Spatial analysis of the participation in agri-environment measures for organic farming

1. Introduction

In 1992, the MacSharry reform of the Common Agricultural Policy (CAP) introduced the agri-environmental measures (AEMs) that provide payments to farmers who voluntarily commit to environmental measures related to the preservation of the environment and to maintaining the countryside. Since the Agenda 2000 reform of the CAP, the application of agri-environmental programs was made compulsory for Member States within the Rural Development Plans (RDPs).

One of the aims of agri-environmental programs is to provide public goods via measures designed to increase positive externalities through agriculture. The conversion and maintenance of organic production is one of the main AEMs in terms of resources supplied by the EU (European Commission, 2010). Almost all AEMs contain payments in favor of the introduction or maintenance of organic farming (Sander et al., 2011). Therefore it is logical to conclude that organic farming support is the key strategy aimed at maintaining viable rural areas through the provision of environmental benefits and with qulity of lofe improvments (Silva et al. 2014) .

During the 2000s, the importance of increasing organic farming support in the agricultural policies became a key strategy in rural development policy in many member countries. Organic farming combines environmental benefits through the reduction of chemical inputs with economic benefits through the diversification of economic activities (Peigné et al., 2015), potentially increasing farmers' income (Kleemann and Abdulai, 2014; Boncinelli and Casini, 2014). Organic farming practices' environmental benefits are numerous, i.e., soil conservation, increased biodiversity as well as reduced soil and aquifer pollution. In addition, consumers are more willing to pay a premium price for food produced less intensively with chemicals, perceived as a healthy and ethical choice (Michaud et al., 2013). The environmental benefits justify the public support. However the ability to combine it with positive private outcomes has involved the strong engagement of the European Union. Public support is indispensable since organic farming entails greater risks than conventional agriculture, and conversion costs from conventional to organic can be an entrance barrier (Gardebroek et al., 2010).

Measure 214-sub-measure A1 (hereafter Measure 214) is the main policy instrument in the EU to incentivize organic farming diffusion (Sanders et al., 2011). Measure 214 provides payments to cover additional costs or income foregone as well as transaction costs (EC Reg. 1257/06). Farmers receive payments for conversion to or maintenance of organic farming in order to compensate them for voluntarily entering into the multi-year prescriptions.

Although Measure 214 is mandatory in the EU, the diffusion and the weight of organic products in total agricultural production today differs substantially among European territories. This is due to differences in climate, soil conditions, farm structures, the institutional environment, market forces, and economic policies (Schmidtner et al., 2012). The spatial variation of these factors is reflected in a spatial heterogeneity of the diffusion of organic production.

Schmidtner et al. (2012) found evidences of economies of agglomeration in organic farming, which are economies of scale external to the farm (Venables, 2009), creating regional agglomerations of organic farms. The factors that determine the spatial heterogeneity of the diffusion of organic farming could play a key role even in the spatial regime associated with the rate of farm participation in rural development plans dedicated to fostering organic farming. Indeed, according to Baumgart-Getz et al. (2012), the spatial distribution of the quality of institutions and extension services entails a non-homogeneous distribution of participation in AESs, including organic farming support. In other words, the areas with a certain rate of farm participation in Measure 214 may be likely to be close to other areas with a similar rate of participation.

The role of "space" is relevant for the study of crucial economic and social phenomena. From the so-called first law of economic geography formulated by Tobler (1970: p. 236), which states, "*Everything is related to everything else, but near things are more related than distant things*", numerous statistical econometrics models (see Fischer and Getis, 2010) have been proposed to analyze the spatial effects of economic and social events. These quantitative tools test the influence of social norms, the effects of production externalities, the localization pattern, and the behavior of social groups (Ward and Gleditsch, 2008; LeSage and Peace, 2009). An investigation into the spatial interactions between agents provides an interpretation of collective behaviors, Marshallian externalities, agglomeration economies and the spillover of local economies. Including spatial interactions in the economic analysis helps to relax the classical hypothesis of the atomistic agent who makes decisions irrespective of the effects of decisions taken by other agents.

The paper's aim is to investigate the spatial distribution of farms' participation in Measure 214. Spatial indicators and a spatial econometrics model are deployed in order to identify the influence of common factors and agglomeration effects on the spatial regimes of the distribution of participation in organic farms, using Tuscany (central Italy) as our case study.

