A Spatial Analysis of the Farm Structural Change: The Case Study of Tuscany Region

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Abstract

This paper aims at investigating the factors affecting relative changes in the average farm size over the period 2000-2010. The objective has been pursued applying an empirical investigation in Tuscany region through observation aggregated at municipality level. By applying spatial analysis and spatial econometric techniques, spatial distribution and determinants of different farm size are detected. Results showing the relevance of spatial analysis, pointed out that farm household and territorial characteristics, such as the productivity, single farm payments and being located at plain altitude, positively affect the average farm size since these agricultural holdings are eased to pursue economies of scale.

Keywords: structural change, spatial econometrics, municipality data, average farm size

1. Introduction

Over the last ten years the structure of Italian farms has been shaped by a continuing farm exit and loss of utilized agriculture area (UAA) with an increase in the average farm size. Tuscany Region is characterized by a strong regional differentiation registering a decline in the number of farms estimated to be around 40% and a consistent increase (+47%) in the average farm size (Census 2010). Enlarging farm size is a key factor affecting farm competitiveness and structural change in the agricultural sector which may reveal a regional differentiation among areas associated to spatial patterns (Braiser 2005). Hence a spatial analysis seems to be a good fit to assess the existence of territorial pattern (Mur, 2013).

This paper presents a spatial analysis evaluating the relative changes in the average farm size in Tuscany over the period 2000-2010. The analysis is conducted at the territorial level taking into account the 285 Tuscany municipalities and using, as dependent variable, the average farm size between those municipalities. Following previous literature, the explanatory variables of farm size changes may be connected with agricultural profitability, agricultural policy, farm and household features, off-farm income opportunities (Piet et al., 2012; Bartolini and Viaggi, 2013) and territorial variables such as the geographic condition where the farm operate (Irwin, 2010). Data used belong to two different sources of data: the 2000 and 2010 micro-data of Agriculture Census and the Regional Agency for payments in Agriculture (ARTEA) database. These databases have been aggregated at municipality level.

The paper is organized as follows: section 2 presents the econometric framework and the model specification. Section 3 presents the main results of the empirical analysis. Finally, section 4 synthesizes the main achievements of the study.

2. Method

The spatial analysis is conducted in two steps, firstly computing ESDA and then applying spatial regression models to identify determinants of changes in the average farm size. EDSA represents a spatial specification of Exploratory Data Analysis and is aimed to detect spatial pattern on the dependent variable. The spatial econometrics model is computed mainly applying spatial lag and the spatial error model. Spatial lag models are aimed at quantifying spatial spillover within the dependent variable; while the spatial error model provides a correction of heteroskedasticity due to spatial dependence in the error term. Following

Breustedt and Habermann (2011), the spatial dependency could be modeled as an extension of the standard linear regression model. See Mur (2013) for formal presentation of the spatial econometrics models.

This paper combines two different sources of data: The 2000 and 2010 Agricultural census realized in Italy by ISTAT and the ARTEA database which provides the payments received by farms. A new database stemming from the previous ones and composed by 285 municipalities observed in 2000 and 2010, has been created. The dependent variable is the relative change in the average farm size between 2000 and 2010 in each municipality. It is measured trough the difference between the average farm size related to 2010 and 2000 weighted by the average value of 2000 at the municipality level (variable named *av_fsize*). Table 1 shows selected the explanatory variables.

Variable code	Variable description	Obs	type	Mean	Std.dev	Min	Max
av_fsize	Average farm size (relative change)	285	continous	54.14	70.09	-78,.55	435.70
so_pf	Value of production per farm (relative changes)	285	continuous	65.99	164.89	-81.29	2,500.15
uaa_rent	Amount of land rented-in (relative changes)	285	continuous	187.44	456.76	-100.00	6,226.67
cond_coltdir	Direct cultivation (relative changes)	285	continuous	-0.73	4.77	-44.95	35.46
totbov_di	Farm with livestock (relative changes)	285	continuous	1.14	4.53	-22.12	22.47
fteext_farm	External labour per farm (relative changes)	285	continuous	0.01	0.19	-1.42	0.74
d_old	Farmers older than 65 years old (%)	285	Binary	40.19	7.35	-	65.22
edu_low	Farmer with education level less than secondary school (%)	285	Binary	67.04	8.66	36.36	89.79
av_etacapaz	Famers age (years)	285	continuous	59.96	2.70	43.10	72.00
p_disacc_farm	SFP per farm (000 €)	285	continuous	6,732.96	8,360.12	-	75,510.2
ln_pay_psr	Total amount of payments received by RDP (€)	285	continuous	5.52	1.63	-	8.76
pay_rdp_farm	Total amount of payments received by RDP (€ per farm)	285	continuous	2.41	2.64	-	27.20
pay_int_ha	Payment for integrated production (€ per ha)	285	continuous	0.05	0.63	-	10.41
pay_int_pf	Payment for integrated production (€ per farm)	285	continuous	18.04	138.50	-	2,236.54
rur_probsv	Municipality located in rural area with developing problems	285	Binary	0.26	0.43	-	1
plain	Municipality located in plain	285	Binary	0.09	0.28	-	1
mountain	Municipality located in plain	285	Binary	0.28	0.45	-	1
density_d	Inhabitants density (relative changes)	285	Continuous	16.83	33.3	-76	208

