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Spatial clustering and nonlinearities in the location of multinational firms

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Abstract

We propose a semiparametric geoadditive negative binomial model of industrial location which allows to simultaneously address some important methodological issues, such as spatial clustering and nonlinearities, which have been only partly addressed in previous studies. We apply this model to analyze location determinants of inward greenfield investments occurred over the 2003-2007 period in 249 European regions. The inclusion of a geoadditive component (a smooth spatial trend surface) allows to control for omitted variables which induce spatial clustering, and suggests that such unobserved factors may be related to regional policies towards foreign investors Allowing for nonlinearities reveals, in line with theoretical predictions, that the positive effect of agglomeration economies fades as the density of economic activities reaches some limit value.

Keywords: Industrial location, Negative binomial models, Geoadditive models, European Union
JEL classification: C14, C21, F14, F23

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1. Introduction

New plants location draws considerable attention among economists and policy makers. By attracting new plants regions can foster their economic development, thereby justifying the investments of (local, national and supranational) institutions to attract firms' establishments. This is all the more true when it comes to the location of multinational firms which can bring foreign technology into a local context and eventually generate significant knowledge and pecuniary externalities (Barba Navaretti and Venables, 2005). The alleged positive effect of foreign establishments contributed to motivate a considerable amount of economic research into the determinants of such a location process. A recent survey of empirical works on the topic reports more than fifty econometric studies, mostly from the last decade and in large proportion focussing on foreign-owned firms (Arauzo-Carod et al., 2010). Despite this extensive amount of research, two issues have hitherto received very little attention: spatial effects and nonlinearities. Whereas the former refers to the spatial clustering of foreign firms' investments, the latter implies that not all regions obey a common linear specification of the industrial location model. Empirical models neglecting these issues may suffer from biased estimates and unreliable significance tests.

In this paper, we address these two issues in the case of the location of greenfield foreign investments in the NUTS2 regions of the Enlarged Europe over the 2003-2007 period. We submit that both spatial clustering and nonlinearities may be relevant in this case. On the one hand, it has been widely documented that multinational firms do not locate randomly in space, but rather they tend to concentrate in few neighbouring regions. This clearly violates the assumption of spatial independence. Regional characteristics included as explanatory variables in the model may partially account for the clustering of foreign firms. However, most likely some spatial correlation remains in the errors, affecting efficiency and consistency of the estimates. This may occur because of partially unobservable spatial factors, reflecting the role of regional amenities and regional policies.

On the other hand, nonlinearities are also very likely to occur in industrial location analysis. For example, theory suggests that a variable effect of agglomeration economies on firms' location decisions might exist according to level of agglomeration. In fact, as agglomeration reaches some critical value a congestion effect may eventually kick-in reducing the attractiveness of a given location. To explore this issue some authors have postulated an inverted-U shaped relation modelled by using squared terms for agglomeration measures (Arauzo-Carod, 2005; Viladecans-Marsal, 2004). Admittedly, this is only one of several competing parametric restrictions which may capture a nonlinear relation. Indeed, nonlinearities can be better accommodated in a semiparametric framework, where the actual shape of the partial effect can be assessed using smooth functions.

The two aforementioned methodological issues are not only far from trivial *per se* but, in our case, are complicated by the fact that, in line with the vast literature on plants location and due the lack of FDI data at regional level, we are forced to use as dependent variable the number of new ventures, i.e. a count which takes discrete and non-negative values. A Generalised Linear Model (GLM) framework, assuming a negative binomial distribution for the conditional expectation of the number of new foreign plants in each region, provides a relatively flexible framework for the analysis of such count data. In fact, as it will be discussed in greater details in Section 4, GLMs lend themselves to an extension into the semiparametric framework, by adding smooth functions of covariates in the conditional expectation. This class of models is known as Generalized Additive Models (GAMs) (Wood, 2006a). Also, by including a *smooth spatial trend surface* - i.e. a nonparametric interaction of latitude (easting) and longitude (northing) - among the regressors, a GAM can be turned into the so-called Geoadditive model (see, *i.a.*, Kammann and Wand, 2003; Wood, 2003; Fahrmeir and Echavarrìa, 2006; Augustin et al., 2009), which allows to take unobserved spatial effects into account.

In sum, we use a Geoadditive Negative Binomial Model (Geo-NB-GAM) and apply it to estimate the determinants of multinational firms' greenfield investment location in the NUTS-2 regions of the Enlarged Europe. To the best of our knowledge only another work uses a semiparametric approach to investigate the determinants of new plant creation in Spanish provinces (Arauzo-Carod and Liviano, 2007). However, our work differs from this one since we thoroughly address spatial effects alongside with nonlinearity, we focus on multinational plants and we take a much broader perspective by studying location in the Enlarged Europe.

Results suggest that multinational firms' location choices are spatially clustered: even controlling for several regional characteristics, such as employment density, market size, Jacobs externalities, human capital, labour cost, unemployment, and density of transport infrastructure, the residuals of a semiparametric additive model turn out to be spatially auto-correlated. A Geo-NB-GAM, which incorporates a smooth spatial trend surface, is able to purge the errors from spatial dependence, leading to unbiased estimates and showing how some omitted factors, mainly regional attraction policies, may lead to cluster of foreign multinationals. The flexibility of the semiparametric approach also allows us to appreciate that whereas some regional characteristics have indeed a linear effect on foreign investments counts, others show some important nonlinearities. In particular, in line with theoretical predictions, the effect of agglomeration economies appear to fade as the density of economic activities reaches some limit value. However, this nonlinear relation does not seem to be well captured by an inverted-U shape: it is monotonically positive but the marginal effect decreases as agglomeration rises and, for a significant portion of our sample, the relation is flat. Therefore, no matter how dense the economic activity becomes, our data suggest that congestion (or competition) effects would never overcome positive agglomeration externalities.

The rest of the paper is organized as follows. Section 2 introduces the dataset on foreign greenfield investments in the European regions and reports the results of an exploratory spatial data analysis which provides some important insights for modelling foreign investment counts. Section 3 presents the theoretical framework which motivates the choice of location determinants included in the empirical model. Section 4 introduces the econometric methodology whereas Section 5 reports the econometric results. Section 6 concludes.

2. Spatial distribution of multinational firms' investments within the European Union

The data we use are retrieved from fDi Markets, an online database maintained by *fDi Intelligence* - a specialist division of the Financial Times Ltd - which monitors cross-border investments covering all sectors and countries worldwide. Relying on media sources and company data, *fDi Markets* collects detailed information on cross-border greenfield investments (available since 2003). Data are based on the announcement of the investment and are daily updated[1]. The database is used as the source for foreign investment project

[1] A team of in-house analysts search daily for investment projects from various publicly available information sources, including, Financial Times newswires, nearly 9,000 media, over 1,000 industry organizations and investment agencies, data purchased from market research and publication companies. Each project identified is cross-referenced against multiple sources, and over 90% of projects are validated with company sources. More information at http://www.fdimarkets.com/.

information in UNCTAD's World Investment Report and in publications by the Economist Intelligence Unit.

