Informational Cascades and Technology Adoption: Evidence from Greek and German Organic Growers

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Abstract

The present study aims to empirically analyze the competing effects of social interactions and conversion subsidies on the adoption of organic farming practices for two samples of olive and cereal growers in Greece and Germany, respectively. To this end we construct two alternative indicators to capture informational cascades created in rural areas, one based on demographic characteristics and one on profitability considerations. Building upon the theoretical findings of Foster and Rosenweig (1995), Munshi (2004), Bandiera and Rasul (2006) and Weber (2012), we find that informational cascades are indeed important in revising farmers' perceptions and adoption behavior in both rural areas of Europe. Our results show that conversion subsidies can enhance social network effects internalizing informational externalities even in areas where there is already a critical mass of adopters.

Keywords: informational externalities, organic farming adoption, conversion subsidies, Germany, Greece.

JEL Codes: *Q12*, *Q16*, *C25*.

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1 Introduction

The farmer's decision to adopt technological innovations is an issue intensively studied since Griliches' (1957) pioneering work on the adoption of hybrid corn in the US.[1] The major body of the existing agricultural economics research on technology adoption has been concerned with the question of what determines the decision of a farmer to adopt or reject an innovation based mainly on farm organizational and demographic characteristics (like size of farm operation, educational level and experience of household members) together with environmental conditions. This extensive literature has provided quite useful insights towards improving our understanding of the driving forces of technology adoption and diffusion in rural areas. However, another strand of the technology adoption literature in agriculture, initiated rather recently, argues that the above economic, structural, demographic and environmental factors cannot explain accurately the diffusion patterns as they are conditional on what farmers know about the new technology at any given point in time (Feder, Just and Zilberman (1985), Besley and Case (1993), Wozniak (1993), Rogers (1995)). This part of the literature actually underlines the importance that information accumulation may have on adoption decisions and therefore on the diffusion of technological innovations in the farming sector.

This is not a new story though, and researchers outside agricultural economics have studied the relative importance of information accumulation in detail for some time. Nelson and Phelps (1966) first suggested that the adoption and the rate of diffusion of a continually changing set of technological innovations is primarily affected by the degree of human capital intensity. Later on, Huffman (1977) analyzing the rate of adjustment to a disequilibrium caused by the increasing degree of the available technological innovations and changing market conditions, found farmers' allocative ability to be the main determinant. In a technological adoption framework, farmers' decisions to adopt or not an innovation depend on their innovative ability (a single dimension of allocative ability), that is their capacity to operate efficiently with the new technology. In turn, innovative ability is closely related to information accumulation by individual producers (Schultz, 1972; Rahm and Huffman, 1984). Information accumulation is expected to enhance resource allocation skills and to increase the efficiency of adoption decisions. Farmers with a high level of resource allocation skills will make more accurate predictions of future yields and profitability and thus will make more efficient adoption decisions. Similarly, imperfect information concerning new technologies may bring risks associated with innovation adoption that may raise the possibility of committing errors (Stigler, 1961; Lin, 1991).

Evenson and Westphal (1995) went one step further, identifying both *tacitness* and *circumstantial* sensitivity of new technologies. Techniques of production are tacit if they are not fully embodied in a set of artifacts like a collection of machines, seeds, manuals or blueprints for example. The tacit elements of the new technology might be employed quite differently across producers

[1] Excellent surveys of the existing literature on technological adoption models are provided by Feder and Umali (1993) and Sunding and Zilberman (2001). In addition, Besley and Case (1993) provide a detailed review of some possible empirical models for studying technology adoption in agriculture.

using ostensibly identical techniques of production. Moreover, the performance characteristics of a particular production technology might be sensitive to the circumstances under which it is used. Non-tradable inputs (most obviously land) vary in characteristics in ways that affect the performance of different technologies. The institutional context in which a new technology is used and in particular the relationship between hired workers and farmers can also influence the performance of production technologies. Furthermore, the general economic or political environment may also affect the application of the new technology and thus adoption rates. If a technology is characterized by these kinds of tacitness and circumstantial sensitivities, then learning and innovation are interrelated whenever it is newly developed, even if the explicit elements of technology are indeed embodied.

To overcome these tacit and circumstantial barriers to adoption, there must be investments in learning.[2] There are two types of learning. Farmers might engage themselves in *learning-by-doing*, experimenting with the new technology to reveal the tacit elements of the technology or to determine the sensitivity of the technology to local conditions. Alternatively, farmers might *learn-from-others*, either from other producers engaged in learning-by-doing, or from locally based researchers and extension agents. The two types of learning have different implications for policy and for the character of agricultural growth. When producers learn from their own experimentation, they actually undertake an investment that yields uncertain returns. When producers learn from each other, not only is there risky investment, but that investment generates an informational spillover. This learning externality underlies some modern models of economic growth and provides a role for government or other social institutions which might supply a mechanism for rewarding experimenters for the positive externality generated by their activities (Romer, 1990; Lucas, 1988).

Among the different types of learning, learning-from-others, termed under the general notion of *social learning*, has attracted the interest of many researchers as an explanation for the adoption and diffusion of technological innovations among rural populations.[3] This recently developed part of the technology adoption literature is based on the early contributions of Banerjee (1992) and Bikhchandani *et al.*, (1992). In summary, social learning essentially describes a process of information accumulation by which an individual producer learns from his neighbours' experiences (their previous decisions and outcomes) about the new technology. Foster and Rosenweig (1995) were the first who explored how learning-from-others can affect choices about new technologies studying the adoption of HYV in rural India. Munshi (2004) showed that individual producers may benefit less from informational spillovers if the performance of the new technology depends on the allocative

[2] Rogers (1995) in a similar context distinguished between the *hardware* and *software* aspects of new technology. The former is the tool or the physical object that embodies the technology (*e.g.*, tractor) whereas the later is the information base needed to use it efficiently. According to Rogers (1995) to pass on software knowledge, potential users need to be able to communicate directly with current users who have accumulated experience with the new technology.

[3] Quantification of learning-by-doing is much more complicated and difficult to be identified on empirical grounds and therefore it has been neglected by the relevant literature. Nagypal (2007) provides a thorough discussion on the empirical problems in identifying learning-by-doing.

ability of current users. Bandiera and Rasul (2006) and Maertens (2009) proceed one step further identifying informational spillovers among farmers' indicated influential peers in the rural areas. Conley and Udry (2010) found that farmers adapt their behaviour following the information they gather from most successful neighbours, while Moser and Barrett (2006) revealed that formal informational channels (*i.e.*, extension personnel) act as substitutes to social learning processes in rural Madagascar. Finally, Weber (2012) tried to disentangle the effect of correlated unobservable variables with the social learning process using a unique dataset from Peruvian coffee producers.

