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Spatial structure of organic viticulture: evidence from Chianti (Italy)

Fabio BONCINELLI[1*], Francesco RICCIOLI[1], Leonardo CASINI[1]

Jel classification, Q12, D13, R12

Abstract

Several studies have stressed the existence of agglomeration effects in organic farming. However, due to a different incentive framework, viticulture can be considered an exception in the light of this general evidence. Applying a spatial Durbin Bayesian probit model to census data for the area of production of Chianti Classico DOCG (Italy), no spatial relation in the farmer's decision to convert to or maintain organic viticulture emerged and spatial spillovers have a marginal role in terms of affecting viticulturists' behaviour. An explanation for this evidence is the existence of quasi-monopsonic power in output markets with strict production standards, which limits spatial agglomeration effects. Structural factors such as small-size farm, farmer education and younger age are the main direct determinants for predicting the likelihood of being involved in organic viticulture.

Keywords: *spatial econometrics, spatial Durbin Bayesian probit model, market power, wine.*

Résumé

Plusieurs études ont mis l'accent sur la présence des effets d'agglomération en agriculture biologique. Toutefois, la viticulture constitue une exception par rapport à ce constat général vu qu'elle bénéficie d'un système d'aides différent. En appliquant un spatial Durbin Bayesian probit model aux données du recensement du domaine viticole du Chianti Classico DOCG (Italie), aucune relation spatiale n'a été mise en évidence en ce qui concerne la décision des agriculteurs de se convertir à la viticulture biologique ou de perpétuer ce mode de production. En outre, les débordements spatiaux n'influent que marginalement sur le comportement des viticulteurs. Ceci s'explique par le pouvoir quasi-monopsonique des marchés de ces produits réglés par des normes de production très strictes qui limitent les effets d'agglomération spatiale. Les facteurs structurels tels que la petite taille des exploitations, le niveau d'éducation et le jeune âge des agriculteurs, sont les principaux déterminants qui permettent de prévoir la probabilité de s'engager dans la viticulture biologique.

Mots-clés: économétrie spatiale, modèle probit de Durbin Bayesian spatial, pouvoir du marché, vin.

1. Introduction

Consumer preferences for wine attributes are generally greater where observable features are concerned, e.g., geographical indications, brand and grapevine (Hertzerg and Malorgio, 2008). However, there is evidence for increasing consumer interest regarding extrinsic features such as typicality (Scozzafava *et al.*, 2016) and sustainability (Sogari *et al.*, 2015). In this context, an emerging demand for organic wine can be observed (Mann *et al.*, 2012).

Organic viticulture is a prominent and relatively new market. Studying organic viticulture is relevant for several reasons. First, organic wines can advantage winemakers with an additional means of differentiation, increasing their competitiveness. Second, it can foster the environmental wellbeing of production areas due to the environmental benefits of organic production (Riccioli *et al.*, 2013; Vincent and Fleury, 2015). Therefore, investigating the determinants of organic viticulture is crucial for improving knowledge about the economic processes and factors affecting the decision to engage in this form of farming and winemaking.

Localization is one of the key factors for understanding the diffusion of organic farming. In particular, several studies have detected organic spatial clusters. Knox (1989) defines a spatial cluster as "a geographically bounded group of occurrences of sufficient size and concentration to be unlikely to have occurred by chance". Many studies have found evidence of this spatial clustering in organic farming (Parker and Munroe, 2007; Lewis *et al.*, 2011; Schmidtner *et al.*, 2012; Wollni and Andersson, 2014; Läpple and Kelley, 2015; Boncinelli *et al.*, 2015), explaining the phenomenon using the theory of social conformability or external economies of scale. However, the particular features of a sector can reduce incentives for farm clusterization in specific areas. Yet some primary sectors such as viticulture may be less influenced by agglomeration factors.

The aim of this paper is twofold: (*i*) verify whether spatial dependence in organic farming, as stressed by the existing literature, is valid in the area of viticulture; (*ii*) provide insights into the determinants of organic viticulture since, to our knowledge, less attention has been devoted to this topic. The paper's objectives are pursued using a spatial Durbin Bayesian probit model in order to analyse data pertaining to the area of production of the Chianti Classico DOCG (Italy).

Enhancing knowledge about viticulture is a relevant issue, as this sector is one of the main agricultural productions in the Mediterranean area where the largest share of vineyards in the world is concentrated. Indeed, Anderson and Aryal (2014) estimate that wine-grape bearing areas in Algeria, Croatia, Cyprus, France, Greece, Israel, Italy, Morocco, Slovenia, Spain, Tunisia and Turkey account for

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58.7% of the world's winegrowing areas. Moreover, wine grapes production and winemaking play a key role for the sustainability of rural economies in Mediterranean countries, particularly for the Northern side of the Mediterranean Sea as demonstrated, for example, by evidence that Spain, France, Italy, Greece and Turkey in 2014 accounted for almost 60% of the world's total wine exported (Comtrade, 2016).