We selected 1,930 greenfield investments in the creation of manufacturing plants carried out by both European and non-European multinational firms in the European Union over the 2003-2007 period. For each project, detailed information is available on the investor (name, country of origin and sector of activity, including both manufacturing and services) and on the destination area (country, state and city). This allowed us to count the number of projects in each NUTS-2 region. Five countries (Bulgaria, Latvia, Cyprus, Luxemburg and Malta) and three Spanish regions (Comunitad Autónoma de Ceuta, Comunitad Autónoma de Melilla and Canarias) have been excluded due to the lack of data. The dataset included therefore 22 EU member states (249 NUTS-2 regions).

The distribution of the 1,930 greenfield investments in the manufacturing sector is right skewed (Panel A in Figure 1), with a share of zeros of about 14%, suggesting a high degree of over-dispersion in the raw data and reveals a substantial degree of geographical clustering (Panel B in Figure 1). The latter is all the more evident if we regress the number of investment projects[2] on the smooth interaction between latitude and longitude, $h(no, e)$. Figure 2 plots the geographical components of such a model, showing a *saddle-pattern* in the spatial distribution of foreign investments. They are clustered in two peripheral areas: one includes regions belonging to the New Member States (Eastern countries), while the other characterizes some western peripheral areas (mainly in Ireland, but also in Spain, Portugal and France).

- **Insert Figure 1 about here** -

[2] The details on how to estimate this effects are provided in Section 4. Suffice here to mention that we have used a thin plate regression spline as smoother (Wood, 2006a).

In sum, the exploratory spatial data analysis suggests to model foreign investment counts bearing in mind on the one hand the issues of non-normality, skewness and over-dispersion and, on the other hand, the presence of spatial clustering. While accounting for the former issue is rather straightforward using negative binomial models, the latter can be tackled modelling the mean function though a set of covariates intended to capture the spatial clustering. In the next section, we discuss some theoretical hypotheses on the location determinants of foreign ventures which suggest a proper set of explanatory variables needed to model the expected mean function. Should regional observable characteristics not be able to account for the clustering entirely, residual spatial dependence would remain in the error term, causing possible biases in the estimated coefficients. We will tackle this issue by including smooth spatial trends surfaces. This will also allow us to highlight where are the unexplained regional clusters, and assess what would be the factors behind their formation.

3. Determinants of the spatial distribution of inward foreign investments

The spatial distribution of foreign investments can be modelled as the result of the interaction between centripetal (or agglomeration) and centrifugal (or competition) forces Among agglomeration forces, we focus on the role of urbanization externalities, while as for centripetal forces we consider the effect of labour cost along with other labour market characteristics[3].

[3] Admittedly, data availability prevents us to include additional determinants. The role of regional policy measures aimed at attracting foreign firms' investments in order to boost regional development have been investigated by several cross-regional studies (see, *i.a.*, Wheeler and Mody, 1992; Head et al., 1999; Crozet et al., 2004). Other studies have analyzed the effect of national policies and national institutional settings

3.1. Urbanization economies

Since Hoover (1948), it is common to distinguish between two sources of agglomeration externalities: *a*) economies external to the firm but internal to the sector (the so-called Marshallian externalities) and *b*) economies external both to the firm and to the sector (the so-called urbanization externalities). According to Marshall, industrial firms tend to localize where other firms of the same industry are already established. The well known benefits of this form of externality are three-fold: *i*) access to a more stable labour market, *ii*) availability of intermediate goods, production services and skilled manpower and *iii*) knowledge spillover between adjacent firms. Marshallian externalities are therefore more suitable to explain "small scale" agglomeration phenomena, such as the emergence of Industrial Districts, that is spatial clusters of firms operating in the same (mainly traditional) industry (for example, clothing or footwear). Unfortunately, we do not have detailed information on the specific industry where the new plant operates so that we are only able to count the total number of manufacturing foreign investments in the regions. In turn, we are forced to consider only the role of urbanization externalities[4] which we model using four different variables: 1) the size of the regional market, 2) the overall employment density in the manufacturing sector, 3) the degree of sectoral diversification and 4) the level of road infrastructures.

(corporate tax, labour market institutions, bureaucratic efficiency and corruption, legal system and intellectual property right protection, product market regulation and openness to FDI) on regions' performance in attracting foreign investors (Basile et al. 2006; Barrios et al., 2008). Finally, European policies (such as the Structural and Cohesion funds allocated to EU laggard regions) can also be important factors affecting the attractiveness of a location (Basile et al., 2008). Unfortunately, comparable data on institutional variables are not be available for all the regions in our sample.

[4] It is worth mentioning that there exist some empirical evidence that urbanization economies outweigh industry-specific localisation economies (Guimarães et al. 2000, Arauzo-Carod and Liviano, 2007).

The *size of regional market* (measured by the log of total value added) is intended to capture externalities which have to do with the "*home market effect*". As first noted by Krugman (1980), under increasing returns to scale and in presence of transport costs, the appeal of a country (or region) as a production site depends crucially on the size of its domestic market. Firms will locate in the region where they can exploit economies of scale to a greater extent and, eventually, export to neighbouring regions.

Employment density in manufacturing (measured as total manufacturing employment per square km) represents the scale of agglomeration economies. We expect that regions with higher density of economic activity attract more foreign investments due to agglomeration effects. However, the occurrence of congestion costs (including higher land prices, higher crime rates, environmental pollution, traffic jams, excess commuting and so on) may compensate the positive effect of agglomeration economies and, thus, determine a threshold effect in the positive impact of employment density. In other words, regions tend to attract foreign investors if, *ceteris paribus,* agglomeration economies overcome congestion costs. Therefore, a nonlinear effect of employment density on the number of inward foreign investments is expected. Some empirical studies upfront assume an inverted-U shaped relationship between agglomeration and location, thereby inserting the measure of agglomeration economies squared as additional regressor (Viladecans-Marsal, 2004; Arauzo-Carod, 2005). Although it is the easiest way to deal with such a nonlinearity in a parametric framework, this is only one of many possible nonlinear parameterizations. In particular, this specification assumes that at some point congestion costs would be higher than positive agglomeration externalities so that an increase in employment density would discourage new investments.

Sectoral diversification within regions (measured by the median of the sectoral specialization indexes[5]) is meant to capture urbanization externalities deriving from diversity or variety of the regional economy (*Jacobs externalities*). According to Jacobs (1969), a diverse sectoral structure increases the chances of interaction, generation, replication, modification and recombination of ideas and applications across different industries. Moreover, a diverse industrial structure protects a region from volatile demand and offers the possibility to switch between input substitutes.

The extent of *road infrastructures* (kilometres of motorways per squared kilometres) should pick up the component of urbanization economies due to the provision of *public goods*. A higher level of public goods (in particular infrastructures) is likely to increase firm productivity and to reduce transport costs, lowering the cost of inputs sourced and facilitating the access to markets. The ensuing increase in private returns to investments makes locations with better infrastructure provisions more attractive for both domestic and foreign investments.