This plenty of empirical evidence clearly underlines that if the diffusion of technological innovations is important for the viability and competitiveness of farming operations, it is rather inevitable to find ways to create informational cascades among the rural population. For European agriculture this is even more vital given its current course towards restructuring the farming sector throughout the EU. The high costs of the farm support programmes, the structural over-supply of agricultural commodities resulting in falling farm income and indebtedness, the environmental damage (through the increased use of chemical inputs) and, the loss of consumer confidence in food safety and quality are issues that both past and future reforms of the CAP should take into account. In this context, organic farming can provide an appealing option at least for some types of farming activities in the European agricultural sector. In summary, organic farming is based on the view that agriculture is a form of agro-ecosystem management, designed to promote sustainable supply of food and other products to the home market. Thus, the farm is considered as a balanced unit, where production, environment and human activities are integrated. Chemical fertilizers and pesticides are replaced by organic forms of fertilizer and non-chemical crop protection strategies minimizing pollution from the farm.

This particular farming technology has been actively promoted in the context of the CAP during the last decades, via mainly subsidy-driven policies (summarized in EU Regulations 1257/1999 and 834/2007). Direct subsidy schemes requiring conversion of at least a portion of a farm's land and continued organic production are available in various European countries. Lampkin and Padel (1994) and Pietola and Oude Lansink (2001) analyzed these policy schemes and found conversion subsidies expanded organic farming significantly throughout Europe at least in the early years. Indeed, financial incentives such as direct subsidies (via which the central government essentially "shares" the risk of adoption) are common and effective means of overcoming farmers' adverse perceptions. These types of incentives are however costly, especially if adoption depends primarily on perceptions about future yields. As the recent theoretical and empirical evidence suggest, a promising and equally effective way to promote organic adoption in the farming sector is the provision of informational incentives that revise producers' perceptions about the profit-effectiveness of new organic farming technologies. Although fixed initial costs are incurred, informational incentives may be less costly than financial incentives in the long-run as information spreads throughout the rural communities. While both information and subsidy policies speed up adoption and diffusion of new technologies, Stoneman and David (1986) have shown that subsidy policies may yield welfare losses in the form of income transfers from other sectors of the economy. Moreover, in their study analyzing EU policies related to organic farming Lohr and Salomonsson (2000) found, in contrast to Lampkin and Padel (1994), that market services and information sources rather than subsidies are more effective in encouraging organic adoption throughout the EU.

In light of the above and building upon the theoretical developments of Foster and Rosenweig (1995), Munshi (2004), Bandiera and Rasul (2006) and, Weber (2012), the objective of this paper is to offer an empirical evaluation of the effects that informational and financial incentives have on a farmer's decision to adopt organic farming using two different samples of olive and cereal growers in Greece and Germany, respectively. Based on Roger's (1995) definition of social networks in rural areas as well as on profitability considerations we suggest two alternative indices for capturing empirically the effects of social learning in individual adoption decisions. Empirical results suggest that indeed informational spillovers are more important factors fostering the adoption of organic farming technology in both Greece and Germany than the conventional policy tools of conversion subsidies.

Section 2 presents the empirical model we suggest to analyze informational externalities within technological adoption decisions of organic farmers while discussing as well the econometric specification and empirical data used; estimation results and some important policy recommendations implied by our findings are provided in section 3; finally, summary remarks are offered in the last section of the paper.

2 An Empirical Model for Organic Farming Adoption

2.1 Social Learning and Adoption Decisions

Let's start assuming that farmers are informed about the new organic farming technology only from other farmers in the area that belong to their social network and they have already experimented themselves with the new organic techniques.[4] Under this assumption, each farmer i utilizes a vector of j variable inputs $x_i^v \in \Re_+^J$ (*e.g.*, intermediate inputs, hired labor) together with a vector of h quasi fixed inputs $x_i^q \in \Re_+^H$ (*e.g.*, land, family labor) to produce a single organic crop output $y_i \in \Re_+$, through a well-behaved technology described by the following non-empty, closed set: $T(n^i) = \left\{(x_i^v, x_i^q, y_i) : y_i \leq f_i\left(x_i^v, x_i^q, n^i\right)\right\}$, where n^i is the social network of organic farmers that share information about the new technology with farmer i and $f_i\left(x_i^v, x_i^q, n^i\right) : \Re_+^{J+H+1} \rightarrow \Re_+$ is a strictly increasing, differentiable concave farm production function, representing the maximal organic output from variable and quasi-fixed inputs given the information set and technological constraints for farmer i. Hence, for farmers facing strictly positive organic crop ($p^o \in \Re_{++}$) and variable input ($w \in \Re_{++}^J$) prices, the maximal short-run profits from organic farming are those

[4] As pointed out by referees, learning-by-doing is not considered in our empirical analysis as with only a cross-section of data it is not possible to identify those learning effects.

obtained from the following optimization problem:

$$\pi_i^o\left(p^o, w, x_i^q, n^i\right) = \max_{x_i^v, y_i}\left\{p^o y_i - w' x_i^v : y_i \leq f_i\left(x_i^v, x_i^q, n^i\right)\right\}$$

where, $\pi_i^o\left(p^o, w, x_i^q, n^i\right)$ is positive linear homogeneous in output and, variable inputs prices, non-decreasing in output price and informational spillover and non-increasing in variable input prices. Under a smooth technology, the maximal profits are achieved at the optimal levels of variable input use and output supply, (x^*, y^*), on the boundary of $T(n^i)$.

