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Abstract:
The objective of this paper is to test for the importance of local agglomeration externalities in determining the Foreign Direct Investment (FDI) intensity that is viewed as a measure of firms' competitive performance in host locations. By analyzing the link between the degree of FDI inflow penetration and its determinants at the regional level, alternative fixed effects panel data model specifications, also extended to include spatial effects, are examined with the aim of testing the hypothesis of (i) panel homogeneity/heterogeneity in slope coefficients; (ii) panel heterogeneity in slope coefficients with uniform (region specific) spatial dependence, and (iii) panel heterogeneity in slope coefficients with varying (region specific) spatial dependence. It is found that sector specificities are relevant in attracting inward FDI in Italy. Significant differences within regions emerge when intra-industry and inter-industry as well as endogenous spatial spillovers are controlled for. There is also evidence that the importance of spatial dependence varies across regions.

Keywords: international capital mobility, agglomeration spillovers, spatial dependence, censored panel data models

JEL classification: C23, C24, F21, F23

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1. Introduction

The objective of this paper is to test for the importance of local agglomeration externalities in determining the Foreign Direct Investment (FDI) intensity that is viewed as a measure of firms' competitive performance in host locations, by analyzing the link between the degree of FDI inflow penetration and its determinants at the regional level, with the explicit consideration of spatial dependence and spatial heterogeneity in the specification of the FDI location model.

Specifically, we are interested in testing i) the hypothesis that FDI intensity is related to the characteristics of the regional economic system - especially in terms of factor endowment, and ii) the hypothesis that sector specificities are relevant in explaining FDI patterns in Italy. Hence, our analysis is able to capture both the "reverse" spillovers, that is positive effects from domestic to foreign firms, and the location advantage due to factor endowment of the host location in terms of infrastructure, labor (skills and costs) and existing levels of capital and technology since they can influence the levels of inward investment in a region and the potential for spillovers from inward investment. In addition, the role of potential changes in sectoral location preferences due to FDI policy incentives and to local conditions may be detected.

Alternative panel data model specifications are introduced as a diagnostic tool to investigate the presence of some type of unobserved heterogeneity, slope heterogeneity and spatial dependence. One of the advantages of using spatial specifications within a panel data framework for empirical verification of spatial externalities contribution, resides in the possibility of testing any remaining spatial autocorrelation avoiding any potential bias sources. Potential endogenous and exogenous spatial spillover effects are controlled for using a spatially lag (spatial LAG) specification. More specifically, fixed effects panel data model specifications, also extended to include spatial effects, are examined with the aim of testing the hypothesis of (i) panel homogeneity/heterogeneity in slope coefficients; and (ii) panel heterogeneity in slope coefficients with uniform/varying spatial dependence. Particular attention is also devoted to the estimation problems involved by each specification and a Generalized Maximum Entropy Estimation procedure (Bernardini Papalia, 2006, 2007) is suggested as a suitable consistent estimator (i) in presence of short panel, when the number of time periods is not sufficiently large; (ii) when the number of regions is greater than the number of time periods, (iii) in presence of collinearity and endogeneity of some explanatory variables.

Our analysis is concentrated in the 1999-2004 period. It is found that sector specificities are relevant in attracting inward FDI in Italy. Significant differences within regions emerge when intra-industry and inter-industry as well as endogenous spatial spillovers are controlled for. There is also evidence that the importance of spatial dependence varies across regions.

The paper is organized as follows. In Section 2 we briefly outline the major theoretical and empirical research directions relative to inward investment and spillovers sourcing. Section 3 introduces panel data censored models in which spatial dependence and spatial heterogeneity are incorporated. The main estimation problems connected to each model are summarized in Section 4. Section 5 includes results of the empirical analysis. Section 6 contains the conclusions.

2. Inward investment and spillovers sourcing

Production and marketing arrangements of multinational enterprises rather than autarchic national development strategies have become the most efficient way of taking advantage of growth opportunities offered by the global economy. In Europe several economies were engaged in proactive FDI policies (De Propis *et al*., 2006), implementing investor friendly measures, and initiating specific institutional developments as the opening of investment-promotion agencies (Tavares and Young, 2003). Incentive concession has become a common practice in most countries, usually legitimated by the evidence that inward investors have usually superior performance compared with domestic firms.

To support such policies a necessary condition is required, that is the host country has positive effects from inward FDI flows. However, a number of empirical works argues that attracting inward investment does not guarantee *per se* positive effects on the host economy, or that the potential benefits can be maximized. There are several channels through which such effects or spillovers may occur, and spillovers can be of various kinds (on technology, productivity, wages, entrepreneurship, etc). The empirical literature on spillovers is extensive (Caves, 1974; Globerman, 1979; Blomstrom and Persson, 1983; Blomstrom and Kokko, 1998; Gorg *et al*., 2001) and highlights very mixed results for different firms and/or countries (Haddad *et al*. 1993; Konings 2001; Damijan *et al*. 2003)[iii]. The main result emerging from these papers is that absorptive capacity is one of the main prerequisite for effective linkage and transfer of firm-specific advantages to domestic firms. Its relevant determinants are: technological gap, cultural and physic distance, geographic proximity, idiosyncratic nature of industries and host countries, degree of foreign ownership, level of development of host economy, relative size of firms, degree of trade protection, and the institutional framework. In addition to the observed positive productivity effects from FDI, many studies following Aitken and Harrison (1999) point to the possibility of negative as well as positive externality effects from external investment. Multinational enterprises entering a host economy may take market share from less efficient indigenous firms, forcing them to produce lower levels of output at higher average cost than was the case before entry. Where this effect is pronounced, it may offset any positive spillover effect derived from the multinational enterprises, so that foreign entry has a net negative effect on domestic productivity. Nevertheless, competition may have a positive effect on domestic productivity in the long run, either by encouraging local firms to become more efficient or by forcing the least efficient out of the business. Thus, sectoral level productivity effects of inward FDI may be negative in the short term, though positive in the long run.

Beside the analysis of FDI effects to host country's firms, a well developed literature addresses the related issue of why multinational enterprises (MNEs) choose to set up production facilities overseas. The most persuasive explanation is based on the coexistence of knowledge capital and market failures in protecting such knowledge. For extensive surveys, see Caves (1996) and Markusen (1995). The theory of location choice suggests that foreign investment will be directed towards the countries or regions ensuring larger profits. Thus, in the empirical literature FDI inflows are assumed to be a

[iii] For a review of the literature see Gorg and Greenaway (2001).