3.2. Labour market characteristics

The role of labour market characteristics as a determinant of inward foreign investments and new plant creation is well established (Friedman et al., 1992). In this paper we follow previous literature by specifying the regional labour market characteristics using three different variables: the average *wages* (measured by the total compensation to labour divided by the number of employees in the region), *labour availability* (approximated by the

[5] The specialisation index for each sector *s* and region *i* is the following employment location quotient: $S_{si} = (E_{si} / \sum_s E_{si}) / (\sum_i E_{si} / \sum_i \sum_s E_{si})$, where E denotes employment. The median of S_{si} is a measure of the number of sectors in which a region shows a revealed comparative advantage: when the median is high it means that a region has a comparative advantage in a large number of sectors and it is therefore diversified; when the median is low, it means that a region is specialized (see De Benedictis and Tamberi, 2004).

unemployment rate) and *human capital* endowment (approximated by the share of population aged 24 or more holding a tertiary education degree). The impact of wages and unemployment is not univocal, however. Lower wages may in fact attract firms seeking lower labor costs (that is firms pursuing *cost reducing strategies*), but high wages may signal highly skilled workers which in turn attract location of higher value added activities. Furthermore, firms may interpret unemployment both as a measure of a large supply of labor, which would attract firms, and as an indicator of a relatively rigid labor market, which would discourage them. In sum, the effects of basic labor market conditions may be in principle characterized by some nonlinearities which should be properly accounted for when modeling foreign investors location decisions.

4. Modelling regional inward foreign investment counts: a geoadditive negative binomial model

The empirical literature on foreign firms' location choice usually appeals to discrete-choice models (conditional, nested and mixed logit models) based on the Random Utility Maximization (RUM) framework. Decision probabilities are therefore modelled in a partial equilibrium setting where foreign firms maximize profits subject to uncertainty that derives from unobservable characteristics. The use of discrete choice models is often hindered by the large dimension of the choice set (in our case 249 regions) which makes estimation very burdensome, however. An alternative modelling strategy aggregates data at the elementary choice level by counting the number of times a given alternative is chosen (i.e. the number of investments in each region) leading to discrete, non-negative integer valued dependent variables (so-called count data). Under relatively mild conditions, the coefficients of a Poisson regression can be proven to be equivalent to those of a conditional logit model

(Guimaraes et al., 2004). Therefore, also the Poisson regression model can be thought as being directly derived from a RUM process.

The Poisson regression model can be accommodated as a special case of the Generalized Linear Model (GLM) framework (McCullagh and Nelder, 1989). Let *y*, be the dependent variable, X a $k \times 1$ vector of explanatory variables and β a $k \times 1$ vector of regression parameters. The canonical smooth monotonic *link function* in the Poisson GLM is

$$g(\mu) = \log(\mu) = \eta = X^{'}\beta\,; \quad \mu = E(y)\,; \qquad y = Poi(\mu) \quad (1)$$

resulting in a log-linear relationship between mean and linear predictor. A characteristic of the Poisson regression model is the assumption of equidispersion, that is $\mu = E(y) = Var(y)$[6].

In practice, however, the classical Poisson regression model is often of limited use in a regional location analysis since empirical inward foreign investment counts typically exhibit over-dispersion, i.e. $Var(y) > E(y)$. A way of dealing with over-dispersed count data is to assume a negative binomial (NB) distribution for $y \mid X$ which can arise as a gamma mixture of Poisson distributions. One parameterization of its probability density function is

$$P\left(Y = y \mid X^{'}\beta, \theta\right) = \frac{\Gamma(y+\theta)}{\Gamma(\theta)\cdot y!} \cdot \left(\frac{\mu}{\mu+\theta}\right)^{y} \cdot \left(\frac{\theta}{\mu+\theta}\right)^{\theta} \quad (2)$$

[6] It is worth mentioning that for GLM, maximum likelihood estimation (MLE) by a Newton type method can expressed as an Iteratively Re-weighted Least Squares (IRLS) scheme.

with mean μ and shape parameter θ (an index of over-dispersion) following a gamma distribution with parameters *a* an *b*, $\Gamma(a,b)$. The variance function is now $V(\mu)=\mu+\mu^2\theta^{-1}$. Note that, for large θ, the model approaches the Poisson model.

A large number of studies on regional inward foreign investment counts have used the standard NB regression model with cross sectional data (Kogut and Chang, 1991; Zhou et al., 2002; Coughlin and Segev, 2000; Barry et al., 2003; De Propis et al., 2005; Arauzo-Carod and Viladecans-Marsal, 2007) or random effects extensions of NB regression for panel data Blonigen (1997), Basile (2004) and Basile et al. (2006) [7]. [8]

A limit of this recent literature on inward foreign investment counts is the assumption that all regions obey a common linear specification of the location model, disregarding likely nonlinearities reflecting spatial heterogeneity in the behaviour of economic agents. In particular, as stated above, we cannot disregard possible threshold effects in the impact of agglomeration externalities on regional attractiveness.

Nonlinearities can be addressed in different ways. Firstly, polynomial expansions up to a cubic can be considered within a GLM approach. Although rather easy to implement, this solution might introduce severe multicollinearity. Secondly, Geographically Weighted Regression (GWR) models represent a standard method to properly handle spatial

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[7] For a detailed description of these and other works, see Arauzo-Carod et al. (2010).

[8] Although negative binomial models capture overdispersion quite well, they are not always sufficient for modelling excess zeros. To overcome this problem, zero-augmented models that incorporate a second model component capturing zero counts have been proposed. Zero-inflation models (Lambert, 1992) are mixture models that combine a count component and a point mass at zero. Hurdle models (Mullahy, 1986) instead combine a left-truncated count component with a right-censored hurdle component. Applications of these models to FDI location analyses are in Tadesse and Ryan (2004), Basile (2004), Tomlin (2000) and Iannizzotto and Miller (2002).

instability problems. However, as far as we know, there are no extensions of GWR models for overdispersed data. A third solution, that will be considered in this paper, is the Generalized Additive Model (GAM) taking advantage of the recent development of a Negative Binomial Additive Model (NB-GAM) to handle Negative Binomial responses (Thurston et al., 2000).

The GAM framework (Hastie and Tibshirani, 1990) extends the GLM by allowing nonlinearity in the relationship between η and the covariates:

$$\eta = g(\mu) = X^{'*}\beta^* + f_1(x_1) + \ldots + f_2(x_2) + f_3(x_3, x_4) + \varepsilon \qquad (3)$$

$$\varepsilon \sim N(0, \sigma_\varepsilon^2) \qquad \mu = E(Y) \qquad Y \sim negbin(\mu, \theta) \qquad \theta \sim \Gamma(a, b)$$

where $f_j(.)$ are unknown smooth functions of the covariates, $X^{'*}$ is a vector of strictly parametric components and β^* is corresponding parameter vector.

Each univariate smooth term in (3) can be represented as $f_j(x_j) = \sum_{k=1}^{K_j} \beta_{jk} b_{jk}(x_j)$, where the $b_{jk}(x_j)$ are known basis functions, while the β_{jk} are unknown parameters to be estimated. One or more measures of '*wiggliness*' $\beta_j^{'}\mathbf{S}_j\beta_j$, where $\mathbf{S}_j$ are positive semidefinite matrices, is associated with each smooth function. Typically, the wiggliness measure evaluates something like the univariate spline penalty $\int f_j^{''}(x_j)^2 dx$ or its thin-plate spline generalization (Wood, 2006a). The penalized spline base-learners can be extended to two or more dimensions to handle interactions. Specifically, Wood (2006a) recommends to use thin-plate regression splines for smooth interactions of quantities measured in the same units (such as the spatial coordinates) and tensor products for smooth interactions of quantities measured in different units.