Table 1. Descriptive statistics for Tuscan municipalities

The first independent variable (*so_pf)* is a proxy of farming added value. *uaa_rent* represents the relative change in the amount of rented land within the municipality. *cond_coltdir* illustrates the relative change in the number of direct cultivation farms within each municipality. *totbov_di* shows the relative change in the number of farm with livestock. *fteext_farm* represents the relative changes of external labor per farm calculated as the change in the full time equivalent. *d_old* and *edu_low* are binary variable indicating the share of farm operator lower than 65 years old and with a low education level. *av_etacapaz* represents the average age of the farm operators located in the municipality. Other variables related to the amounts of public payments received by the municipality are added such as the single farm payments (SFP) per farm (*p_disacc_farm*), total amount of payments received by the Rural Development Programs (RDP) per farm (*pay_rdp_farm*), the payment for integrated production per hectare and per farm (*pay_int_ha, pay_int_pf*). Finally, several territorial variables aimed to identify municipalities location in specific zoning (i.e. rural areas with developing problems *rur_probsv*), altitude (plain or mountain) and population density (*density_d*) are added.

3. Results

Figure 1 illustrates Local Indicator of Spatial Association (LISA) results, showing cluster of similar or dissimilar regimes of spatial associations (Anselin, 1995). All the painted municipalities are those municipalities significant at least at 0.05. The map on the left is done by assuming that spatial effects are driven by contiguity between municipalities, while the map on the right by inverse distance matrix. Red colored municipalities represent the “hot spot” cluster, while blue colored municipalities represent the “cold spot” cluster significant homogenous changes in relative farm size between the two censuses. Both maps show a spatial cluster of spatial association for which significant spatial regimes are detected.

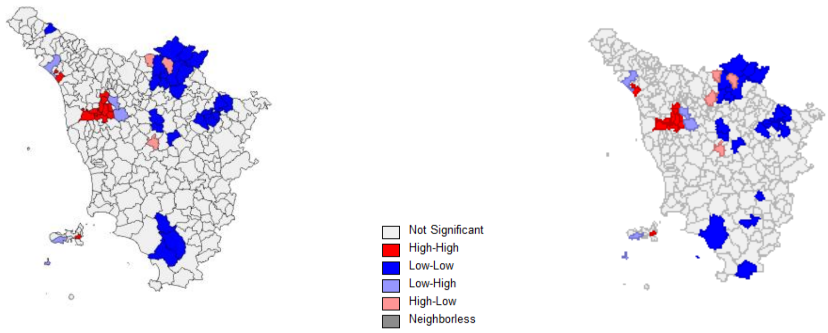

Figure 1. Spatial Clusters of percentage average farm size change between 2010 and 2000 (using contiguity and inverse distance matrix)

As showed by table 2 both alternative weights return positive and significant values implying the existence of spatial regimes. The assumptions about spatial heterogeneity are significant for each weight matrix used and the tests suggest the application of SEM models. Furthermore, results show the significance of spatial dependency only when using first order of contiguity weights matrix and it then allows also SAR for this weight matrix.

Variable	Contiguity (first order queen)	Distances (Inverse distance matrix)
Moran's I	0.103***	0.076*
Spatial error:		
Lagrange multiplier	2.742*	1.873
Robust Lagrange multiplier	5.889***	3.049*
Spatial lag:		
Lagrange multiplier	0.337	0.122
Robust Lagrange multiplier	3.484*	1.298

Table 2. Spatial model diagnostic

The first column of table 3 presents OLS model results (model 1), the second column presents the Spatial Autoregressive (SAR) model results (Model 2) while the third the Spatial

Error (SEM) model (model 3) results. Both spatial regression models are estimates assuming first order contiguity matrix and inverse distances matrix.