function of a set of host country or regional characteristics capable of affecting either the revenues generated or costs incurred by firms. Determinants of location and magnitude of FDI are firm-specific and external (tax regimes, tariffs, trade effects, institutions)[iv]. In addition the decision of how much FDI are invested depends on the relationships between firms, in terms of externalities effects.
The theoretical basis for the importance of agglomeration spillovers, and their ability i) to attract FDI and ii) to benefit local firms, are derived from the theoretical models of industrial development (Markusen and Venables, 1999), where agglomeration increases the potential for technological transfer and therefore improves technological capabilities. Spillovers from FDI inflows have been classified as horizontal (or intra-industry) and vertical (or inter-industry). The former ones deal with knowledge and assets that are sector-specific and, therefore, exploitable also by competitors; they act through human capital mobility and imitation processes. The latter spillovers refer to knowledge flows from and to the MNE through backward and forward linkages of foreign multinational enterprises with local suppliers and customers.
There is a relatively large empirical literature seeking to link inward FDI to agglomeration from the perspective of technology flows (Driffield and Munday, 2000; Cantwell, 1991; Head *et al*., 1995). In addition, the presence of multinational enterprises, as leaders in both technological and capital accumulation, may contribute to further stimulate the possibility for agglomeration in such locations (Cantwell, 1991). However, little attention has been devoted to distinguish between agglomeration externalities of firms belonging to the same sector (Marshall-type and Porter-type or horizontal spillovers; Glaeser *et al*., 1992), and spillovers arising from the diversity of the regional economic structure (Jacobs-type or vertical spillovers; Jacobs, 1969). The issue is very important since theory predicts that spillovers at inter-industry level are more important than at intra-industry level (Blyde *et al*., 2004). MNEs minimize the probability of imitation and try to avoid technology leakages from FDI in favor of domestic producers with absorptive capacity. So subsidiaries will be set up where potential rivals cannot erode MNE's market power. However, positive horizontal externalities can emerge, at least in the long run, through the increased competitive pressure in the local market forcing local firms to use existing technology and resources more efficiently or to search for more efficient technologies. In addition, since MNEs can benefit from knowledge spillovers through downstream and upstream linkages with local firms, vertical flows of generic knowledge leading to inter-industry spillovers will be encouraged. The role played by horizontal (or specialization) economies and vertical (or diversity) spillovers has to be investigated.
From a FDIs measurement point of view, in choosing the appropriate proxy for agglomeration different measures of agglomeration that are only sometimes sector-specific have been chosen in previous analyses[v], as: (i) the ratio of manufacturing employment, or population, to land area (Coughlin *et al*., 1991; Wei *et al*., 1999); (ii) the total number of manufacturing establishments within the area (Woodward, 1992;

[iv] For a detailed discussion see Blonigen (2005).
[v] The significance of agglomeration may capture the correlation between the location of domestic firms and FDI due to the endowment effect, instead of verifying the agglomeration externalities. In order to disentangle the effect of agglomeration from the effect of the geographical distribution of productive factor endowment (Head *et al*., 1995), a set of control variables for factor endowment has to be introduced.

and Basile, 2001); (iii) the degree of industrialization measured by the weight of the manufacturing sector as a percentage of GDP (Wheeler and Mody, 1992; Billington, 1999); (iv) infrastructure endowments and FDI previously accumulated (Wheeler and Mody, 1992). Only a small number of studies consider explicit industry-specific proxies for agglomeration that are more strictly related to the so called Marshall-type externalities. In particular, Braunerhjelm and Svensson (1996) employ a sector specialization index, given by the ratio of sector employees to total manufacturing employees, while Head *et al*. (1994, 1995) use the number of foreign plants already located in the area belonging to the same sector and country of origin. Bronzini (2004) explicitly introduces distinct measures of specialization and diversity externalities able to assess the role of intra-industry and inter-industry spillovers on FDI.

3. The model specification

Economic theory suggests that a foreign firm decides to invest in the region that guarantees the highest expected profits net of any fixed costs, including sunk costs, among a set of *N* regions and *S* industries (De Propis *et al*., 2005).
From an empirical viewpoint, expected profits are not directly observable, but we can observe only the FDI realized in each region so that data are censored and the appropriate statistical model for analyzing FDI determinants is the Tobit model (Tobin, 1958). More specifically, we start by introducing a panel data censored regression model with individual effects that relates the FDI intensity per value added in region *i* at time *t* to a set of industry and period fixed effects, as well as a set of variable of interest as:

$$FDI_{ijt} = \begin{cases} Y^*_{ijt} & \text{if} \quad Y^*_{ijt} \rangle 0 \\ 0 & \text{if} \quad Y^*_{ijt} \le 0 \end{cases} \quad ; \qquad (1)$$

$$Y^*_{ijt} = \mu_i + \mu_t + \theta' x_{it} + \lambda' v_{jt} + \gamma' z_{ijt} + \varepsilon_{jit}$$

where $i = 1, \ldots, N$ refers to a spatial unit, j = 1,…, S refers to an industry, and $t = 1, \ldots, T$ refers to a given time period. Y^*_{ijt} is a latent variable not directly observable, θ, λ and γ represent vectors of unknown parameters, x_i is a vector of region specific variables, v_j is a vector of industry specific variables, and z_{ij} is a vector of the industry and region join specific effects. μ_i and μ_t denote the regional and time fixed effects, respectively; ε_{ijt} ~N(0, σ^2) is a stochastic normal error. FDI_{ijt} are foreign direct investment inflows.
The model for time t, expressed in stacked form is given by:

$$Y^*_t = \theta' x_t + \lambda' v_t + \gamma' z_t + \mu + \mu_t + \varepsilon_t , \qquad (2)$$

where $Y^*_t = (Y_{1t}, \ldots, Y_{NSt})'$, $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{NSt})'$, $\mu = (\mu_1, \ldots, \mu_{NS})'$ and $\mu_t = (\mu_{1t}, \ldots, \mu_{NSt})'$. In the following, we refer to model specification (2) as Model 1.
Conditional on the specification of the variable intercept, the regression equation can be estimated as a fixed effects model where a dummy variable is introduced for each spatial unit as a measure of the variable intercept.

Although the variable intercept model accommodates spatial heterogeneity to a certain extent, the problem remains as to whether the data in such a model are pooled correctly. There is the potential for biased estimates if the panel is heterogeneous, that is if the coefficients vary across spatial units (across regions and industries). When spatial heterogeneity is not completely captured by the variable intercept, a natural generalization is to let the slope parameters of the regressors vary as well. The slope parameters can also be considered fixed or randomly distributed between spatial units. If the parameters are fixed but different across spatial units, each spatial unit is treated separately. For instance, when slope parameters vary across spatial units a set of N separate equations, with the observations stacked by spatial unit over time, is considered by assuming correlation between the error terms in different equations, that is *contemporaneous error correlation*. Such a specification is reasonable when the error terms for different spatial units, at a given point in time, are likely to reflect some common immeasurable or omitted factor. In full-sample notation, the set of N equations can be written in terms of the seemingly unrelated regressions (SUR) model. Henceforth, the SUR model will be indicated as Model 2.

3.1. The Fixed Effects Spatial Error and Spatial Lag Models

Before extending the traditional panel data models with spatial error autocorrelation or a spatially lagged dependent variable, we introduce the following notation. Let W denote a ($N\times N$) spatial weight matrix describing the spatial arrangement of the spatial units and w_{ik} the (i, k)-th element of W, where i and k = (1, . . ., N). It is assumed that W is a matrix of known constants, that all diagonal elements of the weights matrix are zero, and that the characteristic roots of W, denoted ω_i, are known. The first assumption excludes the possibility that the spatial weight matrix is parametric. The second assumption implies that no spatial unit can be viewed as its own neighbour, and the third assumption presupposes that the characteristic roots of W can be computed accurately using the computing technology typically available to empirical researchers. The latter is also needed to ensure that the log-likelihood function of the models we distinguish can be computed. The asymptotic properties of the maximum likelihood estimator, such as $\sqrt{N}$ consistency, depend on the characteristic features of the spatial weight matrix (Lee 2001a, 2001b). When the spatial weight matrix is a binary contiguity matrix, or an inverse distance matrix, this condition is satisfied (Lee, 2001).
The traditional fixed effects model extended to include spatial error autocorrelation (SAR model), expressed in stacked form, can be then specified as:

$$Y_t^* = \theta' x_t + \lambda' v_t + \gamma' z_t + \mu + \mu_t + \phi_t, \qquad \phi_t = \delta W \phi_t + \varepsilon_t, \quad E(\varepsilon_t) = 0, \quad E(\varepsilon_t \varepsilon_t') = \sigma^2 I_{NS}, \tag{3}$$

while the specification model extended with a spatially lagged dependent variable (spatial LAG model) is given by:

$$Y_t^* = \delta W Y_t + \theta' x_t + \lambda' v_t + \gamma' z_t + \mu + \mu_t + + \varepsilon_t, \qquad E(\varepsilon_t) = 0, \quad E(\varepsilon_t \varepsilon_t') = \sigma^2 I_{NS}. \tag{4}$$