The current paper is organized as follows. The 'Determinants of organic farming' section provides a literature review on the topic and the causes of spatial dependence. Following on, 'Modelling economic behaviour and the estimation method' describes viticulturists' behaviour and the spatial econometric model used to test the paper's hypothesis. The 'Data and case study description' section presents a description of the information source and a brief characterization of Chianti. In 'Results and discussions', results are presented followed by a discussion. The paper is summarized in 'Conclusion'.

2. Determinants of organic farming

Recently, the attention of research on the determinants of organic farming has turned to the spatial dependence of organic agriculture (Schmidtner *et al.*, 2012; Wollni and Andersson, 2014; Läpple and Kelley, 2015; Boncinelli *et al.*, 2015). According to these authors, the decision to convert to organic farming is spatially correlated. Therefore, the farmer's decision to convert to organic production depends not only on his characteristics and on the features of his farm, but it is strongly correlated with the decisions of 'the closer' farmers and their characteristics. Therefore, the farm that is close to an organic one has a higher probability of being an organic farm itself. Parker and Munroe (2007) and Schmidtner *et al.* (2012) found a positive correlation between the proportions of organically farmed land in contiguous regions in Sweden and Germany. Others (Lewis *et al.*, 2011; Läpple and Kelley, 2015; Allò *et al.*, 2015) demonstrated that spatial agglomeration can be detected even at the farm level, i.e., farmers are likely to adopt organic production when their neighbours adopt organic production. Wollni and Andersson (2014) and Läpple and Kelley (2015) stressed social conformity to be the main factor in spatial clustering, i.e., the tendency of the individual to behave in compliance with their social group. Boncinelli *et al.* (2015) highlighted the importance of neighbourhoodnetworks and communities to explain the spatial dependence of participation in the policies designed to foster the diffusion of organic farming. They point out that proximity can facilitate the diffusion of information and can reduce transaction costs.

New geographical economics explains the existence of spatial clustering using the concept of economies of agglomeration. Economies of agglomeration include all the benefits that firms receive from being located near one another. Fujita and Thisse (1996) point out that economies of agglomeration arise from Marshallian externalities, i.e., from human capital and technology accumulation, face-to-face communication and repeated economic interaction. These features are positively correlated with the number of firms existing in a limited space. Therefore, economies of agglomeration are often referred to as external economies of scale. These external economies of scale reduce the transaction costs involved in some types of production and increase the probability of this type of production occurring in a limited area.

An additional factor that influences spatial structure is the diffusion pattern of innovations in the primary sector. If we assume that organic farming is an innovation process for the single farm, then spatial structure in organic agriculture can be determined by the diffusion pattern of innovation in the primary sector. Rogers (1995) demonstrates that the diffusion of innovation in agricultural processes is generally performed by innovative farmers and then transmitted to others by an imitation process, or by peer-to-peer contact, mass media campaigns or by the extension of service networks. Neighbouring networks produce effects through imitation and may as a result cause agglomeration by imitation (Bandiera and Rasul, 2006). Several authors (Case, 1992; Conley and Udry, 2010) highlighted imitation as a driver of the diffusion of innovation. In particular, in a given geographical area, when a producer adopts an innovation, he is often mimicked by neighbouring farms. Farming practices, the introduction of a new cultivar and innovative soil conservation techniques, among others, can easily be imitated by local competitors. Therefore, the conditions for the imitation of an innovation are somehow related to closeness among farmers, the interaction between subjects and cluster localization.

Döring and Schnellenbach (2006) showed the existence of a direct relationship between the model of the diffusion of innovations and the economic performance of local areas. In practice, if the diffusion of innovation is geographically determined, the spillover effects will determine a strong spatial relationship, i.e., similar farms will tend to be localized in the same geographical area. Therefore, within a region, it is possible to find similar economic structures, similar sector specialization, similar income levels, similar growth patterns and similar and complementary technologies.

The economic phenomena previously listed explain the clustered spatial regime of organic production. However, a strong market power's influence on the value chain or stringent production standards in the output market may reduce incentives for organic farms to be located within specific local clusters. This may be due to two primary reasons. Firstly, organic viticulture can be viewed as a relatively new process of innovation in viticulture; thus, all underlying factors of external economies of scale can be considered less strongly relative to what happens in other permanent crop productions. Secondly, viticulture has strong vertical and local integration with the local wine industry. Stringent production standards characterize winemaking, which can limit innovation in terms of processes and product differentiation, e.g., organic production. This can be particularly true for grapes used to produce PDO (protected designation of origin) or PGI (protected geographical indication) wines that require specific production regulations and impose stringent viticulturist standards. Moreover, many production areas are linked to wines with a well-established reputation among consumers. Therefore, a quasi-monopsonic market can reduce incentives for innovation and diversification.