Given bases for each smooth term, model (3) can be re-written as a GLM, $g\{\mu\} = X^{'}\beta$ where X includes the columns X^{*} and columns representing the basis functions evaluated at the covariate values, while β contains β^{*} and all the smooth coefficient vectors β_j. The model is estimated by minimizing the penalized deviance:

$$D(\beta) + \sum_j \lambda_j \beta^{'} \mathbf{S}_j \beta \qquad (4)$$

with respect to β, where λ_j are positive smoothing parameters and $D(\beta) = 2\{l_s - l(\beta)\}\phi$ is the model deviance, with l the log-likelihood, l_s the saturated log-likelihood, and ϕ the scale parameter.

Penalized maximum likelihood estimation MLE is performed by Penalized Iteratively Re-weighted Least Squares (PIRLS). Let $\hat{\beta}$ and $\hat{\mu}$ be current best estimates, pseudo value - $z = g^{'}(\hat{\mu})(y - \hat{\mu}) + X\hat{\beta}$ - and weights - $W = \left\{V(\hat{\mu})g^{'}(\hat{\mu})^2\right\}^{-1}$ - are firstly computed. Then, the weighted penalized least square problem of minimizing $\left\|\sqrt{W}(z - X\beta)\right\|^2 + \sum_j \lambda_j \beta^{'} \mathbf{S}_j \beta$ w.r.t. β is solved to obtain the updated $\hat{\beta}$ and $\hat{\mu}$. Iterating these two steps to convergence leads to the penalized likelihood maximizing estimates.

Given λ_j, therefore, computing the estimates $\hat{\beta}_\lambda$ is straightforward. But λ_j are unknown and must be estimated. Woods (2006a, 2008) has proposed different methods for automatic and integrated smoothing parameters selection. The first one is called "*performed iteration*", a grid search provides estimates for λ_j at each PIRL step based on Generalised Cross Validation (GCV). In this case, the parameter θ is chosen in order to ensure that the estimate of the scale parameter is as close as possible to 1, the value that the scale parameter should have. With the second method, termed "*outer iteration*", the scale parameter is set to 1 and a selection criterion for λ_j and for θ is defined to optimize them directly by minimizing the Akaike Information Criterion (AIC). In this case, the PIRL scheme is iterated to convergence for each trial set of smoothing parameters and AIC scores are only evaluated on convergence; optimization is then "outer" to the PIRLS loop. Finally, within the "*outer iteration*" method, it is possible to resort to Restricted Maximum Likelihood (REML), instead of the AIC, due to the possibility of rewriting the penalized GAM as a generalized mixed model (see, Wood, 2006b; Ruppert et al. 2003; Kammann and Wand, 2003). Simulation results suggest that the REML method offers some improvement in mean-square error performance relative to GCV and AIC in most cases (Wood, 2011). Wood has implemented these techniques in the R package *mgcv*.

Both GLM and GAM assume that the errors are independent. In regional location analysis the assumption of spatial independence is often violated, however. As shown in Section 2, indeed, investments from multinational firms tend to cluster over space and this does not necessarily reflect the distribution of observed explanatory variables. Spatial autocorrelation may indeed occur (and should be controlled for when specifying a location model) when unobserved variables are spatially correlated. For example, a number of factors related to culture, policy actions (incentives, corporate taxes and other institutional characteristics) and various forms of amenities can affect the regional attractiveness. Unfortunately, these factors are often either unobservable or cannot be properly measured, especially in samples composed of a lot of small geographical units (as in our case). In so far as these variables are spatially correlated, the residuals will be spatially correlated too.

The issue of spatially correlated unobserved variables can be solved in many ways, among which the most diffused one in the empirical economic literature is the application of spatial econometrics tools (Anselin, 1988; LeSage and Pace, 2009). While the use of spatial lag and/or spatial error models to the analysis of industrial location would be desirable due to their useful interpretation in terms of spatial externalities (Anselin, 2004)[9], there are no extensions of spatial econometrics tools to semiparametric additive models with non-Gaussian response variables.[10] Thus, an alternative solution to account for spatial effects is to extend the GAM framework by incorporating the spatial location as an additional covariate, that is by including the bivariate smooth term of longitude (*northing*) and latitude (*easting*), $h(no, e)$ in model (3), thus generating what is known as the Geostatistical Additive Model (in our case Geo-NB-GAM):[11]

$$\eta = g(\mu) = X^{\prime *}\beta^{*} + f_1(x_1) + \ldots + f_2(x_2) + f_3(x_3, x_4) + h(no, e) + \varepsilon \qquad (5)$$

$$\varepsilon \sim N(0, \sigma_{\varepsilon}^{2}) \qquad \mu = E(Y) \qquad Y \sim negbin(\mu, \theta) \qquad \theta \sim \Gamma(a, b)$$

Geoadditive models are widely used in environmental studies and in epidemiology (see, *i.a.*, Kelvyn and Wrigley, 1995; Kammann and Wand, 2003; Augustin et al. 2009), but are rarely considered for modelling economic data, and, to the best of our knowledge, this is the first application to the location of industrial plants.

5. Evidence from parametric and semi-parametric regressions

In this section we present the results of our econometric analysis. First, the results from a standard GLM results will be illustrated, and then the we highlight to what extent

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9 Example of spatial econometric methods to FDI location models are in Coughlin and Segev (2000), Blonigen et al. (2007), Baltagi et al. (2007, 2008). All these articles adopt a parametric approach, thereby neglecting possible nonlinearities.

10 A semiparametric extension of the spatial lag model in presence of Gaussian responses has been proposed in Basile (2009) and Basile and Girardi (2010).

11 As emphasised in Wood (2003), the spatial term can be estimated using a low-rank thin plate regression spline.

estimating a GAM and a Geo-GAM, which allow for nonlinearities and controlling for spatial dependence, affects the results.

5.1 GLM estimation results

Table 1 reports coefficients and standard errors (in parenthesis) estimated with parametric GLMs. The dependent variable is the regional number of greenfield investment projects from foreign multinationals directed to each region over the 2003-2007 period. As discussed in Section 3, the explanatory variables are *mkt* (the market size, approximated by the regional total value added), *infra* (a measure of transport infrastructure), *Jacobs* (a proxy for Jacobs externalities), *empdens* (the employment density in manufacturing), *wage* (the average labour cost), *ur* (the regional unemployment rate) and *ter* (the level of tertiary education).[12] All coefficients turn out to be statistically significant and with the expected sign both in the Poisson and in the NB regression models. Since all variables are in logarithms, coefficients can be interpreted as elasticities. First, the positive coefficient associated to *mkt* confirms that foreign firms concentrate where demand is highest and possibly serve smaller markets via exporting. Second, the expected number of foreign greenfields increases with the density of transport infrastructures. Third, Jacobs externalities have a strong positive effect, indicating that a more diversified regional economy is conductive of new foreign firms. Fourth, a higher employment density increases the expected number of greenfield investments into the region. Therefore, on average, it seems that congestion costs are more than counteracted by agglomeration externalities. Finally, high wages seem to discourage foreign investments, while high regional unemployment and tertiary education attract foreign investors.

