209–217.

Rigby, D., Cáceres, D., 2001. Organic farming and the sustainability of agricultural systems. Agric. Syst. 68, 21–40.

Saha, A., Love, A.H., Schwart, R., 1994. Adoption of emerging technologies under output uncertainty. Am. J. Agric. Econ. 76, 836–846.