Weiss and Wittkopp (2005) stress that when buyers have market power and have the ability to influence input prices, the incentives for introducing new products in the upstream market is reduced. Moreover, they state that the negative impact on innovation by market power is mitigated if buyer concentration also implies market power towards consumers. Since single wineries have only a small share in the wine market (Contini *et al.*, 2015), this exacerbates the negative impact of market power on the diffusion of organic viticulture.

Certainly, other factors, in addition to location, determine the decision to convert to organic farming. Läpple (2010) found that smaller farmers, in terms of land endowment, are more likely to convert to organic farming. In contrast, Pietola and Lansink (2001) and Gardebroek (2006) stress that farms utilizing large agricultural areas are more likely to adopt organic farming.

Farmer education, gender and age are widely employed as proxies for farmers' attitudes toward innovation and environmental concerns. This is relevant, since Läpple and Kelley (2013) found that the most important factor among farmers for predicting a conversion to organic farming is their attitudes toward environmental concerns. The high probability of finding organic farming among women seems rooted in their greater attention to environmental awareness. Orlitzky *et al.* (2011) note that when women have a key role in the management of a firm, the environmental performance of the firm was higher.

A higher probability of converting to organic farming was found among better-educated farmers (Santucci, 2003; Latruffe and Nauges, 2014). The impact of age was uncertain according to Knowler and Bradshaw (2007); indeed, several authors found a positive, negative or no relation regarding the link between age and the willingness to convert to organic farming.

Tiedemann and Latacz-Lohmann (2013), Gardebroek *et al.* (2010) and Gardebroek (2006) stress the role of risk aversion in the decision to adopt organic agriculture, and conclude that organic farmers show lower average risk aversion. Moreover, Gardebroek *et al.* (2010) stress the evidence that organic farms use more labour in comparison to conventional ones.

Pietola and Lansink (2001) highlight that the decision to farm organic is (where available) strongly correlated with public support. However, Castellini et al. (2014), using a survey on organic wine producers, found that public support played only a marginal role in fostering a conversion to organic farming among viticulturists, as ethical reasons were the main stated motivation for producing organic wine.

3. Modelling economic behaviour and the estimation method

Viticulturist behaviour can be formalized following key ideas presented by Läpple and Kelley (2015), Wollni and Andersson (2014) and Schmidtner et al. (2012). According to these authors, the *i*-th generic viticulturist will be willing to convert to or maintain organic farming if the utility to farm organically ($E[U_i^{or}]$) is greater than the utility of conventional farming ($E[U_i^{co}]$). Therefore, we can observe involvement in organic farming if the above condition is true:

$$E[U_i^{or}(\pi_i^{or} - I)] - E[U_i^{co}(\pi_i^{co})] > 0 \quad (1)$$

where

$$I = TC_i^{or}(d_j,SF) + G_i^{or}(d_j,SF) \quad (2)$$

with the general profit function written as:

$$\pi_i^t = p_i q_i(\boldsymbol{x},d_j,SF) - c(\boldsymbol{x},d_j,SF) + ps \quad (3)$$

where U_i is the utility that *i*-th farmer derives from farming conventional (co) or organic (or) products, π is the profit and I is the cost of converting from conventional to organic farming. TC and G are other fixed and variable converting costs including investments into information-gathering costs, training costs, learning costs, sunk costs and potential losses due to errors or lower yields. In turn, TC is a function of d_j, which is the decision of the j-th neighbouring farmers to convert or not to organic farming; SF are all spatial factors or factors that are spatially available such as an advisory service and distance to markets. Finally, $\pi_i^t = \pi_i^{or} + \pi_i^{co}$ is the total profit of the farm and p_i is the output price; c is the variable cost and ps is the eventual public support for converting to or maintaining organic production and $\boldsymbol{x}$ is the vector of inputs.

Spatial effects may impact on the behaviour of farmers and on the probability for being involved in organic production, which in turn can influence both the cost and/or price of the relations described by equations (2) and (3). Peer effects and external economies of scale reduce converting and production costs for organic farming, and influence the profitability of organic farming. Moreover, conventional or organic output prices are different; generally, organic output prices are greater than conventional output prices and with different elasticity. However, the presence of stringent production standards or quasi-monopsonic output markets can alter this relation. These effects are testable using spatial econometrics methods and spatial statistics (LeSage and Pace, 2009).

In order to estimate a spatial econometrics model or calculate spatial statistics, it is necessary to consider firstly spatial weights (Getis, 2009). Due to weighting, observations pertaining to the spatial regime between the elements in the sample are included in the empirical model. A matrix,

W, collects the weights and is an $N \times N$ matrix for a sample of N elements. W is labelled as the spatial weight matrix and contains a list of weights equal to w_{ij}. The generic element of W is defined as 1 if observations j is one of the n-th nearest (defined somehow) observations to the i-th observation. W is row-stochastic, that is, non-negative and each row sums to 1.

