The Role of Education in Boosting Transition towards Quality and Sustainable Agriculture

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Abstract: The paper analyses the relevance of education in adopting quality products, like organic farming and geographical indications. Through a multinomial logit with random effects we estimate the probability of adoption of quality schemes related to levels of education with a supplementary variable concerning localisation of farms in rural contexts.
Results confirm the goodness of the model by emphasising the strong impact of education in performing adoption of quality production and sustainable methods of farming.

Key words: Education, quality products, sustainable agriculture, rural areas, multinomial logit

1 Introduction

This paper deals with the influence of education in boosting farms' transition towards sustainable models of production based on quality products. More precisely, it analyses different levels of probability to choice or not sustainable system and quality products in different rural areas. The aim of the paper is to test the relevance of education in affecting transition from conventional agriculture towards quality-based and agronomically sound agriculture in Italy. The paper is organized as follows: following introduction (Section 1), in section 2 we put forward the theoretical background, by emphasising recent literature on the role of education in choosing quality options. The aim is not to provide an exhaustive literature review, but to try exploring the links between education and the choice of changing towards quality products and sustainable agriculture on behalf of farmers. Section 3 provides methodological insights, while section 4 discusses results of empirical analysis. Conclusions will end our paper.

2 Theoretical background

New European agricultural model is rooted in four dimensions underlined in a resolution of the European Parliament (van der Ploeg, 2010, 11):

1. "high-added-value farming with high-quality primary and processed products;
2. farming open to regional markets;
3. farming geared to local markets;
4. agronomically sound and sustainable agricultural systems as vital to guaranteeing competitiveness on local, regional and international markets".

This paradigm shift has been marked in literature as a sociotechnical transition (Wiskerke,van der Ploeg, 2004), bringing about rural innovation. A commonly shared concept of rural innovation is relatively recent being it drawn on Knickel et al.'s (2009, 94) definition:

"*innovation involves much more than technology; more and more it relates to strategy, marketing, organization, management and design. Farmers looking for alternatives to industrial agriculture don't necessarily apply 'new' technology. Their novelties emerge as the outcome of different ways of thinking and different ways of doing things*".

Therefore, adoption of quality systems related, for example, to the origin perspective and to organic production process may be considered as new paths of agricultural innovation. According to us, these paths are coherent and in line with the new vision of the modern rurality and rural innovation, as triggered in recent documents of the European rural policy.

Consequently, rural innovation has been defined as a 'must' for rural regions: set in this background, human capital may be identified as a key driver of innovation (OECD, 2007). Empowering human capital is a target to be fulfilled through a double channel: development and attraction of human capital in rural areas. As a matter of fact, as posited in the Development Capitals' approach to boost development in rural areas, human and social capitals are strategic (Carnegie, 2009; Alika, Stan, 2014). The role of education in farming activity has been deeply recognized in recent literature concerning both developing and developed countries. Starting from the seminal work of Becker (1964), an abundant share of literature points out the importance of human capital to increase agricultural productivity and innovation (among others, World Bank, 2006; De Devitiis, Maietta, 2009; Zubovic et al., 2009; Kovàcs et al., 2016). Nonetheless, few studies have been carried out on the relationships between education and transition towards multifunctional agriculture (among other, see Casini, Contini, Romano, 2012). Therefore, there is a gap in recent literature we will try to fill. This paper sets against this background, with the purpose of exploring the links between levels of education and quality orientation in the farming activity.

3 Methodology

Human capital can be measured through indicators such as education, information and knowledge. Our paper focuses on the level of education: our hypothesis to be tested is that the level of education affect the probability to engage in quality schemes of production. Data are collected from official sources, more precisely they are drawn on the database of the Agricultural Economic Inventory Survey (REA) and the Agricultural Accounting Survey (RICA). Data are referred to the year 2014. The sample we worked on was extracted from a large amount of data regarding Italian farms. In order to discriminate propensity to quality schemes, farms adhering to organic farming and/or to geographical indication (protected designation of origin or protected geographical indication) have been taken into account.

In order to estimate the probability of adopting quality products a multinomial logit model with random effects has been carried out. Explicative variables refer to education and farms' territorial location (rural vs urban areas). More precisely, as far as level of education is concerned, 8 levels of education are considered:

1. No title
2. Primary school diploma
3. Middle School diploma
4. Professional diploma
5. High school diploma
6. University diploma (3 years)
7. Graduation (5 years)
8. Postgraduate specialization.