The SAR model is associated to global spatial externalities, where all locations are related to each other. Therefore, a shock affecting one location diffuses to all other locations in the sample while the spatial LAG specification measures the influence of spillovers among neighbouring regions. As the SAR model, the spatial effects captured by the spatial LAG model are global in the sense that the model links all the regions in the system.
In the spatial error specification, the properties of the error structure have been changed, whereas in the spatial lag specification, the number of explanatory variables has increased by one. In the spatial error specification, δ is usually called the spatial autocorrelation coefficient, and in the spatial lag specification, it is referred to as the spatial autoregressive coefficient.
Finally, any of the spatial specifications needs to be integrated with the SUR framework when it is assumed that parameters β_i vary across spatial units, so that the resulting SAR-SUR and spatial LAG-SUR specifications have to be derived. A fixed coefficients spatial error model with varying coefficients for different spatial units is equivalent to a seemingly unrelated regressions model while a fixed coefficients spatial lag model with different coefficients for different spatial units is almost equivalent to a simultaneous linear equation model (Bernardini Papalia, 2006).
These model specifications provide the researcher with a diagnostic tool to judge how widespread a particular relationship is across the panel. This is especially important for cross-region data sets in which there can be considerable heterogeneity. The system approach can be used in testing the slope heterogeneity across spatial units by using a Wald test. One can also estimate the fixed effects model without spatial effects and subsequently test this restricted model against the unrestricted models using, for instance, a Lagrange multiplier (LM) test. The fixed effects spatial error or spatial lag model can be tested against the spatial error or spatial lag model without fixed effects using the F test spelled out in Baltagi (2001).

4. Estimation issues

The estimation of panel data models incorporating both spatial heterogeneity and spatial dependence poses identification, endogeneity and collinearity problems and as a consequence the standard estimation procedures can produce (i) biased parameter estimates, (ii) unbiased but inefficient parameter estimates, or (iii) biased estimates of the standard errors. More specifically, since the ML estimates of the coefficients of a Tobit model with fixed effects is not consistent for T fixed and $N \rightarrow \infty$ (Hsiao 1986, Baltagi 1995, Arellano and Honoré 2001), it is possible to use a semi-parametric estimator proposed by Honoré (1992), that is consistent and asymptotically normal. Nevertheless, the results of Heckman (1981) suggest that the bias of the ML estimates of the Tobit model with fixed effects should not be overestimated. In addition, Arellano (2003) suggests estimating by ML the non-linear model with fixed effects if the ratio N/T is finite and not too large. If the fixed effects model also contains fixed effects for time periods, there are two feasible ways to proceed. First, one may simply add fixed effects for time periods to the set of explanatory variables. This is possible when T is small. Care should be taken concerning the dummy variable trap. For μ_t (t = 1, . . ., T), denoting a dummy referring to the t-th time period, either the restriction $\sum_t \mu_t = 0$ should be imposed or one time dummy should be dropped. Second, one can eliminate the intercepts, μ_i, and μ_t from the regression equation by double demeaning of the Y and X variables and proceed as described above. It automatically follows that for short panels, where T is fixed and $N \rightarrow \infty$, the fixed effects for time periods can be estimated consistently. This is not the case for the spatial fixed effects model. For long panels, where $T \rightarrow \infty$ and N is fixed, the spatial fixed effects model can be estimated consistently, but the time period fixed effects cannot. Finally, when N and T are of comparable size, the spatial and time period fixed effects can be estimated consistently only when N and T are sufficiently large.

Another potential problem is that for large N, the usual spatial econometric procedures are problematic because the eigenvalues of spatial weight matrices of dimensions over 400 cannot be estimated with sufficient reliability (Kelejian and Prucha, 1999). One solution is to use the GMM estimator in the case of the fixed effects spatial error model (Bell and Bockstael, 2000). Another solution, based on maximum likelihood estimation, is not to express the Jacobian term in the individual eigenvalues but in the coefficients of a characteristic polynomial (Smirnov and Anselin, 2001) or to approximate the Jacobian term in its original form, $\ln |I - \delta W|$, using a Monte Carlo approach (Barry and Pace, 1999).

The spatial LAG-SUR specification may be consistently (but not efficiently) estimated by feasible generalized least squares, F-GLS (Zellner 1997), while the SAR-SUR specification cannot be consistently estimated by F-GLS due to the endogeneity of spatial spillovers (Anselin, 1988). Consistent estimates may be obtained for both of these specifications using: (i) a combination of F-GLS and Maximum Likelihood estimation (Anselin 1988), (ii) two-stage estimation procedures (Zellner 1997), or (iii) moment conditions for the GMM estimation derived by Honoré and Hu (2004).

A quite important problem of fixed coefficients models, also expressed in spatial forms, is the large number of parameters causing the estimators to be infeasible. Furthermore, even if the estimators are made feasible by introducing restrictions on the parameters, the quality of the asymptotic approximation used to justify the approach remains rather suspect, unless the ratio N/T tends to zero.

As a suitable alternative, in presence of both endogeneity and ill-posed problems, consistently and asymptotically normal estimates may be obtained by using the Generalized Maximum Entropy estimation approach which avoids some of the strong parametric assumptions required with traditional procedures and performs well over a range of non-Normal error distributions and in presence of small samples (Bernardini Papalia, 2006, 2007). This method is statistically efficient, easy to apply and allows us to impose different behavioural constraints. For background on the generalized maximum entropy (GME) estimation approach, and on related work, see Golan, Judge and Miller (1996).

5. Empirical findings

5.1 Data description and model specification

Using balance of payments data on Italy's inward FDI flows (from 1999 to 2004), collected by Italian Foreign Exchange Office, a wide array of activities related to the internationalization of production is covered, including greenfield investments abroad as well as cross-border M&As. Data on FDI are available by region, and aggregated into agriculture, industry in the strict sense, construction, and services sectors. Other regional data used for the construction of the explanatory variables come from Istat. Appendix A gives descriptive statistics of the regional sample.

The dependent variable of the econometric model is FDI-intensity calculated by using FDI inflow divided by value added, for each region and sector. For region i and sector j the FDI intensity at time t is $Y_{ijt} = (FDI_{ijt}/VA_{ijt})$, for region i and sector j. The number of regions N is 20, the number of sectors S is 4 and the number of time observations T is 6. The value added by region and sector controls for market dimension, factor endowment, investment by acquisition, and other omitted variables. In the empirical literature of FDI determinants the market size, proxied by real GDP or GDP per capita, is highly significant and positive in all studies[vi]. This partly reflects the fact that FDI flows are horizontal in nature, especially in developed economies[vii]. Moreover, regions with favourable factor endowment attract domestic as well as foreign investors (Head *et al*., 1995). As a result, a model testing for agglomeration without controlling for endowment may lead to spurious results for the agglomeration effect. In addition, the FDI-intensity also allows to control for correlation between foreign investment and location of domestic firms due to investment by acquisition, provided that data do not distinguish between greenfield investment and acquisitions (Bronzini, 2004). Finally, with this measure of FDI intensity all omitted factors that attract both foreign and domestic investors, e.g. labor costs and skills, may be taken into account[viii]. To handle the presence of zero for the dependent variable (52 on a total of 480 observations), a constant factor is added to each observation, introducing a log-transformation of the model. All specifications include as regressors regional, time and sectoral fixed effects.