Spatial dependence is often defined as spatial autocorrelation or spatial association (Fotheringham, 2009) and can be detected by spatial econometrics models (see LeSage and Pace, 2009), which explicitly take into account the spatial structures of data using a spatial matrix. This kind of analysis is widely applied in agricultural economic and environmental studies (see, among the most recent, Allaire *et al.*, 2015; Riccioli *et al.*, 2016a; Riccioli *et al.*, 2016b; Wang *et al.*, 2016).

In order to pursue the current paper's aim, the empirical strategy of Läpple and Kelley (2015) was adopted; thus, a spatial autoregressive Durbin (SAD) probit model was applied. SAD is a spatial autoregressive model variant of the conventional probit model (LeSage and Pace, 2009). The SAD model is written as follows:

$$y^* = \rho W y^* + X\beta + WX\theta + \varepsilon, \qquad \varepsilon \sim N(0, I_n) \tag{4}$$

where ρ is a scalar and is the autoregressive parameter that measures the spatial relation between neighbours and the probability of being involved in organic viticulture. The coefficient ρ range is between zero (spatial independence) and one (spatial determined). β is the vector of the parameters associated with structural factors. θ is the spatial vector of parameters of the structural factors of the neighbours and, together with ρ, measures the spatial relation of the dependent variable. Therefore, the spatial pattern of organic viticulture is detected by the combination of the parameters ρ and θ, where the first value measures the influence of neighbours' decisions and the second measures the influence of neighbours' characteristics. Finally, ε is the error term, normally distributed.

We applied this model as it fits the paper's hypothesis, i.e., whether there is a spatial causation among winegrowers' decision for converting to organic farming. The quantity Wy of equation (4) is called spatial lag and measures how the decision of the i-th farmer depends on the same decision of the j-th contiguous farmers; ρ measures the intensity of this connection. Therefore, if ρ is positive and significant it means that organic viticulture is spatially clustered.

Moreover, the inclusion of the spatially weighted neighbouring farmers' features, $WX\theta$, is effected to avoid bias from spatially correlated omitted variables. Indeed, explanatory variables and some latent data reflect some local and spatially dependent conditions such as labour market, soil condition, and credit market. Since these variables are likely to be correlated with the explanatory variable it seems plausible that an omitted variable bias will be detected. Fortunately, LeSage and Pace (2009) demonstrate that using a spatial Durbin model that includes the estimation $WX\theta$ can produce consistent estimates that do not suffer from the omitted variable concerns.

As already noted, the i-th farmer will be involved in organic production if $E(U^{or})>E(U^{co})$; thus, $y^* = E(U^{or}) - E(U^{co})$. The term y^* is unobservable, as it is only observable if a farmer is or is not involved in organic viticulture. Therefore:

$$y^* = \begin{cases} 1 & \text{if } E(U^{or}) > E(U^{co}) \\ 0 & \text{if } E(U^{or}) < E(U^{co}) \end{cases} \tag{5}$$

Defining y^* as the n x 1 vector of binary variables reflecting the latent continuous unobservable expected utility associated with organic viticulture, the econometric model can be estimated via a Bayesian estimation approach. The model parameters β, ρ and θ are estimated by sampling from the conditional distribution used for the dependent continuous models (LeSage and Pace, 2009; LeSage *et al.*, 2011). This conclusion derives from the interpretation of Albert and Chib (1993), where $p(\beta, \rho, \theta \mid y^*) = p(\beta, \rho, \theta \mid y^*, y)$. Therefore, vector y^* can be viewed as a vector of estimated parameters. LeSage and Pace (2009) implemented a Bayesian Markov Chain Monte Carlo (MCMC) estimation procedure for the SAD probit model. Additional details regarding the estimation procedure can be found in LeSage and Pace (2009), LeSage *et al.* (2011) and Lacombe and LeSage (2015).

The interpretation of results of SAD requires further attention. The impact of changes in the explanatory variables on outcomes concerning the likelihood of being an organic viticulturist is not linear. In fact, from equation (4), the expected values of y_i for a change in covariate v for $v = 1;\ldots;k$ can be written as:

$$E(y^*) = (I_n - \rho W)^{-1} \Delta x (I_n \beta_v + W\theta_v) = \partial y / \partial x'_v \tag{6}$$

Therefore, a change in the explanatory variables of the i-th farmer impacts the probability for adopting organic viticulture, as well as the probability of other j-th farmers near to i adopting organic viticulture. Therefore, a change in the explanatory variable has three types of effects, i.e., direct effects, indirect effects and the sum of these two, referred to as the total effect.

The definition of direct and indirect effects is taken from Lacombe and LeSage (2015) and LeSage and Pace (2009). The direct effect is the average of elements in the diagonal of the n X n matrix of elements $\partial y/\partial x'_{v,i}$.