As far as rural areas are considered, we take into account the distinction adopted by the European Union and adopted in the Italian National Strategic Plan (NSP), providing four types of homogeneous areas:

1. Urban poles (A);
2. Areas with intensive agriculture (B);
3. Intermediate rural areas (C);
4. Rural marginal areas (D).

These two variables (farmer's education of and farm's territorial localization) generated random effects on the logistic regression model. This type of non-linear model considers random effects as distinguishing factors. In this way we observed the variation in the probability of choosing or not quality products or processes.

To estimate the likelihood of the farms that adhere to organic farming or quality brands, we used a mixed-effects logistic model. It is a binary regression model (the logistic regression model) is a particular case of linear generalised model, and may be briefly shown in the following way (Lee and Nelder, 1996).

If y_i is a binary dependent variable, and x_i the corresponding vector of covariates (explanatory or predictive variables), the probability of the event $y_i=1$ in the binary model is specified by an increasing function $\mu = \mu(s)$, the inverse link function:

$$\Pr(y_i = 1) = \mu(\boldsymbol{\beta}'\mathbf{x}_i) \qquad (1)$$

being $\boldsymbol{\beta}$ the vector of parameters (fixed effects). The hypotheses underlying the basis of the model are that the binary variables are determinations of independent random variables. It is also assumed that the inverse link function $\mu = \mu(s)$ is continuous, differentiable to the second order and strictly increasing. The function $\eta = \mu^{-1}$ represents the link function. The model (1) may be expressed as $E(y_i \mid \mathbf{x}_i) = \mu(\boldsymbol{\beta}'\mathbf{x}_i)$.

In terms of the link function, then $\eta(E(y_i \mid \mathbf{x}_i)) = \boldsymbol{\beta}'\mathbf{x}_i$, with:

$$Var(y_i) = \Pr(y_i = 1) \times \Pr(y_i = 0) = \mu(\boldsymbol{\beta}'\mathbf{x}_i)(1 - \mu(\boldsymbol{\beta}'\mathbf{x}_i))$$

The inverse link function $\mu = \mu(s)$ is a probability function. In the case of logistic regression, $\mu(s) = e^s/(1+e^s)$. More precisely, we have as follows:

$$\frac{d\mu}{ds} = \frac{e^s}{(i+e^s)^2} > 0, \qquad \frac{d^2 \log g\mu}{ds^2} = -\frac{e^s}{(i+e^s)^2} < 0$$

Besides, the probability function is symmetrical $\mu(-s) = 1 - \mu(s)$.

The model (1) may be generalised by including "random effects" so as to estimate components of regression parameters specific to each group, should the observations making up the groups themselves be considered dependent (Demidenko, 2004). In this case the model (1) becomes (Jiang, 2007):

$$\Pr(y_{ij} = 1 \mid \mathbf{b}_i) = \mu(\boldsymbol{\beta}'\mathbf{x}_{ij} + \mathbf{b}'\mathbf{z}_{ij}) \qquad (2)$$

where the indices i and j define the belonging cluster and the farm, respectively. $\mathbf{Z}_{ij}$ is the vector of fixed effects, while $\mathbf{b}_i$ is the vector of random effects. The advantage of using a random effects model (2), compared with the classical model (1), is that the former is substantially more flexible. Moreover, model (2) includes model (1) as the limit case when the variance of the random effects tends to infinity. Model (2), called in the literature a mixed-effects generalised model (McCulloch and Searle, 2001), envisages further estimation of the vector of random effects $\mathbf{b}_i$, with respect to model (1).

In this study, we assumed normal distribution of random effects, $\mathbf{b}_i \sim \mathrm{N}(\mathbf{0}, \mathbf{D})$, where $\mathbf{D}$ represents the matrix of covariance between random effects. The advantage of assuming normality of random effects is that $\mathbf{b}_i \mathbf{z}_{ij}$ is also a normally distributed vector, with distribution $N(0, \mathbf{z}'_{ij} \mathbf{D} \mathbf{z}_{ij})$. The criterion of maximum likelihood leads to a k-dimensional integral, where k is the dimension of the random-effects vector. Adoption of a number equal to 2 or 3 of this dimension significantly increases the calculation time of the integrals required to estimate maximum likelihood of fixed effects, of random effects, and the matrix of covariance between the random effects. Such calculation difficulties are substantially linked to the numerical squaring of multidimensional improper integrals present in the likelihood function. There are four main methods (McCulloch, 1997) and algorithms for parameter estimation of the mixed-effects logistic model: a) squared maximum likelihood (Diggle et al., 1996; Song et al., 2005), b) penalized quasi-likelihood (Lin and Breslow, 1996), c) approximation with Laplace functions (Breslow and Clayton, 1993), and d) Monte Carlo method for log-likelihood approximation (Booth and Hobert, 1999). The method followed in our research is the squared maximum likelihood. In this context, as stated above, the maximum likelihood method requires a k-dimensional integration. If the integration is exact, the estimates are internally consistent and asymptotically correct, under the condition that the number of groups is substantially high (in theory, it must tend to infinity, as occurs for mixed-effects linear models). The estimates are asymptotically correct even if the number of observations per cluster is limited. The other estimation methods (b), c), and d)) substantially operate starting from an approximation of the likelihood function.