The MNE can benefit from knowledge diffusion but may be damaged by the process of imitation from local competitors. In this case, the profit function depends on vertical as well as horizontal spillovers. The focus on agglomeration spillovers in the host country from and to FDI inward flows requires adequate measures of the externalities associated to a location in the neighborhood of other firms in the diffusion of technological innovation (Glaeser *et al*., 1992): spillovers connected to specialization (Marshall-type and Porter-type economies) and to diversity (Jacobs-type economies).

With reference to Marshall-type agglomeration spillovers, capturing the positive effects of the agglomeration of firms belonging to the same sector, we consider a sector specialization index computed on industry employment (Paci-Usai, 2000):

$$Spec_{ij} = \frac{IS_{ij} - 1}{IS_{ij} + 1}$$

[vi] See Lim (2001) for a survey of the literature.

[vii] Horizontal FDI flows have *market seeking* objectives and aim at replicating abroad the parent company activities. Vertical FDI are instead mainly *resource-seeking*.

[viii] By using the value added as the scale factor a restriction is introduced in the model, that is the coefficient of the value added is restricted to one in a log-linear regression model of FDI on value added. To avoid model misspecification, this restriction asks for appropriate diagnostic tests.

with $IS_{ij} = \dfrac{L_{ij} \Big/ \sum_j L_{ij}}{L_{ITA\,j} \Big/ \sum_j L_{ITA\,j}}$ and $i = 1, \ldots, 20$ $j = ag, inss, c, s$ (5)

where L_{ij} is employment in region i and industry j, and $L_{ITA\,j}$ is employment at national level in industry j. The index is standardized and constrained within the interval (–1, 1).
Other types of agglomeration economies can arise from the diversity of the regional economic structure (Jacobs, 1969), so industrially diversified regions could attract other firms. In this case, knowledge spillovers and reduction of transaction costs may be the source of agglomeration economies related to sector diversity. However, the econometric model is unable to distinguish among these sources of externalities, so we consider both falling into a broad category of non-sector specific agglomeration economies. To measure the so called Jacobs-type externalities we employ the relative Hirschman-Herfindal index:

$$Div_{ij} = \frac{H_{ij}}{H_{ITA\,j}} \qquad \text{with } i = 1, \ldots, 20 \;\; j = ag, inss, c, s \qquad (6)$$

where $H_{ij} = \sum_{j^* \neq j} s_{ij^*}^2$, and $s_{ij^*}^2 = L_{ij} \Big/ \sum_{j^* \neq j} L_{ij^*}$.

For region i and sector j, the index is measured over all the industrial sectors except j and is decreasing with the relative diversity of the area compared with the national average, that is higher indexes indicate less diversified areas. Thus, a positive effect of vertical externalities is detected by a negative sign for the corresponding coefficient.
To account for spillovers among firms localized in the same geographical area (Porter-type spillovers), a district variable has been introduced. Specifically we have considered the number of workers employed in districts, identified by ISTAT, in a region divided by the total number of workers in the same region, as a measure of the local development of firms' networks across Italian regions.
A measure of trade openness has been considered to provide an empirical foundation for characterizing the relationship of complementarity or substitutability between trade and FDI. We have calculated a trade variable by using the sum of imports and exports divided by GDP, for each region and sector. From a general perspective the relationship between trade openness and FDI is rather complex. For host countries, FDI can been seen as substituting for trade openness because foreign affiliates' local sales substitute for imports (of final goods) from the investing country. If inward FDI results in the importation of inputs, especially intermediate goods, this might imply a positive correlation between imports and FDI flows (Fontagné, 1999; Blonigen, 2001). Furthermore, for both horizontal and vertical FDI the relationship between exports and FDI is rather complex too (Helpman *et al*., 2004; Greenaway and Kneller, 2005)[ix]. By interpreting FDI inflow intensity as a measure of local competitive performance, it is interesting to investigate how trade openness influences the level of such absorptive capacity.

[ix] The former have *market seeking* objectives and aim at replicating abroad the parent company activities, thus possibly displacing exportations. The latter are instead mainly *resource-seeking* and often feed intra and inter-industry flows, thus contributing to make the relationship with trade fairly complex.

Different models able to describe firms' competitive effects from inward FDI with i) spatial heterogeneity and ii) spatial dependence, have been tested. As to the former aspect, spatial heterogeneity has been modelled by introducing fixed effects at sectoral and regional level (Model 1, eq. 2) and heterogeneous coefficients across regions (Model 2). All models for FDI intensity have been estimated in log-linear form by maximum likelihood (ML) – based methods. To account for residual spatial dependence, spatial lag and spatial error specifications have also been considered. For the spatial lag model, the approach that is used here for the potential endogeneity of the spatially lagged dependent variable is to instrument this variable (Anselin, 1988). In Model 1 specification with spatial effects a common spatial autocorrelation/autoregressive coefficient is assumed. The model is then estimated using a IV-ML based estimator. In Model 2 heterogeneity with varying (region specific) spatial dependence is introduced and GME estimates are calculated.
The spatial weights are derived by means of a geographic information system. In this case, units are defined 'neighbors' when they are within a given distance of each other, i.e. $w_{ik} = 1$ for $d_{ik} \leq \xi$ and $i \neq k$, where d_{ik} is the great circle distance chosen, and δ is the critical cut-off value. More specifically, a spatial weights matrix W^* is defined as follow:

$$w_{ik}^* = \begin{cases} 0 & if \quad i = k \\ 1 & if \quad d_{ik} \leq \xi, \quad i \neq k \\ 0 & if \quad d_{ik} > \xi, \quad i \neq k \end{cases} \qquad (7)$$

and the elements of the row-standardized spatial weights matrix W (with elements of a row sum to one) result:

$$w_{ik} = \frac{w_{ik}^*}{\sum_{k=1}^{N} w_{ik}^*}, \qquad i, k = 1, \ldots, N. \qquad (8)$$

5.2. Results

Our analysis is firstly focused on the hypothesis of common behaviour of FDIs determinants across all sectors. Then, the analysis is extended to account for heterogeneous effects of specialization and diversity spillovers across sectors (agriculture, industry in the strict sense, construction, and services). All specifications include regional, sector and time fixed effects.
Specifically, we start by assuming: (i) panel homogeneity in slope coefficients (Model 1); (ii) panel regional heterogeneity in slope coefficients (Model 2). In the presence of spatial effects, an assumption of uniform spatial dependence (homogenous spatial autoregressive coefficients for different regions) has been included in Model 1, while varying spatial dependence (heterogeneous spatial autoregressive coefficients for different regions) has been considered in Model 2.

5.2.1 Model 1- results

a) Homogeneity across sectors

In Model 1, regional disparities are captured by regional dummies, while for other determinants the hypothesis of common behaviour across all regions is considered. Results with and without spatial dependence, are detailed in Table 1. In the first two columns we present the results assuming absence of spatial autocorrelation, columns (3)-(4) provide the estimates of the spatial lag model[x]. Evidence suggests that specialization externalities negatively affect FDI intensity. A statistically significant evidence of the influence of diversity externalities does not emerge. Other potential sources of externalities have also been tested, including the trade openness and the district variables. The former one has a negative effect on FDI inflows[xi].

b) Four sectors analysis

The results with and without spatial autocorrelation, are presented in Table 3. Again, in the first two columns we present the results assuming absence of spatial autocorrelation, columns (3)-(4) provide the estimates of the spatial lag model which represents an adequate specification in presence of spatial dependence. In analyzing potential heterogeneity across sectors (agriculture, industry in the strict sense, construction, and services) a positive contribution of specialization spillovers emerges for the manufacturing sector, while a negative effect emerges for the agriculture sector. For diversity externalities a statistically significant evidence of the positive influence of diversity externalities emerges in the agricultural sector and in the construction sector[xii]. Assuming spatial autocorrelation, results do not change[xiii].