Following Foster and Rosenweig (1995), Munshi (2004), Bandiera and Rasul (2006) and Weber (2012), we can now consider each farmer's decision to adopt organic farming practices. Let's assume that the adoption decision is formulated with a discrete choice: $\alpha_{it} = 1$ if farmer i adopts organic technology at period t and $\alpha_{it} = 0$ otherwise.[5] Under this setup, the value of the future stream of profits for farmer i from period t to T depends on the information set owned by him due to interaction with other farmers in his social network and their subjective profitability consideration. They are given by:

$$\begin{aligned} V_{it}\left(n_{t-1}^i\right) &= \max_{\alpha_{is}\in\{0,1\}}\left\{E_t \sum_{s=t}^{T} \delta^{s-t}\Big[\left(1-\alpha_{is}\right)\pi_i^c + \alpha_{is}\pi_{is}^o\left(n_{s-1}^i\right)\Big]\right\} \\ &= \max_{\alpha_{it}\in\{0,1\}}\left\{\left(1-\alpha_{it}\right)\pi_i^c + \alpha_{it}E_t\Big[\pi_{it}^o\left(n_{t-1}^i\right)\Big] + \delta V_{t+1}\left(n_t^i\right)\right\} \end{aligned} \tag{1}$$

where π_i^c are the riskless returns obtainable from a fixed input endowment under conventional farming practices, n_{s-1}^i is the stock of adopters on farmer i social network up to and including period s and, δ is the discount rate.

Under this general setup, farmer i adopts organic technology in period 0 if the following inequality holds:

$$E_0\big[\pi_{i0}^o\left(n_0^i\right)\big] + \delta V_{i1}\left(n_1^i\right) \geq \pi_i^c + \delta V_{i1}\left(n_0^i\right) \tag{2}$$

that is, if the present value of profits from adopting organic technology in period 0 is higher than the present value of leaving crop technology unchanged.

From (2) it is obvious that individual expectations on the adoption rate of organic technology by the members of the social network, have a direct effect on the value of individual expected farm profits. The higher the number of adopters that farmers expect from their social network is, the higher the profit they expect taking advantage of the generated informational spillovers. On the other hand, individual farmers may have an incentive to delay adoption if many members of their social network are expected to adopt organic technology early. Farmers who expect that

[5] We empirically model adoption decisions as discrete choices (adopters, non-adopters) rather than choices over the acreage devoted to organic cultivation due to data limitations.

many of their neighbors will adopt the new organic technology may delay their own adoption as the value of the information that they will receive will be higher. Intuitively, if farmers are myopic they will have less incentive to delay strategically adoption. This creates a positive correlation between the adoption propensity of the farmer and the adoption choices of his network. On the other hand, for more forward-looking farmers this is more likely to be negatively correlated. Both the informational externality and the strategic delay effect are concave in the number of adopters in the network (Bandiera and Rasul, 2006).[6]

2.2 Survey Data

The empirical data used in this study come from two detailed and independent surveys run in Greece and Germany on the adoption and diffusion of organic farming technologies among Greek and German farmers. The surveys were undertaken within the context of the Research Program *FOODIMA* financed by the *European Commission* during the 2007-10 period.[7] Concerning the Greek survey, the final sample consists of 210 randomly selected olive producing farms located in the western part of the island of Crete (in the south of Greece) and refers to the 2006-07 cropping period. Olive farming together with greenhouse cultivation are the most representative farming activities in the south of Greece. Among them organic techniques are quite popular for olive growers validating our choice over this particular crop. Using the *Agricultural Census* published by the *Greek Statistical Service*, olive farms in Crete were classified according to their size, location and farming activities (*i.e.*, organic, conventional). Then, with the assistance of extension agents from the *Regional Agricultural Directorate* of Crete a random sample of olive growers was selected to analyze their adoption behavior.

On the other hand, the German survey contained 72 farms specialized in cereal cultivation (*i.e.*, wheat, barley, oats, rye) for the same cropping year (*i.e.*, 2006-07) randomly selected in the following regions: Saxony-Anhalt, Thuringia, Brandenburg and North-Rhein-Westfalia in central and east Germany. Cereal farms were chosen as they represent a dominant part of organic cultivation in this particular rural areas of Germany. Apart from cereals, surveyed farms were also cultivating sugar beets and corn silage. In both cases surveyed farmers were asked to recall the time of adoption of organic farming technology together with some key variables related to their farming operation on the same year (*i.e.*, production patterns, input use, average yields, gross revenues, structural and demographic characteristics). Farmers were also asked to provide analytical information concerning subsidies received and past innovation behaviour and attitudes. All information was gathered using questionnaire-based field interviews undertaken by the extension personnel from the Regional Agricultural Directorate of Crete and Researchers from the Martin Luther University of Halle-

[6]Strategic delay of technology adoption has been also recognized in the theoretical literature outside agricultural sector (*e.g.*, Caplin and Leahy (1998), Kapur (1995), McFadden and Train (1996))

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

Wittenberg.

The profitability condition in (2) implies that farmers adopt organic technology if the present value of profits from adopting in period 0 is higher than the present value of keeping the conventional crop technology. This condition is determined by informational cascades created in rural areas (*i.e.*, learning-from-others) and by individual perceptions on the profitability of both farming technologies (*i.e.*, farm conditional profits). Apart from those two factors, as it was posed at the outset, organic farming has been actively promoted in the EU in the context of the CAP via mainly subsidy-driven policies summarized in EU Regulations 1257/1999 and 834/2007. According to these EU Regulations, farmers are entitled to a direct subsidy from national authorities if they convert at least a portion of their land and continue organic production for a certain period of time (usually a minimum of five years depending on the crop and the specific region). These subsidies are paid on a acreage basis depending also on the characteristics of the regions where farms are located (*e.g.*, less-favored areas) and therefore differ among growers. Since the institutional framework is known to the farmers before decisions are made, they can easily calculate the final level of subsidy that they are entitled to if they convert part of their land to organic farming. Hence, we can reasonably assume that individual perceptions about the profitability of organic farming technology are also influenced by these conversion subsidies offered by European agricultural policy schemes. In running both surveys, we have explicitly asked farmers who have converted to organic farming to state the exact amount of organic subsidies they received after conversion. In the case of conventional farmers, the amount of potential subsidies has been computed as follows: for each village in the sample, the total amount of subsidies received by the farmers in the village has been divided by the total size of land co! nverted, obtaining thus an average subsidy per unit of land, simultaneously the total amount of converted land in the village at the time of the survey has been divided by the total amount of land in the village to obtain a proportion of converted land in the village. Subsequently for each conventional farmer in a given village, the potential subsidy has been computed as the product of his farm size, the village proportion of converted land and the average subsidy per unit of land. Combining the data on subsidies received by organic farmers and potential subsidies for non-organic farmers a single variable, conversion subsidies, has been created and used as an explanatory variable in analyzing adoption decisions in both the Greek and the German sample.