The indirect effects are the average of the cumulated off-diagonal elements $\partial y/\partial x_v$ for $(i \neq j)$ of the same matrix, i.e., $\partial y/\partial x'_{v,i}$. These elements are cross-partial derivatives and represent spatial spillover impacts. Posing the equation in (6) equal to η, we can obtain the effect of a change in a characteristic pertaining to farmer i and how it influences the likelihood of organic farming on the part of farmer j:

$$\frac{\partial \Pr(y_i = 1)}{\partial x_{v,j}} = pdf(\eta_i)(I_n - \rho W)^{-1}(\beta_v + W\theta_v) \tag{7}$$

where pdf(η_i) is the probability density function evaluated at η_i.

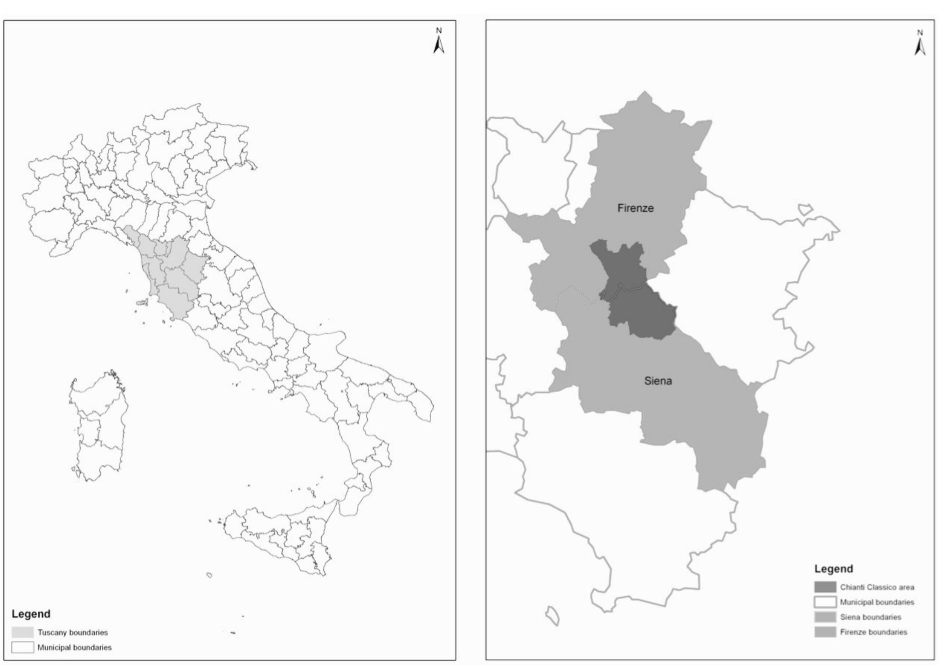
The spatial weight matrix applied to the described model in equation (4) is defined as follows: w_{ij} equal to 1 for the n-th nearest neighbours and 0 otherwise. For the sake of the current paper, we performed three models using three weighting matrices. These weighting matrices are calculated using the 10th, 20th and 30th nearest neighbours.

4. Data and case study description

The present paper uses as a case study organic and conventional grape production in Chianti, in particular, the subarea where Chianti Classico DOCG is produced. The Chianti area is located in Italy, in the southern part of Florence and in the northern part of the Province of Siena; it covers an area of approximately 600 km^2, with a total resident population of roughly 77 000 inhabitants. The Chianti area is characterized by a predominantly hilly topography; the average annual temperature varies between 11.6 and 15°C, while rainfall conditions are estimated at roughly 800 mm per year.

Major land use in Chianti is dedicated to vineyards producing the famous red wine that takes its name from the region. The area investigated for this paper is strictly related to the “Chianti Classico DOCG”, a wine that can be produced using selected wine grapes according to quality and origin. DOCG (controlled and guaranteed designation of origin), with DOC (controlled origin) are the Italian quality assurance labels attributed to wine produced according to strict production standards. These standards are required even for the main raw materials (grapes).

The Chianti Classico area is a sub-region of the larger area of Chianti. It includes 10 municipalities, located in the province of Siena and Firenze: Barberino Val d’Elsa, Castellina in Chianti, Castelnuovo Berardenga, Gaiole in Chianti, Greve in Chianti, Poggibonsi, Radda in Chianti, San Casciano in Val di Pesa and Tavarnelle Val di Pesa (see Figure 1).



The selection of this sub-region for the present study was made primarily for two reasons. Firstly, the area is quite homogeneous in terms of soil and weather conditions; thus, the impacts detected by the model were not related to these variables. Secondly, grape production in this area produces top quality wines that adhere to stringent production standards. Therefore, along the value chain, we found a quasi-monopsonic market, since viticulturists can profitably sell their products to only the Chianti Classico DOCG winemakers.