To investigate the spatial effects is crucial for a better understanding of the causes and patterns that determine the spatial concentration of organic farm support. In turn, this is useful for improving the design of policies. As noted by Wollni and Andersson (2014), studying the spatial pattern of the observed outcomes is crucial for policy planners, because it separates the individual determinants from the contextual determinants of farms' participation in rural development measures. Indeed, whether the influence of neighborhood networks exists, the policy efforts to overcome the entrance barriers to adopting organic production can be sustained at community level. All these results help to identify potential criteria to improve the design of better policies to foster the diffusion of organic farming and promote less intensive agriculture.

The paper is organized as follows. Section 2 reviews the literature. Sections 3 and 4 present the estimation method and the empirical findings on the spatial regime of participation rates in Measure 214 in Tuscany. Section 5 concludes the paper.

2. Literature review

The determinants of organic adoption have been extensively investigated in the agricultural economics literature. Several authors (such as Läpple, 2013; Läpple and Kelley, 2013; Läpple and van Rensburg, 2011; Mzoughi, 2011) have highlighted how organic farming is more likely to be found in larger farms, located closer to urban areas, and carried out by younger and more educated farmers, concerned about environmental issues.

In addition, contextual factors for going organic can be determined. The list includes the influence of local institutions (Blanc and Kledal; 2012; Genius et al., 2006; Morone et al., 2006; Padel et al., 2009); and the geographical framework in which farmers operate (Kostandini et al., 2011).

However, few studies have focused on the role of neighborhood effects in organic production. The hypothesis that the location and distances are central factors for economic activities and market structure is consistently recognized by economic theory, in particular economic geography and regional economy, which have formalized concepts such as spatial interactions, diffusion processes, and hierarchies of places. Schmidtner et al. (2012) stressed that agriculture, which is strongly linked to land as the main production factor, should seem less influenced by the agglomeration effects emphasized by the new economic geography (Fujita et al., 1999; Krugman, 1992), yet organic farming seems to show agglomeration patterns due to external factors (Yang et al., 2014).

Whether or not organic farming is seen as an innovation, the creation of a spatial structure in organic agriculture can be produced by the diffusion model of innovations in the primary sector. In the case of participation in RDP measures, the neighborhood networks produce effects through imitations and spillover information. Using theoretical and empirical models, imitation (Bandiera and Rasul, 2006; Case, 1992; Conley and Udry, 2010; Hübler et al., 2013) and peers experience (Goulet, 2013) has been proven to play a key role in the diffusion of innovation.

Doring and Schnellenbach (2006) demonstrated the existence of a direct relationship between innovation spillovers and local economies. In practice, if the diffusion of innovation is geographically determined, it is possible to find a spatial relationship in the levels of agricultural value-added. Again, Doring and Schnellenbach (2006) stressed that the spillover effects of innovation and knowledge can explain the formation of geographical clusters where there are areas with the same economic structure, sectorial specialization, income levels and growth patterns, as well as similar and complementary technologies.

The previous studies highlight the spatial clustering of organic farming (Schmidtner et al., 2012; Parker and Munroe, 2007) where regions with high proportions of organic farming tend to be close to other regions with high shares of organically farmed land. Others (Lewis et al., 2011; Wollni and Andersson, 2014; Läpple and Kelly, 2014) have reported that there is a spatial regime even at the individual level, i.e., farmers are likely to adopt organic production if their neighborhoods adopt organic production. Wollni and Andersson (2014) and Läpple and Kelly (2014) found that social conformity is the main factor in spatial clustering, i.e., the tendency of the individual to behave in compliance with the individual's social group. In general, the previous studies stress how external economies of scale, norms, neighborhood networks and communities play a key role in the decision of farmers to adopt or maintain organic farms.

However, the spatial effects of rural development policy have not been sufficiently investigated. Bartolini et al. (2013) and Yang et al. (2014) investigated the spatial regime of participation in

Measure 121 in Emilia-Romagna (Italy) and the habitat management, bird conservation and water habitats in Scotland (UK). They underline the importance of spatial analysis in improving the predictability of participation in rural development measures, taking into account agglomeration effects and spatial dependencies.