In order to quantify empirically learning-from-others, we make use of Rogers (1995, p.12) distinction of *homophilic* neighbors. Specifically, we assume that the likelihood of a farmer adopting the organic technology depends on the adoption behavior of farmers who interact with him/her or, in other words, on the existing stock of adopters in a farmer's group of influential farmers. Following Rogers (1995) intuition, we assume that these influential farmers consist of the stock of *homophilic* adopters in the village area, that is, the stock of adopters with common social and demographic characteristics with farmer i.[8] Given our data availability and the feedback we had

[8]Granovetter (1985) argued that social ties between farmers and their family and friends with similar characteristics

from both surveys, we define *homophilic* farmers using farmers' educational levels and age assuming that influential farmers are determined exclusively by social ties in line with Rogers' (1995) initial definition. Farmers in the village area were classified into four quartiles using these two variables and then *homophilic* farmers were defined as those belonging to the same quartile according to both variables. The number of *homophilic* adopters corresponding to each farmer in the sample was then determined as the number of farmers from the aforementioned group who had adopted organic sooner than the given farmer. As an alternative indicator we also utilized individual profitability as the main determinant of influential peers among farmers in the village area.[9] ! Apart from social ties, farmers may also follow or trust the opinion of those farmers in the village that they perceive as being successful in their farming operation, even though they occasionally share quite different social characteristics. In this respect, we used individual gross profit margins to define the stock of *successful adopters* in the village areas. Following the same approach as before, we consider that farmers belonging to the first quartile of gross profit margins in each village define the stock of successful farmers in the village that mainly create informational cascades in rural areas. From this group, the number of successful adopters that are influential to a given farmer is defined as the number of successful farmers in his/her village who have adopted organic farming prior to him/her.

Our survey in both regions contains recall information on the exact date of organic farming adoption. Therefore, it was possible to construct a farm-specific index of the stock of *homophilic* (following Rogers distinction) or successful (following profitability perceptions) adopters using these recall data from each farmer in the sample. As this network is farmer specific and defined within the village, we also control for village effects by including dummy variables to distinguish among villages in the sample. Specifically, in the Greek sample, farmers are located in ten different villages whereas in the German sample the number of villages was only six. Finally, we control for farmers' individual characteristics denoted by the vector $z_i = \{z_{1i}, \ldots, z_{mi}\}$ to capture the precision of their initial beliefs about the parameters of the new technology and other characteristics that determine the costs and benefit of adoption in period 0. In particular, we use the following farm-specific variables.

First, the *size of the farm* measured in stremmas (one stremma equals 0.1 ha). 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 (*e.g.*, developing new markets and distribution channels, financing new activities) and risk considerations.[10] On the other hand, larger farms may have less financial pressure to search for alternative ways to improve their income either by switching

are strong embodying mutual trust and reciprocity. Foster and Rosenweig (1995) and Conley and Udry (2010) provide evidence from similar economic environments that this set of close contacts are the most important for providing information in rural areas. The empirical literature on social learning also defined networks based on geographical or cultural proximity.

[9]This point was raised by one of the reviewers

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

to a different farming technology or by seeking for technical information (Perrin and Winkelmann, 1976; Putler and Zilberman, 1984). Small farms generally adopt more labor intensive technologies as they use relatively more family labor which can have a low opportunity cost (Hayami and Ruttan, 1985). In this context conversion to organic-farming may serve as a good alternative for smaller farms as it requires more on-farm labor than conventional farming practices. Next, the *age* of the household head measured in years as a proxy for his farming experience and planning horizon. Experience provides increased knowledge about the environment in which decisions must be made. Thus, it may serve as a substitute for information or at least it may modify the information set for which decisions are made. Hence, farming experience is expected to affect adoption positively, but younger farmers with longer planning horizons may be more likely to invest in new technologies. On the other hand, if farmers are not faced with significant capital constraints and take future generations' welfare into account, the primary effect of age is likely to increase the likelihood of adopting technological innovations.[11]

Another variable assumed to affect profitability perceptions is the *education level* of the household head measured in years of schooling. More educated farmers may acquire technical information more easily as their capacity to digest information from various sources is assumed to be greater. Educated farmers do read technical bulletins and innovation-describing leaflets more than their less educated counterparts do presumably because they find it profitable to do so (Gervais, Lambert and Boutin-Dufrense, 2001). As a human capital variable, education is also expected to positively affect the efficiency of adoption. More educated farmers are adopting profitable new technologies faster since the associated payoffs from innovations are likely to be greater and the risk is likely to be smaller (Rahm and Huffman, 1984). Thus, one would expect a farmer's education level to be positively correlated with his decision to adopt organic farming and with the information acquisition process. However, 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. Finally, we include the gender of the household head to capture any differences in the innovative ability among genders.

Summary statistics of the data used in the empirical analysis are presented in Table 1 below. First, the upper panel of Table 1 presents descriptive statistics related to individual farmers' characteristics from both the Greek and German survey. Concerning the Greek sample first, the 28.6 per cent (60 farmers) of the surveyed farmers had adopted organic farming techniques in their farming operations until the 2006-07 cropping period. The average age of olive growers in the sample was 55 years while the corresponding figures for organic and conventional sub-samples were 52 and 56 years, respectively. The strong majority of organic and conventional farmers are males who have completed on average twelve years of formal education. The data show that organic farmers have on average larger farms (twice as large) and that the amount of subsidies is larger than the

[11] On the other hand, if there is a credit constrai! nt and farmers' plans are only for the current generation, then the highest probability of adoption will occur for middle-aged farmers (Huffman and Mercier, 1991).

potential amount of subsidies for conventional farmers. In addition, large differences exist between the two groups with respect to the number of adopters among *homophilic* farmers, since it is at least two times bigger on average for organic farmers. The lower panel of Table 1 is devoted to the characteristics of the farmer's network, or in other words, of the farmers with whom the farmers interact. Conventional farmers interact with slightly younger, slightly more educated farmers who exploit considerably smaller farms compared to those with whom organic farmers interact.

Turning now to the German sample, the survey includes 72 cereals producers of which 52 were organic (72.2 per cent) and 20 (27.8 per cent) were conventional. We can see from the upper panel of Table 1 that in the German case organic farmers are slightly older, substantially more educated (17 versus 11 years of education) while their farms are considerably smaller than those of their conventional counterparts. Another notable difference with the Greek sample is that 15 per cent of the organic farmers are female while the corresponding number is 5 per cent for the conventional case. As far as network characteristics are concerned, we can see also some substantial differences with the case of Greek olive growers. In effect, in this case we have that conventional farmers interact with less educated farmers whose farms are larger on average than those of organic farmers networks. Similar to the case of Greece the average age of network members is higher in the case of organic respondents. A notable difference between the two samples is the calculated gross profit margin in both organic and conventional farms. Although on a per stremma basis olive farms are doing better than their cereals counterparts, total gross farm income is considerably higher for German cereal producers (on the average it is 22,310 euros for olive farms and 54,657 euros for cereal farms).