Data used in this study were retrieved from the sixth Italian agricultural census (2010). The dataset contained the explanatory variables at the farm level for 1397 winegrowers in the Chianti Classico production areas. Only 7.52% of these areas cultivated organic grapes.

The dependent variable was coded “1” if a farm cultivated grapevines using organic production processes that were standard in most parts of its utilized agricultural area and "0" otherwise. The covariates included: a dummy variable equal to “1” if the farmer was female; the age of the farmer; a dummy equal to “1” if the farmer had at least a secondary school education; a dummy equal to “1” if the farmer was a part-time farmer (i.e., agriculture was not the primary source of income); the size of farms in terms of utilized agricultural area (UAA); the number of plots; the number of workers; the distance to the closest urban area (defined as a municipality with more than 15 000 inhabitants). Table 1 shows the descriptive statistics calculated for conventional and organic farmers. Organic viticulturists appear to be full-time farmers, younger and better educated. Organic viticulture farms differ from the conventional ones in terms of a greater distance to the closest urban centre and for the payments received for converting to or maintaining organic farming. Although the two types of farms seem to have similar sizes in terms of UAA, the standard deviation of the conventional viticulturists is substantially lower than the standard deviation of organic farms, indicating greater homogeneity.

5. Results and discussion

The model parameters ρ, θ and the posteriors means, β, standard deviations and p-levels are relegated to Annex 1, since changes in estimations do not represent change in terms of the likelihood to adopt organic viticulture. Annex 1 reports estimations using different definitions for the spatial weighting matrix. The results are consistent in terms of significance and estimated impacts, even with different definitions for the spatial weight matrix. Therefore, below, comments are related to the model featuring 20 neighbourhoods.

The ρ is not significant for all estima-

Table 1 - *Mean of explanatory variables.*			
Variables	Pooled Sample[a]	Conventional[a]	Organic[a]
Female farmer	0.27 (0.45)	0.27 (0.45)	0.27 (0.44)
Age of farmer	58.64 (15.80)	59.29 (15.77)	50.69 (13.87)
Farmer education	0.41 (0.49)	0.40 (0.49)	0.58 (0.50)
Part-time farmer	0.11 (0.32)	0.12 (0.32)	0.04 (0.19)
UAA	17.64 (43.38)	17.65 (44.67)	17.62 (22.15)
# Plots	1.91 (1.92)	1.89 (1.95)	2.19 (1.62)
# Workers	4.60 (8.22)	4.57 (8.42)	4.98 (5.20)
Distance to closest urban centre	6.76 (4.65)	6.68 (4.68)	7.83 (4.14)
RDP Payment for organic farming (000)	2.71 (15.79)	2.06 (15.31)[b]	10.70(19.186)

Note: [a] Standard deviations in parenthesis. [b] Conventional viticulturists can receive payments for converting to organic other production rather than grapevines.

Table 2 - *Direct effect estimations.*			
Variables	lower 01	Coefficient	upper 99
Female farmer	-0.063	-0.043	-0.009
Age of farmer	-0.004	-0.004	-0.002
Farmer education	0.003	0.011	0.046
Part-time farmer	-0.252	-0.199	-0.099
UAA	-0.003	-0.002	-0.001
# Plots	-0.004	-0.0001	0.008
# Workers	-0.007	-0.006	-0.003
Distance to the closest urban centre	-0.009	-0.004	0.009
RDP of Payment for organic farming (000)	4.72e-4	6.69e-4	1.80e-3

tions. This implies that there is no spatial dependence based on the behaviour of winegrowers, representing a finding that differs from previously noted works on spatial dependence in organic farming (Parker and Munroe, 2007; Schmidtner *et al.*, 2012; Wollni and Andersson, 2014; Läpple and Kelley, 2015; Boncinelli *et al.*, 2015). This confirms the current paper's hypothesis that spatial clustering in organic agriculture can highlight an exception due to local market systems and the incentives available to a farm.

The magnitude of the direct and indirect estimations provides evidence of spatial spillover. Table 2 shows the direct posterior marginal effects calculated as described in the previous section. The age, gender and education level of farmers, as well as whether they are full-time farmers, the size of the farm, the number of farm workers and payments from RDP show 95% credible intervals, i.e., the posterior distribution for the parameters is far from zero. All variables, with the exception of education and payment from RDP, have a negative direct effect on organic viticulture. Although these variables are statistically significant, the magnitude of the coefficients shows that their impact is limited, with part-time farmers being the exception.