The present paper aims to combine the analysis of the spatial pattern of the adoption of organic farming with the participation rate in Measure 214. The underlying hypothesis is that the same factors that affect the spatial regime of organically farmed land play a key role in a farmer's decision to participate in Measure 214.

3. Empirical strategies

A growing body of literature deals with understanding the spatial pattern of economics and social phenomena. A flourishing literature in the field of agricultural economics has applied spatial analysis to improve the model's ability to understand innovation diffusion, policy impacts and land use changes (Bell and Dalton, 2007; Brady and Irwin, 2011). Several studies include space and location as a proxy for the difference in demand for environmental services (see, for example, Van Leuwen and Dakker, 2013) or for participation costs, while only a few papers have refined the estimation to include the effects of spatial spillover (see Schmidtner et al., 2012).

3.1 Methodology

The spatial spillover of participation rates in Tuscany was analyzed in two steps. First, the spatial correlation of the participation rate in support for organic farming was estimated using Moran's I index, which is used to test spatial correlation against the null hypothesis of no spatial correlation. It was calculated as:

$$I = \frac{n}{\sum_{i=1}^{n} w_{ij}} \cdot \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} (x_i - \bar{x})(x_i - \bar{x}) w_{ij}}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{1}$$

where w_{ij} is the spatial weight obtained by a spatial function between area i and j; and x_i and x_j are the outcomes in the area i and j, respectively. For each geographical unit a weight $w_{ij} = 1$ is assigned if the geographical units i and j are spatially contiguous; $w_{ij} = 0$ otherwise. The definition of contiguity is that two geographical units share a part of their border. The spatial statistics are performed in order to test whether the observations are spatially dependent.

Moran's I indicator is the global measure of spatial autocorrelation which provides an indication of the spatial pattern of the phenomena. The global measure helps to understand the overall spatial nature of the distribution of the participation rate by summarizing different spatial relationships in the data.

However, the global indicators do not contain information for a particular local spatial unit. Therefore, Anselin (1995) proposed the Local Indicator of Spatial Association (LISA), which identifies more effective observations and spatial clustering by decomposing Moran's I to identify and test the regions that most contribute to Global Moran's I. The Local Moran statistic also identifies a specific location of the spatial clustering.

In order to estimate the spatial dependence and control participation factors, a spatial econometric model is applied. The spatial econometric modeling can incorporate the spatial structure in regression models detected by the spatial correlation statistics. Following LeSage and Pace (2009) and Anselin (1988; 2001), the spatial lag model has the following form:

$$y = \rho \mathbf{W} y + \mathbf{X} \beta + \varepsilon \tag{2}$$

$\varepsilon \sim \mathrm{N}(0, \sigma^2 \mathbf{I_n})$;

where y and $\mathbf{X}$ are the dependent variable and the matrix of independent variables, respectively; ρ is the coefficient of spatial association; $\mathbf{W}$ is the matrix of spatial weight built as a function of the contiguity of municipalities (i.e., local geographical administrative areas); ε is the error term with spherical disturbance distributed normally; and $\mathbf{I_n}$ is an identity matrix. The term $\mathbf{W}y$ is called the spatial lag. The application of (2) implies the fundamental hypothesis that the realization of y in the *i-th* region is determined/conditioned by the realization in the contiguity region of j and ρ measures the intensity of this connection. Moreover the spatial lag model is designed to detect evidence of neighborhood effects and, again, ρ measure the intensity of this effect (LeSage and Pace, 2009).

On the assumption that the essential determinants to participate in Measure 214 are sustained at an aggregated level, the empirical model estimates the share of participants in this measure at the municipality level. Therefore, the unit of analysis is the municipality, which is the LAU 2 in Italy according to Eurostat territorial units' classification. The use of the municipality level is for several reasons. As noted by Getis (2009), the spatial structure must be exogenous to the models and must be based on preconceived spatial structures such as administrative boundaries; otherwise, results will be biased. In addition, measurement at local level allows one to consider factors exogenous to the models' unobserved variables such as farm soil condition, and farmers' risk behavior.

4. Data

The variables on the structural features of municipalities are calculated using the data from the sixth Italian agricultural census (2010). Information on the RDP comes from the administrative data of the ARTEA (Regional Rural Payments Agency).