2.3 Econometric Model

Denoting the unobservable present value of net gains from adoption to farmer i in village k as α^*_{ik} the stochastic element in the adoption decision can be modeled by the following general form:

$$\alpha^*_{ik} = f\left(n^i_0, \tilde{n}^i_0, S^i_1, z_i, D_k\right) + u_{ik} \tag{3}$$

where, n^i_0 and $\tilde{n}^i_0$ are the stocks of *homophilic* and *successful* adopters in the village area, S^i_1 are the conversion subsidies received by farmers after adoption, z_i are the farm-specific characteristics (*i.e.*, farm size, farmer's age, educational level and gender), D_k are the village-specific dummy variables and, u_{ik} is a normally distributed error term containing unobserved individual and network characteristics that determine the present value of net gains from adoption.

However, what is observed by the econometrician is whether somebody has adopted organic farming at some point in time prior to the survey date. A convenient representation of this situation is through a probit model, where we define an indicator α_{ik} that takes a value of 1 for those farms that adopt new farming methods and a value of 0 if new technology is not adopted, *i.e.*,

$$\alpha_{ik} = \begin{cases} 1 & \text{if } f\left(n_0^i, \tilde{n}_0^i, S_1^i, z_i, D_k\right) + u_{ik} \geq 0 \\ 0 & \text{if } f\left(n_0^i, \tilde{n}_0^i, S_1^i, z_i, D_k\right) + u_{ik} < 0 \end{cases} \tag{4}$$

Hence, the probability that farmer i adopts the new technology is given by $P(\alpha_{ik} = 1) = P\left(u_{ik} \geq -f\left(n_0^i, \tilde{n}_0^i, S_1^i, z_i, D_k\right)\right)$. Given that the net gains from adopting the new technology may be increasing or decreasing in n_0^i and $\tilde{n}_0^i$ depending on whether the positive effect of the contemporaneous information externality prevails over the negative effect of the incentive to delay, we assume that the effect of informational variables enter into (3) in a non-linear fashion. In addition, since the effect of farmer's age and educational level is non-monotonic, squared terms of both variables were included in the econometric model.

Specifically, relation (3) takes the following general form:

$$\begin{aligned} \alpha_{ik}^* = g\left(n_0^i, \tilde{n}_0^i, S_1^i; \beta\right) &+ \gamma_1 Age + \gamma_{11} Age^2 + \gamma_2 Edu \\ &+ \gamma_{22} Edu^2 + \gamma_3 Size + \gamma_4 Gen + \sum_{k=1}^{K} \delta_k D_k + u_{ik} \end{aligned} \tag{5}$$

where β, γ and, δ are the parameter vectors to be estimated (note that k, number of village, differs between the two samples). In order to be able to identify the presence or absence of potential complementarities between informational channels and conversion subsidies, these were also included into the $g(.)$ function. Following the informative approach similar to Bertrand *et al.*, (2000) and Goolsbee and Klenow (2002) we estimate a quadratic specification for $g(.)$ allowing at the same time for interaction terms between the two indices of social networks and conversion subsidies. Given the model specification in (3)-(5), the marginal effects for any continuous regressor, x_l are computed using the following expresssion evaluated at the mean values of the variables:

$$\frac{\partial P(\alpha_k = 1)}{\partial x_l} = \frac{\partial f\left(\bar{n}_0^i, \bar{\tilde{n}}_0^i, \bar{S}_1^i, \bar{z}, \bar{D}_k\right)}{\partial x_l} \phi\left(f\left(\bar{n}_0^i, \bar{\tilde{n}}_0^i, \bar{S}_1^i, \bar{z}, \bar{D}_k\right)\right), \tag{6}$$

where $\phi(\cdot)$ is the density of the standard normal and $^{-}$ denotes the mean value.

In the case of a dummy explanatory variable such as gender, the marginal effect will be computed as,

$$\Phi\left(\bar{n}_0, \bar{\tilde{n}}_0, \bar{S}_1, \bar{z}^g, Gen = 1, \bar{D}_k\right) - \Phi\left(\bar{n}_0, \bar{\tilde{n}}_0, \bar{S}_1, \bar{z}^g, Gen = 0, \bar{D}_k\right), \tag{7}$$

where $\Phi(\cdot)$ denotes the c.d.f of the standard normal, z^g are the demographic variables excluding gender.

3 Empirical Results

The binary discrete choice model described by equations (3)-(5) above was estimated for both countries separately under the assumption of normal errors. The sets of regressors included in these probit models are the same for both countries in order to facilitate comparisons. The specification of the models assumes that the number of adopters among *homophilic* peers (*i.e.*, n_0^i), the number of successful adopters (*i.e.*, $\tilde{n}_0^i$), and the amount of subsidies (*i.e.*, S_1^i) affect adoption together with their interactions and their squares. This gives enough flexibility to the model so that a change in one of the above three regressors can have both positive and negative effects on the probability to adopt depending on its value.

In order to take into account farmers' own characteristics the four variables described in the previous section, namely, the size of the farm, the gender of the farmer, the age of the farmer and his/her educational level were included in the model, while the square of the latter two was considered as well so as to account for possible nonlinear effects. Finally, potential village fixed effects related to a myriad of factors that are common to farmers in the same village but could differ accross villages are captured by the use of village specific dummy variables. Such village effects include, but are not limited to, factors such as soil quality, the propensity to innovate,the participation in cooperatives and climatic conditions. The probit estimates for Greece are shown in Table 2. In the first two models, learning from "similar" peers and learning from successful neighbors are used alternatively as information variables in the estimation procedure, while in the third model, only subsidies are included. In model 1.4 both information variables, the amount of subsidies and their pairwise products are included as explanatory variables. No significant variations are observed between the estimation results of the four models as far as the sign of the parameters and their statistical significance.