- **Insert Table 1 about here** -

Table 1 also reports some diagnostics tests and measures of goodness of fit. The value of the Akaike Information Criterion clearly works in favour of the NB model. The NB model seems to perform rather well both against the Poisson model, in that is able to account for over-dispersion[13], and against a Zero-Inflated NB model (ZINB) and a Hurdle model, as the null hypothesis of no excess of zeros with respect to the prediction of the NB distribution cannot be rejected.[14] To assess the extent of spatial autocorrelation, we regress the vector of residuals on a spatial trend surface ($res = f(no, e) + \zeta$) and compute an F-test for the overall significance of this smooth term. As Table 1 shows, the GLM models display significant spatial dependence[15].

5.2 GAM estimation results

Tables 2 and 3 summarize the results of different semiparametric GAMs. As a first step, we estimate a nonparametric model where all covariates are allowed for possibly nonlinear effects (Table 2). Although we have some theoretical priors about the functional form of

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12 See the appendix for a thorough definition of the variables.

13 The over-dispersion test is based on the estimation of the simple nonparametric model $|e| = f(y) + u$, where $|e|$ is the absolute value of the residuals of the GLM and y is the vector of fitted values. Under the null hypothesis of equi-dispersion, the smooth term $f(y)$ must be estimated with one degree of freedom and, according to a F test, it should have an insignificant effect on $|e|$ (see, Thurston et al., 2000).

14 As the standard ZINB is not-nested in the NB model, a Vuong test is applied. This test calculates the logarithm of the ratio of the conditional probability of the dependent variable, conditional on the independent variables, for two alternative distribution hypotheses. In our case, the Vuong test statistic proves to be not significant, so that the existence of zero-inflation can be excluded. The Wald test for the NB against an Hurdle model also points towards the use of the NB model.

the relationship between inward investments and some explanatory variables (see Section 3), we prefer to be agnostic about which covariate should enter the model linearly. Therefore, we specify all terms non-parametrically (using cubic regression splines) and test for which variable a parametric specification could not be rejected. This test is based on the Effective Degrees of Freedom (*edf*, henceforth) estimated for each smooth function. If the *edf* is equal to 1, a linear relationship cannot be rejected. However, in order to assess the robustness of the results of the linearity test, we compare the evidences obtained from the three different methods for automatic smoothing parameter choice recalled in Section 4: *i*) GCV, *ii*) AIC and *iii*) REML. The evidence clearly reveals that the *edf* is equal to 1 for *Jacobs, infra* and *ter* regardless of the method used for estimation, while mixed results emerge for *ur* and *mkt*. Since the AIC values of the three models are almost equal, in statistical terms the three models are equivalent. Considering the relatively small size of our sample (249 observations), we believe that a more parsimonious strategy, which minimizes the number of non-parametric terms, has some advantages. Thus, we decided to rely on the REML results and assume a linear parametric form for the effect of *ur* and *mkt*. Finally, since the *edf* is always higher than 1 in the case of *empdens* and *wage*, these two variables undoubtedly enter the model non-linearly.

- **Insert Table 2 about here** -

Given this evidence, in Table 3 we estimate two semiparametric models with all liner terms but for *wage* and *empdens* using REML. In the first specification, we do not introduce any control for spatial effects, whereas the second model introduces the smooth interaction

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[15] As a robustness check, we also computed the Moran test and the presence of spatial correlation is confirmed. However, it should be born in mind that no studies have investigated how accurately this test detects spatial autocorrelation in GLM and GAM errors.

between latitude and longitude (specified using a thin plate regression spline) to capture nonlinear spatial trends. As measured by the AIC, the fit of the more parsimonious model is not worse than the fully non-parametric specifications presented in Table 2. Thus, we are reassured that some terms could enter linearly. At the same time, the AIC of the GAM is much lower than the for the GLM (presented in Table 1), suggesting that indeed allowing for non-linearity in *empdens* and *wage* improves the model fit, It also worth noticing, , that the Geo-NB-GAM encompasses all the other models. Moreover, diagnostics on the residuals, reported in Table 3 reveal that spatial dependence is still significant in the GAM, and only in the Geoadditive model, where the spatial trend surface is included, residuals are purged from spatial dependence. In other words, even controlling for a number of key regional characteristics and allowing for some non-linearities, we are not able to explain all of the actual clustering of foreign investments in European regions. This suggests that some unobserved characteristics may still affect the location patterns. We will return on this issue later in this section.

- **Insert Table 3 about here** -

The upper part of Table 3 reports the estimated parameters and standard error for the parametric terms. Despite the fact that the magnitude of most coefficients do change from the GLM to the GAM and Geo-GAM, they keep the same sign and statistical significance. Thus, our results suggest that controlling for non-linearities and spatial dependence do help reducing some bias in standard GLM estimates, but in this case, the bias is not as strong to induce a wrong interpretation of the effects of our location determinants,

The middle part of the Table reports χ^2-tests and p-values for the overall significance of the smooth terms for *wage* and *empdens*, as well as their *edf*. Low values of the

χ^2-test imply a high probability that the estimated smooth term is not different from zero, while as stated above *edf* is a measure of its nonlinearity. Results from both models support the hypothesis that both *wage* and *empdens* are statistically significant determinants in the location of new foreign-owned plants in European regions and that their relationship with the number of new investments is nonlinear. The spatial smoothing term, $h(no, e)$, is also highly significant, suggesting the presence of a geographical pattern in regional location of foreign investments in Europe even after controlling for all the other covariates.

Figure 3 shows the smoothed partial effects of *wage* (Panel A) and *empdens* (Panel B) on the expected number of foreign investments estimated through the Geo-GAM. The shaded areas highlight the 95% confidence intervals. The wage-plot (Panel A) suggests that regions with low average labour costs tend to attract more foreign investments, after controlling for the other variables. However, the effect of a wage drop appears higher for intermediate wages levels and decreases in regions with either very low or very high wages. This latter results is consistent with the idea that in high-end regions the wage rate does not only captures labour cost, but also proxies for its quality. Thus, an increase in wages may not discourage multinationals after all.

As for *empdens,* the graph in Panel B of Figure 4 shows that the expected number of inward foreign investments increases with the employment density in manufacturing, up to a point where the relation becomes basically flat and not significantly different from zero. This is consistent with the hypothesis that a more dense industrial activity can exert a positive externality which promotes the location of foreign firms but, when the level of agglomeration becomes too high, congestion costs kick-in and gradually reduce the magnitude of the positive externality, up to the point where an increase in employment density as no further effect on foreign entries. It should be noted that, in our sample, the relationship between employment density and location of foreign plants is nonlinear but does not appear to be inverted-U shaped, as most studies using parametric specifications had anticipated. In fact, an inverted-U relation would predict that investments would eventually decline for very high values of *empdens*, whereas our smoothing function does not show such a declining pattern.