In summary, a clear evidence of heterogeneity of coefficients as well as spatial dependence have emerged. The adequacy of this model is supported by the pseudo-R^2, which is better than for the Model 1 with homogeneity across sectors, as well as by the AIC. The estimation of the spatial regression model points in favor of the assumption of cross regional dependence[xiv].

5.2.2 Model 2- results

a) Homogeneity across sectors

The results for Model 2, without spatial dependence, are presented in Table 3. Mixed evidence emerges for specialization and diversity spillovers for most of the regions. More specifically, a positive effect of specialization spillovers emerges only for three regions (Val d'Aosta, Veneto and Basilicata). A negative effect of horizontal externalities for regions Lazio and Sicilia is the only evidence pointing in favor of the theoretical prediction of a negative effect of a high sectoral specialization on the MNE's decision to invest in a location. For diversity externalities, we find mixed evidence across regions. A positive effect has been obtained for Campania, Puglia and Sicilia and a negative one for Val d'Aosta, Veneto, Friuli Venezia Giulia, Emilia Romagna and Abruzzo. For the remaining regions no clear or significant evidence emerges. Spillovers

[x] IV Tobit ML estimates have been obtained using sectoral value added per worker and other exogenous regressors as instruments for the FDI *spatial lag* variable.

[xi] Other FDI determinants were also tested, as the value added and a price index by region and sector. However their exclusion is not rejected by the standard variable omission tests.

[xii] The trade openness coefficient is negative, while the district one is not significant.

[xiii] When the value added by region and sector is introduced, the coefficient of specialization spillovers for industry and service sectors becomes not significant, while other results are unchanged. The addition of a price index variable does not modify all results. The trade openness coefficient is negative, while the district one is not significant.

[xiv] Another approach to test for cross sectional dependence is to directly test if the cross-correlations of the errors are zero. In our estimates, cross section dependence is confirmed by Breusch and Pagan's (1980) Lagrangian multiplier (LM) test, while it is not by Pesaran (2004) CD test. See Hsiao et al. (2007) for a description of diagnostic tests of cross section independence for Tobit models.

connected to district areas seem to be relevant in regions characterized by a district organization of the production process, such as Friuli Venezia Giulia, Abruzzo, Molise and Basilicata, with the exception of the negative coefficient for Veneto. Previous results on the negative effect of trade openness are confirmed for Veneto, Lazio and Campania.

b) Four sectors analysis

Results for Model 2, the spatial lag model with varying (region specific) spatial dependence (Table 4) confirm the high heterogeneity of all types of spillovers across regions, mostly concentrated in Centre and Northern regions. Due to the panel data size, standard techniques cannot be applied when heterogeneity in coefficients of explanatory variables across both regions and sectors is introduced; estimates are then computed using a Generalized Maximum Entropy estimation approach. Specialization externalities have mixed effects on FDI intensity. With reference to vertical linkages across industries, no clear evidence comes out, except for agriculture and construction where inter-industry externalities positively influence MNE's investment decisions. Finally, there is evidence that the importance of spatial dependence varies across regions. Endogenous spillovers connected to geographical proximity produce diversified effects on regions: FDI intensity in a region is positively affected by FDI flows in neighboring regions for Piemonte, Lombardia, Veneto, and Toscana. The effect is negative for Liguria, Umbria, Marche, Lazio, and Sardegna. Differences in the estimated coefficients on the region-specific spatial dependence terms emerge for regions that are contiguous to the North and Center of Italy while peripheral regions experience much smaller and negligible effects.

6. Conclusions

In this study the role played by local agglomeration externalities on the degree of inward FDI intensity has been analyzed through panel data models extended to include spatial heterogeneity and spatial dependence. Firms' competitive effects from FDI inflows have been studied with data on foreign direct investment inflows in Italy, collected by the Italian Foreign Exchange Office for all economic sectors (1999-2004). Our study in analyzing determinants of inward FDI aims at distinguishing the relative importance of intra-industry, inter-industry and endogenous externalities and controlling for omitted and unobservable factors both at regional and sectoral level. Potential endogenous spillover effects are controlled for using a LAG-SUR model specification.

Alternative fixed effects panel data model specifications, also extended to include spatial autocorrelation, have been examined by testing the hypothesis of (i) panel homogeneity/heterogeneity in slope coefficients; and (ii) panel heterogeneity in slope coefficients with uniform/varying spatial dependence. More specifically, fixed coefficients models with common slope coefficients as well as seemingly unrelated regression models have been introduced, and for all models a spatial lag specification has been also considered.

It is empirically confirmed the hypothesis that different types of agglomeration externalities, such as Marshall-type economies related to the sector specialization of a specific geographical area, and Jacobs-type externalities linked to sector diversity, contribute to affect FDI inflows. Heterogeneity in coefficients across both regions and sectors have been identified and the presence of foreign multinational firms seems to be connected to the linkages with the local context. Inter-industry and intra-industry externalities have shown mixed effects across sectors. A positive effect of specialization externalities on FDI intensity has been found for the manufacturing sector, and mixed evidence has come out with reference to vertical linkages across industries. However, for the agricultural sector, spillovers stemming from the presence of a low degree of specialization in a certain location seems to determine an increase in the international involvement of the local areas, while inter-industry externalities positively influence MNE's investment decisions. Finally, results related to the spatial LAG SUR specification seems to confirm the role of endogenous spillovers connected to geographical proximity showing diversified effects for Italian regions.

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Appendix A: Description of data

Data related to Italy's inward FDI flows by (destination) region and economic sector are collected by the Italian Foreign Exchange Office (Ufficio Italiano Cambi, UIC) and come from the balance of payments statistics. FDI is defined as "the category of international investment that reflects the objective of a residence entity in one economy obtaining a lasting interest in an enterprise resident in another economy" (IMF, 1993). Following the IMF guidelines, the UIC provides the following definition: the investment in a foreign company is classified as FDI when it involves 10 per cent or more of the company's share; it is classified as a portfolio investment when it is less than 10 per cent. Using balance of payments data on Italy's inward FDI flows (from 1999 to 2004), a wide array of activities related to the internationalization of production is covered, including greenfield investments abroad as well as cross-border M&As. "Non-equity" forms of internationalization, such as some kinds of commercial or technical joint ventures, as well as international subcontracting, are instead not covered. Data on FDI are collected by region, and broken down into one-digit sectors (as detailed in table A1). Descriptive statistics of the regional sample aggregated by the authors into four macro-sectors (agriculture, industry in the strict sense, construction, and services) are reported in Tables A2-A3-A4. Other data on value added, employment, and trade flows come from Istat, as described in Table A5.
Since some variables are not strictly positive, to allow the logarithmic transformation we add a unit constant to the dependent variable of the regional model that is sometimes equal to zero and to the variable measuring MAR externalities *Spec,* which assumes negative values. The dependent variable of the econometric model is FDI-intensity defined as the log of FDI inflow divided by the value added, by each region and sector; $y_{ijt} = \ln(1+Y_{ijt})$, where $Y_{ijt} = (FDI_{ijt}/VA_{ijt})$ is the FDI intensity at time t, for region i and sector j. Among regressors regional, time and sectoral fixed effects have been included.