The information and subsidy parameter estimates in the first three models indicate the presence of positive effects which are hampered by the presence of the negative coefficients for the quadratic terms. For model 1.4 the interpretation of the parameter estimates in the first panel of Table 2 is complicated by the fact that quadratic terms and interactions appear in the model making it difficult to uncover the direction of the effects of changes in the involved regressors. However, the marginal effects of n_0^i, $\tilde{n}_0^i$ and S_1^i are easily computed using the formulas presented in (6)-(7) and thus for the first panel we will discuss only the latter which are presented at the bottom panel of the Table. The highest marginal effect is achieved by the information variable n_0^i and the lowest by the information variable $\tilde{n}_0^i$ and the results show that an additional adopter in the *homophilic* group of adopters has an effect on the probability of adoption that is almost five times bigger than the effect of an additional adopter in the group of successful farmers. Moreover the aforementioned effect on the probability to adopt is four times as large as the effect of a one thousand euros increase in the subsidies amount. The empirical results support the importance of learning from-others, especially from "similar" peers, in the diffusion process relative to the granting of subsidies and reveal that learning from peers is the most conducive information variable in the adoption of organic farming. Therefore information diffusion is more important than blind provision of production subsidies to internalize information externalities.

In addition to examining the marginal effects of our variables on the adoption probability, it is of interest to analyze how these effects respond to changes in any of the three variables of interest (n_0^i, $\tilde{n}_0^i$ and S_1^i). To this effect, the analytical formulas for the derivatives of the three marginal effects with respect to the three aforementioned variables were used to find their signs (at the mean values of the regressors) for both countries and these are reported in Table 4. Each entry in the aforementioned table should be interpreted as the sign of the derivative of the marginal effect of the column variable with respect to the row variable whereas due to symmetry only the upper half is reported. Thus, the marginal effect of an increase in the number of *homophilic* adopters is decreasing in the number of adopters while it increases with the number of successful farmers who are adopters and with the amount of subsidies. This means that information on the use of the new technology was found to become less important as technology is spread among the population of farmers, implying that any internalization of the information externalities would be more effective at the early stages of the adoption. This also means that well informed farmers are less influenced by increases in the number of *homophilic* adopters than less informed farmers, a finding that is consistent with Bandiera and Rasul (2006) while they are more influenced by increases in the number of successful adopters. Moreover, an increase in the amount of subsidies seems to be more adoption promoting when the number of *homophilic* adopters or the number of successful adopters are high than when they are small. Therefore, subsidies are more effective in attracting new adopters for those farmers who already interact with adopters.

The size of the farm affects positively the probability of adoption of organic farming techniques in Greek olive oil production, while females are less likely adopters than their male counterparts. The estimates for the age related parameters imply that adoption rates are lower at younger ages and at older ages. The lack of experience in the case of young farmers might act as a deterrent to adoption while farmers past a certain age, which in the case of Greece is 61.3 years, might find it not worthwhile changing their farming activity due to the proximity of retirement age. Our results for education are very similar to the ones for age, confirming therefore the findings by Dinar and Yaron (1990) whereas there is a threshold level of education after which the probability of adoption diminishes. In the case of Greece the threshold level is 13.15 years of education. These results imply that direct information provision would enhance technology adoption if it was directed to specific groups of farmers. Specifically, information provision should target middle-aged farmers having education levels up to high-school, and who are owners of larger farms. Turning now to the village dummies, it is the case that negative dummies correspond to villages that are more remote or farther away from urban centers. Therefore, adoption rates are higher in villages that are close to urban centers where it is the case that organic food is usually marketed and consumed. This may be an indication of weaknesses in distribution channels for organic products. The marginal effects of the demographic variables are reported at the bottom panel of Table 2 and indicate that for the average greek farmer an additional year of age increases the probability of adoption by 0.0078, an additional year of education increases it by 0.0052 while a unit increase in the farm size increases the probability by 0.0035. The large negative marginal effect for the gender value could be caused by the lack of female farmers in the greek sample.

If we turn to the case of Germany we will see that most of the above results are reproduced here as well. The probit estimates for the alternative model specifications are shown in Table 3. As mentioned before, the same models where estimated for the German case so as to make results comparable. The parameters in the first three models were found to have the expected signs, implying positive and decreasing marginal effects of the information variables and of subsidies. Again, learning from *homophilic* adopters has the largest marginal effect but in contrast to the case of Greece, its relative importance is much lower now. In effect a unit change in the number of adopters has a marginal effect that is comparable to that of an increase in the amount of subsidies by a thousand euros. It is worth noting as well that the magnitude of the marginal effects is quite different across countries. In the case of n_0, the effect for Greece is almost twice as big as the one for Germany while for the other two variables the reverse occurs. It could be argued that farmers in the greek sample seem to be much more influenced by "similar" peers than farmers in the german sample. In terms of second order effects (from the square and interaction terms) the same pattern as in the case of Greece emerges in Table 3. Marginal effects are decreasing in their own variables implying that although positive they are decreasing.

Turning now to Table 4, the same pattern emerges for the German sample, *i.e.*, increases in the level of each one of the variables enhances the marginal effects of the other variables while it hampers its own marginal effects. Since the results for German cereal production are so similar to those for Greek olive production, the same policy implications can be derived in terms of information externalities. The size of the farm turns out to be not significant and neither is the quadratic term for the age variable, the latter fact implying that the probability of adoption increases with age. The threshold level for education is 15.6 in the case of education and therefore the probability of adoption increases with education up to this threshold level while it decreases thereafter. As is the case for the Greek sample, female farmers are less likely to adopt organic farming than male farmers. Turning to the village dummies, significant negative estimates correspond to villages that are not located in the Westfalia region. The marginal effect of age in the case of Germany is twice as large as the one for Greece while for education it is three times smaller. In the case of Germany, information provision should target more experienced or older farmers who have a university degree.

The results presented above show that information and subsidy policies interact with each other when trying to enhance the adoption of organic farming techniques. European Union policies aiming at boosting the adoption and diffusion of new technologies in the farm sector should recognize the importance of promoting information about the new techniques. In this sense, increasing the operation of public extension programs and the provision of agricultural practice seminars can contribute to the spread of information about the new techniques. Moreover, these programs should target middle-aged (for Greece) or older farmers (for Germany) who have completed the basic education and are engaged in professional farming activities since they are the most innovative socio-economic group in rural areas and the more likely group to adopt the new technology. This in turn would create informational cascades among farmers in the area. Subsidy policies on their own are not as effective in the diffusion process as information dissemination but they can help accelerate this process as information is being spread. Specifically, subsidies accelerate the rate of adoption as the number of adopters grows. As the process of adoption proceeds, the people who have not adopted yet are those who look to organic farming with more distrust (the harder to convince people) and therefore subsidies can compensate for this distrust. Early adopters are innovative people willing to take risks so they do not need subsidies as much as those farmers who are not as keen to innovate.