- **Insert Figure 3 about here** -

Finally, Figure 4 displays the perspective (Panel A) and the map (Panel B) plot of the geographical components of the geoadditive model. The plots show that, after controlling for the most relevant variables and allowing for nonlinearities, there are still some unexplained clusters of foreign investments in the north England and in Ireland and, to a lesser extent, in Spain and in Portugal. This evidence can be interpreted in the light of the quite effective policies to attract foreign investors that some national and regional institutions have adopted. Due to the lack of comparable information across countries and regions on policies towards foreign investors, we cannot account explicitly for the different effectiveness of such policies. However, these unobserved regional characteristics are picked up by the spatial trend surface, so from a statistical point of view, in our Geo-GAM the omission of these variables does not lead to biased estimates.. It is worth mentioning, that if we compare the plots in Figure 2 (where we did not control for any regional characteristic) with those in Figure 4, we notice that the strong clustering in Eastern European countries, which was evident in Figure 2, has almost vanished in Figure 4, suggesting that it can be explained mainly by the explanatory variables (most likely the wage rate).

- **Insert Figure 4 about here** -

6. Conclusions

This paper contributes to the extensive literature on the determinants of industrial location by addressing two largely unexplored issues: spatial clustering and nonlinearities. Using data on greenfield projects in the NUTS-2 European regions, we have estimated first a semiparametric count data models and then a geoadditive one. The use of these models presents some advantage over standard parametric models which neglect spatial correlation. First, the estimated parameters of the variables entering linearly the models can have some remarkable change in magnitude with respect their parametric counterparts. In other terms, failing to take into account non linearities and spatial correlation might lead to biased estimates. Beyond this, the use of these models allows us to highlight the role of spatial correlation and nonlinearities. As for the former, it cannot be fully accounted for in our sample spatial by several spatially varying covariates, such as urbanization externalities and labour market characteristics. The use of a geoadditive model for overdispersed count data incorporating a spatial trend surface, not only is able to purge spatial correlation in the residuals but also allows us to show that, after controlling for the most relevant variables, some relevant clusters of foreign investors in the UK, Ireland, Spain and Portugal still emerge. Not surprisingly, these countries are also those that have introduced many policy actions to attract foreign firms' investments within their regional development strategies. However, the introduction of the additive geographical component prevents these unobserved variables to bias the results. Finally, we have also been able to identify some important nonlinearities. In particular, we have provided evidence that, in line with theoretical predictions, the effect of agglomeration economies fades as the density of economic activities reaches some limit value.

To sum up, our result do suggest that the use of these flexible and general models has some clear advantages over those traditionally employed in the analysis of industrial location. Given the availability of ready-to-use routines, a widespread use of these models is to be welcomed.

Appendix: definition of explanatory variables

- ***Market size***: log of total value added in the region (source: Cambridge Econometrics).
- ***Jacobs externalities***: median specialisation index for each sector *i* and region *j*. Each sectoral index is calculated as the following employment location quotient: $S_{ij} = (E_{ij} / \sum_i E_{ij}) \big/ (\sum_j E_{ij} / \sum_j \sum_i E_{ij})$, where E denotes employment (source: Cambridge Econometrics)
- ***Employment density:*** number of people employed in the manufacturing industry per km^2.
- ***Public infrastructure:*** Length of highways and other roads network (in kilometres) divided by total population in the region.
- ***Tertiary education:*** share of adults (population aged 25-64) with tertiary education (ISCE97 codes 5 and 6) averaged over the 1999-2002 period (source: Eurostat). For the regions DE41 and DE42 data on tertiary education were available only for the years 2004 and 2005.
- ***Labour cost***. Source: Cambridge Econometrics. For German and UK NUTS2 regions, for which data are available only at the NUTS1 level, we have attributed the value of the NUTS1 they belong to.
- ***Unemployment rate***. Source: Cambridge Econometrics.

Since we estimated the effect of all these variables over the 2003-2007 period, we used – if possible – all explanatory variables averaged over the 2000-2002.

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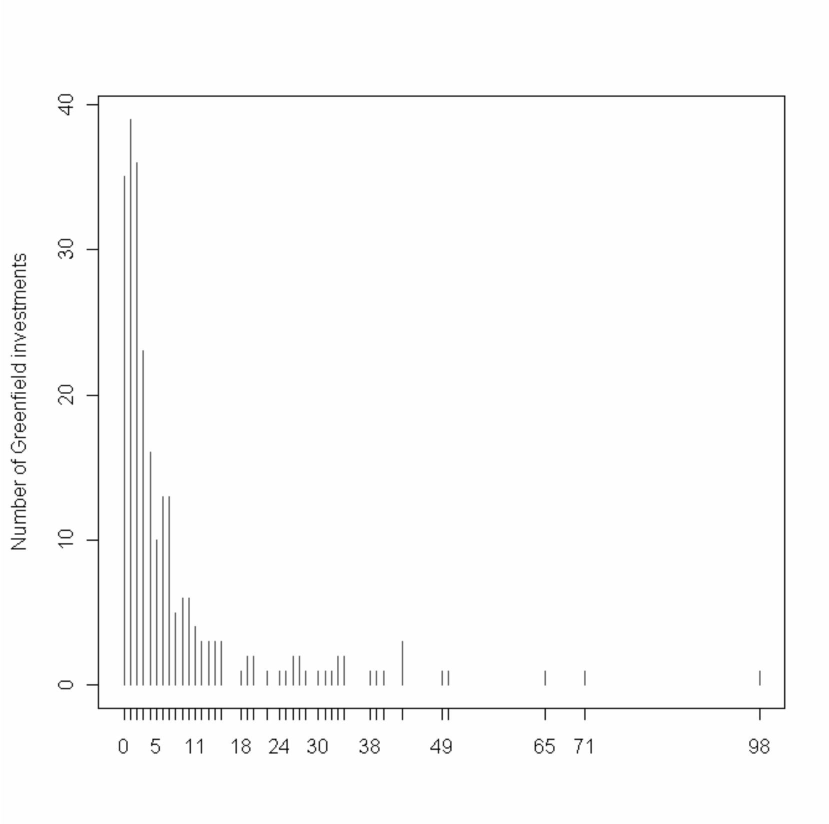
Figure 1 – Regional distribution of foreign investments in the European Union