Other farmer features also play an important role in predicting winegrowers' behaviour. Being female and an older farmer decreased the likelihood of farms being organic. The more educated the farmers, the more likely they were to grow organic grapes. Age was shown to have a significant role in predicting organic viticulture; a farmer older than 10 years, keeping all other factors constant, has a lower probability of partaking in organic production by almost 4%. This may be due to a different level of risk aversion being present between younger and older farmers (Boncinelli *et al.*, 2016). Furthermore, risk-averse farmers will be less likely to adopt organic farming (Läpple, 2010), while younger farmers appeared to have more remarkable environmental attitudes. An alternative explanation may be that older farmers have more consolidated skills than their younger counterparts with regard to conventional farming and as such, their learning cost for converting to organic farming will be greater.

In terms of UAA and on-farm labour endowments, bigger farms showed a lower probability for being involved in organic farming. In fact, additional workers or hectares of UAA decreased the probability of organic adoption by 0.6% and 0.2%, respectively. Therefore, organic farming can be a suitable investment for smaller farmers, rather than their larger counterparts. This finding is in line with the conclusions of Gardebroek *et al.* (2010). One explanation for this result may be the need of small farms to find alternative markets for their products to that of monopsonistic purchasers, or for winemakers to establish diversification opportunities for their products. Finally, public incentives, as expected, played a positive role in fostering organic conversion, even if the impact it effected was very low. Indeed, every €1 000 received as the result of public support increased the probability for converting to organic production by 0.07%.

Indirect effects measured the spatial spillovers in terms of the adoption of organic viticulture (Table 3). The parameters pertaining to indirect effects were similar to those that had direct effects in terms of sign and burden. Farmer features, i.e., gender, age, part-time/full-time farmer and farm characteristics, i.e., the size of the farm and its number of workers, had a significant spatial effect in terms of predicting organic adoption. Other variables, i.e., number of plots, distance to the closest urban centre and RDP payment had no significant indirect effect on the decision to convert to organic viticulture.

Female farmers had a negative impact on the adoption of organic viticulture of their neighbours. On the other hand, younger farmers had a relevant influence on the likelihood of involvement in organic farming. Farmer education had no significant indirect effect and neither did distance to the closest urban centre. This latter variable had no direct or indirect effect on the utility of organic production. This was in line with the findings of Schmidtner *et al.* (2012) and Läpple and Kelley (2015), but not with the findings of Wollni and Andersson (2014). A possible explanation for this is that organic grapes are generally sold at local markets. Wollni and Andersson (2014) studied the coffee sector, where coffee is generally exported with no substantial transformation. Therefore, we can assume that the impor-

Table 3 - *Indirect effect estimations.*

Variables	lower 01	Coefficient	upper 99
Female farmer	-0.052	-0.028	-0.005
Age of farmer	-0.004	-0.0032	-0.001
Farmer education	-0.007	-0.0014	0.023
Part-time farmer	-0.224	-0.166	-0.049
UAA	-0.002	-0.002	-0.0004
# Plots	-0.001	-0.001	0.004
# Workers	-0.009	-0.005	-0.001
Distance to the closest urban centre	-0.004	-0.002	0.005
RDP of payment for organic farming (000)	-3.052e-04	-8.305e-05	8.821e-4

Table 4 - *Total effect estimations.*

Total	lower 01	Coefficient	upper 99
Female farmer	-0.105	-0.065	-0.014
Age of farmer	-0.008	-0.006	-0.003
Farmer education	0.003	0.018	0.07
Part-time farmer	-0.415	-0.325	-0.148
UAA	-0.004	-0.0035	-0.001
# Plots	-0.0042	-0.0002	0.011
# Workers	-0.015	-0.01	-0.004
Distance to the closest urban centre	-0.013	-0.005	0.013
RDP of payment for organic (000)	0.001	0.0011	0.00003

tance of distance to the nearest selling market depends on the typology of goods and its relative market. Farm size and the number of workers have a negative indirect effect and reinforce the idea that organic viticulture is a viable option for small farms.

The total effects of the structural factors considered in this estimation summarize the direct and indirect effects previously described. Table 4 shows that part-time farmers preferred to engage in conventional farming, as did female farmers. The evidence that women viticulturist are less likely to engage in organic farming is in contrast with Läpple and Kelley (2013) and Orlitzky *et al.* (2011).

On the other hand, young and highly-educated farmers were willing to be involved in organic production more so than older farmers with a low level of education. This is likely due to the evidence indicating that organic farming requires different skills and that the acquisition of these skills can increase transition costs, as noted by Boncinelli *et al.* (2015).

Although RDP payments had a statistically significant impact on the probabilities for converting to organic production, the economic burden was shown as not significant, since an additional support of €1000 increased the likelihood of converting by only 0.1%. This is in line with the conclusions presented by Castellini *et al.* (2014).

6. Conclusion

The spatial dependence of organic viticulture was tested in this paper. The findings indicate that organic viticulture does not show any evidence of spatial dependence. Although previous studies detected spatial dependence in organic farming as it pertains to viticulture, this evidence was not confirmed. Therefore, the primary conclusion of this research is that clustering in organic farming is not a regularity, but that exceptions can nonetheless occur. Moreover, an additional finding of this work is that the values of indirect effects, which measured the economies of agglomeration, had low coefficients. Therefore, the impact of spatial determinants was found to be negligible.