4 Concluding Remarks

The present paper uses the data from two surveys of farmers to analyze the effects that informational and financial incentives have on individual farmers' decisions to adopt organic farming practices using two different samples of olive and cereal growers in Greece and Germany, respectively. Building upon the methodological developments of Foster and Rosenweig (1995), Munshi (2004), Bandiera and Rasul (2006) and Weber (2012) and based on Roger's (1995) approach in defining social networks in rural areas as well as on profitability considerations we suggest two alternative indicators for measuring empirically the effects of social learning in adoption decisions.

Both surveys, provide the same answers as to the effects of social interactions and subsidies on the probability of adoption. Our results show that the probability that a farmer adopts organic farming increases with the number of *homophilic* adopters but this increase diminishes as the number of *homophilic* adopters rises. The same kind of behavior is displayed by the number of successful farmers in the village and by the level of subsidies. As the farmer acquires more information about organic farming he/she is more likely to adopt but each successive increase in the amount of information is every time less effective. Subsidizing early adopters has been advocated as a means to internalize these information externalities. Our results show that subsidies can enhance rural network effects even in those cases where there is already a critical mass of adopters. These results turn to be robust regarding both model specification and the definition of social networks (*i.e.*, *homophilic* or successful farmers).

The results show as well that for both countries the probability to adopt increases with increases in the education level up to a certain threshold and diminishes thereafter confirming the empirical findings of Dinar and Yaron (1990). In the case of Greece, adoption is more likely to take place for larger farms and middle-aged farmers while for Germany older farmers of medium size are more likely to adopt. Farming experience as proxied by farmer's age turns to be a crucial factor in revising adoption decisions. Therefore, our results show that the socio-economic groups that should be targeted for accelerating the pace of diffusion of organic production differs across the two countries. Finally, proximity to urban centres and therefore to markets of organic produce seems to play an important role for individual farmers to convert their farming operations.

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Tables

Table 1: Summary Statistics of the Variables: Greek and German Samples

		Greek Farms			German Farms		
		All	Organic	Conventional	All	Organic	Conventional
No of Farms		210	60	150	72	52	20
(%)		(100%)	(28.6%)	(71.4%)	(100%)	(72.2%)	(27.8%)
Farm Characteristics:							
Farmer's Age (years)	Age	54.9	52.2	56.3	48.3	49.2	46.1
		(18.3)	(17.4)	(19.1)	(23.2)	(24.0)	(22.6)
Farmer's Gender: Female (%)	Gen	7.1	8.3	6.7	12.5	15.4	5.0
Farmer's Education (years)	Edu	12.0	11.8	12.1	15.4	17.1	11.1
		(4.3)	(4.4)	(3.2)	(3.8)	(3.7)	(3.3)
Farm Size (stremmas)	$Size$	55.9	89.4	42.5	893.3	753	1258
		(14.3)	(17.2)	(8.2)	(131.2)	(122.3)	(244.2)
No of *Homophilic* Adopters	n_0^i	3.2	5.4	2.3	2.4	3.2	0.4
		(0.6)	(1.2)	(0.6)	(0.7)	(1.2)	(0.1)
No of Successful Adopters	$\tilde{n}_0^i$	1.7	2.5	1.4	1.6	2.1	0.4
		(0.3)	(1.0)	(0.3)	(0.4)	(0.8)	(0.2)
Conversion Subsidies (ths euros)	S_1^i	5.9	6.5	2.3	57.9	62.9	44.8
		(2.1)	(2.3)	(2.4)	(12.3)	(15.9)	(13.1)
Farmer's Network Characteristics:							
Farmer's Age (years)	$NAge$	45.7	46.2	45.5	47.7	48.3	46.3
		(21.7)	(23.6)	(21.2)	(23.3)	(24.1)	(19.1)
Farmer's Education (years)	$NEdu$	9.9	9.5	10.1	16.2	16.3	15.8
		(3.2)	(3.3)	(4.3)	(4.5)	(4.4)	(3.7)
Farm Size (stremmas)	$NSize$	58.9	95.3	44.3	763.1	745.0	810.3
		(13.4)	(12.4)	(13.2)	(122.4)	(114.4)	(112.1)
Gross Profit Margin (in euros per stremma)	$NGPF$	231.4	244.3	226.2	59.2	60.1	56.7
		(33.2)	(37.7)	(29.3)	(12.3)	(11.5)	(10.3)

* In parenthesis are the respective standard deviations. Data from both samples were collected during the 2007-08 cropping year.

Table 2: Parameter Estimates for Alternative Model Specifications: Greek Olive Farms