Below we specify the likelihood function starting from the inverse covariance matrix of random effects, that $\mathbf{D}$ is $\mathbf{D}^*$ (also known as the precision matrix). In particular, the log-likelihood function assumes the form:

$$l(\beta, D^*) = -\frac{NK}{2}\log(2\pi) + \frac{N}{2}\log\left|\mathbf{D}^*\right| + \boldsymbol{\beta}'\mathbf{r} + \sum_{i=1}^{N}\log\int_{R^k} e^{h_i(\boldsymbol{\beta},\mathbf{u})} d\mathbf{u},$$

Where, $\mathbf{r} = \sum_{i=1}^{N}\sum_{j=1}^{n_i} y_{ij}\mathbf{x}_{ij}$ and:

$$h_i = \mathbf{k}_i'\mathbf{u} - 0.5\mathbf{u}'\mathbf{D}^*\mathbf{u} - \sum_{j=1}^{n_i}\log\left(1 + e^{\boldsymbol{\beta}'\mathbf{x}_{ij} + \mathbf{u}'\mathbf{z}_{ij}}\right), \quad k_i = \sum_{i=1}^{N}\sum_{j=1}^{n_i} y_{ij}\mathbf{z}_{ij}\ .$$

The first order derivatives are:

$$\frac{\partial l}{\partial \boldsymbol{\beta}} = r - \sum_{i=1}^{N}\frac{\mathbf{I}_{i3}}{I_{i1}}, \qquad \frac{\partial l}{\partial \mathbf{D}^*} = \frac{1}{2}\ ND - \sum_{i=1}^{N}\frac{\mathbf{I}_{i2}}{I_{i1}}$$

with:

$$I_{i1} = \int_{R^k} e^{h_i(\boldsymbol{\beta},\mathbf{u})} d\mathbf{u},$$

$$\mathbf{I}_{i2} = \int_{R^k} \mathbf{u}\mathbf{u}' e^{h_i(\boldsymbol{\beta},\mathbf{u})} d\mathbf{u},$$

$$\mathbf{I}_{i2} = \int_{R^k} \left\langle \sum_{j=1}^{n_i}\mathbf{x}_{ij}\, \frac{e^{\boldsymbol{\beta}'\mathbf{x}_{ij} + \mathbf{u}'\mathbf{z}_{ij}}}{1 + e^{\boldsymbol{\beta}'\mathbf{x}_{ij} + \mathbf{u}'\mathbf{z}_{ij}}} e^{h_i(\boldsymbol{\beta},\mathbf{u})} \right\rangle d\mathbf{u}$$

The maximum likelihood estimates for $\boldsymbol{\beta}$ and $\mathbf{D}^*$ are the solutions to the score equations $\partial l / \partial \boldsymbol{\beta} = \mathbf{0}$ and $\partial l / \partial \mathbf{D}^* = \mathbf{0}$. Score equations may be solved with iterative methods, such as the Empirical Fisher Scoring (EFS) method. The covariance matrix $\mathbf{D}$ is hypothesised as structured and thus covariance is estimated among the random effects described in the model.

4 Results

The following tables describe the sample of farms according to the adhesion to quality certification schemes. In Table 1, farms either implementing or not quality products are classified according to level of education, while in Table 2, quality farms are distinct for NSP areas.

Table 1 - Quality firms according to education.

Education / Quality	1	2	3	4	5	6	7	8	TOT. %
No %	759 3.28 %	1952 8.42 %	6153 26.55 %	2376 10.25 %	4385 18.92 %	93 0.40 %	662 2.86 %	5 0.02 %	16385 70.71 %
Yes %	177 0.76 %	652 2.81 %	2213 9.55 %	891 3.85 %	2257 9.74 %	81 0.85 %	504 2.18 %	12 0.05 %	6787 29.29 %
TOT. %	936 4.04 %	2604 11.24 %	8366 36.10 %	3267 14.10 %	6642 28.66 %	174 0.75 %	1166 5.03 %	17 0.07 %	23172 100.00 %

1. No title
2. Primary school diploma
3. Middle School diploma
4. Professional diploma
5. High school diploma
6. University diploma (3 years)
7. Graduation (5 years)
8. Postgraduate specialization.