Tab. A1: Description of sectors

Macro-sector	Sector	Description
A		**AGRICULTURE**
	A1	**AGRICULTURE**
		Agriculture, hunting, forestry and fishing
B		**INDUSTRY**
	B1	**INDUSTRY IN THE STRICT SENSE**
		Paper, paper products and printing
		Agricultural and industrial machinery and equipment
		Office, accounting and computing machinery
		Electrical materials
		Transport equipment
		Ferrous and non-ferrous minerals and metals
		Non-metallic mineral products
		Food products, beverages, and tobacco products
		Chemicals products
		Energy products
		Rubber and plastics products
		Metal products except transport equipment
		Textiles, leather, footwear and clothing
		Other manufacturing products
	B2	**CONSTRUCTION**
		Construction in private and public sectors
C		**SERVICES**
	C1	**MARKET SERVICES**
		Supporting and auxiliary transport activities
		Hotels and restaurants
		Land transport
		Water and air transport
		Maintenance and repair of motor vehicles, personal and household goods
		Telecommunications
		Other trade services
	C2	**NON-MARKET SERVICES**
		Public administration
		Private households with employed persons
	C3	**FINANCIAL INTERMEDIATION**
		Financial intermediation, except insurance and pension funding
		Insurance and pension funding

Tab. A2: FDI inflows by region
(share of national total, percentage values)

	Regions	1999	2000	2001	2002	2003	2004	2005
1	PIEMONTE	7.22	17.39	10.72	12.72	12.80	8.88	13.96
2	VALLE D'AOSTA	0.13	0.04	0.04	0.09	0.02	0.01	0.003
3	LOMBARDIA	35.04	34.30	42.88	37.52	48.85	62.40	62.90
4	TRENTINO ALTO ADIGE	0.37	0.19	0.36	0.53	0.59	0.29	0.15
5	VENETO	4.76	4.35	2.58	5.84	7.95	4.86	3.92
6	FRIULI VENEZIA GIULIA	0.66	0.21	0.26	0.27	0.18	0.03	0.09
7	LIGURIA	0.77	0.28	0.40	1.51	0.23	0.23	0.46
8	EMILIA ROMAGNA	2.44	3.12	2.96	1.61	1.51	3.15	2.22
9	TOSCANA	0.75	9.30	16.50	13.55	4.32	5.06	3.23
10	UMBRIA	0.04	0.04	0.36	0.05	0.93	1.36	0.88
11	MARCHE	0.21	0.66	0.21	0.18	0.07	0.14	0.05
12	LAZIO	10.58	11.72	5.31	2.31	9.82	4.54	5.56
13	ABRUZZO	0.16	0.10	0.08	0.10	0.09	0.11	0.05
14	MOLISE	0.09	0.001	0.001	0.001	0.01	0.02	0.13
15	CAMPANIA	0.40	0.24	0.42	0.25	0.36	0.27	0.23
16	PUGLIA	0.07	0.22	0.05	0.09	0.02	0.05	0.09
17	BASILICATA	0.004	0.01	0.002	0.02	0.01	0.01	0.14
18	CALABRIA	0.02	0.02	0.03	0.02	0.01	0.01	0.01
19	SICILIA	0.22	0.07	0.05	0.02	0.05	0.03	0.04
20	SARDEGNA	0.09	1.24	0.06	0.09	0.04	0.02	0.02
	NOT INDICATED	35.97	16.51	16.72	23.23	12.13	8.54	5.88
	TOT. ITALY	100	100	100	100	100	100	100

Tab. A3: FDI inflows by sector and region, share of national total
(time averages, percentage values)

	Regions	Agriculture	Industry in the strict sense	Construction	Services
1	PIEMONTE	0.30	13.53	2.63	15.75
2	VALLE D'AOSTA	0	0.06	0.22	0.01
3	LOMBARDIA	97.89	56.09	52.38	53.05
4	TRENTINO ALTO ADIGE	0.04	0.39	0.67	0.42
5	VENETO	0.15	1.69	8.88	14.14
6	FRIULI VENEZIA GIULIA	0.004	0.13	0.63	0.32
7	LIGURIA	0.02	0.41	2.79	0.76
8	EMILIA ROMAGNA	0.63	3.73	6.19	2.15
9	TOSCANA	0.28	15.80	2.90	0.58
10	UMBRIA	0.05	1.46	0.09	0.13
11	MARCHE	0.02	0.26	0.35	0.24
12	LAZIO	0.09	5.78	19.01	11.24
13	ABRUZZO	0.04	0.17	0.48	0.05
14	MOLISE	0	0.02	0.01	0.01
15	CAMPANIA	0.01	0.35	1.40	0.40
16	PUGLIA	0.01	0.05	0.45	0.13
17	BASILICATA	0	0.01	0.01	0.01
18	CALABRIA	0.03	0.01	0.15	0.03
19	SICILIA	0.02	0.02	0.23	0.09
20	SARDEGNA	0.001	0.05	0.52	0.51
	TOT. ITALY	100	100	100	100

Tab. A4: FDI inflows by sector and region, share of regional total
(time averages, percentage values)

	Regions	Agriculture	Industry in the strict sense	Construction	Services	Total
1	PIEMONTE	0.10	57.02	0.14	42.73	100
2	VALLE D'AOSTA	0.00	90.28	4.10	5.62	100
3	LOMBARDIA	7.95	56.79	0.68	34.58	100
4	TRENTINO ALTO ADIGE	0.48	57.55	1.28	40.68	100
5	VENETO	0.11	15.46	1.04	83.38	100
6	FRIULI VENEZIA GIULIA	0.10	38.27	2.38	59.24	100
7	LIGURIA	0.14	43.52	3.85	52.50	100
8	EMILIA ROMAGNA	0.97	71.14	1.52	26.37	100
9	TOSCANA	0.14	97.33	0.23	2.30	100
10	UMBRIA	0.26	94.38	0.07	5.29	100
11	MARCHE	0.33	62.21	1.06	36.40	100
12	LAZIO	0.05	43.57	1.84	54.54	100
13	ABRUZZO	1.46	80.69	2.88	14.97	100
14	MOLISE	0.00	61.73	0.41	37.85	100
15	CAMPANIA	0.09	55.68	2.86	41.38	100
16	PUGLIA	0.54	34.77	4.24	60.45	100
17	BASILICATA	0.00	67.11	0.80	32.09	100
18	CALABRIA	7.72	39.29	5.39	47.59	100
19	SICILIA	1.51	23.17	3.52	71.80	100
20	SARDEGNA	0.02	12.82	1.75	85.40	100
	TOT. ITALY	4.62	66.82	0.74	37.06	100

Tab. A5: Description of other regional data

VAAG	Value Added in agriculture
VAINSS	VA in industry in the strict sense
VAC	Value Added in construction sector
VAS	Value Added in services
LAG	Units of Labour in agriculture
LINSS	Units of Labour in industry in the strict sense
LC	Units of Labour in construction
LS	Units of Labour in services
LD	Domestic employees in districts
L	Total domestic employees
PAG	Price index for agricultural products
PINSS	Price index for industrial products
PC	Price index for the construction of a residential building
PS	Consumer price index for services
IMPAG	Imports in agriculture
IMPINSS	Imports in industry in the strict sense
IMPC	Imports in construction sector
IMPS	Imports in services sector
EXPAG	Exports in agriculture
EXPINSS	Exports in industry in the strict sense
EXPC	Exports in construction sector
EXPS	Exports in services sector

Note: monetary values in current prices and millions of Euro; employment in thousand of units. Source: Istat.