	Model 1.1		Model 1.2		Model 1.3		Model 1.4	
	Estim.	t-ratio*	Estim.	t-ratio	Estim.	t-ratio	Estim.	t-ratio
Information Variables and Subsidies:								
n_0^i	0.7634	(2.897)	-	-	-	-	0.7832	(2.342)
$(n_0^i)^2$	-0.0198	(2.213)	-	-	-	-	-0.0201	(2.432)
$\tilde{n}_0^i$	-	-	0.3243	(1.983)	-	-	0.1412	(2.091)
$(\tilde{n}_0^i)^2$	-	-	-0.0415	(1.098)	-	-	-0.0512	(1.113)
S_1^i	-	-	-	-	0.2837	(2.761)	0.2651	(2.652)
$(S_1^i)^2$	-	-	-	-	-0.0130	(2.099)	-0.0141	(1.880)
$n_0^i \times \tilde{n}_0^i$	-	-	-	-	-	-	0.0121	(1.871)
$n_0^i \times S_1^i$	-	-	-	-	-	-	0.0120	(1.712)
$\tilde{n}_0^i \times S_1^i$	-	-	-	-	-	-	0.0254	(1.919)
Farm Characteristics:								
Size	0.2131	(1.988)	0.2098	(1.871)	0.2212	(1.918)	0.0125	(1.871)
Gen	-5.6323	(2.091)	-5.0921	(2.112)	-5.3231	(2.312)	-3.6938	(2.112)
Age	0.3012	(2.534)	0.3112	(2.092)	0.3332	(2.312)	0.2820	(2.112)
Age^2	-0.0021	(1.563)	-0.0023	(1.643)	-0.0027	(1.762)	-0.0023	(1.654)
Edu	0.2523	(2.112)	0.2653	(2.736)	0.2452	(2.312)	0.2131	(2.412)
Edu^2	-0.0093	(1.761)	-0.0087	(1.891)	-0.0089	(1.876)	-0.0081	(1.944)
Village Dummies:								
D_1	-9.3212	(2.231)	-8.9823	(2.093)	-8.9813	(2.042)	-4.5232	(2.091)
D_2	1.7877	(2.123)	1.5323	(1.8172)	1.1232	(1.632)	1.7316	(1.981)
D_3	-11.3242	(2.342)	-6.4342	(2.543)	-8.9429	(2.421)	-7.1213	(2.332)
D_4	0.8932	(0.523)	0.3444	(0.653)	0.4134	(0.712)	3.4312	(0.981)
D_5	-8.9382	(2.131)	-7.7363	(2.312)	-8.3232	(2.342)	-8.7126	(2.822)
D_6	0.7652	(1.312)	0.8944	(1.331)	0.8923	(1.112)	0.8611	(1.312)
D_7	-9.8873	(2.213)	-9.9831	(2.241)	-9.5343	(2.312)	-8.3632	(2.065)
D_8	0.7431	(0.662)	0.5231	(0.622)	0.4924	(0.621)	0.7125	(0.871)
D_9	-9.9813	(2.324)	-10.3242	(2.423)	-10.3232	(2.763)	-7.6162	(2.523)
Constant	-14.2931	(3.021)	-10.2312	(3.112)	-11.3230	(3.212)	-7.5332	(3.019)
pseudo R-squared	0.4532		0.4651		0.4734		0.5144	
Bayesian IC	-0.2452		-0.2234		-0.2467		-0.3736	
Marginal Effects:								
n_0^i	0.1080		-		-		0.2059	
$\tilde{n}_0^i$	-		0.0368		-		0.0431	
S_1^i	-		-		0.0445		0.0496	
Age	0.0120		0.0118		0.0126		0.0078	
Edu	0.0049		0.0113		0.0108		0.0052	
Size	0.0362		0.0421		0.0757		0.0035	
Gen	-0.9944		-0.5093		-0.7568		-0.9333	

* The absolute values of the t-ratios are in parenthesis. Standard errors were obtained using block re-sampling techniques which entails grouping the data randomly in a number of blocks of farms and re-estimating the model leaving out each time one of the blocks of observations and then computing the corresponding standard errors (Politis and Romano 1994).

Table 3: Parameter Estimates for Alternative Model Specifications: German Cereal Farms

	Model 1.1		Model 1.2		Model 1.3		Model 1.4	
	Estim.	t-ratio*	Estim.	t-ratio	Estim.	t-ratio	Estim.	t-ratio
Information Variables and Subsidies:								
n_0^i	0.3954	(2.323)	-	-	-	-	0.3420	(2.532)
$(n_0^i)^2$	-0.0127	(2.635)	-	-	-	-	-0.0187	(2.736)
$\tilde{n}_0^i$	-	-	0.2863	(2.091)	-	-	0.1512	(2.213)
$(\tilde{n}_0^i)^2$	-	-	-0.0129	(1.635)	-	-	-0.0361	(1.762)
S_1^i	-	-	-	-	0.4642	(2.322)	0.3212	(2.982)
$(S_1^i)^2$	-	-	-	-	-0.0022	(2.342)	-0.0054	(1.902)
$n_0^i \times \tilde{n}_0^i$	-	-	-	-	-	-	0.0145	(1.789)
$n_0^i \times S_1^i$	-	-	-	-	-	-	0.0131	(1.918)
$\tilde{n}_0^i \times S_1^i$	-	-	-	-	-	-	0.0312	(2.092)
Farm Characteristics:								
Size	0.093	(1.323)	0.0112	(1.231)	0.0102	(1.092)	0.0098	(1.112)
Gen	-8.8362	(2.312)	-8.9832	(2.726)	-5.9872	(2.435)	-9.3242	(2.453)
Age	0.1983	(2.019)	0.2131	(1.889)	0.2423	(1.982)	0.2212	(2.212)
Age^2	-0.0013	(1.623)	-0.0015	(1.233)	-0.0017	(1.313)	-0.0018	(1.242)
Edu	0.2123	(1.763)	0.1983	(1.872)	0.2234	(2.093)	0.2312	(1.872)
Edu^2	-0.0046	(1.672)	-0.0052	(1.534)	-0.0058	(1.342)	-0.0074	(1.645)
Village Dummies:								
D_1	-8.3212	(3.039)	-7.9887	(3.221)	-8.9872	(3.093)	-9.3241	(2.983)
D_2	0.6352	(0.832)	0.7382	(0.982)	0.8923	(0.726)	0.9821	(0.873)
D_3	-7.3242	(2.312)	-7.9832	(2.341)	-9.7124	(2.413)	-7.4353	(2.543)
D_4	0.5932	(0.423)	0.4353	(0.452)	0.5643	(0.542)	0.6732	(0.452)
D_5	-6.9382	(2.311)	-7.4245	(2.121)	-7.8224	(2.312)	-7.3232	(2.423)
Constant	-6.5453	(2.019)	-6.4344	(2.122)	-7.4324	(2.312)	-8.2121	(2.091)
pseudo R-squared	0.3884		0.3745		0.3982		0.4012	
Bayesian IC	-0.2311		-0.2434		-0.2312		-0.3523	
Marginal Effects:								
n_0^i	0.0722		-		-		0.1154	
$\tilde{n}_0^i$	-		0.0963		-		0.0833	
S_1^i	-		-		0.1424		0.1108	
Age	0.0157		0.0268		0.0248		0.0155	
Edu	0.0155		0.0148		0.0149		0.0015	
Size	0.0020		0.0044		0.0033		0.0032	
Gen	-0.0273		-0.0042		-0.1556		-0.0706	

* The absolute values of the t-ratios are in parenthesis. Standard errors were obtained using block re-sampling techniques which entails grouping the data randomly in a number of blocks of farms and re-estimating the model leaving out each time one of the blocks of observations and then computing the corresponding standard errors (Politis and Romano 1994).

Table 4: Relationship between Informational Variables and Conversion Subsidies.

	Changes in Marginal Effects		
Changes in	n_0^i	$\tilde{n}_0^i$	S_1^i
Greek Farms			
n_0^i	(-)	(+)	(+)
$\tilde{n}_0^i$		(-)	(+)
S_1^i			(-)
German Farms			
n_0^i	(-)	(+)	(+)
$\tilde{n}_0^i$		(-)	(+)
S_1^i			(-)