Table 2 - Quality businesses according to NSP areas.

NSP Areas / Quality	A	B	C	D	TOT %
No %	2426 10.47 %	5397 23.29 %	5377 23.20 %	3185 13.75 %	16385 70.71 %
Yes %	354 1.53 %	1359 5.86 %	2439 10.53 %	2635 11.37 %	6787 29.29 %
TOT %	2780 12.00 %	6756 29.16 %	7816 33.73 %	5820 25.12 %	23172 100.00 %

1.Urban poles (A);

2.Areas with intensive agriculture (B);
3.Intermediate rural areas (C);
4.Rural marginal areas (D).

The random-effect logistic regression model, which we used, has the following expression:

$$\mathrm{logit}_{D,t} = \mathbf{X}_{Dt}\boldsymbol{\beta} + \mathbf{1}v_{1,D}$$

Where $v_{1,D}$ represent the random effect "NSP zone". A random effect model is studied when the following conditions generally apply (in this case-study the model is nonlinear):

1. Information is to be considered as properly evaluated only by introducing effects that differentiate relationship between variable-response and regressors in domains previously introduced in search (eg. either spatial or temporal domains, etc.);
2. For each domain of interest, the omitted effects are so numerous and heterogeneous to be considered as the realization of a random variable not correlated with the regressors.

We have seen that with the introduction of random effects in the model, the regression line moved up or down depending on the extent of the resulting value. The regression curve function holds a $\boldsymbol{\beta}_1$ that is fixed and a $\boldsymbol{\beta}_0$ that changes with the introduction of random effects.

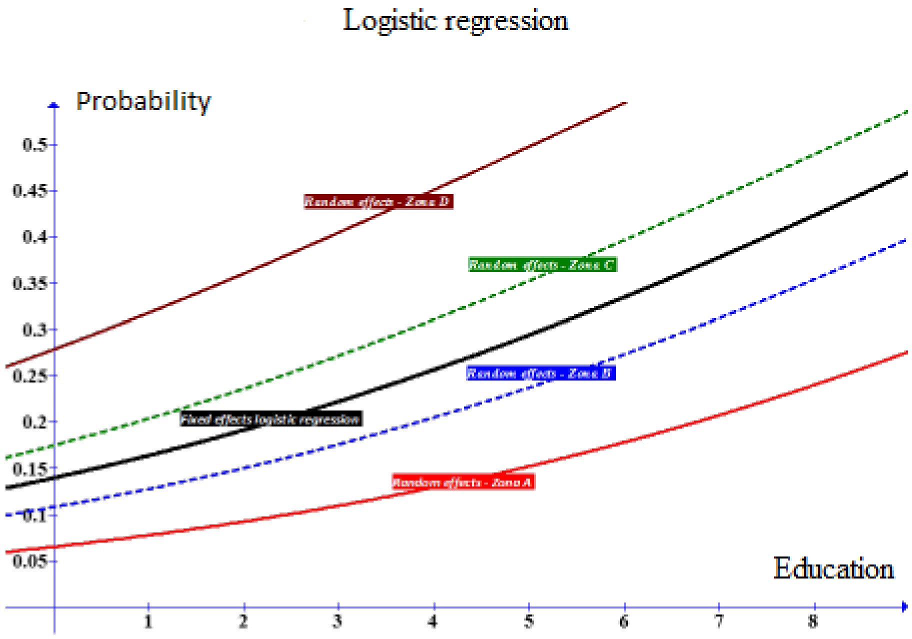
If we analyse the random effect "NSP Zone" $v_{1,D}$, the estimation column shows the values generated by the model. These values change $\boldsymbol{\beta}_0$, negatively for A area and more positively for D area.

Table 3 - Random effects linked to PSN areas.

Effect	PSN Areas	Estimate	Forecast	Df	t value	Pr > t
PSN Areas	A	-0.8393	0.4103	23155	-2.05	0.0408
PSN Areas	B	-0.2908	0.4088	23155	-0.71	0.4769
PSN Areas	C	0.2661	0.4087	23155	0.65	0.4769
PSN Areas	D	0.8640	0.4087	23155	2.11	0.0345

More precisely $\boldsymbol{\beta}_0$ is the intercept of the function, so we can see graphically what happens (figure 1).

Figure 1- Logistic regression line chart.