Appendix B: Results

Table 1: Model 1 (Homogeneous slope coefficients across regions and sectors)
Dependent variable: *y* = ln (1+FDI/VA) - ML-based estimates

Explanatory variables	(1)	(2)	(3)	(4)
y spatial lag			-1.18**	-1.21**
			0.55	*0.54*
ln(*1+spec*)	-0.04**	-0.04**	-0.04**	-0.04**
	0.02	*0.02*	*0.02*	*0.02*
ln(*div*)	-0.02	-0.02	-0.02	-0.02
	0.01	*0.01*	*0.01*	*0.01*
open		-0.01*		-0.01**
		0.003		*0.004*
district		-0.001		-0.002
		0.001		*0.001*
Log Likelihood	599.79	603.52	1649.48	1655.03
Standard error of estimate	0.056	0.056	0.057	0.055
Pseudo-R^2	0.358	0.369	0.207	0.213
AIC	-2.370	-2.377	-3168.959	-3172.066
Left censored observations	52	52	52	52
N. of observations	480	480	480	480

Standard error in italics; all estimates include regional, sector and time dummies. The McKelvey and Zavoina's pseudo R^2 is calculated in (1) and (2), while the R^2 between the predicted and observed values is obtained in (3) and (4).
* 1%; ** 5%; *** 10% significance levels

Table 2: Model 1 with heterogeneity across agriculture, industry in the strict sense, construction and services.
Dependent variable: *y* = ln (1+FDI/VA) – ML-based estimates

Explanatory variables	(1)	(2)	(3)	(4)
y spatial lag			-0.75***	-0.77**
			0.40	*0.39*
ln(1+spec) in sector 1	-0.19*	-0.19*	-0.23*	-0.23*
	0.03	*0.03*	*0.04*	*0.04*
ln(1+spec) in sector 2	0.14*	0.12**	0.22*	0.21*
	0.05	*0.05*	*0.07*	*0.07*
ln(1+spec) in sector 3	-0.01	-0.01	-0.07	-0.08
	0.09	*0.08*	*0.09*	*0.09*
ln(1+spec) in sector 4	-1.29***	-1.01	-1.03	-0.76
	0.77	*0.78*	*0.81*	*0.82*
ln(div) in sector 1	-0.28**	-0.35*	-0.33*	-0.39*
	0.11	*0.12*	*0.12*	*0.12*
ln(div) in sector 2	-0.04	-0.10	-0.01	-0.07
	0.09	*0.10*	*0.10*	*0.10*
ln(div) in sector 3	-0.14	-0.20***	-0.19***	-0.25**
	0.10	*0.11*	*0.11*	*0.12*
ln(div) in sector 4	-0.08	0.01	0.003	0.09
	0.12	*0.13*	*0.13*	*0.14*
open		-0.01***		-0.01***
		0.004		*0.004*
district		-0.0007		-0.001
		0.001		*0.001*
Log Likelihood	624.12	626.27	1694.02	1698.05
Standard error of estimate	0.053	0.053	0.053	0.053
Pseudo-R^2	0.424	0.429	0.332	0.337
AIC	-2.446	-2.447	-3234.05	-3234.107
Left censored observations	52	52	52	52
N. of observations	480	480	480	480

Standard error in italics; all estimates include regional, sector and time dummies. The McKelvey and Zavoina's pseudo R^2 is calculated in (1) and (2), while the R^2 between the predicted and observed values is obtained in (3) and (4).
* 1%; ** 5%; *** 10% significance levels.

Table 3: Model 2 (Heterogeneous slope coefficients across regions)
Dependent variable: *y* = ln (1+FDI/VA) - ML-based estimates

Regions	constant	open	district	ln(1+spec)	ln(div)
1 Piemonte	-0.14	-0.01	0.005	-0.84	-0.03
	0.27	*0.02*	*0.01*	*0.54*	*0.29*
2 Valle d'Aosta	0.07*	0.004*	0.00	0.93*	0.22*
	0.02	*0.001*	*0.00*	*0.21*	*0.08*
3 Lombardia	0.85	-0.001	-0.01	4.77	-0.67
	2.63	*0.21*	*0.01*	*3.01*	*1.78*
4 Trentino-Alto Adige	0.01	-0.01	-0.002	-0.18	-0.07
	0.05	*0.01*	*0.004*	*0.14*	*0.07*
5 Veneto	-1.25*	-0.24*	-0.001*	0.54*	0.90*
	0.23	*0.04*	*0.0003*	*0.14*	*0.15*
6 Friuli-Venezia Giulia	-0.02*	-0.001	0.0004*	-0.01	0.05**
	0.01	*0.001*	*0.0001*	*0.01*	*0.03*
7 Liguria	-0.05	0.001	0.00	-0.15	-0.17
	0.06	*0.002*	*0.00*	*0.16*	*0.11*
8 Emilia-Romagna	0.30	0.01	-0.001	0.36	1.29***
	0.19	*0.02*	*0.001*	*0.42*	*0.73*
9 Toscana	-0.15	-0.15	-0.02	-0.79	-0.14
	0.67	*0.17*	*0.02*	*0.52*	*0.66*
10 Umbria	-0.22	-0.02	0.00	-0.06	1.16
	0.28	*0.02*	*0.00*	*0.99*	*0.78*
11 Marche	-0.12	-0.01	-0.001	-0.15	0.23*
	0.10	*0.01*	*0.001*	*0.09*	*0.08*
12 Lazio	-1.60	-0.16**	0.00	-1.28***	0.10
	0.69	*0.07*	*0.00*	*0.75*	*0.41*
13 Abruzzo	-0.03	0.002	0.002***	0.07*	0.06***
	0.04	*0.002*	*0.001*	*0.03*	*0.03*
14 Molise	0.01	0.001	0.001***	0.00	0.05
	0.02	*0.001*	*0.001*	*0.09*	*0.06*
15 Campania	-0.08**	-0.02**	0.00	-0.06	-0.13**
	0.04	*0.01*	*0.00*	*0.06*	*0.05*
16 Puglia	-0.004	0.00	0.00	-0.02	-0.05**
	0.003	*0.00*	*0.00*	*0.02*	*0.03*
17 Basilicata	0.01	0.00	0.0002**	0.05**	0.02
	0.01	*0.001*	*0.00*	*0.02*	*0.02*
18 Calabria	-0.003	0.00	0.00	0.01	0.002
	0.01	*0.00*	*0.00*	*0.01*	*0.005*
19 Sicilia	-0.004	0.00	0.00	-0.01*	-0.01**
	0.004	*0.00*	*0.00*	*0.003*	*0.002*
20 Sardegna	-0.04***	-0.001	0.00	-0.04	-0.10
	0.02	*0.002*	*0.00*	*0.04*	*0.08*

Standard error in italics; all estimates include sector and time dummies.
* 1%; ** 5%; *** 10% significance levels.