VARIABLES	Model 1 (OLS)	Model 2 (Spatial Lag)		Model 3 (spatial error)	
Code	a-spatial	Contiguity	Inv. Distance	Contiguity	Inv. Distance
so_pf	0.0827***	0.0850***	0.0834***	0.112***	0.111***
uaa_rent	0.0103	0.0107	0.0105	0.0111*	0.0128*
cond_coltdir	-9.866***	-9.563***	-9.814***	-6.001**	-7.300***
totbov_di	3.056***	3.110***	3.028***	3.260***	2.798***
fteext_farm	34.61*	33.46*	34.37*	26.51	21.92
d_old	2.593**	2.583**	2.574**	2.387**	1.764
edu_low	1.236***	1.262***	1.258***	0.863**	1.048***
av_etacapaz	-6.383*	-6.393**	-6.404**	-7.001**	-5.538*
p_disacc_farm	0.0177***	0.0177***	0.0175***	0.0145***	0.0146***
ln_pay_psr	-4.790	-5.843*	-5.149	-8.262***	-4.854*
pay_rdp_farm	0.198	0.215*	0.204*	0.238**	0.249**
pay_int_ha	98.19*	96.86*	98.59*	63.68	89.80*
pay_int_pf	-0.575**	-0.573**	-0.577**	-0.432**	-0.544**
rur_probsv	18.21	19.42	17.86	37.93**	26.54
plain	17.7	22.54	19.63	21.76*	31.91**
mountain	-19.81	-19.61	-19.1	-34.25**	-26.23
density_d	0.243*	0.246**	0.245**	0.152	0.167*
Constant	251.3	261.7	262.7	339.9*	241.8*
Rho (Spatial lag coeff.)	-	-0.1	-0.162	-	-
Lambda (Spatial error coeff.)	-	-	-	-0.937***	-5.493**
R-squared	0.398	0.456	0.491	0.399	0.398
ADJR-squared	0.3397	0.361	0.344	0.399	0.398

Table 3. Results of regression models. (285 observations). **(***** significance at 0.01; ** significance at 0.05, * significance at 0.1; not significant variables are omitted**)**

OLS results show that enlarging herd size positively affected the farmland size. Such increasing is due to higher land demand for the restriction of spreading manure (Bartolini and Viaggi 2013). Municipalities with high share of ageing and less educated show positive effects on enlarging farm size process. This may be explained by the lower off-farm opportunities due to lower expectation of external income and a lacking attitude to diversification which represents opposite strategy to increase farm income or to reduce farm risk exposure (McNamara and Weiss, 2005). Further, older farm operators are more likely to sell their UAA to the surviving farms which in turn increase their average size. Results confirm the relevant impact of policy showing positive effects of SFP on the farm size change (Ciaian and Swinen, 2006). Meanwhile, RDP payments received by the municipalities show negative effects on the farm size, since the RDP recipients increase differentiation and the added value of the farm (Bartolini and Viaggi, 2013). Conversely, the intensity of the payment per ha shows positive and significant effect on the farm enlargement. According to OLS results territorial variables are not significant. The spatial lag coefficient (rho) shows no spatial patterns among spatially related municipality. Conversely, the SEM Model, by correcting heteroskedasticity adding spatial error components, shows significant coefficient of spatial error coefficient (lambda) and it returns very dissimilar results from the OLS model confirming the significant effect of the geographic location of farms. The mountain altitude negatively affects the farm size, whilst the location in plain determines an enlarging of the farm size, due to higher marginal rate of return of enlarging farm size in plain areas. Positive effects are shown also for rural areas with developing problem, where agriculture represent the main income opportunity and the ageing and depopulation determined a high reduction of farms.

4. Conclusions

The paper provides a spatial analysis of the relative change in the average farm size in Tuscany at Municipality level over the period 2000-2010. Spatial analysis allows to improve model quality compared with standard approaches due to possibility to capture spatial autocorrelation pattern and spatial associations of explanatory variable or in the error term. The model shows a predictive capacity of farm and territorial variables in explaining changes in farm size. At the farm level results show that the farm's profitability contributes to enlarge the average farm size at the municipality level. Actually, farmers committed to increase the economy of scale need larger size, as one of the main option to increase farm household income. At the territorial level being located in plain areas increases average size due to lower production costs and proximity to markets. Finally, public payments have played a key role. Results shows that first pillar payments strongly affect changes in farm size, by increasing return for and by ensuring liquidity to invest. Conversely, RDP payments have puzzled effects, confirming controversial previous studies (Bartolini and Viaggi, 2013). Our results shows that meso-level data (municipality level) allows a better understating of the farm structural change since it is affected by territorial features such as off-farm income expectations, diversification services demand, urban sprawling process, and quality of infrastructure.

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