The black curve shows the fixed effects model where the growing trend is generated only by the growth of the title of study. The introduction of the random effect bound to the "NSP zone" moves the curve up or down. We can say that being in the D area is positively affecting the introduction of PDO and PGI products. Instead, the probability of producing quality products is lower in A area. From a statistical point of view, curves related to A and D areas are statistically significant, while curve of B and C areas are indicative. The statistical model used returns a probability distribution. It is possible to calculate odds ratio through such probabilities. Odds ratio are calculated by making the relationship between the probability of making a probability of not doing a certain thing.

The odds ratio for a variable in logistic regression represents how the odds change with a 1 unit increase in that variable holding all the other variables constant. It is very important to separate probability and odds. Basically, what this means is that the odds can have a large magnitude even if the underlying probabilities are low.

Odds and probability are closely linked through a function. From the table below we can see the odds ratios that derive from the regression and its probabilities.

Table 4 – NPS areas and ODDS.

	NSP areas	ODDS	PROBABILITY	%
DIPLOMA	**A**	0.6601	0.3976266489970	**39.76**
	B	0.7109	0.4155123034660	**41.55**
	C	0.7606	0.4320118141543	**43.20**
	D	0.9689	0.4921021890396	**49.21**
GRADUATIO N	**A**	0.9729	0.4931319377566	**49.31**
	B	1.0237	0.5058556110095	**50.59**
	C	1.0734	0.5177003954857	**51.77**
	D	1.2817	0.5617302888197	**56.17**

SPECIALIZATION	**A**	1.1293	0.5303620908280	**53.04**
	B	1.1801	0.5413054447044	**54.13**
	C	1.2298	0.5515292851377	**55.15**
	D	1.4381	0.5898445510849	**58.98**

This table shows that the likelihood of using PDO or PGI is higher for entrepreneurs with a higher level of education. Moreover, this probability is higher in C and D areas for all levels of education. We can say that the level of education affects all areas positively but affects more in C and D areas.

If we then report the odds ratio of the education levels for all NSP areas on the odds ratio for any title (AT) we see that the situation is even clearer. The following table shows the relationship between odds ratio.

Table 5 – Oddsratio with random effects.

ODDS RATIO		A area	B area	C area	D area
A area	Diploma/AT	1.59871471			
	Graduation/AT	2.185839576			
	Specialization/AT	2.555888723			
B area	Diploma/AT	**3.95824205**	1.59871471		
	Graduation/AT	**5.411898741**	2.185839576		
	Specialization/AT	**6.32809979**	2.555888723		
C area	Diploma/AT	**6.262628593**	**2.529445225**	1.59871471	
	Graduation/AT	**8.562566757**	**3.458379062**	2.185839576	
	Specialization/AT	**10.01215645**	**4.043861288**	2.555888723	
D area	Diploma/AT	**15.92674864**	**6.432736301**	**4.065757205**	1.59871471
	Graduation/AT	**21.77581608**	**8.79514619**	**5.558898627**	2.185839576
	Specialization/AT	**25.46232733**	**10.28411015**	**6.49998585**	2.555888723

On the diagonal of Table 5 we find the odds ratio of the fixed-rate logistics branch (black curve figure 1). The diagonal values are all the same because the random effect associated with the NSP zone is not considered. However, we use oddsratio to compare NSP categories. The other values in Table 5 indicate the incidence of the random effect linked to the NSP area on oddsratio. Moving from A area to D area we can see a consistent increase in the probability ratio. Moreover, odds ratio between Specialization and Any Title is higher in the D area. This means the propensity to make quality for those who have specialization over any title is 25,4623 times higher in D area than in A area. The odds ratio still shows that in D areas the likelihood of producing quality products is greater.

Conclusions

This works has to be considered a first attempt to test the relevance of education in performing higher levels of adoption of quality schemes in agricultural activity. In order to put forwards an empirical analysis in Italy we have applied a multinomial logit model with random effect, by taking into account education and farms' territorial localisation in rural/urban contexts.

The results of our model show higher propensity towards quality products for entrepreneurs with a higher level of education. Furthermore, farmers located in the most disadvantaged rural areas (D areas) evidence the highest probability to move towards quality agriculture if well educated, then escaping from the price-costs squeeze through strategies of product differentiation (Marsden, van der Ploeg, 2008). Policy implications are evident, in terms of need for empowering farmers, above all in rural areas. The first priority of recent rural development policy focuses on knowledge transfer and lifelong learning. An effective application of this priority at European level may facilitate transition towards a more coherent model of agricultural activity, above all in rural and marginal areas.

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