Table 4: Model 2 with heterogeneity across agriculture, industry in the strict sense, construction and services
Dependent variable: y = ln (1+FDI/VA) – Generalized Maximum Entropy estimates

Regions	constant	*y* spatial lag	open	district	ln(1+spec) in sector 1	ln(1+spec) in sector 2	ln(1+spec) in sector 3	ln(1+spec) in sector 4	ln(div) in sector 1	ln(div) in sector 2	ln(div) in sector 3	ln(div) in sector 4
1 Piemonte	0.00	2.90*	-0.25*	0.30*	-5.68*	-8.97	-2.62***	-45.46*	-39.99*	24.03	-50.38*	22.76*
	0.00	*0.41*	*0.00*	*0.00*	*0.05*	*19.76*	*1.28*	*6.13*	*0.00*	*22.01*	*0.21*	*0.16*
2 Valle d'Aosta	0.62	-0.01	-0.001	0.00	0.28*	-6.53*	3.92*	1.84	-3.47*	5.85*	2.49*	-2.09
	0.38	*0.01*	*0.00*	*0.00*	*0.02*	*0.00*	*0.24*	*2.05*	*0.02*	*0.00*	*0.20*	*2.14*
3 Lombardia	-13.10*	3.57*	-0.69*	-126E-17*	-20.32*	-67.34*	47.05*	-78.30*	-127.72*	-90.70*	-77.56*	77.35*
	2.95	*0.04*	*0.01*	*0.00*	*0.00*	*1.59*	*0.12*	*0.88*	*0.00*	*0.55*	*0.16*	*0.01*
4 Trentino-Alto Adige	0.48*	-0.01	-0.05*	7.61E-16**	1.85**	1.41	1.80*	-1.84	2.03**	-1.59	2.44	1.68
	0.05	*0.01*	*0.01*	*0.00*	*0.54*	*0.73*	*0.36*	*1.54*	*0.90*	*1.37*	*2.14*	*1.38*
5 Veneto	9.04*	0.20**	0.59***	-0.001*	4.39*	10.60*	-0.56**	-10.72*	3.83*	-5.33*	-4.35***	6.12*
	2.93	*0.08*	*0.31*	*0.00*	*0.00*	*0.00*	*0.23*	*1.23*	*0.00*	*0.00*	*2.16*	*0.16*
6 Friuli-Venezia Giulia	-0.09**	-0.10	0.00	-0.01*	0.01	-0.14	0.03	-0.05	-1.00	-0.07	-1.14	0.13
	0.04	*0.56*	*0.00*	*0.00*	*0.07*	*1.10*	*0.11*	*1.18*	*2.76*	*0.77*	*3.03*	*2.36*
7 Liguria	-3.10*	-0.29*	0.01	1.455E-8*	-0.18	-0.45	-0.03	-1.74	-5.67	10.83*	-7.13*	6.82*
	0.30	*0.02*	*0.02*	*0.00*	*0.21*	*2.88*	*0.04*	*3.00*	*3.61*	*0.32*	*0.24*	*0.40*
8 Emilia-Romagna	-1.64*	0.09	0.10*	-0.01*	-1.52*	5.75*	-1.62	4.91	15.86*	-5.97*	-14.42*	-9.70**
	0.04	*0.10*	*0.01*	*0.00*	*0.46*	*1.73*	*2.78*	*12.14*	*0.00*	*0.64*	*1.23*	*3.93*
9 Toscana	3.78**	1.05*	-0.30*	0.00	1.48*	24.06*	2.58*	0.87*	-1.01**	14.92*	-1.58*	-0.24*
	1.36	*0.14*	*0.00*	*0.00*	*0.05*	*0.29*	*0.07*	*0.09*	*0.47*	*0.99*	*0.28*	*0.04*
10 Umbria	-0.54*	-7.55*	0.02*	0.00	2.89*	-23.30*	-1.81***	6.01*	4.77	4.80***	4.62	-2.28**
	0.00	*1.32*	*0.00*	*0.00*	*0.55*	*7.49*	*0.98*	*2.53*	*3.05*	*2.64*	*3.53*	*1.04*

Standard error in italics; all estimates include sector and time dummies.
* 1%; ** 5%; *** 10% significance levels.

Table 4 (continue): Model 2 with heterogeneity across agriculture, industry in the strict sense, construction and services
Dependent variable: y = ln (1+FDI/VA) – Generalized Maximum Entropy estimates

Regions	**constant**	***y* spatial lag**	**open**	**district**	**ln(1+spec) in sector 1**	**ln(1+spec) in sector 2**	**ln(1+spec) in sector 3**	**ln(1+spec) in sector 4**	**ln(div) in sector 1**	**ln(div) in sector 2**	**ln(div) in sector 3**	**ln(div) in sector 4**
11 Marche	0.11	-0.12*	0.01	0.00	-0.005*	-3.81*	0.00	0.82**	-1.01*	0.20	0.16	-0.22**
	0.07	*0.01*	*0.01*	*0.00*	*0.00*	*0.92*	*0.00*	*0.37*	*0.02*	*0.12*	*0.28*	*0.09*
12 Lazio	0.00	-0.72*	0.20	-5.40*	5.35*	5.50**	-4.66*	-21.24*	-17.47**	0.17	12.30*	18.23*
	0.00	*0.10*	*0.18*	*1.45*	*0.49*	*2.14*	*0.63*	*0.67*	*7.63*	*7.59*	*0.00*	*0.00*
13 Abruzzo	0.00	0.02	-0.02*	0.01*	0.03	0.08	0.07	-0.56	-1.22*	-0.89	-0.29	0.04
	0.00	*0.30*	*0.00*	*0.00*	*0.03*	*0.59*	*0.25*	*4.13*	*0.43*	*0.80*	*0.72*	*0.37*
14 Molise	1.32E-16*	0.04	-0.004**	0.00	0.08	-0.12	0.27**	-0.07	-0.19	-0.01	-0.35***	0.02
	0.00	*0.03*	*0.00*	*0.01*	*0.07*	*0.12*	*0.12*	*0.71*	*0.21*	*0.08*	*0.17*	*0.23*
15 Campania	0.00	0.17	0.03	-0.07	-0.27	-1.33	0.00	-0.18	-1.61*	1.41	0.94	0.22
	0.00	*16.68*	*0.13*	*0.60*	*18.28*	*13.37*	*15.83*	*194.90*	*0.31*	*25.40*	*65.38*	*15.00*
16 Puglia	0.00	9.93	0.00	0.00	0.13	-0.22	0.00	0.05	-0.05	-0.02	0.02	-0.01
	0.00	*0.00*	*0.04*	*0.01*	*2.75*	*3.22*	*2.55*	*32.78*	*2.68*	*7.14*	*4.44*	*4.76*
17 Basilicata	0.00	0.05	0.00	0.01	-0.01	0.00	0.00	0.00	0.03	0.00	-0.01	0.00
	0.00	*3.88*	*0.01*	*0.01*	*0.47*	*0.20*	*0.83*	*1.46*	*0.80*	*0.39*	*0.65*	*0.30*
18 Calabria	-0.01	0.09	0.00	0.00	-0.13	-0.04	0.01	0.06	0.17	0.24	0.08	0.08
	0.81	*94.69*	*0.08*	*0.00*	*5.86*	*1.83*	*3.56*	*19.81*	*6.49*	*3.83*	*5.08*	*7.11*
19 Sicilia	0.00	3.23	0.00	-0.02	-0.01	0.00	0.00	-0.01	-0.01	0.00	-0.01	0.00
	0.00	*0.00*	*0.00*	*0.06*	*0.43*	*0.22*	*0.39*	*1.00*	*0.34*	*0.43*	*0.55*	*0.16*
20 Sardegna	0.00	-0.04**	0.03*	-2.91*	-3.10*	-1.27	-1.54	-2.26	-8.05*	4.64	-6.65**	5.74*
	0.00	*0.02*	*0.00*	*0.03*	*0.12*	*1.01*	*4.00*	*7.32*	*0.00*	*2.97*	*2.49*	*2.00*

Standard error in italics; all estimates include sector and time dummies.
* 1%; ** 5%; *** 10% significance levels.