The covariates are classified into four categories. The first category is related to the territorial characteristics. A first variable is related to the share of Nature 2000 areas within each municipality. Then, the classification of the areas is described with dummy variables to check for an altitude effect. Finally a factor variable is added using the municipalities' classification in terms of RDP design. The area of the region was classified into five categories, based on inhabitants' density and the share of agricultural labor in the total labor. Location variables are crucial in the model's geographical rendering of the region, managing different demands on the environmental services. Moreover, locations in different geographical areas may encounter different opportunity costs when shifting productions towards organic farming due to the availability of alternative crop mixes or differences in climate and soil characteristics (Espinosa-Goded et al., 2013).

The second group concerns the farmers' characteristics: the share of farms with male owners, farmers aged below 40, farmers with an agricultural background or a degree, and the proportion of part-time farmers. These variables are widely used by the agricultural economics literature to model farmers' behavior in terms of innovation and farmers' attitudes towards environmentally friendly practices (Läpple and Van Rensburg, 2011). Several authors show that young and highly educated farmers are more likely to participate in agri-environmental schemes due to the low transaction costs to apply the measure (Falconer, 2000).

The third category of variables describes farm structures: the number of cooperatives, the share of individual farms, the share of farms with a potential successor, farms that use only household labor, average UAA of farms, ratio of UAA and total land, and average number of plots in each municipality. Inclusion of those variables in covariates may be done for different reasons. Firstly, a fixed cost of participation may reduce the likelihood of observing participation among small farms (Ducos et al., 2009), while the plots' fragmentation increases operative costs and may have positive effects in explaining participation (Bartolini and Brunori, 2014). The involvement in cooperatives or networking may produce differences in the quality of information held by farmers and may reduce the transactions costs (Defrancesco et al., 2008). The fourth category is related to the farming system: the number of farms with arable crops, the number of farms with RDP support (other than 214) and with PDO production, and the number of farms involved in other activities such as agritourism, recreational activities, school activities, handicrafts, food processing, energy production, woodworking, aquaculture, agricultural and non-agricultural services, animal breeding, gardening, forestry and animal-feed production, and other activities. Table 1 shows the descriptive statistics for all the covariates.

5. Empirical results

A total of 5 % of farmers in Tuscany participated in Measure 214. The land under Measure 214 accounted for over 10 % of the total regional UAA. Figure 1 shows the distribution of the share of beneficiaries across the municipalities in Tuscany.

The municipalities of central Tuscany and the northeast had higher participation rates. Lower rates of beneficiaries were found in the northwest. The municipalities with a similar level of participation tended to be grouped in the same areas. The spatial distribution shown in Figure 1 seems to highlight various spatial patterns underlying participation in Measure 214, thus providing evidence of spatial dependence. However, to establish a relation between participation and location, it is necessary to measure the spatial correlation. Figure 2 presents the Moran scatter plot, which provides a graphical interpretation of the spatial association among municipalities.

Global Moran's *I* of 0.43 indicates a positive, significant and relatively high spatial correlation. The significance is tested against the null hypothesis of no spatial correlation, that is to say the randomness of the cases. Therefore, Global Moran's *I* indicates a stronger geographical clustering; that is, the values of the participation rate in Measure 214 for neighboring municipalities are similar to one another. The z is the standardized variable and Wz is the geographically weighted standardized variable. The slope of the fitted line is equal to Moran's I. In the first quadrant, the points represent the municipalities with high participation rates that are contiguous to other municipalities with high rates. The third quadrant shows municipalities with low participation rates together with neighboring municipalities with low rates. Spatial outliers are in the third and fourth quadrants, i.e., neighboring municipalities with different participation rates.

For each municipality the Local Moran is computed and tested for significance by randomization. Figure 3 shows the distribution of Local Moran's I values for each municipality in Tuscany (Local Indicator of Spatial Association, LISA).

The hot and cold spots have the highest values indicating the areas with the strongest association pattern. These municipalities, therefore, are the main "contributors" to the positive and significant global measure of spatial autocorrelation with the rate of participation in Measure 214.

Significant local clusters and spatial outliers are shown in grayscale. The municipalities with the darker color show the "hot spots" or "cold spots", which highlight the spatial clusters. In the hot spots (high-high) the positive spatial association arises from each unit and neighboring units with high participation rates. In the cold spots (low-low) the positive spatial autocorrelation emerges from each unit and the neighboring low values of the variable. The hot spots of participation are located in central and northeast areas, cold spots in the northwest. In addition, Figure 3 highlights that the hot and cold spots in Tuscany are particularly concentrated in geographically distinct areas. This result suggests evidence of the location pattern of participation rates in Measure 214.