A – Hystogram



B – Circle map

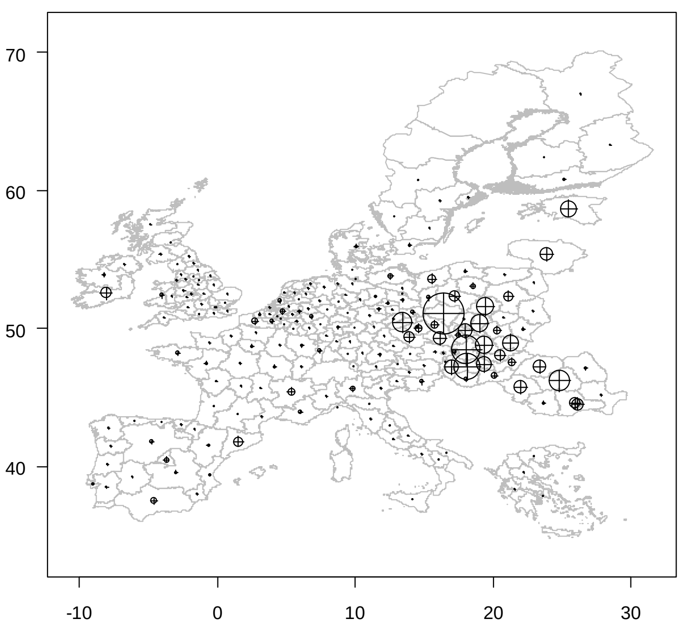
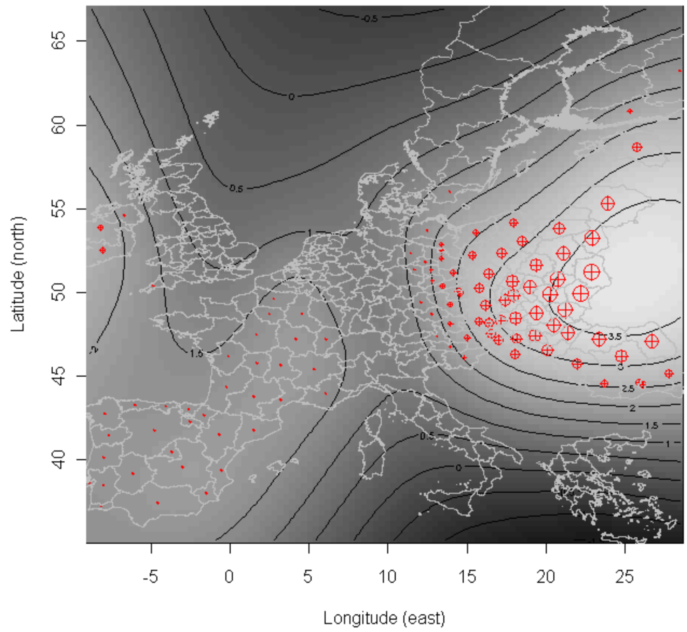


Figure 2 – Smooth trend surface of foreign investments in the European Union

A - Map plot



B – Fit perspective plot

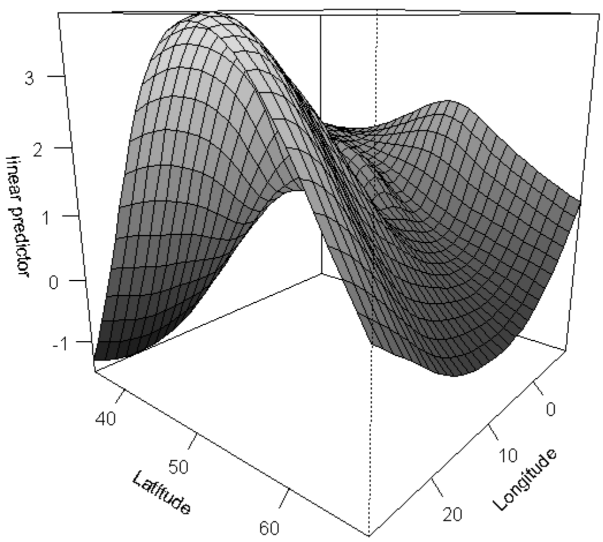
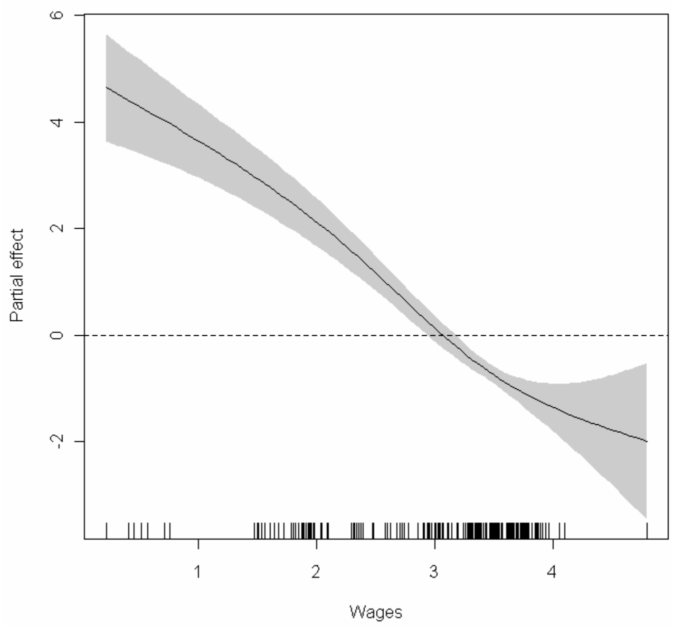


Figure 3 – Smooth effects in the semiparametric Geo-GAM

A – Wages



B – Employment density

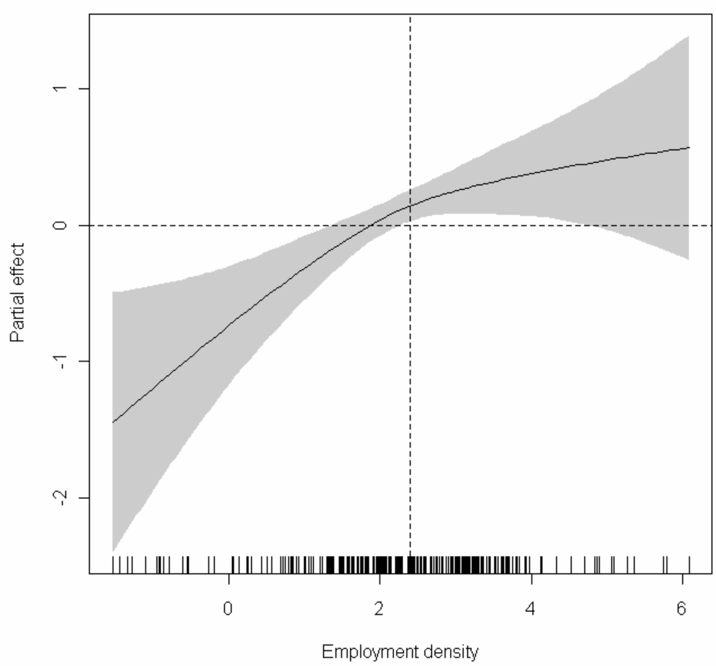
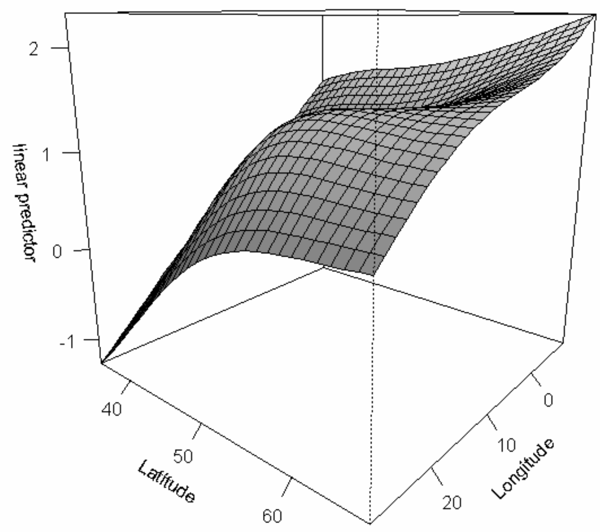