Spatial heterogeneity may be related to the heterogeneity of a farmer's willingness to convert to organic viticulture. Since the willingness to convert is randomly distributed among farmers, it would be probably random spatially distributed. However, this implies that within viticulturist, social norms should be less strong than general farmers or, again, the incentives against clustering are sronger than social norms.

Several structural factors can affect the likelihood of adopting organic production in viticulture. From the results of this study, a clear typology of the organic grape producer emerges. Young, well-educated male farmers with small farms are prevalent figures in organic viticulture.

In addition, public incentives do not appear to play a role in fostering organic conversion. Policy makers whose objective is to promote environmentally sustainable practices in areas historically dedicated to viticulture must therefore better structure their interventions.

Finally, the evidence that organic winegrowing is more common between smaller farms in terms of UAA and workers is a relevant issue that deserves further investigation in order to better understand the causes for which the organic winegrowers have this structural characteristic. Indeed, this fact may relate to the evidence that organic viticulture is only a small market niche served by a few small specialized producers. On the other hand, smaller winegrowers should convert to organic farming for pursuing diversification strategies for alleviating the market power of winemakers. If the diffusion of organic viticulture is limited, it will result in Mediterranean areas receiving lower environmental benefits compared to areas with less chemically intensive farming practices.

The primary limitation of this paper is common among studies that apply spatial econometrics models. This class of econometric model has the advantage of detecting spatial structures in data generation processes; however, they do not directly detect the source of the spatial route that generates this process. In other words, hypotheses concerning the existence of peer-effects, imitation and knowledge diffusion are often purely speculative. Therefore, further research and testing on spatial structures in organic viticulture is needed in order to detect the source – or lack - of spatial processes.

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Annex 1

Table 5 - *Estimations with different definition of spatial matrix.*

variables	Model with 10 neighbours			Model with 20 neighbours			Model with 30 neighbours		
β	Posterior Mean	Std. Dev.	p-level	Posterior Mean	Std. Dev.	p-level	Posterior Mean	Std. Dev.	p-level
Constant	-1.3419	1.0436	0.1985	-0.5024	1.4335	0.726	1.158	1.6168	0.4739
Gender	-0.0683	0.1283	0.5945	-0.0724	0.1233	0.5572	-0.0445	0.1213	0.7141
Age	-0.0157	0.0039	0.0001	-0.0163	0.0042	0.0001	-0.0163	0.0044	0.0002
Education	0.3562	0.1239	0.004	0.3738	0.1299	0.004	0.3848	0.1309	0.0033
Part-time farmer	-0.7552	0.244	0.002	-0.7958	0.2614	0.0023	-0.7554	0.2673	0.0047
UAA	-0.0065	0.0029	0.0263	-0.007	0.0035	0.0456	-0.0062	0.0029	0.0324
# Plots	0.0566	0.0283	0.0456	0.0612	0.031	0.0485	0.0589	0.0298	0.0477
# Workers	-0.0167	0.0105	0.1096	-0.0209	0.0104	0.0451	-0.0209	0.0105	0.0470
Distance to urban centre	0.0338	0.0549	0.5381	0.0702	0.0535	0.1897	0.0637	0.054	0.2376
Payment for organic	0.00001	0.000003	0.00001	0.00001	0.000003	0.00003	0.00001	0.000003	0.00003
θ									
W-Gender	-0.3610	0.4335	0.405	-0.2318	0.6063	0.7023	-0.5333	0.7107	0.453
W-Age	0.013	0.0148	0.3681	0.0052	0.0214	0.8071	-0.0160	0.0244	0.5123
W-Education	0.3382	0.4115	0.4111	-0.386	0.4965	0.4369	-0.6059	0.674	0.3687
W-Part-time farmer	0.6751	0.7365	0.3593	1.8312	1.20868	0.1298	0.0188	1.3336	0.9888
W-UAA	0.0014	0.0077	0.8524	0.0038	0.01	0.6999	-0.0054	0.0083	0.5158
W-# Plots	-0.1389	0.0863	0.1075	-0.225	0.1089	0.0389	-0.1845	0.1104	0.0946
W-# Workers	0.0481	0.0382	0.2074	0.0557	0.0377	0.1401	0.0729	0.0363	0.0448
W-Distance to urban centre	-0.0131	0.0561	0.8154	-0.0458	0.0532	0.389	-0.05	0.0543	0.3568
W-RDP of Payment for organic	0.00001	0.00001	0.5235	-0.000002	0.00002	0.9195	-0.00002	0.00002	0.2868
ρ	0.2499	0.1272	0.0494	0.3101	0.1697	0.0677	0.2694	0.1901	0.1564