The areas with negative Local Moran coefficients originating from significant high and low surrounding values, and areas with negative Local Moran coefficients resulting from low and high surrounding values are sources of spatial non-stationarity. A noteworthy point in Figure 3 is that negative values are only found on a small part of the total area of Tuscany. One may conclude that participation in Measure 214 exhibits elements of strong spatial concentration.

Table 2 shows results of the spatial lag model. The spatial autoregressive coefficient (Rho) has an important influence on the distribution of the farms that apply for funding through Measure 214, thus suggesting the existence of agglomeration effects between areas. If, all other things being equal, the share of participants in a municipality increases by 1 %, then the estimated share of participants in the neighboring municipalities increases by 0.329 %.

With regard to the other significant variables included in the model, we can note that the zoning used to design the RDP plan and altitude are significant, but with a weak effect on participation. The location in plain and marginal areas negatively affects the rate of participation in organic farming. Therefore extreme operating contexts (the best and the worst) have the same effects in predicting the participation rate in Measure 214. The lower participation rate in plain areas could be due by the higher opportunity costs for converting to organic (Wollni and Anderson, 2014) and thus participating in Measure 214. However the same hypothesis does not hold in the case of the marginal areas where the opportunity costs are substantially lower than in the plain areas. Thus lower likelihood of participating to Measure 214 seems to be related to the predominance of the transaction costs, since Khaledi et al. (2010) stressed that the lack of infrastructures and services increases these kinds of cost and discourages organic farming.

The farm typology within the municipality does not affect the rate of participation, since the only significant variables are the education rate of farmers and the proportion of full-time farmers. Areas with highly-educated and full-time farmers are most likely to participate in Measure 214. The results confirm previous literature findings on the role of education in reducing transaction costs associated with the measure's application. Moreover other social studies have found that well-educated farmers show a strong pro-environmental orientation

(Henning, 2008). In addition, large farms and those involved in farm holidays or PDO production are also more likely to participate in organic measures. This result seems to indicate that zones oriented to traditional production have some positive interaction factors with organic production. Probably the compliance with PDO rules is in many cases similar to organic standard. This can induce farmers to participate in organic farming measures due to the lower costs of compliance with organic production methods. These results confirm the existence of second-order effects of diversification activity on the creation of areas with higher environment quality (Bartolini et al., 2014).

Finally, a positive factor is the number of farmers who already participate in other RDP measures. This may be explained by the cost involved in obtaining information or the transaction costs of participating in RDP measures as suggested by Rørstad et al. (2007).

6. Conclusions

The paper's aim was to investigate the determinants of participation rates in Measure 214 taking into account spatial patterns. The results highlight an important spatial dependence in the participation rate highlighted by the significant and positive Rho coefficient in the spatial lag model. This implies that neighborhood effects exist, i.e., spatial spillover. In addition, if the results of LISA are considered, it is possible to conclude that the spatial regime is evident. Hence, the application of a spatial econometrics model is a viable tool to detect the diffusion of agri-environmental schemes.

The results confirm the literature regarding the spatial dependency of participation in AEMs (Yang et al., 2014). The latter study found that spatial agglomeration can depend on heterogeneity in agricultural systems due to the effects of climate regimes, and on the farms' specializations. It can also depend on the different quality of support for RDP applications and the networking of farmers regarding the related regulations.

The areas with a high share of farms that receive support for organic farming are more likely to have neighboring municipalities with high rates. By contrast, areas with low public support are likely to be close to areas with low rates of farms receiving support.

The results of the econometric analysis are similar to the findings of Bartolini et al. (2013) for Measure 121. Therefore, we make generalizations stressing that the RDP participants are not randomly distributed, but are spatially clustered.

The factors that explain spatial participation patterns are the same as those that have been previously discussed in the literature (Schmidtner, 2012; Wollni and Andersson, 2014; Läpple and Kelly, 2014). However, the main underlying determinants seem to be the information spillovers and economies of scale economies external to the farm which enable farmers to reduce the information and transaction costs of participating in RDPs measures. Less important is the social conformity discussed by several authors (Wollni and Andersson, 2014; Läpple and Kelly, 2014); on the other hand imitation may play a role (Müller and Rode, 2013) as well as knowledge shared by peers (Goulet, 2013).