Figure 4 – Geographical components of geoadditive model

A – Perspective plot



B – Map plot

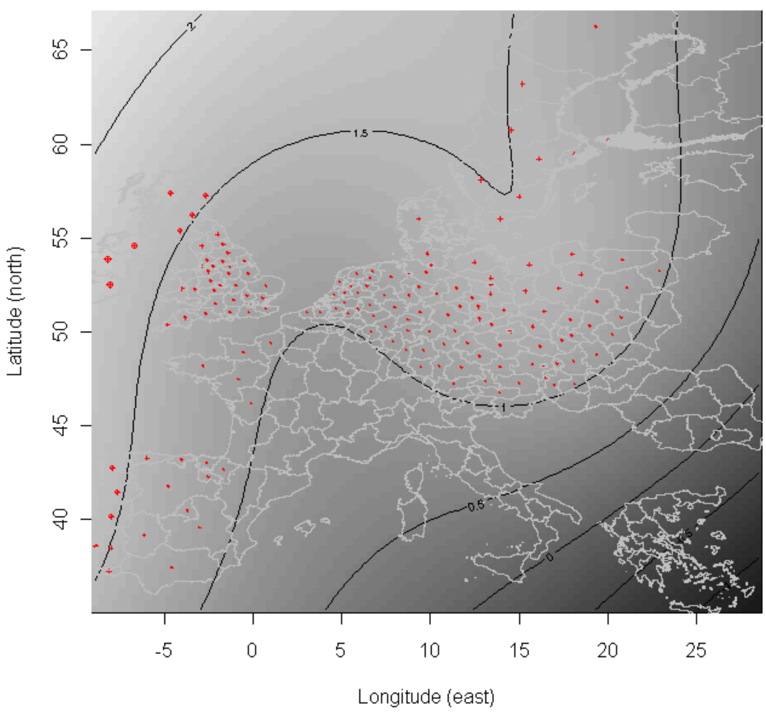


Table 1 – GLM results

	Poisson	**Negative Binomial**
mkt	0.349***	0.522***
	(0.037)	(0.098)
infra	0.329***	0.305***
	(0.033)	(0.087)
Jacobs	1.263***	1.295***
	(0.151)	(0.380)
empdens	0.422***	0.351***
	(0.030)	(0.075)
wage	-1.232***	-1.576***
	(0.046)	(0.146)
ur	0.520***	0.309**
	(0.042)	(0.130)
ter	0.452***	0.669***
	(0.067)	(0.203)
AIC	2,078	1,335
Over-dispersion	10.390	0.031
	[0.000]	[0.860]
Spatial dependence	2.449	2.215
	[0.000]	[0.002]
$\hat{\theta}$		1.183
Vuong		0.309
		[0.378]
Wald-Hurdle		0.281
		[0.998]

Notes: The over-dispersion test is based on the F test of the overall ("approximate") significance of smooth term $f(y)$ in the nonparametric estimation of absolute residuals, $|e|$, on fitted values, y. Spatial dependence is assessed by means of an F-test on the overall significance of a bivariate smooth term of longitude and latitude in explaining the residuals ($res = f(no, e) + \zeta$). $\hat{\theta}$ is the estimated NB shape parameter. Vuong is a non-nested hypothesis test statistic asymptotically distributed $N(0,1)$ under the null that the models ZINB and NB are indistinguishable. Wald-Hurdle tests the null hypothesis that no-zero-hurdle is required in hurdle regression models for count data. The same set of regressors is used in the hurdle model for both the count component and the zero hurdle component. Standard errors are in parentheses and p-values are in square brackets.

Table 2 - Nonparametric NB-GAM results

		Performance. iteration (GCV)	Outer iteration (AIC)	Outer iteration (REML)
Nonparametric terms		F *test and p-values*	χ^2 *test and p-values*	
$f(mkt)$		13.113***	47.432***	42.234***
	Edf	2.658	2.810	1.000
$f(infra)$		8.996***	10.852***	9.859***
	Edf	1.000	1.000	1.000
$f(Jacobs)$		7.164***	8.385***	7.375***
	Edf	1.000	1.000	1.000
$f(empdens)$		7.309***	25.344***	27.383***
	Edf	2.688	2.668	2.855
$f(wage)$		33.298***	132.983***	149.513***
	Edf	3.080	2.999	3.089
$f(ur)$		4.735**	8.087**	5.178**
	Edf	1.000	2.547	1.000
$f(ter)$		9.235***	17.350***	18.121***
	Edf	1.476	1.426	1.390
AIC		1,308	1,306	1,307
Over-dispersion		0.161	0.277	0.123
		[0.689]	[0.599]	[0.726]
Spatial dependence		2.370	2.264	2.289
		[0.000]	[0.001]	[0.000]
$\hat{\theta}$		1.672	2.070	1.867

Notes: F and χ^2 tests are used to investigate the overall ("approximate") significance of smooth terms. *Edf* (effective degrees of freedom) reflect the flexibility of the model. An *Edf* equals to 1 suggests that the smooth term can be approximated by a linear term. In such cases, parametric terms have been used. Standard errors are in round parentheses and p-values are in square brackets. The over-dispersion test is based on the F test of the overall ("approximate") significance of smooth term $f(y)$ in the nonparametric estimation of absolute residuals, $|e|$, on fitted values, y. Spatial dependence is assessed by means of an F-test on the overall significance of a bivariate smooth term of longitude and latitude in explaining the residuals $(res = f(no,e) + \zeta)$. $\hat{\theta}$ is the estimated NB shape parameter.

Table 3 - Semiparametric NB-GAM results

		Semiparametric GAM	***Semiparametric Geo-GAM***
Parametric Terms		*Coefficients and standard errors*	
mkt		0.586***	0.622***
		(0.090)	(0.092)
infra		0.256***	0.249***
		(0.080)	(0.086)
Jacobs		0.938***	1.056***
		(0.342)	(0.327)
ur		0.267**	0.260**
		(0.118)	(0.113)
ter		0.737***	0.672***
		(0.180)	(0.190)
Nonparametric terms		χ^2 *test and p-values*	
$f(empdens)$		27.290***	11.330**
	Edf	2.851	2.213
$f(wage)$		149.410***	114.690***
	Edf	3.085	2.719
$f(lat,long)$			38.560***
	Edf		4.592
REML		656.6	646.4
AIC		1,307	1,281
Over-dispersion		0.155	1.608
		[0.695]	[0.206]
Spatial dependence		2.294	0.931
		[0.000]	[0.550]
$\hat{\theta}$		1.862	2.113

Notes: F and χ^2 tests are used to investigate the overall ("approximate") significance of smooth terms. *Edf* (effective degrees of freedom) reflect the flexibility of the model. An *Edf* equals to 1 suggests that the smooth term can be approximated by a linear term. In such cases, parametric terms have been used. Standard errors are in round parentheses and p-values are in square brackets. The over-dispersion test is based on the F test of the overall ("approximate") significance of smooth term $f(y)$ in the nonparametric estimation of absolute residuals, $|e|$, on fitted values, y. Spatial dependence is assessed by means of an F-test on the overall significance of a bivariate smooth term of longitude and latitude in explaining the residuals $(res = f(no,e)+\zeta)$. $\hat{\theta}$ is the estimated NB shape parameter.

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