The key role of the neighborhood networks in reducing information and transaction costs for the farmers' participation suggests that extension services aimed at specific areas may be effective as individually addressed services, as noted by Wollni et al. (2010). The results that show that policy participation in other measures affects the participation rate in 214 demonstrates the existence of transaction costs and entrance barriers to participating in RDP measures. Therefore policy makers need to design eligibility criteria in order to minimize these kinds of costs. If they do not, they will jeopardize the diffusion of organic farming and limit the environmental benefits of this method of production.

One aspect that has not been sufficiently addressed, due to the lack of data, is the analysis of individual farms and farmers' characteristics and attitudes to participation in Measure 214. The use of secondary data at the LAU 2 level with mean values for each municipality does not take into account the heterogeneity of farms present in the locality.

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Table 1: Descriptive statistics

Variables	Mean	Std. Dev.	Min.	Max.
Participation rate	0.049	0.053	0	0.352
Nature 2000	0.109	0.166	0	0.997
Mountain	0.018	0.132	0	1
Inner hill	0.491	0.501	0	1
Costal hill	0.137	0.344	0	1
Plain	0.088	0.283	0	1
Intensive agricultural areas	0.109	0.312	0	1
Rural areas in transaction	0.316	0.466	0	1
Declined rural areas	0.246	0.431	0	1
Rural areas with development problems	0.260	0.439	0	1
Gender	0.310	0.071	0.048	0.625
Young farmer	0.090	0.040	0	0.343
Agricultural education	0.037	0.028	0	0.237
Part-time farmer	0.157	0.057	0	0.317
Involved in cooperative	0.000	0.002	0	0.015
Individual farmers	0.927	0.050	0.724	1
Only household labor	0.942	0.051	0.581	1
UAA	11.069	9.825	1.143	67.023
UAA/total land ratio	0.704	0.133	0.308	0.957
With potential successor	0.020	0.016	0	0.087
Average plots	3.325	2.642	1.220	19.563
Arable land	48.669	27.713	1.755	98.701
Still involved in RDP	0.068	0.060	0	0.430
PGI land	0.003	0.008	0	0.057
Agritourism	0.055	0.048	0	0.276
Recreational activities	0.004	0.007	0	0.044
School activities	0.004	0.007	0	0.036
Handicrafts	0.001	0.004	0	0.063
First output transformation	0.007	0.013	0	0.094
Food processing from vegetable output	0.011	0.020	0	0.183
Food processing from animal output	0.008	0.013	0	0.098
Energy production	0.004	0.008	0	0.094
Woodworking	0.007	0.023	0	0.287
Aquaculture	0.001	0.003	0	0.040
Sub-contracting	0.018	0.018	0	0.190
Non-agricultural sub-contracting	0.003	0.005	0	0.044
Animal breeding	0.002	0.006	0	0.063
Gardening	0.005	0.009	0	0.105
Forestry	0.024	0.069	0	0.556
Animal-feed production	0.001	0.003	0	0.030
Others activities	0.006	0.009	0	0.091

Table 2: Results of spatial lag model

Variables	Coef.		St. Dev.
Nature 2000	-0.003		0.014
Mountain	-0.02		0.017
Inner hill	-0.026		0.016
Costal hill	-0.032		0.017
Plain	-0.034	**	0.017
Intensive agricultural areas	0.006		0.007
Rural areas in transaction	-0.001		0.007
Declined rural areas	-0.006		0.009
Rural areas with development problems	-0.034	**	0.016
Gender	0.053		0.031
Young farmer	-0.001		0.062
Agricultural education	0.191	**	0.090
Part time farmer	0.122	***	0.047
Involved in cooperative	2.683		1.590
Individual farmers	0.025		0.090
Only household labor	0.045		0.085
UAA	0.002	***	0.000
UAA/total land ratio	-0.020		0.023
With potential successor	0.022		0.186
Average plots	-0.002	**	0.001
Arable land	-0.000		0.000
Still involved in RDP	0.103	**	0.047
PGI land	0.646	**	0.287
Agritourism	0.237	***	0.088
Recreational activities	-0.385		0.369
School activities	0.745		0.418
Handicrafts	0.243		0.806
First output transformation	0.145		0.247
Food processing from vegetable output	0.064		0.144
Food processing from animal output	-0.044		0.205
Energy production	0.069		0.392
Woodworking	0.150		0.105
Aquaculture	-0.093		0.509
Sub-contracting	-0.198		0.162
Non-agricultural sub-contracting	0.000		0.467
Animal breeding	-0.294		0.388
Gardening	-0.107		0.209
Forestry	0.005		0.047
Animal-feed production	0.646		0.609
Others activities	0.509		0.592
Constant	-0.064		0.076
Rho	0.329	**	
Log likelihood=562.281			
Squared corr.=0.599			
Wald test of Rho=0 chi2(1)=21.393 (0.00)			
Lagrange multiplier test of Rho=0: chi2(1)=17.883 (0.00)			

Note: *** p<0.01, ** p<0.05

Figure 1: Spatial distribution of the share of farms participating in Measure 214.

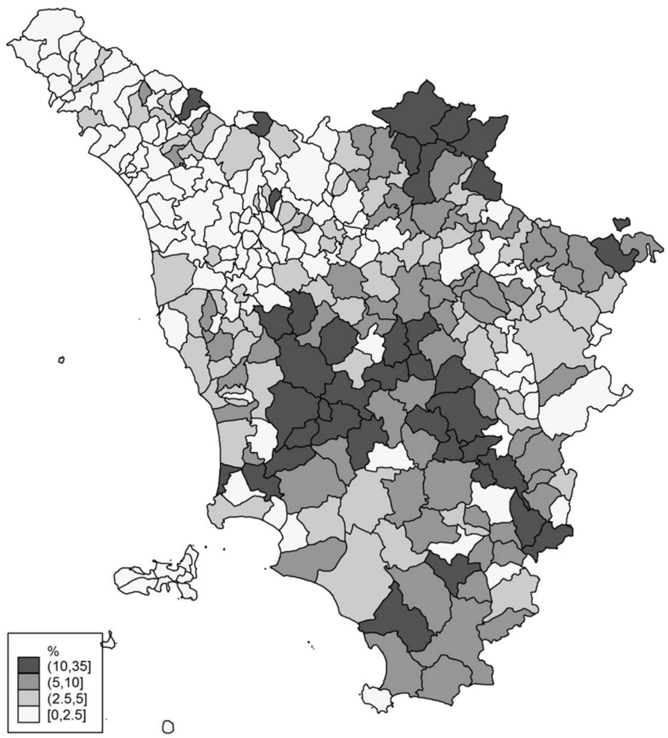

Figure 2: Moran scatter plot for the share of farm participation in Measure 214.

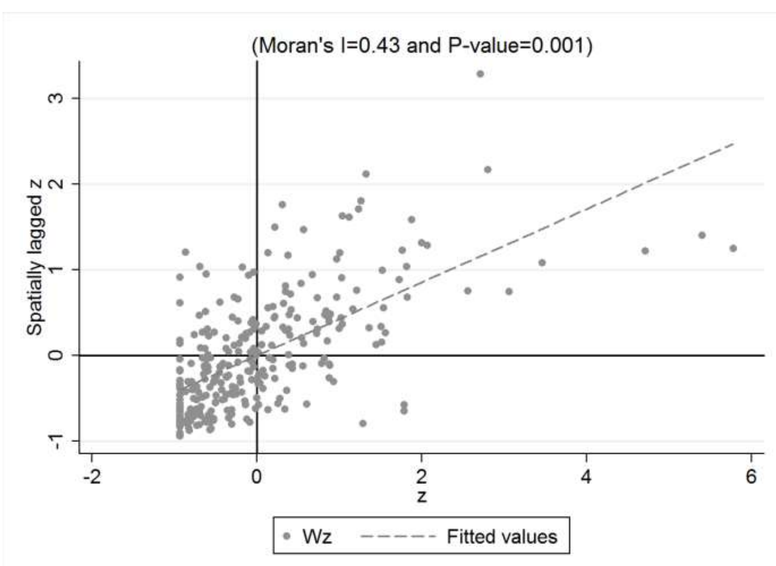

Figure 3. LISA of participation rates in Measure 214